SIMULATION OF THE GAME FOR A THREE-DIMENSIONAL ANALYSIS DURING BLOCK JUMP-LANDINGS IN VOLLEYBALL AND ITS POSSIBLE IMPLICATIONS IN LOWER LIMB INJURIES. "SAVIA" PROJECT

DOCTORAL PROGRAMME IN BIOMEDICINE
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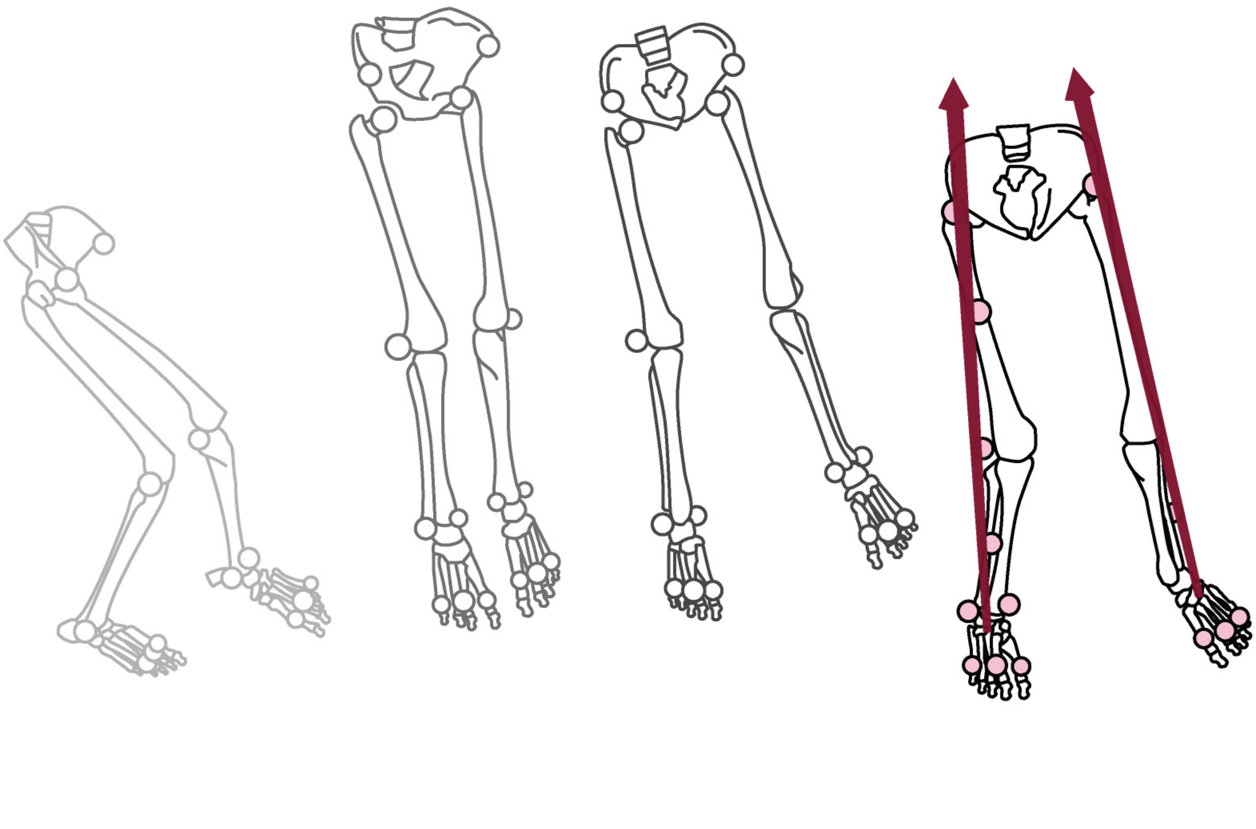

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Simulation of the game for a three-dimensional analysis during block jump-landings in volleyball and its possible implications in lower limb injuries. “SAVIA” Project.

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"***Los locos abren*** *los* ***caminos*** *que más tarde recorren los* ***sabios.***"

Carlo Dossi

A mi familia y a la familia que se elige.

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Abbreviations

- **ACC**: accuracy
- **ACL**: anterior cruciate ligament
- **AI**: Artificial Intelligence
- **ANN**: Artificial Neural Network
- **CAST**: Calibrated anatomical system technique
- **FIVB**: International Federation Volleyball
- **GCS**: Global coordinate system
- **ISB**: International Society of Biomechanics
- **LCS**: Local coordinate system
- **QTM**: Qualisys Track Manager
- **RF**: Random Forest
- **SAVIA**: Specific Actions of Volleyball Injury Avoidance
- **TS**: Taboo Search
- **VGRF**: Vertical Ground Reaction Force

Resumen

El motivo de estudio de la presente Tesis Doctoral Internacional fue analizar la técnica del aterrizaje durante el bloqueo de voleibol mediante la simulación de situaciones cercanas al juego real. A partir de aquí, la dominancia de la dirección del salto de aterrizaje en bloqueo, el papel de las piernas y las situaciones planificadas y no planificadas fueron estudiadas para analizar cómo afectan a las estrategias de movimiento de las extremidades inferiores. De esta manera, fueron identificados posibles factores que afectan al rendimiento y que podrían estar asociados con las lesiones más comunes de las extremidades inferiores. Por consiguiente, el principal objetivo fue proporcionar información que enriquezca a la revisión de los modelos de aprendizaje técnico y al entrenamiento físico y preventivo en los aterrizajes en bloqueo de voleibol.

Así pues, se investigaron las estrategias de movimiento entre la pierna dominante y no dominante durante los aterrizajes del salto de bloqueo en voleibol, cuando las jugadoras se movían en dirección dominante y no dominante, y sus piernas desempeñaban el papel de líder o de arrastrada, tanto para situaciones planificadas como no planificadas. Variables cinemáticas y cinéticas de las articulaciones del tobillo, de la rodilla y de la cadera dominante y no dominante fueron registradas en 376 aterrizajes durante bloqueos realizados por catorce jugadoras de categoría nacional senior de voleibol. Se realizaron pruebas de análisis de varianza de medidas repetidas (ANOVA). Aparte, se usaron dos métodos de Aprendizaje Automático ("Machine Learning"), Redes Neuronales Artificiales y Random Forest, con los que se generaron modelos a partir de los datos. El conjunto de datos se dividió en dos partes: entrenamiento y prueba, a través de un proceso de muestreo aleatorio. Como pre-procesamiento previo a la construcción de los modelos, se realizó una selección de características. Adicionalmente, también se utilizaron árboles de decisión para detectar qué variables eran más relevantes para discernir las estrategias de movimiento entre las piernas que lideran y las que son arrastradas y cuando realizan el mismo papel.

Los resultados experimentales mostraron diferencias estadísticamente significativas entre la pierna que lidera y la que es arrastrada: para la cadera en los ángulos de flexión, momentos y velocidad angular; para la rodilla en ángulos de flexión, momentos, rigidez, potencia y absorción de energía; y para el tobillo en la dorsiflexión y absorción de potencia y energía. Todas estas diferencias muestran una tendencia a que la pierna que lidera parece tener una relación más alta con los factores de lesión que la pierna arrastrada. Al considerar situaciones planificadas versus no planificadas, hubo diferencias estadísticamente significativas para la rodilla en

los ángulos de flexión, momentos, potencia y absorción de energía; y para la cadera en el ángulo de contacto, velocidad angular de flexión y absorción de energía. Parece ser que las diferencias muestran una ligera tendencia a que quizás hay una mayor relación con los factores de lesión en las situaciones planificadas. Adicionalmente, se observaron diferencias al comparar las estrategias de movimiento entre la pierna que lidera y la que arrastra al moverse hacia la dirección dominante con una precisión predictiva del 97% y al moverse hacia la dirección no dominante con una precisión predictiva del 94%. Pero, además, al comparar entre piernas cuando se mueven en las diferentes direcciones, pero desempeñando el mismo papel, ya sea el de líder o el de arrastrada, se observaron diferencias en la estrategia de movimiento con una precisión predictiva superior al 96% y 97%, respectivamente. Del mismo modo, cuando analizamos qué variables fueron más relevantes para discernir las estrategias de movimiento entre las piernas en todas las condiciones, el plano coronal y transversal tuvieron una mayor influencia.

Los resultados de esta Tesis Doctoral Internacional sugieren que las situaciones planificadas, no se corresponden con la realidad del juego, ya que podrían tender a generar más estrés músculo-esquelético que las no planificadas. Además, más que las diferencias entre la pierna dominante o no dominante, existen diferencias dependiendo del papel que desempeñan, ya que la pierna que lidera parece tener más estrés músculo-esquelético que la pierna arrastrada, tal vez debido a un aumento en la carga. Por lo tanto, esto podría darnos información relevante sobre cómo mejorar el rendimiento de los jugadores y cómo planificar el entrenamiento para evitar una sobrecarga que podría conllevar a un mayor riesgo de lesión. Finalmente, también nos hace cuestionarnos los modelos de aprendizaje, si las variables que se han considerado hasta ahora en la biomecánica realmente son las más relevantes, y si el uso de técnicas de Aprendizaje Automático podría cambiar el paradigma a la hora de interpretar las estrategias de movimiento de las piernas y el riesgo de lesión en acciones específicas del deporte.

Abstract

The overall aim of the present International Doctoral Thesis is to analyse the landing technique during a volleyball three-step block approach simulating natural game conditions. Therefore, the dominance direction of the block jump-landing, limb role and planned and unplanned situations were studied to determine how limb movement strategies were affected. In this way, possible factors that affect performance can be identified and could be associated with the most common lower limb injuries. Thus, the principal objective is providing information that would enrich the review of technical learning models and physical and preventative training in volleyball block jump-landings.

Therefore, movement strategies between the dominant and non-dominant limb during block jump-landings in volleyball were analysed, when players were moving to the dominant and non-dominant sides and when the limbs performed the lead and trail limb role, for both planned and unplanned situations. Kinematic and kinetics variables for the dominant and non-dominant ankle, knee and hip joints were recorded from 376 block jump-landings performed by fourteen female senior national volleyball players. Repeated measures analysis of variance (ANOVA) test were used. Additionally, Machine Learning techniques were applied to build models, namely, Artificial Neural Networks (ANN) and Random Forests (RF). The dataset was divided into training data and test data, through a random sampling process. As a pre-processing step a feature selection was carried out. Moreover, decision trees were also used to detect which variables were relevant to discern the strategies between the lead and trail limbs.

The results showed statistically significant differences between the lead limb and the trail limb in the hip flexion angles, moments and velocity; in the knee flexion angles, moments, stiffness, power and energy absorption; and in the ankle dorsiflexion, power and energy absorption. All these factors showed a tendency where the lead limb seems to have a higher relationship with injury factors than the trail limb. When considering planned versus unplanned situations, there were statistically significant differences in knee flexion angles, moments, power and energy absorption; and hip contact angle, flexion angular velocity and energy absorption. All these differences may suggest a slightly greater relationship with injury factors in the planned situations. Additionally, differences were seen when comparing the movement strategies between the lead and trail limb when moving to the dominant direction with a predictive accuracy of 97% and when moving to the non-dominant direction with a predictive accuracy of 94%. In

addition, when comparing between limbs when moving in the different directions but performing the same role as the lead or trail limbs, differences in movement strategy were seen with a predictive accuracy over 96% and 97%, respectively. Likewise, when it was analysed which variables were more relevant to discern the movement strategies between limbs in all conditions the coronal and transverse plane had a greater influence.

The findings from this International Doctoral Thesis, suggest that planned situations, apart from being away from a real game situation, may generate more musculoskeletal stress than unplanned situations. Moreover, as well as differences between dominant or non-dominant limbs, there are differences depending on the role which the limb performs, with the lead limb having more musculoskeletal stress than the trail limb, perhaps due to an increase in load. Therefore, this could provide relevant information about how to improve the performance of the players and how to plan the training in order to avoid an overload that could lead to risk of injury. Finally, it also raises questions about the learning model and if the variables that have been considered so far in science really are the most relevant and if the use of Machine Learning techniques could change the paradigm in the way of interpreting the risk of injury in sport-specific actions.

GENERAL INTRODUCTION

The importance of block jump-landings

When volleyball players are performing block jump-landings, their principal objective is trying to block the attack, and therefore they need to be as fast as their opponents to have success. Additionally, they have to be coordinated with their own team and get ready to jump as fast as possible at any moment in any direction, which depends on how the opponents organize their attack strategy. Therefore, the unplanned situations of the game combined with the necessity to perform directional movements and the high velocity of them produces a great demand on the musculoskeletal system [1]. The harmful components within the high repetition of specific actions could cause lower performance in competition and even cause injuries that would incapacitate the player. Injuries appear to occur most often just after the initial contact with the ground or during passive loading when the impact peak occurs [2]. Due to all these reasons, this International Doctoral Thesis focussed on landings after block jumps.

Efficiency in the block jump approach

When a block jump-landing is performed, depending on the direction of movement each limb has a specific role position. To differentiate between limb roles, it was defined the lead limb as the exterior limb during the landing with the trail limb being the interior limb. Previous studies have compared different footwork techniques for the lateral movement approach in volleyball blocking. Cox et al. [3] compared the two principal footwork approaches:

1. **The slide step**: where the lead foot moves laterally and the trail foot follows close to the leading foot, whilst maintaining a front facing position of the body with respect to the net.
2. **The cross over step**: where the lead foot performs a short slide in the direction of movement, followed by the trail foot crossing over the lead foot followed by the lead foot crossing back.

It was demonstrated that the cross over step was better in terms of getting the blocker off the ground and getting into a better blocking position quickly [3]. In this way, a slightly rotation during the jump allowed a higher performance.

The impact of automatisms of the spike approach in directional jumps

When a volleyball player is trying to get the greatest spike performance, they use a three-step approach which is determined by the dominant hand which performs the hit [3]. In this way, players are used to landing with their non-dominant limb when they are performing a spike. Therefore, we have considered the dominant direction for the block jump-landing as the direction in which players have the same approach as in a spike approach. For example, for a right-handed player, the usual three-step approach during a spike should be left-right-left, which should be the same sequence as a block jump-landing when moving to the right side (moving from zone III to zone IV), and thus moving in the dominant direction (**Figure 1**). Contrarily, if the player is moving to the opposite direction (moving from zone III to zone II) during a block, their usual three-step approach should be right-left-right, and thus moving in the non-dominant direction. In **Figure 2**, the court zones can be seen. Therefore, the direction of the block jump-landing will vary within the game situation, resulting in a change to their normal three-step technique when moving in the non-dominant direction, which in turn will affect the jump-landing movement strategy. This can produce different motor patterns between limbs during jump-landing, and subsequently highlights possible asymmetries in strength and balance [4].

Figure 1. *Spike approach footwork sequence for a right-handed player. Extracted from Valadés et al. [5]*

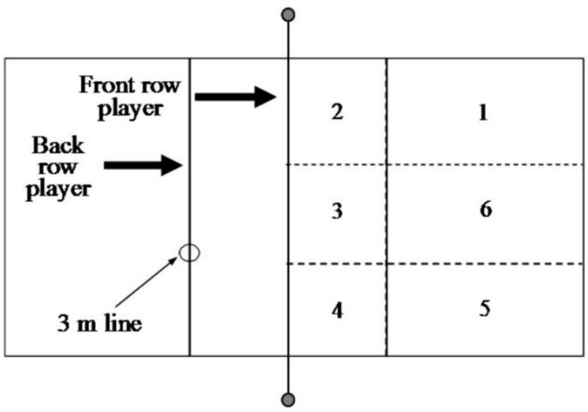

Figure 2. *Volleyball court zones. Extracted by Palao et al. [6]*

Muscle imbalances have been shown to be useful in the identification of athletes at risk of lower limb injuries. These may be associated with strength differences [7] side to side differences due to incomplete or improper recovery from an injury [8, 9] or repetitive limb use [4]. Muscle loading patterns experienced around the knee may alter the balance of strength under high velocity conditions [4]. However, little is known regarding the influence that limb preference or playing position may have on lower-extremity muscle strength and asymmetry [7].

Therefore, in order to improve the performance in elite players it is fundamentally important to provide efficiently designed training and preventative programs which allow the coaches and trainers to promote balanced motor patterns through a correct sport technique. This could minimize imbalance between limbs to might reduce injury risks.

Overuse injuries and risk factors in volleyball

The analysis of sports performance is a field of study of great relevance in interaction sports, since it allows us to understand the factors that govern the game in elite teams. One of the characteristics of volleyball is that there is no direct interaction with the rival team, therefore the majority of injuries are caused by the repetitive solicitation generated during practice, favouring overload and the appearance of lesions in various anatomical structures [10]. These factors are therefore key to this field of study and map to all our objectives.

Volleyball is considered one of the most popular sports in the world, with approximately more than 800 million participants. There is a significant incidence of injuries in this sport of four injuries per 1000 hours played [11]. It has been reported that the hip, knee and ankle are the most commonly injured joints in volleyball [12], with the knee representing the highest percentage of lower limb injuries in the physically active population [13], with the main cause being overuse or joint overload. It has also been reported that females are more frequently affected by traumatic and knee overuse injuries [14]. In addition, knee problems represent a significant part of primary health care and is therefore a financial burden to health services [15].

The paradigm of high performance has evolved to integrate the need to protect the athlete and prevent the harmful components within the high repetition of specific skills. The identification of risk factors that predispose it to the appearance of sports injuries could facilitate their prevention [1]. However, it has been considered that the orientation of prevention programs is limited by a lack of understanding of the specific risk factors that influence injuries within different sports [16].

Injury risk factors

In chronic injuries, abnormal frontal plane loading has been reported to be the inciting factor that can lead to injury [17]. This is characterised by an abduction moment which is often attributed to excessive hip abduction and internal rotation, often caused by a decrease in the ability of the hip musculature to absorb energy/force during the deceleration phase of landing tasks [18]. Injury to the anterior cruciate ligament (ACL) is one of the most devastating and frequent injuries of the knee [19]. In volleyball, ACL injuries can occur when landing from a jump, for example when players move from the middle of the court to block a spike [20]. A knee flexion angle of less than 30 degrees has also been shown to increase the ACL load during landing [21], with the highest peak load occurring approximately 40ms after landing [22]. Additionally, stiff landings can be characterized by an initial contact with the ground with the joints of the lower limb being in a flexed position, which is followed by only small amounts of additional flexion during the deceleration phase [23]. Also, there are some factors which significantly increased ACL strain and increase the risk of ACL injury, these include greater internal or external rotations of the knee [2], a single-leg landing [24] or a higher valgus loading of the knee joint [25]. Norcross et al., [26] found a greater sagittal plane power absorption during the initial contact phase, which indicates greater ACL loading. It has also been suggested that angular velocities in all three planes may be a better measurement of lower limb control [27].

All this evidence indicates that it is highly probable that lower limb injuries are more likely to involve multi-planar rather than single-planar mechanisms [21]. Therefore, it is essential to understand the movement strategies to identify the risk factors in a real game situation to allow the development of better trainings and targeted prevention programmes.

The uncertainty of the real game

In volleyball, a player who is going to perform a block jump-landing is prepared to deal with more than one attack situation. Therefore, the player usually cannot plan in which direction they would have to move. When the player voluntarily executes the movement and plans where and when they have to move, a different situation from the real game is created.

From the motor control framework, following Poulton [28], there are two motor skills division, which have been considered for the protocol used in this Doctoral thesis:

- A "close skill" refers to allowing time for conscious planning, which would correspond with the planned situations.
- An "open skill", presented in conditions of no choice reaction time, which would correspond with the unplanned situations.

The "close skill" is presented in conditions of choice reaction time. Although the players managed to reproduce the same movement time as in the "open skill," there would be differences in the response time (Reaction Time + Movement Time) because the optomotor Integration time would be subjected to considerably greater stress than if a single stimulus were given [29]. At this point, it might be interesting to analyse the biomechanical variations in two situations, one of pressure on the peripheral nervous system (open skills or unplanned situations) or another with no demand in that regard (close skills or planned situations).

Thus, only a small change in the contextual situation can cause the player to have to modify his or her movement strategies [30]. However, the majority of studies that have considered the movement strategies during tasks associated with injury risk factors have not considered the unplanned situations and speed of the real game due to difficulties in controlling such factors in a laboratory situation [31]. Most interventions, whose principal aim is to improve motor control in order to reduce the incidence of injuries during sports games, are delivered through training using isolated tasks [32]. However, injuries very seldom occur while performing an isolated task in a predictable environment, while they occur more in unplanned environments. Leukel et al. [33] showed that muscle activation patterns are modified in unplanned situations when compared to situations where the subjects have had to plan what task they are about to execute.

The question of what an expert athlete should focus their attention on when performing their skill has long been of interest [34]. Gray et al. [35] suggested that expert athletes perform better when their attention is focused externally in comparison with when their attention is focused internally [35]. This may also be relevant when considering unplanned movements being associated with unconscious or automatic processes and planned associated with a more conscious type of control that constrains the motor system and disrupts automatic control processes, as it focuses the athlete's attention on their own body movements [36]. In addition, Podromos et al. (2008) propose that the stability of the joint through the coordination of the neuromuscular system can be defined as the ability to control movement [37].

Our hypothesis is that between planned and unplanned situations there will be no differences in movement time, but there will be in the response time, due to in the former case the player had any stimulus, and therefore this will change the limb movement strategies. In that case, this will open new questions, such as if the internal focus in the planned situations could guide the focus of attention towards body movements and not to the objective of action, or if the unplanned situations could be associated with an external focus.

Therefore, there is an interest in studying the differences between planned and unplanned situations and how this affects limb movement strategies.

From the laboratory to the field:

The biomechanical demands of training and competition are still not well understood, primarily due to the difficulty of quantifying biomechanical loads in a field environment [31]. A major issue that limits the progress in understanding biomechanical load-response pathways is that measuring it *in vivo*, remains very difficult or even impossible with the current technologies, especially in a field-based context [31]. However, the recent advances have shown the potential for real-time analysis [38]. The use of motion-capture systems, force platforms and/or electromyography synchronously seems to indirectly estimate the in vivo loads action on individual structures through musculoskeletal modelling techniques [39]. Notwithstanding, those technologies are restricted to laboratories and their analysis are laborious and time consuming [31]. However, a systematic review [40] confirms the ability to detect specific movement and position patterns for a more efficient training design and to evaluate the possible causes of injury.

Sport scientists should consider the value and limitations of biomechanical load-response and keep pursuing new methods to measure these kinematic and kinetic variables [31]. Therefore, it is essential to design and develop protocols close to the real game to better understand the movement strategies that occur in the field within and outside the laboratory.

Necessity of protocols as real as possible

Previous studies have shown that specific kinematic and kinetic variables can be associated with lower limb injury risks [41, 42] and differences in limb roles [43], although those protocols have not necessarily reflected real match situations. The majority of previous work have not considered both limbs, jumping distance, the velocity of the game, jump-landing from different directions, unplanned situations or the movement of the joints of the lower limbs in 6 degrees of freedom, due to the difficulties in simulating a real game situation within the laboratory [31]. Lobietti et al. [20] highlighted the importance of standardizing conditions including; direction, dominance, distance, and height of the jumps so that players land in a manner closer to that of during a competition. To the author's knowledge, no investigation exists which considers all these points during block jump-landings.

Therefore, a further aim of this Doctoral Thesis was to design and apply a protocol that was able to overcome the challenges of measuring all potentially biomechanical relevant variables in situations as close as possible to the real game to further understand the in vivo movements which may help our understanding of preventative strategies to mitigate against injury risk.

The use of Machine Learning in sports

The discovery of new methods and algorithms during the last few years have led the field of Artificial Intelligence (AI) towards a golden age. Advances in AI promise to be disruptive in all fields of the human sphere, such as medicine, engineering, communication, etc. A current field of active application is sports. A recent systematic review suggested that the application of AI methods in team sports has the potential to grow further and produce new insights in the predictive performance of sports practice [44].

Performance analysis in sport science has experienced considerable recent changes, due largely to the availability of improved technology and increased applications from computer science [45]. The consideration of as many relevant risk factors as possible is necessary to understand the movements during the multifactorial nature of sports injuries [46]. However, the analysis of all these variables requires the utilization of complex methods of data analysis. An imminent area in sports biomechanics that overcomes this issue is the use of advanced Machine Learning approaches to identify and/or predict biomechanical variables of interest [47]. Machine Learning is the field of AI based on methods which are able to automatically learn complex patterns inherent in a dataset and apply them to new data to predict future behaviour.

The number of papers which have used Machine Learning to gain an improved perspective of a larger number of variables and how they are related is increasing. Machine Learning has been utilised in many sports such as, Australian football, rugby, golf, swimming, running, alpine ski and bowling [48-54]. Machine Learning has also been applied to volleyball, proposing a relational-learning based approach for discovering strategies in matches based on optical tracking data [55] or even doing analysis on the physical and technical performance indicators for deciding the winning strategies of games [56].

As a result, these techniques can be applied to the classification of tasks by assigning a class or a label to new data based on what has been previously learned. Other recent systematic review demonstrated the capacity of such techniques to improve the understanding of sport movements and skill recognition, and how this can be applied to performance analysis using Machine and Deep Learning methods to automate sport-specific movement recognition [45].

This Doctoral Thesis explores the use of two Machine Learning methods: Artificial Neural Networks [57] and Random Forest [58], with the aim to classify conditions for limb dominance and jump-landing directions using kinematic and kinetic data. Additionally, a pre-processing step was carried out to perform a feature selection. This means that we were able to "open the black box" in order to analyse which variables were less or more relevant to compute the output and keeping only those that were found to be meaningful. Thus, we were able to specify which biomechanical variables had greater influence in the movement strategy for each limb and each condition, considering both dominance direction and planned/unplanned situations. Furthermore, decision trees were chosen to infer understandable rules to produce easy to understand connections between the variables and the questions [59].

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OBJETIVOS

La presente tesis doctoral centra su interés en la técnica del aterrizaje durante los bloqueos de voleibol simulando condiciones del juego. Para ello se ha estudiado principalmente cómo afecta la secuencia dominante de la batida del salto, el papel de las piernas y las condiciones de incertidumbre del juego a las diferentes estrategias de movimiento de las piernas. De esta manera, podemos identificar posibles factores que afecten al rendimiento y que podrían asociarse al riesgo de las lesiones más comunes del tren inferior. Y con ello, pretendemos enriquecer la revisión de los modelos de aprendizaje técnico y entrenamiento físico y preventivo en el bloqueo de voleibol.

Objetivos principales

Por tanto, los objetivos principales de esta Tesis Doctoral son:

1. Estudiar las diferencias entre situaciones de ejecución de bloqueo planeadas frente a las situaciones no planeadas y cómo afecta a la estrategia de movimiento de las piernas.
2. Estudiar las diferencias entre la pierna arrastrada frente la que lidera y cómo afecta a la estrategia de movimiento.
3. Estudiar las diferencias entre hacer un salto de batida en dirección dominante frente a uno no dominante y cómo afecta a la estrategia de movimiento de las piernas.
4. Diseñar y aplicar un protocolo que permita medir las variables cinemáticas y cinéticas del movimiento simulando condiciones reales del juego
5. Determinar si el uso del Aprendizaje Automático (*Machine Learning*) constituye un método de análisis capaz de identificar patrones motores durante tareas específicas del deporte.

Objetivos específicos

- Determinar las estrategias de movimiento de la pierna dominante y no dominante en situaciones planeadas del juego.
- Determinar las estrategias de movimiento de las piernas dominante y no dominante en situaciones no planeadas del juego.

- Determinar si existen diferencias entre la estrategia de movimiento de las piernas cuando la pierna dominante realiza el rol de la pierna arrastrada y la no dominante realiza el rol de la que lidera.
- Determinar si existen diferencias entre la estrategia de movimiento de las piernas cuando la pierna dominante realiza el rol de la pierna que lidera y la no dominante realiza el rol de la arrastrada.
- Determinar si existen diferencias entre moverse en dirección hacia el lado dominante y no dominante para las piernas que lideran.
- Determinar si existen diferencias entre moverse en dirección hacia el lado dominante y no dominante para las piernas arrastradas.

AIMS

The overall aim of the present Doctoral Thesis is to analyse the landing technique during a volleyball three-step block simulating natural game conditions. Therefore, we have studied how the effect of limb dominance and direction of the block jump-landing, the limb role and how the planned and unplanned situations of the game affect the limb movement strategies. In this way, we can identify possible factors that affect performance, and which could be associated with the most common lower limb injuries. Thus, we would be able to provide information that would enrich the review of technical learning models and physical and preventative training in volleyball block jump-landings.

Principal objectives

1. To investigate if there are differences between planned and unplanned situations and how these affect limb movement strategies.
2. To investigate if there are differences between the lead and trail limb and how these affect limb movement strategies.
3. To investigate if there are differences between moving to the dominant and non-dominant direction and how these affect limb movement strategies.
4. To design and develop a protocol which allows the measurement of kinematic and kinetic variables within the movement strategies in conditions as real as possible to the game.
5. To determine if the use of Machine Learning is an analysis method capable of identifying different motor patterns during sporting tasks.

Specific Objectives

- To determine the movement strategies for the dominant and non-dominant limb in planned situations.
- To determine the movement strategies for the dominant and non-dominant limb in unplanned situations.
- To determine if significant differences exist between limbs when the dominant limb performed the role of the trail limb and the non-dominant limb performed the role of the lead limb.

- To determine if significant differences exist between the dominant limb performing the role of the lead limb with the non-dominant limb performing the role of the trail limb.
- To determine if significant differences exist between movements in the dominant and non-dominant directions between the lead limbs.
- To determine if significant differences exist between movements in the dominant and non-dominant directions between the trail limbs.

METHOD

Study design and variables

The Specific Actions of Volleyball Injury Avoidance (SAVIA) project was a within-subjects design. The variables considered in this Doctoral Thesis included:

- **Limb related variables:** Two limbs were measured for each participant, so to define each limb we considered:
  - **Direction dominance:** the dominant direction was considered as the direction in which the participant performed their normal three-step approach when performing a volleyball spike.
  - **Limb role:** depending on the direction, each limb will have the role as the lead or trail limb. The lead limb was defined as the exterior limb during the jump-landing with the trail limb being the interior limb.
  - **Limb dominance:** the dominant limb was determined as the preferred leg to kick a ball [1], which was the same as the preferred arm.

These variables are interrelated, because it is possible to know the third variable depending on the other two. Our participants included thirteen right-handed and one left-handed female volleyball players. Depending on their limb dominance, we were able to calculate their dominance direction and, therefore, the limb role in each condition (**Table 1**).

Table 1. *Limbs related variables according to their limb dominance*

	Direction dominance	**Role**	**Limb**	**From zone III to**
Right-handed player	Dominant	Lead	Non-Dominant	Zone IV
		Trail	Dominant	
	Non-Dominant	Lead	Dominant	Zone II
		Trail	Non-Dominant	
Left-handed player	Dominant	Lead	Non-Dominant	Zone II
		Trail	Dominant	
	Non-Dominant	Lead	Dominant	Zone IV
		Trail	Non-Dominant	

- **Planned/Unplanned variables:** The participants were informed that they had to go at full speed and block the simulated attack in both conditions. Attacks were simulated using FitLights Trainer™ (**Figure 3**). Both planned and unplanned situations were considered before the start of the three-step block approach. In this context, planned refers to allowing time for conscious planning, whereas unplanned refers to the initiation of the block approach immediately on the cue of one of the three lights offering no time for conscious planning.

    - **Planned situations:** there was only an attack, so players knew the attack they had to block, and they started when they were ready. These situations correspond to learning exercises of the ball-free blocking technique that are frequently used in volleyball.
    - **Unplanned situations:** the player has three possible attacks which are displayed randomly and their task was to move and block them in the shortest possible time. This situation corresponds to a strategy of the game that is called "optional block" and consists of defending a "first time attack" reading blocking system (waiting to see the set) where one of the side attacks is prioritized. This tactical strategy is frequently used by middle blockers, since they have difficulty to defend serving all possible attack positions. In addition, the outside blocker can be located in a more central position to be able to defend against the “first time attack” and, if necessary, assist the side that corresponds to a “second time attack” (**Figure 4**).

Figure 3. Fitlights Trainer™ in tripods. Extracted from https://www.bernell.com/product/FTL/Sports-Vision

In **Figure 4**, above it is represented an example of a right-handed blocker in unplanned situation in front of three options of attack. The Fitlight 1 correspond with a frontal jump, the Fitlight 2 correspond with a short lateral jump and the Fitlight 3 correspond with a three-step block approach moving to the dominant direction, which is the specific action which was analysed. Below it is represented an example of a trial during competition in which the right-handed blue central blocker (in zone III) has all possibilities of attack. The "Square A" represents the three attacks moving to their non-dominant direction and the "Square B" represents the three attacks moving to the dominant direction. The two arrows inside both squares correspond with two possibilities of "first tempo attack" which likewise correspond with Fitlights 1 and 2. The lateral arrows of each square correspond with two possibilities of a "second tempo attack" which likewise correspond with the Fitlight 3, in "A" when moving to the non-dominant direction and in "B" when moving to the dominant direction.

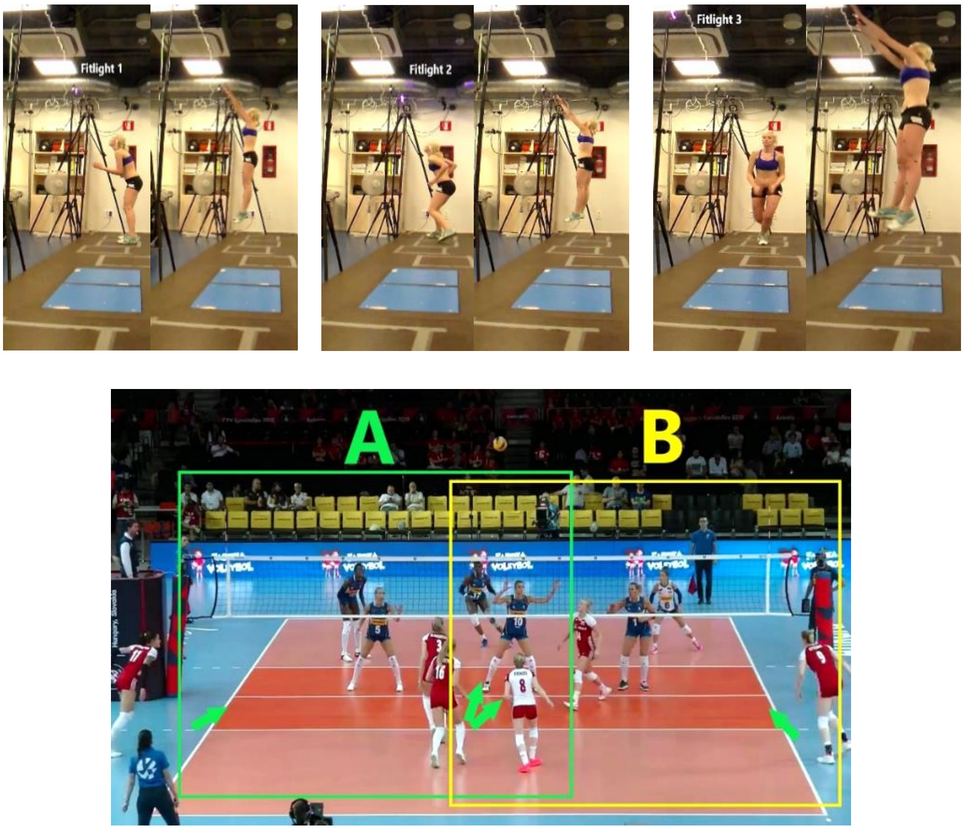


Figure 4. *Above a simulated three-step block jump-landing in an unplanned situation. Below an example of a trial during competicion.*

- **Biomechanical variables:** including kinematic and kinetic variables:
    - **Joint angles (degrees):** calculated using Visual 3D (joint_angle) for the hip, knee and ankle in all planes.
    - **Angular velocities (degrees/s)**: calculated using Visual 3D (joint_velocity) for the hip, knee and ankle in all planes.
    - **Joint moments (Nm/kg):** calculated using Visual 3D (joint_moment) for the hip, knee and ankle in all plane, with data being normalized to subject mass.
    - **Joint power absorption (J/kg):** calculated using Visual 3D (joint_power) for the hip, knee and ankle in the sagittal plane. Calculated using [Power = Moment x angular velocity].
    - **Vertical Ground Reaction Force (Newtons)**: calculated using Visual 3D (Z axis) for both force plates.
    - **Loading Rate (Newtons/s)**: calculated using Visual 3D (Z axis) for both force plates.
    - **Energy absorption:** for the hip, knee and ankle (J/kg) in the sagittal plane. Calculated as the integral of the power.
    - **Stiffness:** for the hip, knee and ankle (M/deg) in sagittal plane. Calculated by the change in normalised joint moment divided by the change of angle using the formula [$kj = \Delta M/\Delta\theta$] following Mager et al. [2].

Subjects and Ethics

Fourteen female senior national volleyball players; aged 20.43±2.17 years, height 171.24±3.3 cm, and mass 65.65±6.34 kg, who played in a national league participated in the study. The participants had no history of hip, knee or ankle surgery within the previous 6 months. This study was approved by the Ethics Committee for Human Research at the University of Granada (

Annexe I. The Ethics Committee approved for this thesis). Prior to testing, the aims of the study and the experimental procedures were explained to the participants who then signed an informed consent form (**Annexe II**. Informed consent and information for participants).

Experimental Setup

Ground reaction force data were collected at a sampling rate of 250 Hz using two force plates (9260AA Kistler Instruments, Hampshire, UK) embedded in the floor. Synchronously, an eight camera Oqus motion capture system (Qualisys, Sweden) was used to collect kinematic data at a sampling frequency of 250 Hz. Twenty-three retro-reflective markers were placed on each subject prior to data collection [3].

In order to create the unplanned jumps, participants performed a FitLight Trainer™ sequence programming protocol (Fitlight Sports Corp., Canada). This allowed a light sequence which was used as a target to create visual reaction, such as showing the blocking direction, whilst checking that the block has been made at the correct height.

Protocol

The experimental setting was based on a real game situation with the upper edge of the net set at 2.24m. To normalise the height of the jump, in unplanned situations the three Fitlight discs were suspended in the space located 0.20 m above the edge of the net and on the opponent's side of the court, which were used to simulate an attack and to determine if the block was effective [4]. Participants were asked to arrive at the net as fast as possible in both, planned and unplanned situations, with the difference that in planned situations the participant could begin when they wanted without any time pressure, allowing time for conscious planning. In unplanned situations there was uncertainty as the participants had to initiate their block movement as soon as one of the three lights was switched on, allowing no time for conscious planning of their movement. In addition, in unplanned situations, to block the three Fitlights which simulated attacks the participants had to perform: 1) a frontal jump, 2) a short lateral jump, and 3) a three-step block approach (**Figure 4**). Additionally, the time taken for a player to turn off the lights was used as a biofeedback to motivate the players, but this was not recorded. The evaluator only accepted trials when the movement was as fast as possible and additionally in unplanned situations the light was turned off. In addition, the evaluator assessed if both limbs landed on the force platforms, but care was taken to explain to the participants that they were not to target the plates. However, during the analysis with Qualisys Track Manager, the flight time of each jump in both situations was recorded and no significant differences in time were found between the planned and unplanned situations.

Each trial represents one block jump-landing and six successful jump-landings were recorded under each situation and each direction. All trials which did not accomplish these characteristics were discarded. The two force plates were embedded in the floor, and the Fitlight discs were placed so that in a normal jump the players landed on the two platforms.

The participants performed the tests in a single session during the course of 1 day. Before data collection, all subjects performed a 20 minute warm-up consisting of stretching the lower and upper extremities. Five training attempts followed the warm-up. At the start of each trial, the subject performed block jump-landings, from the left or right side, the direction of which was randomized. The participants were informed that they had to go at full speed and block the simulated attack. After each sequence a rest period of 5 minutes was allowed, and then the protocol was repeated in the opposite direction. Participants then performed block jump-landings using a blinded randomised sequence of attacks. Thus trying to simulate a real game context with block spikes from both sides, simulating moving to zone II and to zone IV of the court (**Figure 5**). Fatigue was assessed using the Borg scale (6-20) after each sequence which was controlled so that it remained under a threshold of fifteen.

Figure 5. *A right-handed player performing two block jump-landings: moving to her non-dominant direction (above) and moving to her dominant direction (below).*

In this way, the jump landing situations were as realistic as possible to increase the ecological validity of the protocol. Therefore, we were able to record 4 different conditions (**Figure 6**).

Each trial represents one block jump-landing and six successful jump-landings were recorded under each condition. An evaluator checked if the players were making the jump at maximum speed from the Fitlight data in unplanned conditions and observationally in planned conditions. However, during the analysis with Qualisys Track Manager, the flight time of each jump in both conditions were recorded and no differences in time were found between the planned and unplanned conditions. In addition, the evaluator assessed if both limbs landed on the force platforms, but care was taken to explain to the participants that they were not to target the plates. All trials which did not accomplish these characteristics were discarded. The two force plates were embedded in the floor, and the Fitlight discs were placed so that in a normal jump the players landed on the two platforms. Participants had to block in the different directions indicated by the lights.

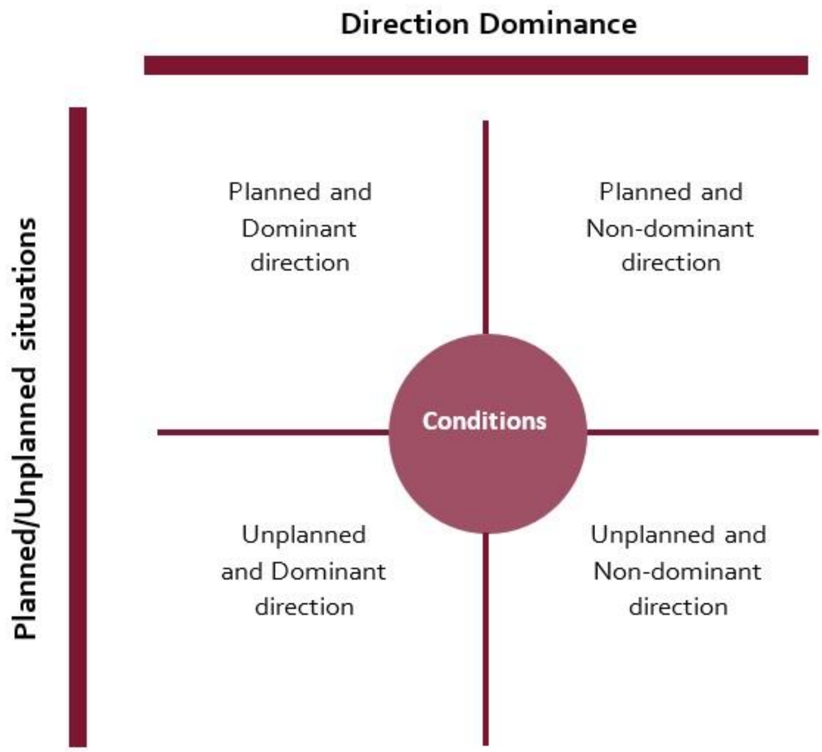


Figure 6*. All conditions of this protocol combining planned/unplanned situations and dominance direction.*

The participants performed the tests in a single session during the course of 1 day. Before data collection, all subjects performed a 20 minutes warm-up consisting of stretching the lower and upper extremities **(Table 2).** Five training attempts followed the warm-up. At the start of each trial, the subject performed a block jump-landing, from the left or right side, the direction of which was randomized. The participants were informed that they had to go at full speed and block the simulated attack. After each sequence a rest period of 5 minutes was allowed, and then the protocol was repeated in the opposite direction. Participants then performed block jump-landings using a blinded randomised sequence of attacks. Fatigue was assessed using the Borg scale (6-20) after each sequence which was controlled so that it remained under a threshold of fifteen (**Annexe III.** Borg Scale 6-20).

Table 2. *Warm-up previous to perform the protocol*

Range of motion warm-up		Dynamic Balance		Running technique
Leg raise	Lateral leg raise	Front lunge	Front lunge agrupation	Skipping
				
Stretch jump	Arms swing	Lateral lunge agrupation	Lateral lunge rotation	Short jumps with sprints
				

Data recording and processing

Calibration and synchronization for cameras and force platforms.

A system of eight infrared high-speed cameras (Qualisys, Sweden) at a rate of 250 Hz, collected the reflective marker locations. The calibration of the space was done with a wand (length of 751.1 mm) before each data collection. Qualisys Track Manager v.2.12 (QTM) was used to collect data. Moreover, two force plates where calibrated with markers and synchronized with the cameras to define the 3D coordinates in the space with an L-Frame (**Figure 7**).

Figure 7. *Calibration of the 3D coordinates in the space with an L-Frame.*

The calibrated anatomical system technique (CAST) was used to model each body segment in six degrees of freedom [5]. The CAST technique involves the identification of anatomical landmarks through external palpation of the proximal and distal areas of the body segments [6]. The lower limb model used for this current Doctoral Thesis in QTM had 23 reflective markers according with the International Society of Biomechanics (ISB) standard [3] (**Figure 8**). In order to define the anatomical reference frames of the pelvis, thigh, shank and foot segments, retroreflective markers were attached to the following: second-third metatarsal head, medial and lateral malleolus, large posterior surface of calcaneus, femoral rectus, lateral and medial femoral epicondyle, anterior superior iliac spine, coccyx and acromioclavicular joints. A model with 7 segments were built, allowing six degrees of freedom per segment.

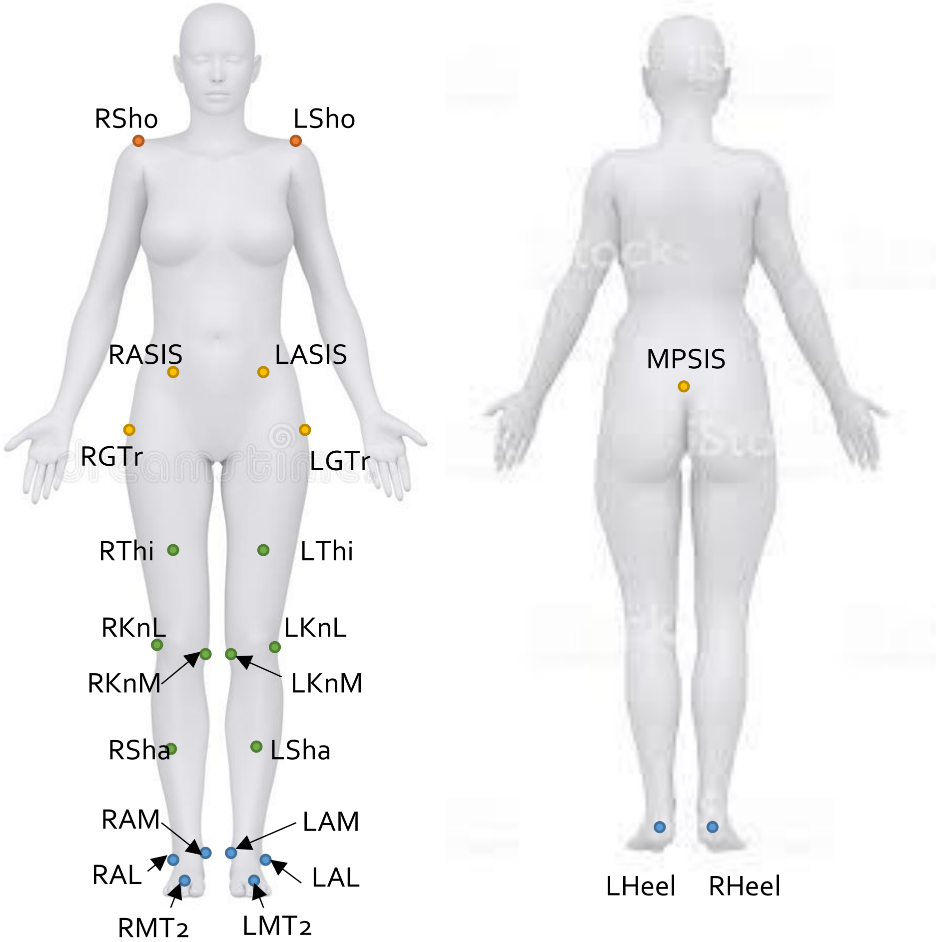


Figure 8. *"SAVIA project" markerset*

Defining anatomic terms: planes and axis

Prior to any motion capture, an anatomical position for the participant was taken, in which a person stood in an upright posture, with the feet together over the platforms and the arms by the sides of the body with the palms forwards. Through the anatomical position we were able to describe the motion of the limbs using three reference planes (**Figure 9**): the sagittal plane which divides the body into right and left sides; the frontal or coronal plane which divides the body into anterior and posterior sides; and the transverse plane which divides the body into superior and inferior sides.

An axis is an imaginary line at right angles to the plane about which the body can rotate. Flexion is a movement in the sagittal plane, which decreases the angle at the moving joint. The extension is the opposite movement, which increases the angle at the joint. Abduction and adduction are movements in the frontal plane and involve moving the body part away or towards an imaginary centre line, respectively. Rotation movements are in the transverse plane and include any twisting motion. The ankle joint has specialised movements: dorsiflexion is the flexion movement and plantarflexion is the extension movement; inversion is the movement of turning the sole of the foot inwards and eversion is the movement of turning the sole of the foot outwards. When the ankle joint realises a dorsiflexion, adduction and inversion is called supination, and when it realises an extension, abduction and eversion is called pronation.

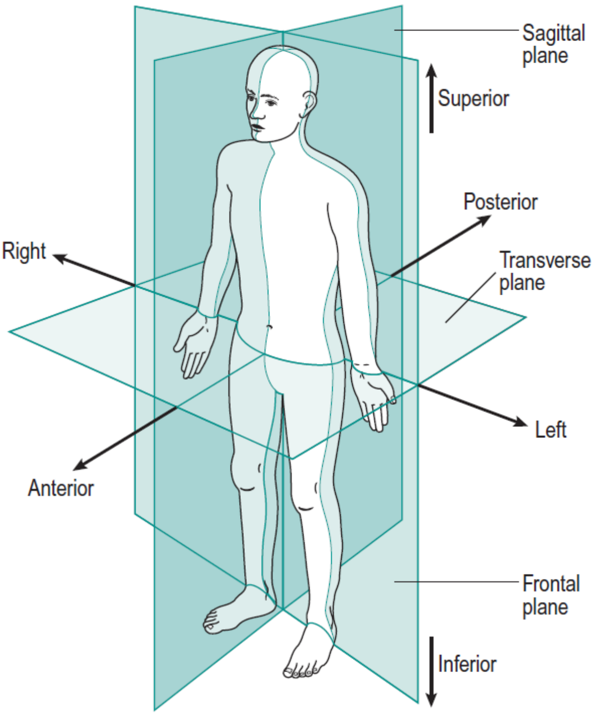
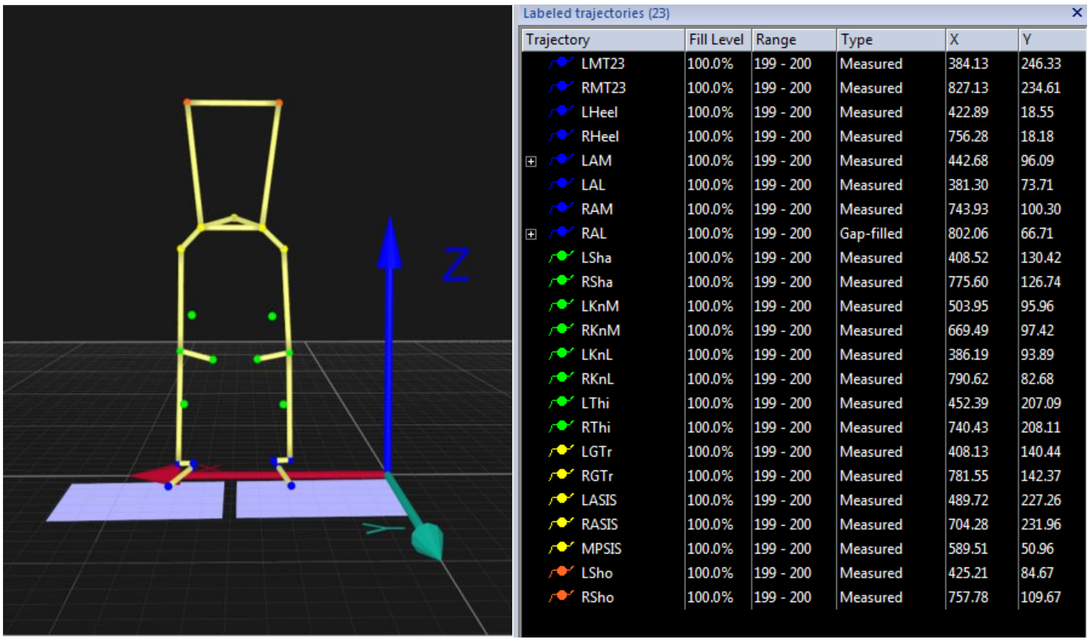


Figure 9. *Anatomical planes and axis. Extracted from Whittles, Levine and Richards [7].*

Analysing with QTM

After having collected the data, it is necessary to create the markerset in QTM and to label the markers to create trajectories (**Figure 10**). The process of labelling in QTM is semi-automatic but it is necessary to check the trajectories in all planes and sometimes to correct them if the markers became confused within the software. Once all the files were tagged and filtered, they were exported in ".c3d" files.

Additionally, during the data analysis with QTM, the flight time of each jump in planned and unplanned conditions were collected, defined as the time from the last foot in take-off before the jump to the first foot in touch the force platform while landing, and there were no significant differences in time between them.



Trajectory	Fill Level	Range	Type	X	Y
LMT23	100.0%	199 - 200	Measured	384.13	246.33
RMT23	100.0%	199 - 200	Measured	827.13	234.61
LHeel	100.0%	199 - 200	Measured	422.89	18.55
RHeel	100.0%	199 - 200	Measured	756.28	18.18
LAM	100.0%	199 - 200	Measured	442.68	96.09
LAL	100.0%	199 - 200	Measured	381.30	73.71
RAM	100.0%	199 - 200	Measured	743.93	100.30
RAL	100.0%	199 - 200	Gap-filled	802.06	66.71
LSha	100.0%	199 - 200	Measured	408.52	130.42
RSha	100.0%	199 - 200	Measured	775.60	126.74
LKnM	100.0%	199 - 200	Measured	503.95	95.96
RKnM	100.0%	199 - 200	Measured	669.49	97.42
LKnL	100.0%	199 - 200	Measured	386.19	93.89
RKnL	100.0%	199 - 200	Measured	790.62	82.68
LThi	100.0%	199 - 200	Measured	452.39	207.09
RThi	100.0%	199 - 200	Measured	740.43	208.11
LGTr	100.0%	199 - 200	Measured	408.13	140.44
RGTr	100.0%	199 - 200	Measured	781.55	142.37
LASIS	100.0%	199 - 200	Measured	489.72	227.26
RASIS	100.0%	199 - 200	Measured	704.28	231.96
MPSIS	100.0%	199 - 200	Measured	589.51	50.96
LSho	100.0%	199 - 200	Measured	425.21	84.67
RSho	100.0%	199 - 200	Measured	757.78	109.67

Figure 10. *Labelled markers and model in QTM*

Biomechanical model and coordinate systems

A biomechanical model is a collection of rigid segments. A segment's interaction with other segments is described by joint constraints permitting zero to six degrees of freedom, and subject specific scaling is defined using palpable anatomical landmarks, and those rigid segments represent skeletal structures [8]. In Visual 3D v.6.0 (C-Motion Inc., Germantown, USA) a lower limb model with 7 segments was created from a static capture, including pelvis and both thighs, shanks and feet.

The cameras and the Force Plates where calibrated and synchronized in QTM to define the axis of the global coordinate system (GCS), which refers to the capture volume in which we represent the 3D space of the motion-capture system and the coordinates of the laboratory (**Figure 11**).

Subsequently, when we defined the model, each segment was defined in Visual 3D with a local coordinate system (LCS) which moves correspondingly to the movements of the segment. The orientation of the LCS with respect to the GCS defines the orientation of the body or segment in the GCS, and it changes as the body or segment moves through the 3D space [8] (**Figure 12**).

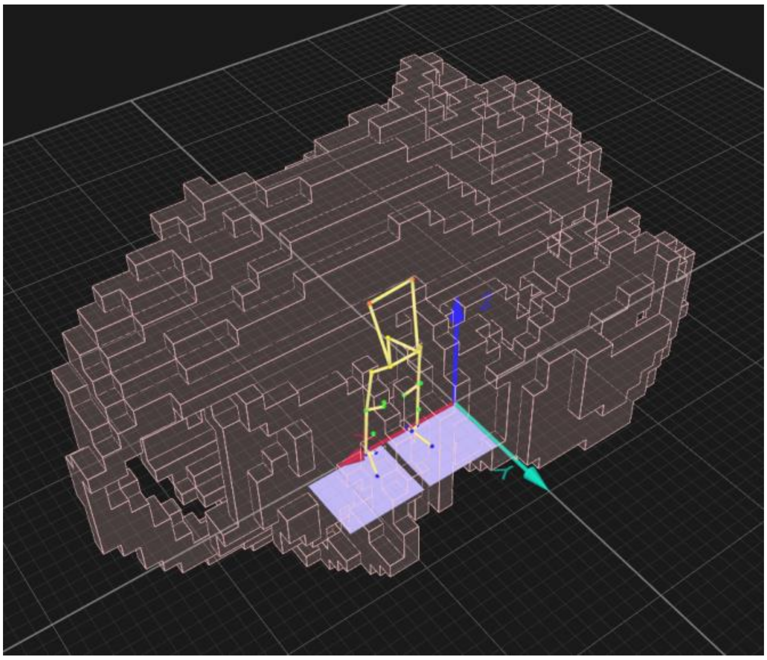


Figure 11. *Calibrated 3D space of the motion-capture system.*

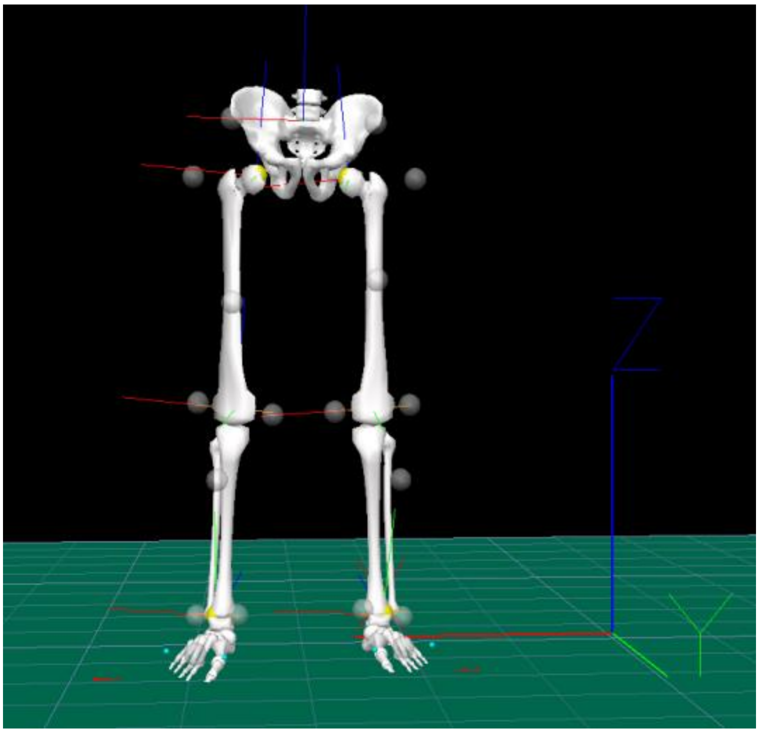


Figure 12. *Model and segment coordinate definition of each segment and the GCS in the sagittal view in Visual 3D.*

The joint centres of ankle, knee were defined as centre of the line between the medial and lateral markers of each joint. Hip joints and pelvis were calculated in a more complex way according to the works of Bell, Pedersen and Brand [9]. The pelvis segment angle was computed with its orientation relative to the laboratory. To calculate a joint angle, one segment (1) is calculated as the transformation from another segment (2) using its LCS as reference.

For the joint angle calculi, the ordered Euler/Cardan sequence of rotations (x, y, z) were selected. This Cardan rotation sequence X-Y-Z is often used in biomechanics [10]. This sequence assumes that the "X" axis is the sagittal plane, the "Y" axis is the coronal plane and the "Z" axis is the transverse plane. Therefore, these were the directions for the joints (**Table 3**):

Table 3. *X-Y-Z axis sequence in all planes for joint angle, angular velocity and moments.*

Sagittal plane	*Hip*	*+ Flexion*
		- Extension
	Knee	*+ Flexion*
		- Extension
	Ankle	*+ Dorsiflexion*
		- Plantarflexion
Coronal plane	*Hip*	*+ Abduction*
		- Adduction
	Knee	*+ Valgus*
		- Varo
	Ankle	*+ Inversion*
		- Eversion
Transverse plane	*Hip*	*+ Internal rotation*
		- External rotation
	Knee	*+ Internal rotation tibial*
		- External rotation tibial
	Ankle	*+ Abduction foot*
		- Adduction foot

The joint angles of the model were calculated using the X-Y-Z cardan sequence described above. The joint angles were computed as:

- The hip joints were calculated using the pelvis as a reference segment and the thigh. The angle interpretation in each axis is represented in **Figure 13**.

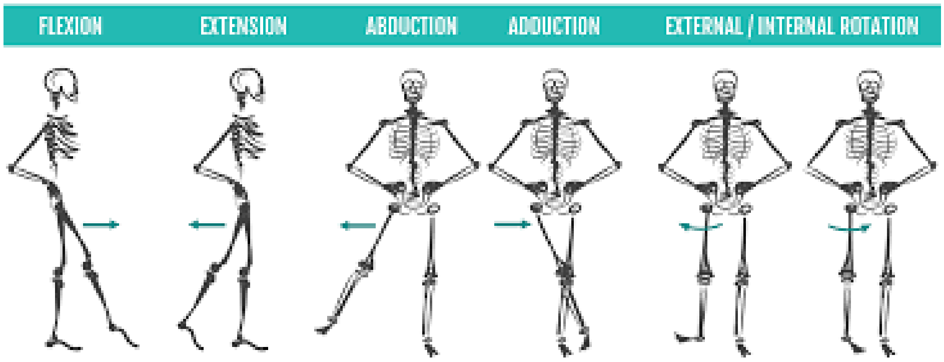


Figure 13. *Hip movements in all planes. Extracted from* https://www.pinterest.es/pin/405535141442705800/?lp=true

- The knee joints were calculated using the thigh as a reference segment and the shank. The angle interpretation in each axis is represented in **Figure 14**.

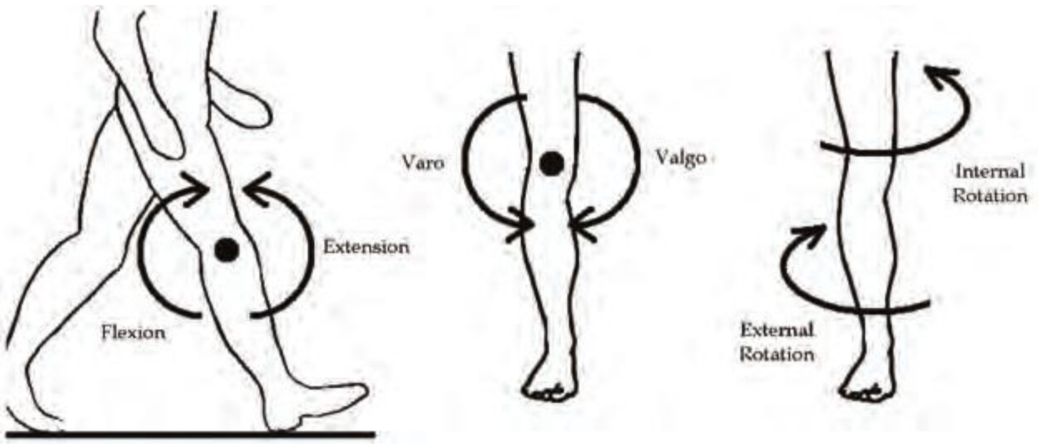


Figure 14. *Knee movements in all planes. Extracted from de Pina, Dutra & Santos [11].*

- The ankle joints were calculated using the shank as a reference segment and the virtual foot. The angle interpretation in each axis is represented in **Figure 15a**. For the ankle joint angle, a virtual foot segment was created using the heel to toe method defined by Visual 3D software. Firstly, two landmarks were created in the first and fifth metatarsal head of feet, secondly, the ankle and toe joint centres were created, after that, the virtual foot was modelled with the landmarks and joint centres created (**Figure 15b**). For the ankle joint angle calculation, the segment coordinate system of the virtual foot segment as the X axis was rotated (red axis of **Figure 15b**) representing the flexion/extension of the ankle, the Y axis (green axis of **Figure 15b**) representing the inversion/eversion, and the Z axis the abduction/adduction of the ankle (blue axis of **Figure 15b**).

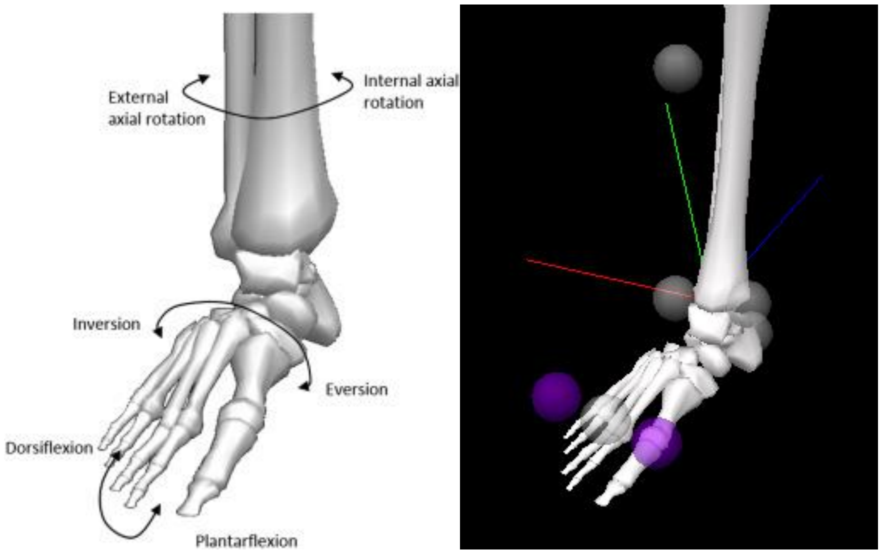


Figure 15. *(a) Ankle movement in all planes (extracted by Brockett and Chapman, 2016) [12] – (b) virtual foot created in Visual 3D.*

However, the body has two limbs (the right and left), so for one of the limbs we have to change their segment coordinate system to negate the "Y" and "Z" axis. Moreover, the "X" axis of the knee joints had also been negated to consider them as flexion when the values were positive as the hip and ankle joints. In this way, we were able to compare the data of all joints and variables.

Event detection

The start of each trial was determined by the first occurrence of a ground reaction force > 20 N on each force plate, and the end was defined by the maximum flexion of each knee. Depending on the direction of the jump-landing a different limb was used to land first, although it was usually the trail limb. Therefore, each trial was checked to detect which foot landed first. In visual 3D, if the right foot was the first to land we created the event "RON" for the contact moment with the platform and the event "MF_RKnee" for the maximum flexion angle of the right knee (**Figure 16**). As well, if the left foot was the first to land we created the event "LON" for the contact moment with the platform and the event "MF_LKnee" for the maximum flexion angle of the left knee.

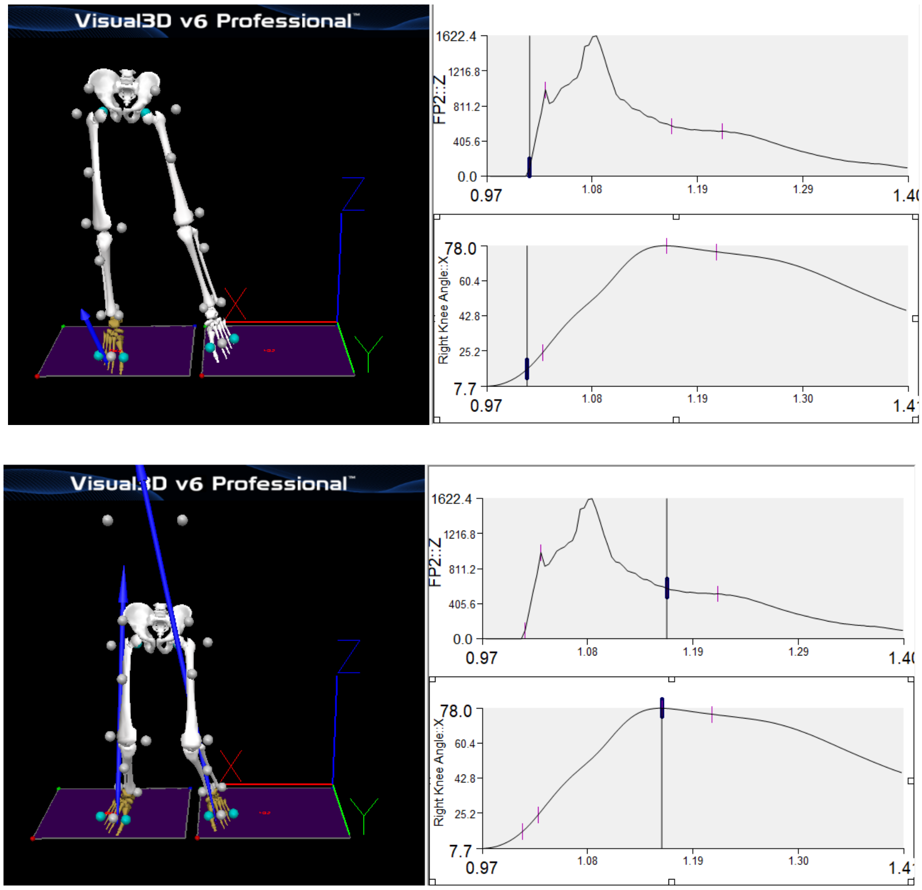


Figure 16. *Example of a landing from the platform contact to the maximum flexion of the knee and the representation in the VGRF and sagittal plane of the knee graphs.*

Data and statistical analysis

The marker data were processed using QTM and exported into ".c3d" format to Visual3D which was used to calculate the three-dimensional ankle, knee and hip kinetics and kinematics. From Visual 3D a pipeline was created to export all data to a data base in excel.

For this Doctoral Thesis, traditional statistics and Machine Learning methods have been applied to answer the proposed objectives:

For the **objective 1**, which was to investigate if there are differences between planned and unplanned situations and how affect to limb movement strategies, we performed:

- **Traditional statistic:** 2 x 2 repeated measures analysis of variance (ANOVA) tests were used to explore the differences between dominant/non-dominant limbs and planned/unplanned situations. All the data showed a normal distribution according to the Shapiro-Wilks test.
  We found statistical differences in some variables.
- **Machine Learning methods:** two Machine Learning methods were used to generate the models from the dataset, ANN and RF. These were used to classify differences between conditions for limb dominance and planned/unplanned situations from the kinematic and kinetic data.
  The accuracy of the models when we compared between planned and unplanned were not high, so we discarded those models. However, we had higher models when we compared between directions and limbs (**Annexe IV**. Classification of conditions in Machine Learning).

For **objective 2**, which was to investigate if there are differences between the lead and trail limb and how these are affected by different limb movement strategies, and for **objective 3**, which was to investigate if there are differences between moving to the dominant and non-dominant direction and how this is affected by different limb movement strategies:

- **Traditional statistic:** 2 x 2 repeated measures analysis of variance (ANOVA) tests were used to explore the differences between dominant/non-dominant directions and dominant/non-dominant limbs. All the data showed a normal distribution according to the Shapiro-Wilks test.
  We found statistical differences in most of the variables analysed.
- **Machine Learning methods:** two Machine Learning methods were used to generate the models from the dataset, ANN and RF. These were used to classify differences between conditions for limb dominance and limb roles from the kinematic and kinetic data.
  The accuracy of the models was higher than 94% in all our questions, so this supported the significance of traditional statistics but considering all the variables together and with a greater depth of analysis.

Machine Learning: model training and testing

The measurements of 32 variables from 376 block jump landings from both limbs were analysed between initial contact and the maximum knee flexion moment, and following Olsen et al. [13] the first Vertical Ground Reaction Force (VGRF) peak, which occurs just after the initial contact during passive loading, were selected for each trial and each limb. Data were imported into the R statistical software and transformed into a matrix of 752 rows by 32 columns. Each row was labelled according to: 1) lead or trail limb, 2) limb dominance, and 3) dominance direction.

The dataset was divided into training data (80% of the matrix) and test data (20%), through a random sampling process. The training data were used to fit and tune the Machine Learning models, while the test data were used to evaluate the performance of the fitted models. All the data features were numeric and there were no missing values. All data were normalized (centred and scaled) using the interval [0-1] for each model, where the minimum value was mapped to 0 and the maximum value to 1. The accuracy (ACC) was used to measure the performance of the models using the test data, where 1 would correspond with 100% effectivity. ACC is represented as the proportion of correctly classified instances over the total number of test instances.

Two Machine Learning methods were used to generate the models from the dataset, ANN and RF, these were used to classify differences between conditions for limb dominance and limb roles from the kinematic and kinetic data. The ANN was implemented using the *mlp* function of the *RSNNS R package*. A multilayer perceptron (fully connected feed-forward networks) with 3 layers (input, hidden and output) and sigmoid activation function was used. In addition, different sizes of the hidden layer (3, 5 and 7) and the learning rate parameter (0.1, 0.15, and 0.2) were used during the training. The RF was implemented using the *RRF* function of *the RRF R package*. The RF algorithm was used without regularization and with a variable number of trees (100, 200, 300, 400 and 500).

As a pre-processing step ahead of the actual training, a feature selection was carried out (**Annexe V**. Example of feature selection for the Question 3). A wrapper approach driven by taboo search (TS) was used (**Annexe VI.** Example of Taboo Search for the Question 3 and 4). This performed a feature selection, by discarding input variables that were not useful or were less relevant to compute the output and keeping only those that are found to be meaningful, which were the variables used in all iterations with [80-100]% average. Therefore, we were able to discern which variables had greater influence in the movement strategy for each limb in each role position when moving to the dominant and non-dominant direction. Additionally, decision trees were also used since they allow to extract understandable rules. The decision trees were adjusted using some R package (*RPART*, *party*, *C50 and tree*). The decision trees were painted based on the best model of the package with a better accuracy.

The performance of the Machine Learning methods depends on several hyperparameters, specific for each method. To select the best combination of these parameters a grid search was carried out based on a 10-fold cross-validation on the training data and the models attaining the higher average ACC values were selected. A model with these combinations of hyperparameters was then used to fit the complete training set. These were then used to perform the prediction of the classification on the test data to explore the proposed study questions.

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RESULTS AND DISCUSSION

SECTION 1. Can kinematic and kinetic differences between planned and unplanned volleyball block jump-landings be associated with injury risk factors?

Introduction

Athletes endure physiological, physical and psychological stresses, all of which can be associated with injury risks [1]. The combination of specific tasks in volleyball with fast approach movements puts a great demand on the musculoskeletal system [2]. However, prevention programs are still limited by a lack of understanding of the specific risk factors that can influence injuries within different sports [3]. The knee joint has been reported as having the highest percentage of all lower limb injuries, especially in physically active populations [4, 5], with overuse being identified as the main cause [6]. It is therefore necessary to increase our understanding about the risk factors associated with knee injuries within volleyball.

Injury to the anterior cruciate ligament (ACL) is one of the most devastating and frequent injuries of the knee [7]. In volleyball, ACL injuries can occur when landing from a jump, for example when players move from the middle of the court to block a spike [8]. Stiff landings can be characterized by an initial contact with the ground with the joints of the lower limb being in a flexed position, which is followed by only small amounts of additional flexion during the deceleration phase [9]. A knee flexion angle of less than 30 degrees has also been shown to increase the ACL load during landing [10], with the highest peak load occurring approximately 40 ms after landing [11]. Also, there are some factors which significantly increased ACL strain and increase the risk of ACL injury, these include greater internal or external rotations of the knee [12], a single-leg landings [13] or a higher valgus loading of the knee joint [14]. Norcross et al., [15] found a greater sagittal plane power absorption during the initial contact phase, which indicates greater ACL loading. Angular velocities have also been suggested as measures of control of the knee joint [16] and have also been related to force generation and muscle activation [17].

In volleyball, only a small change in the contextual situation can cause the player to have to modify his or her movement patterns [18]. One example of this is a response to an unpredictable or unplanned situation such as a change of direction to block a shot. However, the majority of studies that have considered the movement patterns during tasks associated with injury risk factors have not taken into account the uncertainty and speed of the real game due to difficulties in controlling such factors in a laboratory situation. Most interventions, whose principal aim is to improve motor control in order to reduce the incidence of injuries during sports games, are through training using isolated tasks [19]. However, injuries very seldomly occur while performing an isolated task in a predictable environment, but happen more much frequently in unplanned environments. Leukel et al. [20] showed that muscle activation patterns are modified in unplanned situations when compared to situations when the subjects are planned about what task they have to execute. The question of what an expert athlete should focus their attention on when performing their skill has long been of interest [21]. It has been suggested that expert athletes perform better when their attention is focused externally in comparison with when their attention is focused internally [22]. This may also be relevant when considering unplanned movements being associated with unconscious or automatic processes and planned associated with a more conscious type of control that constrains the motor system and disrupts automatic control processes, as it focuses the athlete's attention on her own body movements [23].

Previous studies have identified limb dominance [24, 25] and lateral directional movements [26, 27] as important factors when considering knee injury risks. Side to side differences in the movement of the lower extremities has been considered an injury risk, although asymmetries occur in healthy individuals as well [28]. The development of side to side differences in the lower extremity and limb dominance in an athlete can stem from strength differences [29], incomplete or improper recovery from an injury [30, 31] or repetitive use of a limb for a task [32]. When a volleyball player is trying to achieve the greatest spike performance he or she uses a natural sequence of a three-step technique during the jump which is determined by the dominant hand to favour the kinetics of the hit [33]. In this way, players tend to land with their non-dominant limb when they are performing a spike. For example, for a right-handed player, her usual step pattern during a spike should be left-right-left, which should be the same pattern than a block jump-landing when is moving to the left side (moving to zone IV), and thus moving to the dominant direction. Contrarily, if this player is moving to the other side (moving to zone II) during a block, her usual step pattern should be right-left-right, and thus moving to the non-dominant direction. However, when players are performing a block jump-landing depending on the direction of movement, which in turn depends on the game, they may have to change their natural three step technique, and therefore their jump-landing movement strategy. Therefore, it is necessary to promote balanced motor patterns (sports technique) that can help prevent injuries through early detection of risks, which may be used in the planning of preventative programs.

For these reasons, the study of the risk factors in situations that approximate the characteristics of real movements during competition and training is relevant. Therefore, demands on the velocity, distance of jumping and uncertainty within the tasks, combined with limb and direction dominance are factors that are necessary for a more complete analysis and understanding of joint movements. Thus, the purpose of this study was to investigate mechanics between dominant and non-dominant limbs when moving in dominant and non-dominant directions, for both planned and unplanned block jump-landings. We hypothesized there would be different strategies between limbs in all planes depending on whether an individual lands in a dominant or non-dominant direction. Furthermore, we hypothesized that there would be differences between planned and unplanned situations.

Methods

Study Design

This study was a within-subjects design where the independent variables were: 1) a natural three-step block approach when moving in different directions with 2 levels: a) the dominant direction, and b) the non-dominant direction; 2) limb dominance, with 2 levels: a) the lead limb, and b) the trail limb; and 3) planned/unplanned situations, with 2 levels: a) planned block jump-landing, and b) unplanned block jump-landing (Figure 16). The dominant direction was considered as the direction in which the participant performed their normal three-step sequence used when performing a volleyball spike. The dominant limb was determined as the preferred leg to kick a ball [34], which was the same as the preferred arm, with twelve right-handed and one left-handed players. Moreover, the lead limb was defined as the exterior limb during the jump-landing with the trail limb being the interior limb.

Figure 17. *Example of a player performing a three-step block jump-landing moving to zone II (from the left to the right side) during an unplanned situation.*

In this research, we considered planned and unplanned situations before the start of the block approach. In this context, planned refers to allowing time for conscious planning, whereas unplanned refers to the initiation of the block approach immediately on the cue of one of the three lights offering no time for conscious planning. The landing biomechanics were analysed to see if there were differences in movement strategies between "planned" and "unplanned" situations during landing. In both situations participants were asked to arrive at the net as fast as possible. These situations correspond to learning exercises of the ball-free blocking technique that are frequently used in volleyball. However, in the unplanned situation the player has three possible attacks which are displayed randomly and their task was to move and block them in the shortest possible time. This situation corresponds to a strategy of the game that is called "optional block" and consists of defending a "first time attack" reading blocking system (waiting to see the set) where one of the side attacks is prioritized. This tactical strategy is frequently used by middle blockers, since they have difficulty to defend serving all possible attack positions. In addition, the outside blocker can be located in a more central position to be able to defend against the "first time attack" and, if necessary, assist the side that corresponds to a "second time attack" (**Figure 4**).

Subjects, experimental setup and protocol

Described in the method of this Doctoral Thesis in page 58

Data and statistical analysis

The marker data were processed using Qualisys Track Manager (QTM, Qualisys Inc., Gothenburg, Sweden) and exported into c3d format. Visual3D (C-Motion, Inc., Rockville, MD, USA) was used to calculate the three dimensional ankle, knee and hip kinetics and kinematics. The start of each trial was determined by the first occurrence of a ground reaction force > 20 N on each force plate, and the end was defined by the maximum flexion of each knee. The joint stiffness was calculated by the change of moment divided by the change of angle using the formula [$kj = \Delta M / \Delta\theta$] following Mager et al. [35], and the power absorption was calculated using [Power = Moment x angular velocity] and the energy absorption as the integral of power. The stiffness, power and energy absorption were only calculated for the sagittal plane.

All the data showed a normal distribution according to the Shapiro-Wilks test. 2 x 2 repeated measures analysis of variance (ANOVA) tests were used to explore the differences between dominant/non-dominant directions and planned/unplanned tasks on the dominant and non-dominant limbs separately. Further post hoc tests were performed using a Bonferroni correction to reduce Type I error, with the alpha level set to 0.05. IBM SPSS Statistics 22 software was used for all statistical tests (SPSS, Inc., and IBM Company, Chicago, IL).

Results

Kinematic and kinetic variables for the non-dominant hip, knee and ankle joints during the block jump-landing are shown in **Table 4**. For the non-dominant limb, there was a significant difference in the hip, knee and ankle angles between dominant and non-dominant directions with the non-dominant direction showing greater flexion in the hip ($F(1,12) = 9.204$, $p = .010$, $\eta 2 = .119$) and knee joints ($F(1,12) = 6.765$, $p = .022$, $\eta 2 = .364$), and a greater amount of plantarflexion at initial contact ($F(1,12) = 5.600$, $p = .036$, $\eta 2 = .318$). Significantly greater peak hip ($F(1,12) = 9.810$, $p = .009$, $\eta 2 = .450$) and knee flexion moments ($F(1,12) = 9.096$, $p = .011$, $\eta 2 = .431$) and ankle dorsiflexion moment ($F(1,12) = 9.372$, $p = .010$, $\eta 2 = .439$) were seen in the movements in the dominant direction, with greater peak hip ($F(1,12) = 10.468$, $p = .007$, $\eta 2 = .466$) and knee power absorption ($F(1,12) = 13.988$, $p = .003$, $\eta 2 = .538$), and significantly greater energy absorption at the knee ($F(1,12) = 15.544$, $p = .002$, $\eta 2 = .564$) and ankle ($F(1,12) = 11.319$, $p = .006$, $\eta 2 = .485$) when moving in the dominant direction. Peak hip flexion angular velocity was significantly greater in the non-dominant direction ($F(1,12) = 8.059$, $p = .015$, $\eta 2 = .402$), and lower peak joint stiffness was seen in the knee ($F(1,12) = 21.654$, $p = .001$, $\eta^2 = .643$) and ankle ($F(1,12) = 17.518$, $p = .001$, $\eta^2 = .593$), with a trend toward significance in the hip ($F(1,12) = 4.476$, $p = .056$, $\eta^2 = .272$).

Table 4. *Kinematic and kinetic variables for the Non-Dominant limb during a block jump-landing in the sagittal plane (mean ± standard deviation)*

	Planned		Unplanned				Anova *p*-value		
Hip	Non-Dominant Direction	Dominant Direction	Non-Dominant Direction	Dominant Direction	*p*-value P v UnP	Effect Size	*p*-value Direction	Effect Size	Interation
Peak hip flexion (deg)	56.6±12.9	54.32±14.25	60.13±11.44	54.09±11.81	0.227	0.119	**0.010***	0.434	0.105
Contact hip angle (deg)	20.97±3.67	22.27±5.75	23.95±4.38	22.17±4.05	0.098	0.211	0.784	0.007	0.106
Peak hip flexion moment (Nm/kg)	1.75±0.61	2.33±0.83	1.60±0.49	2.46±1.07	0.963	0.000	**0.009***	0.450	0.403
Peak hip stiffness (M/deg)	2.13±1.03	3.19±2.20	2.16±1.10	2.71±1.07	0.325	0.081	0.056	0.272	0.421
Peak hip power absorption (Mω)	1.75±1.43	3.45±2.54	1.31±0.96	2.73±2.62	0.125	0.185	**0.007***	0.466	0.764
Hip energy absorption (J/kg)	0.173±0.127	0.152±0.163	0.168±0.105	0.134±0.156	0.691	0.014	0.553	0.030	0.795
Peak hip flexion velocity (deg/s)	431.3±113.5	372.9±107.9	400.7±123.5	372.3±95.7	0.252	0.108	**0.015***	0.402	0.157
Knee									
Peak knee flexion (deg)	68.22±10.12	64.93±10.21	68.93±9.72	63.13±8.84	0.221	0.122	**0.022***	0.364	0.205
Contact knee angle (deg)	12.69±5.23	11.62±4.31	12.52±5.71	11.10±4.24	0.598	0.024	0.192	0.136	0.724
Peak knee flexion moment (Nm/kg) †	1.51±0.50	1.75±0.57	1.26±0.36	2.20±0.64	0.361	0.070	**0.011***	0.431	**0.000***
Peak knee stiffness (M/deg)	0.43±0.15	0.61±0.17	0.38±0.14	0.57±0.16	0.169	0.152	**0.001***	0.643	0.895
Peak knee power absorption (M.ω)	9.33±3.79	14.26±4.81	7.64±3.69	12.77±5.47	**0.005***	0.496	**0.003***	0.538	0.896
Knee energy absorption (J/kg)	0.763±0.384	1.177±0.528	0.583±0.326	1.134±0.541	**0.017***	0.391	**0.002***	0.564	0.275
Peak knee flexion velocity (deg/s)	588.68±51.94	604.52±76.70	587.53±52.16	590.10±69.4	0.517	0.036	0.527	0.034	0.560
Ankle									
Peak ankle dorsiflexion (deg)	23.51±4.42	23.70±3.25	22.52±5.13	23.75±4.69	0.357	0.71	0.298	0.090	0.235
Contact ankle angle (deg)	-34.60±6.29	-32.99±5.03	-35.89±6.79	-33.73±5.00	0.137	0.175	**0.036***	0.318	0.609
Peak ankle dorsiflexion moment (Nm/kg)	1.29±0.30	1.61±0.39	1.23±0.39	1.71±0.38	0.726	0.011	**0.010***	0.439	0.069
Peak ankle stiffness (M/deg)	0.06±0.01	0.10±0.03	0.07±0.02	0.10±0.03	0.531	0.034	**0.001***	0.593	0.943
Peak ankle power absorption (M.ω)	21.79±5.68	24.53±6.65	20.19±545	25.09±5.35	0.499	0.039	0.088	0.223	0.129
Ankle energy absorption (J/kg)	0.916±0.215	1.087±0.309	0.836±0.202	1.208±0.267	0.510	0.037	**0.006***	0.485	0.059
Peak ankle dorsiflexion velocity (deg/s)	1180.0±171.8	1147.9±155.1	1157.6±148.3	1151.1±157.	0.479	0.043	0.554	0.030	0.307

* Significance ($p \leq 0.05$). † Significant interaction between Non-Dominant - Dominant direction and Planned (P) – Unplanned (UnP). Deg – degrees; N – Newton; m-metre; kg – kilogram; M – Moment Joint; ω – angular velocity; J – Joule; s – second.

For the knee power absorption and knee energy absorption there were differences between planned and unplanned tasks ($F(1,12) = 11.794$, $p = .005$, $\eta 2 = .496$) and ($F(1,12) = 7.700$, $p = .017$ $\eta 2 = .391$), with greater values in the planned movements. A statistically significant interaction was observed for the peak knee flexion moment ($F(1,12) = 34.476$, $p < .001$, $\eta 2 = .742$), further analysis showed a statistically greater knee moment in the dominant direction ($F(1,12) = 22.903$, $p < .001$, $\eta 2 = .656$). However, the peak knee flexion moments decreased with unplanned movements in the non-dominant direction ($F(1,12) = 8.025$, $p = .015$, $\eta 2 = .401$), and increased in the unplanned movements in the dominant direction ($F(1,12) = 8.447$, $p = .013$, $\eta 2 = .413$).

Kinematic variables for the dominant hip, knee and ankle joints during the block jump-landing are shown in **Table 5**. These showed a similar response to the non-dominant limb, with significantly greater flexion in the hip ($F(1,12) = 5.316$, $p = .002$, $\eta 2 = .561$) and knee joints ($F(1,12) = 15.368$, $p = .002$, $\eta 2 = .562$) when moving to the dominant direction, however no significant difference was seen in the ankle joint at initial contact. The flexion moments also showed a similar response with greater peak hip ($F(1,12) = 12.505$, $p = .004$, $\eta 2 = .510$) and knee flexion moments ($F(1,12) = 23.523$, $p < .001$, $\eta 2 = .662$) and ankle dorsiflexion moment ($F(1,12) = 10.585$, $p = .007$, $\eta 2 = .469$), with greater peak knee and ankle power absorption ($F(1,12) = 12.609$, $p = .004$, $\eta 2 = .512$; $F(1,12) = 6.048$, $p = .030$, $\eta 2 = .335$) and energy absorption ($F(1,12) = 24.207$, $p < .001$, $\eta 2 = .669$; $F(1,12) = 13.074$, $p = .004$, $\eta 2 = .521$) respectively, when moving in the non-dominant direction. Peak hip flexion angular velocity was significantly greater in the dominant direction ($F(1,12) = 20.682$, $p = .001$, $\eta 2 = .633$), with a lower peak knee joint stiffness ($F(1,12) = 8.276$, $p = .014$, $\eta 2 = .408$).

A statistically significant interaction was observed for the hip angle at contact ($F(1,12) = 4.828$, $p = .048$, $\eta 2 = .287$), showing a lower angle in the non-dominant direction for the planned landings ($F(1,12) = 7.541$, $p = .018$, $\eta 2 = .386$). Further analysis showed that there was a significant difference in the contact hip angle ($F(1,12) = 6.224$, $p = .028$, $\eta 2 = .342$) between planned and unplanned landings, showing a greater angle in unplanned landings, with greater peak knee flexion and peak flexion moment in the planned landings ($F(1,12) = 6.656$, $p = .024$, $\eta 2 = .357$; $F(1,12) = 6.024$, $p = .030$, $\eta 2 = .334$, respectively). Moreover, a statistically significant interaction was seen in the peak hip power absorption ($F(1,12) = 5.745$, $p = .034$, $\eta 2 = .324$). It was found that the power absorption decreased with unplanned movements in the non-dominant direction ($F(1,12) = 5.037$, $p = .044$, $\eta 2 = .296$) but increased in the planned movements in the dominant direction ($F(1,12) = 4.800$,

$p=.049$, $\eta2=.286$), with greater hip energy absorption in the unplanned landings ($F(1,12)=5.801$, $p=.033$, $\eta2=.326$),whereas the knee showed lower energy absorption in the unplanned landings ($F(1,12)=5.252$, $p=.041$, $\eta2=.304$). A significant interaction was also seen in the peak ankle dorsiflexion angular velocity ($F(1,12)=18.336$, $p=.001$, $\eta2=.604$), with the highest peak in the dominant direction and the lowest in the non-dominant direction.

Kinematic and kinetic variables for the dominant and non-dominant knee in the coronal and transverse plane are shown in **Table 6**. There were significant differences in the peak knee valgus ($F(1,12)=15.514$, $p=.002$, $\eta2=.564$), the contact angle ($F(1,12)=13.591$, $p=.003$, $\eta2=.531$) and the contact knee angle in the transverse plane ($F(1,12)=6.621$, $p=.024$, $\eta2=.356$) between dominant and non-dominant directions with the non-dominant direction showing greater valgus knee angle. A statistically significant interaction was observed for the knee valgus angle ($F(1,12)=10.567$, $p=.007$, $\eta2=.468$), showing a lower angle in the non-dominant direction for the unplanned landings ($F(1,12)=7.584$, $p=.017$, $\eta2=.387$). Significantly greater peak knee valgus moment ($F(1,12)=13.823$, $p=.003$, $\eta2=.535$) were seen in movements in the dominant direction. For the knee internal rotation moment differences were seen between planned and unplanned tasks ($F(1,12)=6.258$, $p=.028$, $\eta2=.343$). Additionally, significant interactions were observed for peak knee internal rotation angular velocity ($F(1,12)=6.713$, $p=.024$, $\eta2=.359$), showing higher values in planned tasks in the dominant direction.

For the dominant knee there was a significant difference in the peak knee valgus ($F(1,12)=16.742$, $p=.001$, $\eta2=.582$), between dominant and non-dominant directions with the dominant direction showing a greater valgus knee angle. Greater peak knee valgus moments were seen when moving in the non-dominant direction compared with the dominant direction ($F(1,12)=13.052$, $p=.004$, $\eta2=.521$). A significant interaction was observed for the peak ($F(1,12)=8.596$, $p=.017$, $\eta2=.389$) and contact internal rotation angle ($F(1,12)=10.314$, $p=.019$, $\eta2=.379$), showing a lower angle in the non-dominant direction in the planned landings ($F(1,12)=12.338$, $p=.004$, $\eta2=.507$). However, higher peak knee internal rotation moments ($F(1,12)=19.903$, $p=.001$, $\eta2=.624$) were seen in the movements in the non-dominant directions compared with the dominant direction.

Table 5. *Kinematic and kinetic variables for the Dominant limb during a block jump-landing in the sagittal plane (mean ± standard deviation)*

	Planned		Unplanned		Anova *p* -value				
Hip	Non-Dominant Direction	Dominant Direction	Non-Dominant Direction	Dominant Direction	*p*-value P v UnP	Effect Size	*p* -value Direction	Effect Size	Interation
Peak hip flexion (deg)	51.31±12.85	60.01±12.86	54.18±13.42	59.04±11.35	0.370	0.067	**0.002***	0.561	0.075
Contact hip angle (deg) †	21.30±5.09	23.76±6.35	24.44±4.24	24.13±4.97	**0.028***	0.342	0.278	0.097	**0.048***
Peak hip flexion moment (Nm/kg)	2.04±1.07	1.26±0.37	1.83±0.60	1.24±0.37	0.412	0.057	**0.004***	0.510	0.527
Peak hip stiffness (Nm/deg)	2.51±1.00	2.38±1.99	2.52±0.81	2.48±2.32	0.789	0.006	0.869	0.002	0.819
Peak hip power absorption (Mω) †	2.74±2.38	1.75±1.20	1.54±1.33	3.88±3.65	0.352	0.072	0.170	0.151	**0.034***
Hip energy absorption (J/kg)	0.159±0.249	0.262±0.233	0.238±0.249	0.276±0.197	**0.033***	0.326	0.216	0.124	0.431
Peak hip flexion velocity (deg/s)	344.6±100.4	455.6±126.3	337.0±83.38	382.6±112.8	**0.026***	0.350	**0.001***	0.633	0.123
Knee									
Peak knee flexion (deg)	63.53±9.64	69.55±10.06	62.92±11.19	67.52±8.06	**0.024***	0.357	**0.002***	0.562	0.315
Contact knee angle (deg)	11.29±4.43	13.03±5.06	10.75±4.29	13.52±6.31	0.961	0.000	**0.014***	0.406	0.393
Peak knee flexion moment (Nm/kg)	2.21±0.44	1.29±0.42	1.96±0.38	1.22±0.39	**0.030***	0.334	**0.000***	0.662	0.132
Peak knee stiffness (M/deg)	0.52±0.24	0.36±0.10	0.48±0.11	0.37±0.10	0.577	0.027	**0.014***	0.408	0.543
Peak knee power absorption (M.ω)	11.54±5.81	7.16±1.51	10.37±3.51	6.85±2.32	0.125	0.184	**0.004***	0.512	0.431
Knee energy absorption (J/kg)	1.046±0.363	0.661±293	0.993±0.369	0.493±0.197	**0.041***	0.304	**0.000***	0.669	0.326
Peak knee flexion velocity (deg/s)	582.95±54.29	578.39±65.54	577.29±64.94	551.0±44.28	0.167	0.153	0.444	0.050	0.081
Ankle									
Peak ankle dorsiflexion (deg)	23.72±3.66	23.38±3.86	23.09±4.05	23.03±3.33	0.314	0.084	0.761	0.008	0.728
Contact ankle angle (deg)	-32.11±4.59	-34.03±4.53	-33.41±4.93	-34.15±5.01	0.266	0.102	0.087	0.224	0.269
Peak ankle dorsiflexion moment (Nm/kg)	1.74±0.32	1.34±0.43	1.85±0.27	1.40±0.48	0.157	0.160	**0.007***	0.469	0.676
Peak ankle stiffness (M/deg)	0.036±0.06	0.020±0.02	0.033±0.02	0.015±0.02	0.641	0.019	0.167	0.153	0.925
Peak ankle power absorption (M.ω)	25.09±5.21	21.71±6.76	25.65±4.34	24.07±7.90	0.967	0.000	**0.030***	0.335	0.481
Ankle energy absorption (J/kg)	1.157±0.246	0.900±0.282	1.239±0.256	0.891±0.308	0.445	0.049	**0.004***	0.521	0.366
Peak ankle dorsiflexion velocity (deg/s) †	1094.8±129.5	1183.3±135.3	1120.0±154.9	1127.1±144	0.357	0.071	0.070	0.248	**0.001***

* Significance ($p \leq 0.05$). † Significant interaction between Non-Dominant - Dominant direction and Planned (P) – Unplanned (UnP). Deg – degrees; N – Newton; m-metre; kg – kilogram; M – Moment Joint; ω – angular velocity; J – Joule; s – seconds

Table 6. *Kinematic and kinetic variables for the Dominant and Non-Dominant knee during a block jump-landing in coronal and transverse planes*

Non-Dominant	Planned		Unplanned		Anova p-value				
Knee in the coronal plane	Non-Dominant Direction	Dominant Direction	Non-Dominant Direction	Dominant Direction	p-value P v UnP	Effect Size	p-value Direction	Effect Size	Interation
Peak knee valgus angle (deg) †	10.13±5.81	6.67±4.74	9.23±6.38	7.60±4.42	0.959	0.000	**0.002***	0.564	**0.007***
Contact knee angle (deg)	0.59±3.84	1.41±3.96	0.19±3.93	1.35±3.69	0.157	0.160	**0.003***	0.531	0.213
Peak knee valgus moment (Nm/kg)	0.03±0.10	0.26±0.26	0.04±0.13	0.24±0.19	0.777	0.007	**0.003***	0.535	0.614
Peak knee valgus angular velocity (deg/s)	121.6±58.3	103.3±44.3	117.5±60.1	101.3±39.8	0.702	0.013	0.156	0.160	0.912
Knee in the transverse plane									
Peak knee internal rotation tibial angle (deg) †	2.61±4.36	3.96±4.74	3.63±4.47	3.35±4.67	0.463	0.046	0.449	0.049	**0.017***
Contact knee angle (deg) †	1.43±4.23	3.37±4.91	2.52±4.59	2.68±4.76	0.564	0.028	0.101	0.208	**0.019***
Peak knee internal rotation tibial moment (Nm/kg)	0.01±0.05	0.08±0.06	0.01±0.04	0.08±0.06	0.495	0.040	**0.001***	0.624	0.879
Peak knee internal rotation tibial ang.vel (deg/s)	66.3±61.3	51.9±44.4	74.7±55.0	68.2±53.8	0.085	0.227	0.326	0.080	0.671
Dominant	Planned		Unplanned		Anova p-value				
Knee in the coronal plane	Non-Dominant Direction	Dominant Direction	Non-Dominant Direction	Dominant Direction	p-value P v UnP	Effect Size	p-value Direction	Effect Size	Interation
Peak knee valgus angle (deg)	6.31±3.76	8.92±4.00	6.75±3.91	8.29±5.04	0.674	0.015	**0.001***	0.582	0.076
Contact knee angle (deg)	1.83±3.18	1.46±2.94	2.00±3.29	1.37±2.63	0.833	0.004	0.050	0.282	0.445
Peak knee valgus moment (Nm/kg)	0.08±0.20	-0.06±0.14	0.12±0.19	0.01±0.17	0.091	0.220	**0.004***	0.521	0.735
Peak knee valgus angular velocity (deg/s)	83.4±51.0	82.2±47.0	72.4±47.5	69.8±54.9	0.275	0.98	0.798	0.006	0.950
Knee in the transverse plane									
Peak knee internal rotation tibial angle (deg)	3.93±4.34	3.38±3.44	3.27±4.67	3.30±3.61	0.287	0.094	0.691	0.014	0.416
Contact knee angle (deg)	3.33±4.76	0.96±3.31	2.77±5.00	1.38±4.75	0.879	0.002	**0.024***	0.356	0.311
Peak knee internal rotation tibial moment (Nm/kg)	-0.001±0.06	-0.017±0.04	0.013±0.06	-0.008±0.04	**0.028***	0.343	0.128	0.183	0.701
Peak knee internal rotation tibial ang.vel (deg/s) †	90.1±49.3	122.9±80.2	96.9±45.0	95.1±73.9	0.202	0.132	0.296	0.091	**0.024***

* Significance ($p \leq 0.05$). † Significant interaction between Non-Dominant - Dominant direction and Planned (P) – Unplanned (UnP). Deg – degrees; N – Newton; m- metre; kg – kilogram; s – second.

Discussion

The results of this study suggest that there were different strategies between the lead limb and trail limb when participants performed a block jump-landing, showing a tendency where the lead limb may have a higher implications on possible overuse injuries than the trail limb. Furthermore, planned situations may have greater musculoskeletal implications than unplanned situations. This highlights the importance of considering not only the lead and trail limb, but also the necessity to create situations as similar as possible to that of competition during training.

There are controversies about lower limb symmetry during landing tasks. Some authors reporting that there are no differences between limbs [36-38] and others reporting asymmetries. In agreement with Sinsurin et al. [26], we observed a similar response in the hip and knee joint angles for both limbs, with the trail limb having higher flexion angles with the ankle in less plantarflexion, therefore reducing the possible power absorption at the ankle. Skazalski et al. [39] showed that landing-related ankle injuries mostly result from rapid inversion without a substantial plantarflexion. However, the opposite response occurs when the peak dorsiflexion joint moments, power absorption and stiffness are considered. Zahradnik et al. [25] suggested that greater knee moments and power absorption present a greater risk of injury during the impact phase. Hinshaw et al. (2018) showed increased knee valgus moments and internal rotation angles for the lead limb [40]. For these variables, the trail limb had lower values, and consequently the lead limb may have the higher injury risk. In addition, the knee and ankle joints on the lead limb showed greater energy absorption, which could be related to the lead limb being the external limb and consequently taking greater loads during landing. Thus, our results suggest that the limb with more injury risk is the lead limb, independently of whether it is the dominant or non-dominant limb. Moreover, asymmetries due to strength, repetitive skills and the strategies could increase the magnitude of these differences.

Leukel et al. [20] confirmed that when there is an unplanned situation during a jump or landing, muscle activity and tendomuscular stiffness was reduced. The comparison of planned and unplanned three-step block jump-landings showed, for the non-dominant limb, the peak knee power absorption and the knee energy absorption were greater in planned than in unplanned jump-landings. In planned landings, energy absorption at the hip decreases with an increase in angular velocity on the dominant side. Additionally, for the dominant knee, the peak flexion angle and moment, the energy absorption, and the peak internal rotation tibial moment and angular velocity were greater in planned situations, indicating greater implications to possible overuse injuries. Moreover, the knee on the dominant limb had a greater flexion moment during planned compared to unplanned landings. According to Wulf, McNevin, and Shea [41] "when performers use an internal focus of attention (focus on their movements) they may actually constrain or interfere with automatic control processes that would normally regulate the movement". This could be explained by restrictions in the "Top - Down" system [42] in reference to the mechanism of neuronal activation for discrimination of relevant information when preparing a goal-oriented response. A possible explanation could be due to planned movements using an internal focus which changes the movement strategies, whereas in unplanned movements the volleyball players had an external focus. An external focus on the movement promotes the utilization of unconscious or automatic processes, whereas an internal focus results in a more conscious type of control that constrains the motor system and disrupts automatic control processes [43], and focuses the athlete's attention on his or her own body movements [23].

This current study created a protocol that integrated the majority of all planes variables that have been previously reported as risk factors in lower limb injuries. In addition, we considered both velocity and approach distance under the different situations, which provided greater ecological validity to the real game situation of performing block jump-landings [44]. Notwithstanding, this study did have some limitations; firstly, we only measured women from the same volleyball team with the same block jump-landing technique, secondly we only considered lower limb movements in the analysis, and finally, although jump speed was controlled for each individual approach speed was not, moreover participants moved as fast as possible but they had to control their jump-landings onto the force platforms, which does not replicate a real game situation. Future studies should measure males and females from different competition levels to get a better understanding of landing strategies. Moreover, it would be interesting to include different stimuli during the flight phase, to explore the effect of adjustments of the player's upper limbs which may vary the biomechanical parameters of the lower limbs during landing. For practical applications, coaches and trainers should plan training which considers the coordination in both directions and limbs and performs preventative exercises unilaterally to minimize asymmetries. Furthermore, adapting training to simulate competition where players have unplanned situations could improve their performance which may reduce injury risk.

In conclusion, there were different strategies between limbs in all planes when participants performed a block jump-landing after three-step approach in two conditions. It seems that the role of the limb, either lead or trail, is more important than the limb dominance when performing directional three-step block jump-landings. Our results suggest that the lead limb may have a greater risk of injury than the trail limb. Furthermore, when there was a planned situation, the athletes may have more conscious thought about their movement, or an internal focus, which might have changed their strategy, indicating greater implications to possible overuse injuries than in the unplanned situations which encourages an external focus.

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SECTION 2. Which kinematic and kinetic variables are most relevant when comparing limb movement strategies between limb role and direction dominance in block jump-landing in volleyball?

Introduction

Muscle imbalances have been shown to be useful in the identification of athletes at risk of lower limb injuries. These may be associated with strength differences [1], side to side differences due to incomplete or improper recovery from an injury [2, 3], or repetitive limb use [4]. Muscle loading patterns experienced around the knee may alter the balance of strength under high velocity conditions [4]. However, little is known regarding the influence that leg preference or playing position may have on lower-extremity muscle strength and asymmetry [1]. Therefore, there is a necessity to study the differences between the dominant and non-dominant limbs.

Previous studies have shown that specific kinematic and kinetic variables can be associated with lower limb injury risks [5, 6] and differences in limb roles [7], although previous protocols have not necessarily reflected real match situations. The majority of previous work has not considered both limbs, jumping distance, the velocity of the game, jump-landing from different directions or the movement of the joints of the lower limbs in 6 degrees of freedom, due to the difficulties in simulating a real game situation within the laboratory [8]. To the authors' knowledge, no investigation exists which considers all these points during block jump-landings. Lobietti et al. (2010) [9] highlighted the importance of standardizing conditions including; direction, dominance, distance, and height of the jumps so that players land in a manner closer to that of during a competition.

There is a necessity to protect athletes and prevent the incidence of injury. In performance sports, the repetition of specific skills along with the high physical, physiological and psychological demands have been associated with greater risk of suffering an injury [10]. In volleyball specific tasks such as spiking, jumping, landing or blocking the ball, these movements need to be combined with fast directional movements, which produces a great demand on the musculoskeletal system [11]. It has been reported that the hip, knee and ankle are the most commonly injured joints in volleyball [12], with the knee representing the highest percentage of lower limb injuries in the physically active population [13], with the main cause being overuse or joint overload. It has also been reported that females are more frequently affected by traumatic and knee overuse injuries [14]. In addition, knee problems represent a significant part of primary health care and is therefore a financial burden to health services [15]. Therefore, it is essential to identify the risk factors in a real game situation to allow the development of targeted prevention programmes.

In chronic injuries, abnormal frontal plane loading has been reported to be the inciting factor that can lead to injury [16]. This is characterised by an abduction moment which is often attributed to excessive hip abduction and internal rotation, often caused by a decrease in the ability of the hip musculature to absorb energy/force during the deceleration phase of landing tasks [17]. Consistently, anterior cruciate ligaments (ACL) injuries typically occur during the early phase of landing when individuals demonstrate high vertical ground reaction forces (VGRF), small knee flexion angles, increased knee abduction and internal rotation angles [7]. All this evidence indicates that it is highly probable that lower limb injuries are more likely to involve multi-planar rather than single-planar mechanisms [18]. It has also been suggested that angular velocities in all three planes may be a better measurement of lower limb control [19]. In addition, the stability of the joint through the coordination of the neuromuscular system can be defined as the ability to control movement [20].

The consideration of as many relevant risk factors as possible is necessary to understand the movements during the multifactorial nature of sports injuries [21]. However, the analysis of all these variables requires the utilization of complex methods of data analysis. Machine Learning is a subfield within Artificial Intelligence based on methods which are able to automatically learn complex patterns inherent in a dataset, and apply them to new data to predict future behaviour. As a result, these can be applied to the classification tasks by assigning a class or a label to new data based on what has been previously learned. In addition, they allow to identify which variables are most relevant to specific questions such as injury risk. Some authors have used Machine Learning to classify movement patterns such us: in biathlon [22], bowling [23], weight training [24], cycling and triathlon [25, 26] and swimming [27]. A systematic review demonstrated the capacity of those techniques to improve the understanding of sport movements and skill recognition, and how this can be applied to performance analysis using Machine and Deep Learning methods to automate sport-specific movement recognition [28].

In this study, the use of two Machine Learning methods was explored: ANN [29] and RF [30], with the aim to classify conditions for limb role when the dominant and non-dominant limb performed as the lead and trail limb using kinematic and kinetic data. In addition, decision trees were chosen to infer understandable rules using these methods to consider all the relevant variables in an ecological situation. Therefore the hypothesis were: 1. There are significant differences between limbs roles when the dominant limb performed the role as the trail limb and the non-dominant limb performed the role as the lead limb, and 2. There are significant differences between the dominant limb performing the role as the lead limb with the non-dominant limb performing the role as the trail limb during block jump-landings. Additionally, 3. Machine Learning offers an analysis method capable of identifying different motor patterns during sporting tasks.

Method

Study Design and variables

The variables were described in the method of this Doctoral Thesis in page 55. Additionally, this study was a within-subjects design where the independent variable was the limb role: as the lead or trail limb, with the lead limb defined as the ipsilateral limb and the trail limb defined as the contralateral limb during the jump-landing. Therefore, depending on the direction, the dominant and the non-dominant limb had different roles (**Figure 18**).

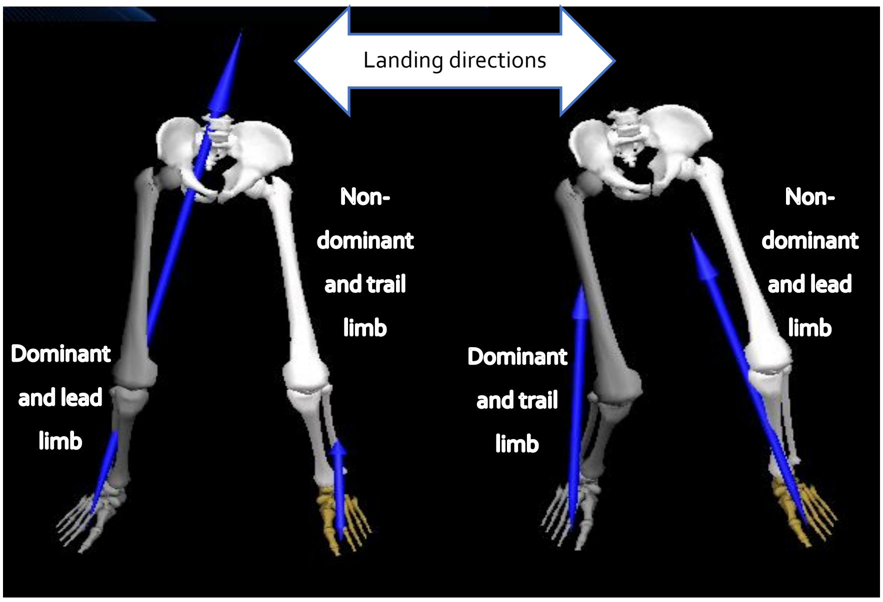

Figure 18. *Example of a right-handed volleyball player who performed block jump-landings when moving in the different directions.*

The independent variables considered in the Machine Learning classification methods included; hip, knee and ankle angles (deg), angular velocities (deg/s) and joint moments (Nm/kg) in all planes. In addition, joint power absorption (J/kg) in the sagittal plane, the VGRF (N) and loading rate (N/s) were considered.

Subjects, experimental setup and protocol

Described in the method of this Doctoral Thesis in page 58

Statistical analysis, model training and testing

The model training and testing was described in the method of this Doctoral Thesis in page 72. Both ANN and RF strive for the best accuracy, but lack in interpretability, therefore we also used decision trees which allows to extract easy to understand rules.

Results

Artificial Neural Network and Random Forest models:

Table 7. *Accuracy average in precision of methods: Artificial Neuronal Network and Random Forest.*

	Accuracy average	
Lead vs Trail:	Artificial Neural Network	Random Forest
Q1. When the DL is the trail limb and the NDL is the lead limb	**0.972**	0.972
Q2. When the DL is the lead limb and the NDL is the trail limb	0.947	**0.960**
Comparing limb role:	Artificial Neural Network	Random Forest
Q3. When the role is the lead limb: DL vs NDL	**0.960**	0.933
Q3. When the role is the trail limb: DL vs NDL	0.933	**0.973**

*DL: Dominant limb; NDL: Non-dominant limb

Table 7 shows the performance results of ACC for each model when trained on data from variables for each question. When comparing between limbs in the jump-landings different movement strategies were seen between the lead and the trail limb with a predictive accuracy > 94%. In addition, when comparing between limbs when moving in the different directions performing the same role differences in movement strategy were seen with a predictive accuracy > 93%.

Decision trees

Question 1 considered if significant differences exist between limbs roles when the dominant limb performed the role as the trail limb and the non-dominant limb performed the role as the lead limb. We can see that there was a different strategy between limbs with a predictive accuracy of > 97.2% with both Machine Learning methods. **Figure 19** shows the decision tree built to explore the lead limb strategy which tends towards less abduction ankle moment in the transverse plane and a higher abduction hip angle in the coronal plane in 38% of the trials. In addition, in 48% of the trials the trail limb strategy tended towards a higher abduction ankle moment in the transverse plane, a higher valgus moment in the coronal plane and a lower peak vertical ground reaction force than the lead limb.

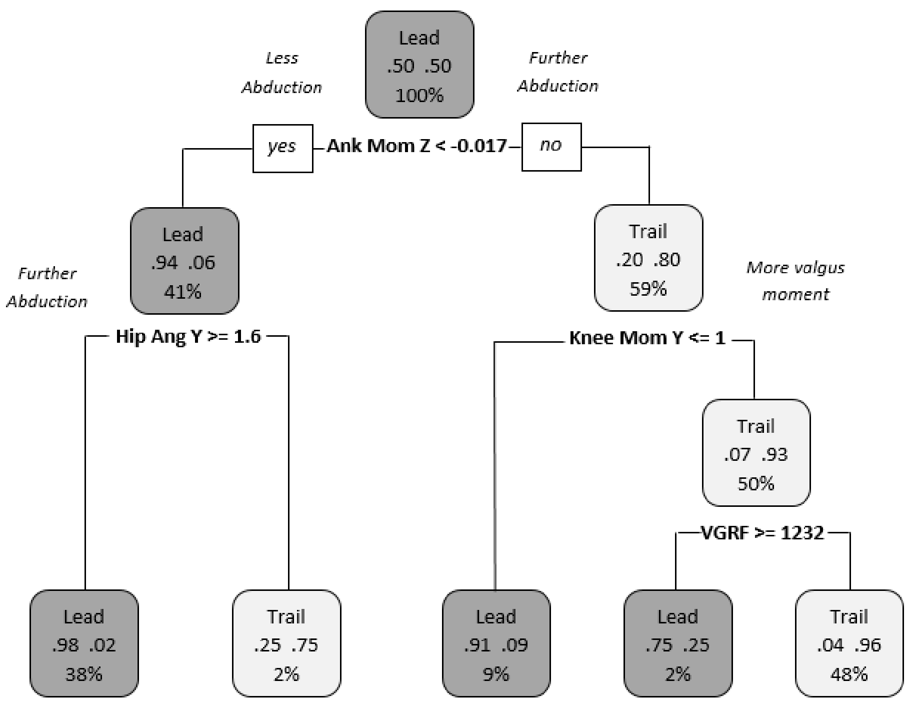

Figure 19. *Differences between the lead and trail limbs in jump-landings when the dominant limb performed the role as the trail limb and the non-dominant limb performed the role as the lead limb.*

Question 2 explored if significant differences exist between limbs roles when the dominant limb performed the role as the lead limb and the non-dominant limb performed the role as the trail limb. In this case we observed a prediction accuracy of both models (accuracy > 94.7%). **Figure 20** shows that the lead limb strategy tends to less internal rotation of the tibia and lower hip abduction angular velocity in 39% of the trials. Furthermore, in 51% of the trials, the trail limb strategy tended towards a higher internal rotation of the tibia and greater hip abduction angular velocity.

Questions 1 and 2 highlights that there were clear differences in the strategy between the lead and the trail limb in a block jump-landing, but these were also dependent on the limb dominance.

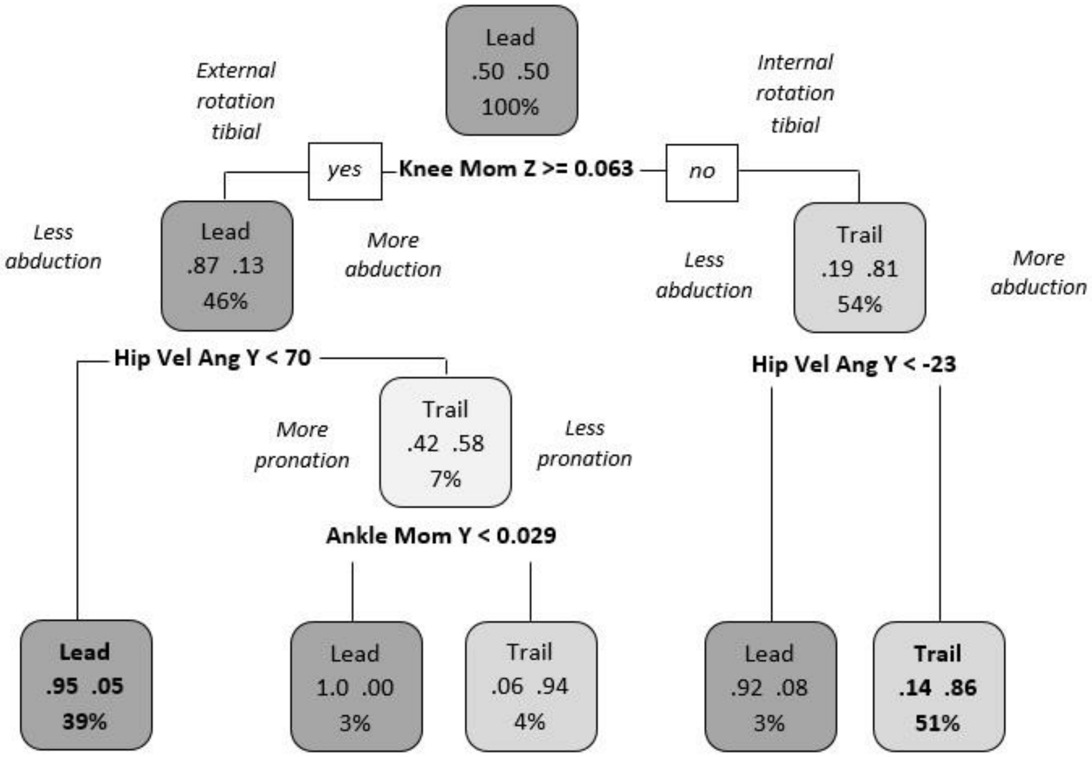

Figure 20. *Differences between the lead and trail limbs in jump-landings when the dominant limb performed the role as the lead limb and the non-dominant limb performed the role as the trail limb.*

Question 3 considered if significant differences exist between dominant and non-dominant limb when both are performing the lead role. We can see that both models exhibited a predictive accuracy > 93.3% when we compared the lead limbs during jump-landing, indicating a difference in landing strategy between dominant and non-dominant limbs. **Figure 21** showed that the dominant limb strategy tended towards less ankle abduction moment and higher ankle dorsiflexion angular velocity in 37% of the trials. Moreover, in 46% of the trials, the non-dominant limb strategy tended towards a higher ankle abduction moment, a greater amount of hip internal rotation and a higher ankle moment than the dominant limb.

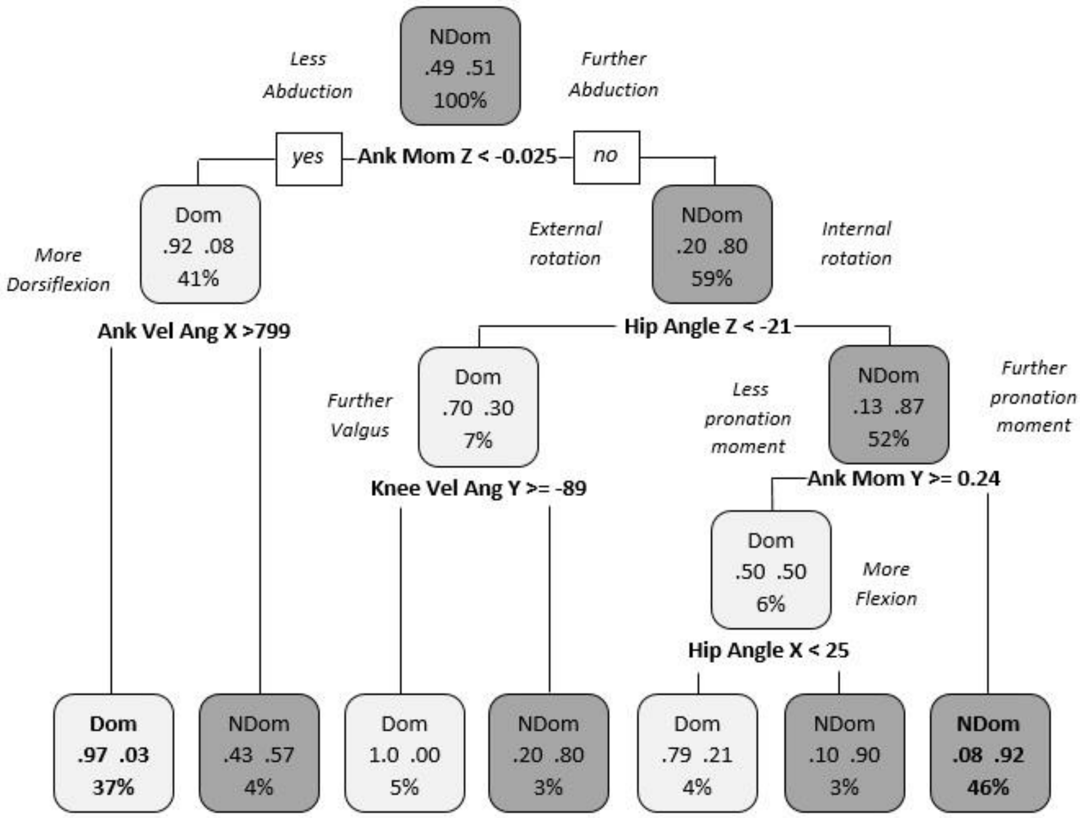

Figure 21. *Differences between the dominant and non-dominant limb when both are performing the lead role.*

Finally, question 4 examined if significant differences exist between dominant and non-dominant limbs when both are performing the trail limb role. We observed a predictive accuracy of 97.3% indicating a difference in landing strategy. **Figure 22** showed that the dominant limb strategy tended towards greater ankle abduction and pronation moment in 43% of the trials. Moreover, in 30% of the trials, the non-dominant limb strategy tended towards a lower ankle abduction and pronation moment than the dominant limb.

Questions 3 and 4 demonstrate that the dominant and non-dominant limb had different strategies even when they are performing the same role independent of their position as the lead or the trail limb.

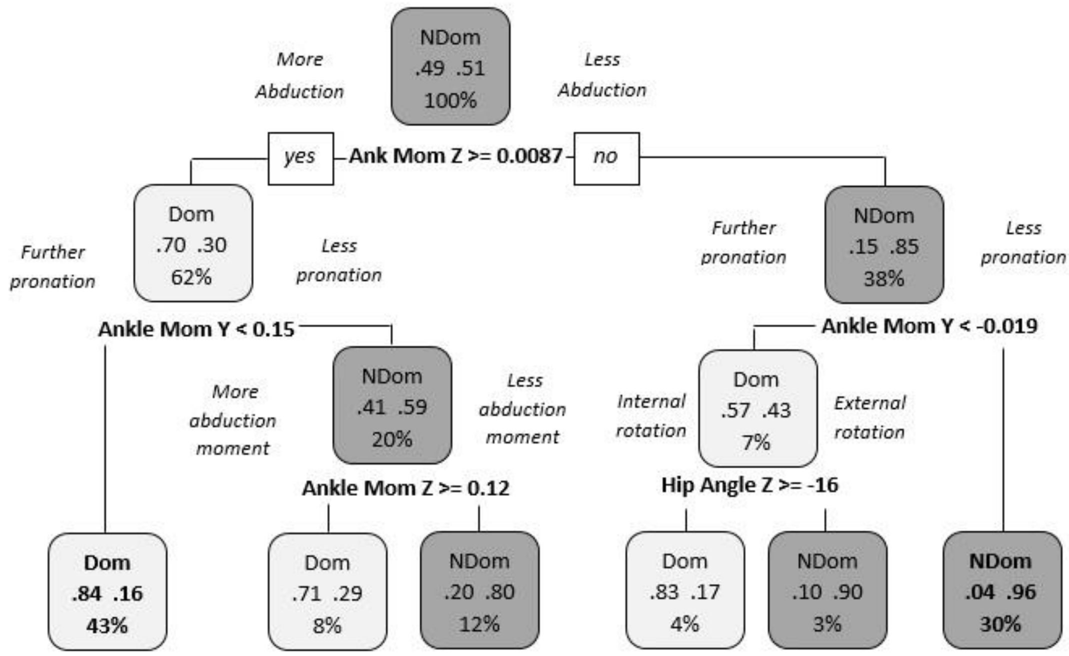

Figure 22. *Differences between the dominant and non-dominant limb when both are performing the trail role.*

Discussion and implications

The results of this study suggest that differences in movement strategies exist between the lead and trail limb independent of limb dominance, confirming the hypothesis. Moreover, Machine Learning allows to build models that can classify differences between conditions for limbs performing the lead and trail role during directional block jump-landings. This highlights the importance of considering not only the lead and trail limb, but also the limb dominance when considering biomechanical variables which may be associated with injury risk.

In this study, the volleyball players performed a block jump-landing as fast as possible in a situation as ecologically valid as possible under laboratory conditions. Previous studies found symmetry between limbs [31, 31]. Some authors have studied the importance of considering both limbs and roles [5, 7], directions [33, 34], and ecological protocols [35-37], however these only considered a limited number of variables. In this current study we included all variables which have previously been considered as injury risk factors during block jump-landings, and also included an approach from at least 3 meters to simulate the real game situation and natural jump-landing technique. This study identified differences between the dominant and non-dominant limbs when performing the lead and trail limb roles considering all these factors.

Previous studies have observed that ankle injuries are mostly the result of contact with another player, up to 59% [38]. A typical mechanism resulting in an acute ankle inversion injury is within the conflict zone beneath the net where one player's foot lands on the foot of the opposing player [38]. In figure 2, when we compared between the lead and trail limb when the dominant limb performs as the trail limb and the non-dominant as the lead limb, we could see that the lead foot tends towards supination more than the trail limb. Moreover, in agreement with Hinshaw et al. [7] we found that the lead limb had a higher VGRF than the trail limb, but contrarily participants showed increased knee valgus moments for the trail limb when it is performed by the dominant limb. In figure 3, when we compared between the lead and trail limb when the dominant limb is the lead limb and the non-dominant is the trail limb, it seems that the trail limb tends towards a higher tibial internal rotation and hip abduction than the lead limb. An explanation of this could be that in this case, the trail limb corresponds with the non-dominant limb (**Figure 18**), which is the one in which athletes tended to land on when performing a spike [9]. However, when players are performing a block jump-landing depending on the direction of movement, which in turn depends on the game, they may have to change their natural three-step technique, and therefore the jump-landing movement strategy. Therefore, this fact may alter the strength balance and promotes asymmetries [4], and subsequently produces different movement patterns between limbs during jump-landing. Moreover, these asymmetries could be accentuated due to an improper recovery from a previous injury or strength differences [1-3]. Our work emphasizes the importance of planning training where bilateral coordination is considered in the lead and trail limb for both in the dominant and non-dominant limb, to try to minimize the imbalance and thus reduce injury risks.

In sport science the use of performance analysis has experienced considerable recent changes, due largely to access to improved technology and increased applications from computer science [28]. McGrath et al. [23] showed that Machine Learning could accurately assess fast bowling events using different inertial measurement units and the models produced exhibited high accuracy (>95%). Maier et al. [22] predicted future hits and misses by marksmen during biathlon competitions using different Machine Learning methods. Some studies have used these models in training or competition settings in elite sports [25-27]. Morgan et al. [39] illustrated the potential use of decision trees to identify attacker-defender interactions in hockey. Automating sport movement recognition and its application towards coding has the potential to enhance both the efficiency and accuracy of sport performance analysis. We used Machine Learning methods to analyse all variables together during the phase of movement where injuries most frequently occur [40-41]. The ability to quantify differences between limbs and role positions using Machine Learning methods and the possibility to classify conditions with decision trees offers a valuable analysis. In this study, we provided greater ecological validity to the real game situation of performing block jump-landings. Future work may look to adopt, adapt and expand on current models associated with a specific sports movement to work towards flexible models for mainstream analysis implementation [28].

However, this study had some limitations; firstly, we only measured women from the same volleyball team, secondly we only considered lower limb movement in the analysis, and finally, although participants moved as fast as possible, they had to control their jump-landings onto the force platforms, which does not replicate a real game situation. Future studies should consider more participants and the use of Machine Learning methods which may in turn have practical applications for coaches and trainers. This work indicates that coaches and trainers should plan training which considers the coordination in both limbs when performing the lead and trail role simulating the real game, to reduce automatism which may highlight asymmetries, and performing preventative exercises unilaterally to minimize imbalance and thus perhaps avoid future lower limb injuries.

Conclusions

In conclusion, it is necessary to consider the differences between the dominant and non-dominant limb to understand which strategies are used in the lead and trail limb during a block jump-landing. Moreover, the use of Machine Learning along with decision trees offers an analysis method to explore how the joints of both limbs interact during sporting tasks. This allows the identification of the variables which act as the strongest predictors, which help understand differences in movement strategy. This could provide a greater understanding of specific movement strategies which may be associated with injury risk.

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GENERAL

DISCUSSION

Main findings of the present doctoral thesis

The present doctoral thesis contributes to a better understanding of the three-step block jump-landing technique from a biomechanical perspective in conditions as close as possible to the actual game, considering direction dominance, limb roles and planned/unplanned situations. Details and a valuable description of the kinematic and kinetic variables were given which could provide relevant information about how to improve the performance of the players and how to plan the training in order to avoid an overload that could lead to risk of injury.

The importance of dominance direction and limb roles in block jump-landings

There are controversies about lower limb symmetry during landing tasks. Some authors reporting that there are no differences between limbs [1-3], and others reporting asymmetries [4-6]. According with authors who reported asymmetries between limbs, we showed that there were different movement strategies between limbs when a player is performing a block jump-landing in volleyball (Result and discussion of this Doctoral Thesis). Thus, in Section 1 and 2 our results suggest that there are differences between the lead and the trail limb, and the limb which might be more at risk of injury is the lead limb, independently of whether it is the dominant or non-dominant limb. This could be related to the lead limb being the external limb and consequently taking greater loads during landing. Additionally, in Section 2 and Annexe VI, it was found that there were differences in limb movement strategies when moving in the different directions but performing the same role independent of their position as the lead or the trail limb.

In volleyball, the dominant hand determines the three-step approach technique and therefore the jump-landing movement strategy when the athlete is trying to get the greatest spike performance. So, when a player is moving to the non-dominant direction this seems to change their natural three-step approach technique, and consequently the jump-landing movement strategy. Therefore, these automatisms may alter the strength balance and promotes asymmetries [7], and subsequently produces different motor patterns between limbs during jump-landing. Moreover, these asymmetries could be accentuated due to an improper recovery from a previous injury or strength differences [8-10].

Cox et al. [11] demonstrated that the cross over step was better in terms of getting the blocker off the ground and getting into a better blocking position quickly. To perform this approach, it is necessary to make a turn in the air, therefore it does not seem strange to us that the coronal and transverse planes, and thus the rotations and abduction/adduction of joints were relevant in the movement strategies. For all joints, the multi-planar mechanism was crucial when discerning between the dominant and non-dominant limb movement strategies [12]. However, depending on the role, some joints are more relevant than others. In Section 2 and Annexe VI of this Doctoral Thesis, it was showed that when limbs movement strategies are compared when they were performing their role as the trail limbs, we could see that both the hip and ankle had a principal importance. Contrarily, when limbs movement strategies are compared when they were performing their role as the lead limb, any joint is more relevant than other for the landing technique. This could mean that the greatest differences between the dominant and non-dominant movement strategies when they were performing their role as the trail limb were the stability of the knee through the motor coordination of the hip and ankle during landing.

This highlights that there is a necessity to consider the learning models, in which the spike approach (unilaterally) is taught before the block approach (bilaterally). We support the idea of teaching bilateral approach jump automatisms before learning the spike, in order to improve coordination and to avoid asymmetries between limbs. As a result, it is important to consider the dominant and non-dominant directions and the limb role position when considering technical learning models, and physical and preventive training in volleyball block jump-landings to try to minimize the asymmetries and thus reducing injury risks.

Use of unplanned situations in trainings

During the game, blockers have to be prepared to deal with different possibilities of attack. This contextual situation creates an uncertainty where the player cannot plan in which direction the attack will be, and therefore players might have to modify their movement strategies [13]. Thus, when the player voluntarily executes the movement and plans where and when he or she has to move, a different situation from the real game is created. Accordingly, with the complexity of the block jump-landing, which is related to anticipation, movement speed, decision-making and jumping ability [14], in this Doctoral Thesis it was analysed if there were differences between planned and unplanned situations for the dominant and non-dominant limbs. Both situations had undergone experimentation finding significant differences.

Overall, the main finding of the present section is that our results suggest that planned landings have a tendency for higher risk in possible factors that affect performance, and which could be associated with a higher number of lower limb injuries, than in unplanned landings. In Section 1, it was analysed the comparison of planned and unplanned jump-landings for the dominant and non-dominant limb. Through the application of traditional statistics (ANOVA), it was found statistically differences in some variables, which could discern between conditions. The application of Machine Learning methods on the same data did not produce models accurate enough, so they were discarded. Leukel et al. [15] confirmed that when there is an unplanned situation during a jump or landing, muscle activity and tendomuscular stiffness was reduced. Similarly, in our results the comparison of planned and unplanned jump-landings showed, for the non-dominant limb, the peak knee power absorption and the knee energy absorption were greater in planned than in unplanned jump-landings. For the dominant limb, energy absorption at the hip decreases with an increase in angular velocity in planned landings, indicating maybe a higher risk of injury. Moreover, the knee on the dominant limb had a greater flexion moment during planned compared to unplanned landings. In essence, some relevant variables which have been selected for the risk of overuse injury are giving us information about a possible increase in risk in the planned situations, and which are also not aspects of the game.

Planned and unplanned situations were compared and no differences were found in movement time, but there were in the response time, since in the former case the player had some stimulus. This could be due to planned movements using an internal focus which changes the movement strategies, whereas in unplanned movements the volleyball players had an external focus. An external focus on the movement promotes the utilization of unconscious or automatic processes, whereas an internal focus results in a more conscious type of control that constrains the motor system and disrupts automatic control processes [16], and focuses the athlete's attention on his or her own body movements [17]. Therefore, if players train in a planned situation, the movement pattern does not correspond to the game action, being able to lose transfer to the competition and furthermore being able to affect a greater load that could be an increase in the risk of injury.

Therefore, as practical implications, coaches and trainers should plan and adapt training to simulate competition where players have unplanned situations, to improve their performance and might avoid overloads that could lead to risk of injury

The necessity of protocols as real as possible

In sport, when the main objective is to achieve the maximum performance, the athlete endures physical, physiological and psychological stresses all of which have been associated with a greater risk of suffering an injury [18]. This means that, it is necessary to improve performance and minimize the risk of injury, promoting balanced motor patters through an efficient technique. Hence the relevance of the saying "prevention is better than cure".

However, prevention programs are still limited by a lack of understanding of the specific risk factors that can influence injuries in sports [19], primarily due to the difficulty of quantifying biomechanical loads in a field environment [20]. Previous studies analysed biomechanical variables between limb dominance [1, 21], limb roles [4, 22, 23], directions [5, 24], and ecological protocols [6, 25-27], however these only considered a limited number of variables. In this Doctoral Thesis it was designed and applied a protocol which simulate the real game inside the laboratory. Therefore, it was included planned and unplanned situations, direction dominance and limb role, simulating moving to zone II and to zone IV of the court. In addition, it was considered both velocity and approach distance under the different conditions, which provided greater ecological validity to the real game situation of performing block jump-landings [28]. Moreover, all biomechanical variables which have previously been considered as injury risk factors during block jump-landings were analysed. In addition, Machine Learning methods were applied to develop models aimed at a global understanding of all variables in the same context. To the author's knowledge, no investigation exists which consider all these variables; therefore, we believe that this Doctoral Thesis contributes to a better understanding about movement strategies getting closer to the game and considering relevant variables. This valuable information leads to new questions in order: to improve performance, to think about new technical learning models and preventive trainings, and also to wonder whether the variables that have considered as relevant for injury risk in the literature are really the most important for block jump-landings in volleyball.

There is a necessity to break the line between laboratory and field, and in agreement with Verheul et al. [20], keep pursuing new methods to measure biomechanical variables in situations as real as possible, for a better understanding of the specific movements in order to design efficient trainings and preventive programs.

Application of Machine Learning to sports

Data characterizing human movement are high-dimensional, heterogeneous and growing in volume due largely to access to improved technology and increased applications of Computer Science [29]. To harness the power of these data and make research more effective and efficient, modern Machine Learning techniques complement traditional statistical tools [30]. However, the application within the sporting domain of Machine Learning and automated sport analysis coding for consistent uniform usage appears currently a challenging prospect, considering the dynamic nature, equipment restrictions and varying environments arising in different sports [29].

Notwithstanding, it is easy to find in the literature how some authors are including automating sport movement recognition and how its application towards coding has the potential to enhance both the efficiency and accuracy of sport performance analysis. McGrath et al. [31] showed that Machine Learning could accurately assess fast bowling events using different inertial measurement units and the models produced exhibited high accuracy (>95%). Maier et al. [32] predicted future hits and misses by marksmen during biathlon competitions using different Machine Learning methods. Other studies have used these models in training or competition settings in elite sports [33-36]. Morgan et al. [34] illustrated the potential use of decision trees in identifying attacker-defender interactions in hockey. Kautz et al. [37] showed that detailed player monitoring in beach volleyball was feasible using wearable sensors using Deep Learning, however, unsatisfactory results were obtained from the Machine Learning models. Van Haaren et al. [38] identified several relevant strategies from teams through their time-space patterns inside the game, analysing videos from the 2014 FIVB (International Volleyball Federation) Volleyball World Championship. Furthermore, vision and Deep Learning approaches have demonstrated the ability to track and classify team sport collective court activities and individual player specific movements in volleyball [39].

Although research at the interaction of Machine Learning and biomechanics offers great promise for advancing human movement research, as models become more complex, they also often become more difficult to interpret [30]. Machine Learning methods can learn highly complex nonlinear relationships from large data and outperform humans at many tasks, yet their opaqueness inspires little confidence in biomedical scientists [30]. Lack of interpretability is particularly challenging in biomechanics, due to the body being able to compensate the instability of the movement with corporal adjustment. If a "black box" model predicts with high confidence that a player has different limbs movement strategies based on his or her kinematic and kinetic variables, but offers no insight into the specific features of injury risk, it is unclear how this knowledge could be used to improve the player's performance. For these reasons, it is advisable to use methods with complex models which prioritize predictive accuracy over interpretability, such as Artificial Neural Networks, but also for diagnosis tools and implementation it is currently better to use transparent models, such as decision trees [30].

For these reasons, Machine Learning methods have been used to analyse all variables together during the phase of movement where injuries most frequently occur [40, 41]. The ability to quantify differences between direction dominance and limb roles using Machine Learning methods and the possibility to classify conditions with decision trees offers a valuable analysis. In this Doctoral Thesis, it was provided a detailed description of the movement strategies for the limbs. Moreover, in order to understand the "black box," the factors within our models were analysed. This allowed the exploration of which variables could be more relevant to discern between limbs under the different conditions. Thus, there is a necessity to understand how the technique is done, and after that, how to avoid the imbalance between limbs in order to improve performance and avoid the possibility of injury. I believe that more and more, engineers and scientists will work together to unravel the complex relationships of limbs movement strategies, and thus favour a better understanding of the technique for optimizing sports performance. Future work may look to adopt, adapt and expand on current models associated with a specific sports movement to work towards flexible models for mainstream analysis implementation [29].

Strengths, limitations, future research directions and practical applications

This International Doctoral Thesis has tried to make up for some limitations that were found in how limbs movement strategies have been analysed previously from a multidisciplinary perspective. It was created a protocol which integrated the majority of all planes, variables that have been previously reported as risk factors in lower limb injuries. In addition, many factors were considered: velocity, approach distance, direction dominance and planned/unplanned situations under the different conditions, which provided greater ecological validity to the real game situation of performing block jump-landings. Finally, data were analysed through both traditional statistics and Machine Learning methods. The built models allowed to understand from a more global perspective what are the movement strategies performed by the limbs and which variables are the most relevant in those strategies.

However, the integration of these variables has had an impact on also having limitations: firstly, we only measured women from the same volleyball team, secondly we only considered lower limb movement in the analysis, and finally, although participants moved as fast as possible, they had to control their jump-landings onto the force platforms, which does not replicate a real game situation.

This Doctoral Thesis is the initial part of the "SAVIA" Project (Specific Actions of Volleyball Injury Avoidance). The underlying idea of this project is to understand the different movement strategies of the limbs in the conditions studied in this thesis, and subsequently to identify possible factors that affect performance, and which could be associated with the most common lower limb injuries. In this way, developing an intervention which improves the physical and preventive training from a targeted prevention program. Moreover, future studies should measure males and females from different competition levels to get a better understanding of jump-landing strategies and to consider the use of Machine Learning methods which may in turn have practical applications for coaches and trainers.

For practical applications, coaches and trainers should plan training which considers the coordination in both directions and limbs when performing the lead and trail role simulating the real game, to reduce automatism which may highlight asymmetries, and performing preventative exercises unilaterally to minimize imbalance and thus perhaps avoid future lower limb injuries. Additionally, it would be advisable to teach the sequence of three steps bilaterally during the jump before the consolidation of automatisms in the performance of volleyball spikes. Furthermore, adapting training to simulate competition where players have unplanned situations could improve their performance which may reduce injury risk.

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CONCLUSIONES

Conclusión general

Los resultados de esta Tesis Doctoral Internacional evidencian que la dominancia en la dirección, los papeles de las piernas y las situaciones planificadas y no planificadas influyen en las estrategias de movimiento de las extremidades inferiores durante la realización de bloqueos en voleibol. Parece ser que las situaciones planificadas generan un mayor estrés músculo-esquelético que las no planificadas. Además, más que diferencias entre pierna dominante o no dominante, hay diferencias en función del papel que desempeñan, siendo la pierna que lidera la que tiene más estrés músculo-esquelético respecto a la que es arrastrada. Por tanto, esto podría darnos información relevante: de cómo mejorar el rendimiento de los jugadores y de cómo planificar los entrenamientos de manera que se intente evitar una sobrecarga que pueda dar lugar a riesgo de lesión. Finalmente, también nos hace cuestionarnos los modelos de aprendizaje, si las variables que se han considerado hasta ahora en la biomecánica realmente son las más relevantes, y si la aplicación de Aprendizaje Automático podría cambiar el paradigma en la forma de interpretar el riesgo de lesión en acciones específicas del deporte.

Conclusiones específicas

- Las piernas realizaron diferentes estrategias de movimiento durante el aterrizaje cuando realizaron saltos de bloqueo. Por lo tanto, es necesario diseñar y desarrollar protocolos que sean lo más ecológicamente válidos posible, para una mejor comprensión de los movimientos específicos a fin de diseñar entrenamientos adecuados y programas preventivos eficientes.
- En una situación planificada, los atletas pueden tener un pensamiento más consciente sobre su movimiento, o un enfoque interno, lo que podría cambiar su estrategia produciendo una mayor relación con los factores de lesión que en las situaciones no planificadas fomentadas por un enfoque externo.
- El papel de la extremidad, ya sea la que lidera o la arrastrada, es más importante que el hecho de que sea la pierna dominante o no dominante cuando se realizan saltos direccionales. Además, la pierna que lidera parece tener un mayor riesgo de lesiones que la arrastrada, debido a mayores cargas durante el aterrizaje.
- Es necesario considerar la dirección dominante y no dominante, debido a las diferencias observadas entre las estrategias de movimiento de las extremidades generadas por la batida del remate durante un aterrizaje de salto de bloqueo.

- El uso de técnicas de Aprendizaje Automático como, por ejemplo, redes neuronales artificiales o Random Forest, ofrece un método de análisis para explorar las diferencias entre las estrategias de movimiento de las extremidades. También, permite explorar cómo interactúan las articulaciones de ambas extremidades y la identificación de las variables que actúan como los predictores más fuertes a la hora de comprender las diferencias en la estrategia de movimiento.

CONCLUSIONS

Overall conclusion

Findings from this International Doctoral Thesis evidence that dominance in the direction, limb roles and the planned and unplanned situations influence the movement strategies of the lower extremities. It seems that planned situations may generate more musculoskeletal stress than unplanned ones. Moreover, there are clear differences depending on the role played by the limb, with the lead limb having more musculoskeletal stress than the trail limb, perhaps due to an increased load. This Thesis provides relevant information about how to improve the performance of the players and how to plan the training in order to avoid an overload that could lead to risk of injury. Finally, it also raises questions about the learning models that are being used, if the variables that have been considered so far in science really are the most relevant, and if the application of Machine Learning could change the paradigm in the way of interpreting the risk of injury in sport-specific actions.

Specific conclusions

- Lower limbs had different strategies during the landing when participants performed a block jump-landing. Therefore, it is necessary to design and develop protocols to be as ecologically valid as possible, for a better understanding of the specific movements in order to design efficient trainings and preventive programs.
- In the planned situation, the athletes may be more consciously thinkikng about their movement, or an internal focus, which might change their strategy producing a greater relationship with injury factors than in the unplanned situations which encourages an external focus.
- It appears that the role of the limb, either lead or trail, is more important than the limb dominance when performing directional jump-landings. Moreover, the lead limb may have a higher risk of injury than the trail limb, due to taking greater loads during landing.
- It is necessary to consider the dominant and non-dominant direction, due to the differences seen between limbs movement strategies generated by the three-step spike approach during a block jump-landings.
- The use of Machine Learning methods, such us Artificial Neural Networks and Random Forests, is an effective analysis method to explore jump-landing training techniques and the differences between limb movement strategies. Moreover, it allows to explore

how the joints of both limbs interact during sporting tasks. This allows the identification of the variables which act as the strongest predictors, which help understand differences in movement strategy.

ANNEXES

Annexe I. The Ethics Committee approved for this thesis

UNIVERSIDAD DE GRANADA

Vicerrectorado de Investigación y Transferencia

COMITE DE ETICA EN INVESTIGACION DE LA UNIVERSIDAD DE GRANADA

La Comisión de Ética en Investigación de la Universidad de Granada, visto el informe preceptivo emitido por la Presidenta del Comité en Investigación Humana, tras la valoración colegiada del Comité en sesión plenaria, en el que se hace constar que la investigación propuesta respeta los principios establecidos en la legislación internacional y nacional en el ámbito de la biomedicina, la bioteconología y la bioética, así como los derechos derivados de la protección de datos de carácter personal,
Emite un Informe Favorable en relación a la investigación titulada: 'ANÁLISIS ESPECÍFICO DEL VOLEIBOL PARA LA PREVENCIÓN DE LESIONES. PROYECTO "SAVIA"' que dirige D./Dña. ELIA MERCADO PALOMINO, con NIF 74.735.533-T, quedando registrada con el nº: 389/CEIH/2017.

Granada, a 03 de Julio de 2017.

EL PRESIDENTE
Fdo: Enrique Herrera Viedma

EL SECRETARIO
Fdo: Fernando Cornet Sánchez del Águila

Gran Vía de Colón 48, 2 Planta. 18071 GRANADA
http://investigacion.ugr.es

Annexe II. Informed consent and information for participants

CONSENTIMIENTO INFORMADO PARA JUGADORES/AS DE VOLEIBOL

Título: Análisis específico del voleibol para la prevención de lesiones. Proyecto "SAVIA".

Nombre del investigador: Elia Mercado Palomino

Director de la Tesis Doctoral: Aurelio Ureña Espá

Departamento: Educación Física y Deportiva

Estimado/a participante:

Mediante la presente usted es invitado a participar en el estudio de investigación que Elia Mercado Palomino, estudiante del programa de Doctorado en Biomedicina en la Facultad de Ciencias del Deporte de la Universidad de Granada, va a realizar para el desarrollo de su tesis doctoral. Este estudio tien como objetivo analizar la calidad de su bloqueo de voleibol. En base a la información obtenida, se desea generar conocimiento basado en investigación que permita la mejora del rendimiento en voleibol.

Si decido participar en el estudio, comprendo que durante el proceso deberé de comprometerme a:

1. Asistir a la totalidad de las sesiones de toma de datos iniciales: peso, estatura, envergadura.
2. Informar con antelación a los investigadores de mi intención de abandonar el estudio en caso necesario.
3. Indicar cualquier problema, síntoma o condición que sea relevante de mi estado de salud que pueda afectar directamente mi seguridad o rendimiento durante el ejercicio.
4. Indicar al responsable del estudio si he tenido alguna lesión en los miembros inferiores previo a 6 meses.
5. Llevar ropa adecuada para los marcadores epidérmicos 3D.

Posibles riesgos

Los riesgos que podrían desarrollarse en las actividades llevadas a cabo en este estudio son los mismos que podrían aparece en cualquier práctica deportiva de entrenamiento y competición, asumidos por una federación del deporte a practicar.

Formulario de consentimiento informado

Si decido participar en el estudio, recibiré información por parte del equipo investigador sobre mi estado y rendimiento en las variables analizadas. Soy consciente de que la participación es totalmente voluntaria y que podré dejar de participar en el estudio en cualquier momento Ningún dato de este estudioserá utilizado para otros fines manteniéndose la información obtenida en completa confidencialidad.

He leído el documento, entiendo las declaraciones contenidas en él y la necesidad de hacer constar mi consentimiento, para lo cual lo firmo libre y voluntariamente, recibiendo en el acto copia de este documento ya firmado

CONSENTIMIENTO POR ESCRITO DEL PACIENTE O PARTICIPANTE

Título del estudio: Análisis de aterrizajes en acciones específicas de bloqueo en voleibol desde la perspectiva del riesgo de lesión.

Yo, (nombre y apellidos) ...., con D.N.I. nº................................

He hablado con el profesional responsable del estudio..

....

....

He leído la hoja de información que se me ha entregado.

He podido hacer preguntas sobre el estudio.

He recibido suficiente información sobre el estudio.

Comprendo que mi participación es voluntaria.

Comprendo que puedo retirarme del estudio:

Cuando quiera.

Sin tener que dar explicaciones.

Sin que esto repercuta en mis cuidados médicos.

Presto libremente mi conformidad para participar en el estudio.

Las muestras obtenidas en este estudio sólo serán utilizadas para los fines específicos del mismo.

Fecha Firma del paciente o participante

Fecha Firma del profesional responsable del estudio y D.N.I.

CONSENTIMIENTO POR ESCRITO DEL REPRESENTANTE

Título del estudio: Análisis de aterrizajes en acciones específicas de bloqueo en voleibol desde la perspectiva del riesgo de lesión.

Yo, (nombre y apellidos) ...., con D.N.I. nº................................

en calidad de (relación con el participante) ....

de (nombre del participante) ....

He hablado con el investigador responsable del estudio..

He leído la hoja de información que se me ha entregado.

He podido hacer preguntas sobre el estudio. /profesional responsable del estudio

He recibido respuestas satisfactorias a mis preguntas.

He recibido suficiente información sobre el estudio.

Comprendo que la participación es voluntaria.

Comprendo que puede retirarse del estudio:

Cuando quiera.

Sin tener que dar explicaciones.

Sin que esto repercuta en sus cuidados médicos.

Y presto mi conformidad con que (nombre del participante) ....participe en este estudio.

Fecha Firma del representante

Fecha Firma del profesional responsable del estudio y D.N.I.

iMUDS Instituto Mixto Universitario Deporte y Salud

FACULTAD DE CIENCIAS DEL DEPORTE Universidad de Granada

ugr Universidad de Granada

INSTRUCCIONES para PARTICIPAR en el PROYECTO "SAVIA":

Para la evaluación, los participantes deben venir "preparados", lo cual implica el cumplimiento de las siguientes **INSTRUCCIONES**, muchas de ellas relacionadas con la **INDUMENTARIA**:

- **CALENDARIO**: las evaluaciones se fijarán del 27 al 31 de marzo del 2017.

- **LUGAR:** las pruebas se realizarán en el iMUDS (Instituto Mixto Universitario Deporte y Salud), en Calle Menéndez Pelayo, nº32. Centro situado dentro del Parque Tecnológico de la Salud (PTS).

- **CONDICIONES**: No haber tenido ninguna lesión en los miembros inferiores en los últimos 6 meses.

- Consideraciones para la prueba de **COMPOSICIÓN COPORAL:**
  - Debe acudir al lugar de evaluación, como mínimo, 2 horas después de haber realizado su última comida. En las 24 h previas no realizar esfuerzos físicos intensos.
  - No llevar consigo accesorios metálicos (anillos, pulseras, colgantes).
  - Una vez terminada esta prueba puede comer.

- Consideraciones para el **ANÁLISIS BIOMECÁNICO:**
  - Es necesario realizar la prueba con ropa ajustada. Para ello recomendamos los pantalones cortos de competición en el caso femenino y unas mallas deportivas (preferiblemente cortas) en el caso masculino, y camiseta ajustada de tirantes o top.
  - Es necesario traer zapatillas deportivas.

Annexe III. Borg Scale 6-20

Borg Rating of Perceived Exertion

6	No exertion at all
7	Extremely light
8	
9	Very light
10	
11	Light
12	
13	Somewhat hard
14	
15	Hard (heavy)
16	
17	Very hard
18	
19	Extremely hard
20	Maximal exertion

Annexe IV. Classification of conditions in Machine Learning

Clasificador de condición del salto para la nueva base de datos (con momentos de fuerza)(piernas interior y exterior)

18/04/18

Introducción

En este trabajo se han ajustado clasificadores de condición de los saltos. Las condiciones que se clasifican son por un lado Control-Incertidumbre, y por otro lado Dominancia-No dominancia. Se han ajustado dos clasificadores por cada una de los dos pares de condiciones anteriores. Para el primer clasificador se ha empleado una red neuronal (con 5 neuronas en la capa oculta), y para el segundo clasificador un Random Forest que además contiene una función de regularización de variables. En cada uno de los ajustes de los clasificadores se ha empleado una validación cruzada (con k=10) para evaluar los resultados de los mismos y garantizar que son independientes de la partición entre datos de entrenamiento y prueba.

Para entrenar y testear los clasificadores se han extraído de la nueva base de datos los valores en los momentos F1 y F2 (momentos obtenidos a partir de las plataformas de fuerza) de todas las variables de la nueva base de datos para cada una de las jugadoras en cada uno de los saltos individuales que han realizado para cada condición, hayan sido marcadas dichas variables como más relevantes en los indicadores de riesgo o no. *En este caso se han empleado los datos de las hojas 2, que no hacen diferencia entre pierna izquierda o derecha, sino entre pierna interior y exterior.* Luego en total se tienen 372 saltos, quedando en cada iteración de la validación cruzada 335 saltos para entrenamiento y 37 saltos para test.

Dichas variables son 72, y están formadas por las 36 variables anteriores (ángulos y velocidades angulares), a las que además se les añaden las 36 variables nuevas (momento de fuerza y potencia). *Adicionalmente a las anteriores, en este estudio también se han incluido 4 variables correspondientes a los valores de fuerza en las plataformas FP1 y FP2 en el eje Z en los momentos F1 y F2, diferenciando en este caso en valores de fuerza para la pierna interior o exterior*

Para cada uno de los saltos se ha establecido una etiqueta en función de su condición, para un primer análisis:

- Control (C)
- Incertidumbre (U)

Y para un segundo análisis:

- Dominante (D)
- No Dominante (N)

Por último, como medidas de bondad del ajuste se han empleado el accuracy (ACC)(es el número de aciertos entre el total de testeo), y el área bajo la cueva roc (AUC)(es una representación de la sensibilidad frente a la especificidad para un sistema clasificador binario lo que se puede interpretar como el ratio de verdaderos positivos frente a la razón o ratio de falsos positivos).

Análisis para Control - Incertidumbre (C - U)

Red neuronal

Para el momento F1

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.5946776	0.6432426

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	0.7027027	0.7027027	0.5833333	0.6486486	0.5526316	0.4210526	0.6486486	0.5135135	0.5789474	0.5945946
AUC	0.6088235	0.8377193	0.6501548	0.6926471	0.5791667	0.5236111	0.7264706	0.5789474	0.6069444	0.6279412

Para el momento F2

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.5779674	0.6250271

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	0.5675676	0.6216216	0.6111111	0.6216216	0.5263158	0.5263158	0.5405405	0.6756757	0.7105263	0.3783784
AUC	0.6661765	0.6432749	0.6145511	0.6117647	0.6236111	0.5222222	0.5205882	0.7426901	0.7083333	0.5970588

Random Forest

Para el momento F1

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.643267	0.7127705

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	0.6486486	0.7567568	0.6666667	0.6486486	0.4473684	0.6578947	0.7027027	0.5945946	0.5526316	0.7567568
AUC	0.6764706	0.7880117	0.8120035	0.6852941	0.5638889	0.6916667	0.7941176	0.5906433	0.7013889	0.8235294

Número promedio de características seleccionadas en cada iteración:

```
## [1] 29.8
```

Para el momento F2

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.6403588	0.7008914

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	0.7027027	0.7027027	0.7222222	0.5945946	0.6315789	0.5526316	0.5945946	0.8108108	0.6052632	0.4864865
AUC	0.7882353	0.7134503	0.8049536	0.5852941	0.7069444	0.6236111	0.7338235	0.8216374	0.6736111	0.5573529

Número promedio de características seleccionadas en cada iteración:

```
## [1] 29.6
```

Análisis para Dominante - No dominantes (D - N)

Red neuronal

Para el momento F1

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.97289	0.9837719

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	0.9729730	0.8918919	0.9166667	1	1	1	1	1	0.9473684	1
AUC	0.9722222	0.9181287	1.0000000	1	1	1	1	1	0.9473684	1

Para el momento F2

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.9600284	0.9600877

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	1	1	1	0.9459459	1	0.9210526	0.8648649	1	0.9473684	0.9210526
AUC	1	1	1	0.9444444	1	0.9210526	0.8669591	1	0.9473684	0.9210526

Random Forest

Para el momento F1

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.9622965	0.9625731

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	0.9729730	0.9459459	0.9444444	0.9459459	0.9729730	0.9736842	0.9729730	0.9729730	0.9210526	1
AUC	0.9722222	0.9473684	0.9444444	0.9473684	0.9722222	0.9736842	0.9736842	0.9736842	0.9210526	1

Número promedio de características seleccionadas en cada iteración:

```
## [1] 9.7
```

Para el momento F2

Media de los ACCs y AUCs obtenidos durante la validación cruzada, y valores de los ACCs y AUCs obtenidos en cada iteración de la validación cruzada:

ACC_promedio	AUC_promedio
0.9569622	0.9570175

	Iter1	Iter2	Iter3	Iter4	Iter5	Iter6	Iter7	Iter8	Iter9	Iter10
ACC	0.9459459	1	0.9444444	0.9729730	0.9459459	0.9473684	0.9189189	0.9729730	0.9473684	0.9736842
AUC	0.9459064	1	0.9444444	0.9736842	0.9444444	0.9473684	0.9210526	0.9722222	0.9473684	0.9736842

Número promedio de características seleccionadas en cada iteración:

```
## [1] 10.8
```

Annexe V. Example of feature selection for the Question 3

Aplicación de la selección de características sobre la pregunta 2.1. ¿Existen diferencias significativas entre la pierna exterior cuando esta va hacia el lado dominante y cuando va hacia el lado no dominante?

Los datos

Las variables que se han tomado en consideración para este estudio son **32 variables:** 9 variables referentes a la magnitud **Angle** en la cadera, tobillo y rodilla en los ejes X, Y y Z; 9 variables correspondientes a la magnitud **Vel_Ang** también en las mismas articulaciones y ejes; 9 variables correspondientes a **Mom** en idénticas condiciones; 3 variables referentes a **Pow** en las articulaciones pero sólo en el eje X, y 2 variables correspondiente a las plataformas de fuerza, **FP** y **FP_loading rate** en el eje Z. Todas estas variables se han considerado para ambas piernas (ya sea izquierda-derecha, exterior-interior, o dominante-no dominante) por lo que se va tener dos valores por variable en función de que sea una pierna u otra.

El número de jugadoras es de 14, y el total de todos los saltos de las jugadoras es de 376 saltos. cada uno de estos saltos puede ser hacia el lado dominante de la jugadora o hacia el lado no dominante. Para cada uno de los saltos de cada jugadora se obtiene el valor de las 32 variables en su **momento F1** (en este caso no se va a usar el momento F2 (estos momentos como ya sabemos son obtenidos a partir de las plataformas de fuerza) para cada una de las piernas (ya sean izquierda-derecha, exterior-interior, o dominante-no dominante). Por lo tanto, se va a tener por cada salto de una jugadora dos filas, cada una con los valores de las 32 variables para cada pierna. Además, cada una de estas dos filas van a estar etiquetadas en función de la pierna a la que se corresponden y según el salto es hacia el lado dominante o no.

Así pues, la matriz de datos está compuesta por 32 columnas correspondientes a las variables anteriormente nombradas, y 752 filas correspondientes a los valores de esas variables en cada una de las piernas en los saltos de las jugadoras (376 saltos por dos piernas). Pero como **en este estudio se pide contrastar la diferencia de la pierna exterior cuando el salto es hacia el lado dominante y cuando el salto es hacia el lado no dominante**, solo se tienen en cuenta para el análisis las filas en las que las variables son de la pierna exterior, que son la mitad de las filas, y por lo tanto las filas resultantes van a estar etiquetadas únicamente en función del tipo de salto:

- *Salto dominante* en la pierna exterior *(D)*
- *Salto no dominante* en la pierna exterior *(N)*

¿Qué se ha hecho?

En este trabajo se ha llevado a cabo un proceso de selección de características mediante los métodos implementados en el paquete (en R) FSinR. Para ello, se ha empleado un método de tipo wrapper combinado con los siguientes métodos de búsqueda:

- Sequential forward selection (sfs)
- Sequential floating forward selection (sffs)
- Sequential backward selection (sbs)
- Sequential floating backward selection (sfbs)
- Genetic algorithm (ga)
- Whale optimization algorithm (woa)
- Ant colony optimization (aco)
- Simulated annealing (sa)
- Tabu search (TS)
- Hill-Climbing (hc)
- Las Vegas wrapper (lvw)

Como método de evaluación del wrapper se ha usado un clasificador sobre la condición de los saltos. Este clasificador se obtiene mediante el uso de los métodos del paquete caret, más en concreto se emplea un clasificador basado en red neuronal (mlp del paquete RSNNS) con unos valores del parámetro size = (3, 6, 9, 12). A caret también se le ha especificado realizar una normalización de los datos consistente en un centrado y en un escalado, y realizar una validación cruzada de 10-folds como estrategia de remuestreo en el wrapper. Finalmente, también se le ha especificado el precisión en clasificación como la métrica con la que se evalúan los resultados de clasificación.

Para determinar si hay diferencia entre la pierna exterior cuando esta va hacia el lado dominante o cuando esta va hacia el lado no dominante, las etiquetas de los saltos sobre las que trabajan los clasificadores se han simplificado al sentido del salto, dominante y no dominante.

Es importante destacar que todo este proceso se ha llevado a cabo sobre los datos de entrenamiento del proceso de experimentación. El porcentaje de datos usados para entrenamiento es de un 80%, por lo tanto la matriz de datos sobre la que se trabaja tiene 301 instancias en lugar de las 376 originales. Además, también se ha seguido una estrategia de validación cruzada para la aplicación del proceso de selección de características. Después de la selección de características, los datos de entrenamiento se han dividido en 5-folds y la selección de características se ha aplicado sobre cada uno de los conjuntos de datos.

Selección de características con red neuronal como medida de evaluación en el wrapper

Sequential forward selection (sfs)

Las variables seleccionadas junto con precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	1	1	1	1	1	100
Hip Angle Y	1	1	1	1	1	100
Hip Angle Z	1	1	1	1	1	100
Knee Angle X	1	1	1	1	1	100
Knee Angle Y	1	1	1	1	1	100
Knee Angle Z	1	1	1	1	1	100
Ankle Angle X	1	1	1	1	1	100
Ankle Angle Y	1	1	1	1	1	100
Ankle Angle Z	1	1	1	1	1	100
Hip Vel_Ang X	1	1	1	1	1	100
Hip Vel_Ang Y	1	1	1	1	1	100
Hip Vel_Ang Z	1	1	1	1	1	100
Knee Vel_Ang X	1	1	1	1	1	100
Knee Vel_Ang Y	1	1	1	1	1	100
Knee Vel_Ang Z	1	1	1	0	1	80
Ankle Vel_Ang X	1	1	1	1	1	100
Ankle Vel_Ang Y	1	1	1	1	0	80
Ankle Vel_Ang Z	1	1	1	1	1	100
Hip Mom X	1	1	1	1	1	100
Hip Mom Y	1	1	1	1	1	100
Hip Mom Z	0	1	1	1	1	80
Knee Mom X	1	1	1	1	1	100
Knee Mom Y	1	1	1	1	0	80
Knee Mom Z	1	1	1	1	1	100
Ankle Mom X	1	1	1	1	1	100
Ankle Mom Y	1	1	1	1	1	100
Ankle Mom Z	1	1	1	1	1	100
Hip Pow X	1	1	1	1	0	80
Knee Pow X	1	1	1	1	1	100
Ankle Pow X	1	1	1	1	1	100
FP Z	1	1	1	0	1	80
FP_loading rate Z	1	1	1	1	1	100

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.974	0.983	0.975	0.975	0.979	**0.977**

Sequential floating forward selection (sffs)

Las variables seleccionadas junto con la precisión promedia obtenida han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	0	0	0	0	0	0
Hip Angle Y	1	0	1	0	0	40
Hip Angle Z	1	0	1	1	1	80
Knee Angle X	0	0	0	0	0	0
Knee Angle Y	0	0	0	0	1	20
Knee Angle Z	0	1	1	1	1	80
Ankle Angle X	1	1	1	1	1	100
Ankle Angle Y	0	0	1	0	0	20
Ankle Angle Z	0	1	1	0	1	60
Hip Vel_Ang X	0	1	1	0	0	40
Hip Vel_Ang Y	0	0	0	1	0	20
Hip Vel_Ang Z	1	1	1	0	0	60
Knee Vel_Ang X	1	1	1	0	0	60
Knee Vel_Ang Y	1	1	1	0	1	80
Knee Vel_Ang Z	0	0	0	1	0	20
Ankle Vel_Ang X	0	1	1	0	0	40
Ankle Vel_Ang Y	0	0	0	1	0	20
Ankle Vel_Ang Z	1	1	1	0	1	80
Hip Mom X	0	0	0	0	0	0
Hip Mom Y	0	0	0	0	0	0
Hip Mom Z	0	0	0	1	1	40
Knee Mom X	0	0	0	1	1	40
Knee Mom Y	0	0	0	0	0	0
Knee Mom Z	1	0	0	1	1	60
Ankle Mom X	1	1	1	1	1	100
Ankle Mom Y	1	0	0	0	0	20
Ankle Mom Z	0	1	1	0	1	60
Hip Pow X	0	1	0	0	0	20
Knee Pow X	1	0	0	0	0	20
Ankle Pow X	0	1	1	0	0	40
FP Z	0	0	1	1	0	40
FP_loading rate Z	0	1	0	0	0	20

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.971	0.974	0.979	0.963	0.974	**0.972**

Sequential backward selection (sbs)

Las variables seleccionadas junto con la precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	0	0	0	0	0	0
Hip Angle Y	0	0	0	0	0	0
Hip Angle Z	1	1	0	1	1	80
Knee Angle X	0	1	0	0	0	20
Knee Angle Y	0	1	1	0	1	60
Knee Angle Z	0	1	1	1	1	80
Ankle Angle X	0	0	0	1	0	20
Ankle Angle Y	0	0	0	0	0	0
Ankle Angle Z	0	0	0	0	0	0
Hip Vel_Ang X	0	0	0	0	0	0
Hip Vel_Ang Y	0	0	0	0	0	0
Hip Vel_Ang Z	0	0	0	0	0	0
Knee Vel_Ang X	0	0	0	0	0	0
Knee Vel_Ang Y	0	1	0	0	1	40
Knee Vel_Ang Z	1	1	0	0	0	40
Ankle Vel_Ang X	1	0	0	0	0	20
Ankle Vel_Ang Y	0	0	0	1	0	20
Ankle Vel_Ang Z	1	1	1	0	1	80
Hip Mom X	0	0	0	0	0	0
Hip Mom Y	0	0	1	0	0	20
Hip Mom Z	1	0	0	1	0	40
Knee Mom X	0	0	0	0	0	0
Knee Mom Y	0	0	0	0	0	0
Knee Mom Z	0	0	0	1	0	20
Ankle Mom X	0	1	1	0	0	40
Ankle Mom Y	0	0	0	0	0	0
Ankle Mom Z	1	1	1	0	1	80
Hip Pow X	0	0	0	0	0	0
Knee Pow X	0	0	0	0	0	0
Ankle Pow X	0	0	0	0	0	0
FP Z	0	0	0	0	0	0
FP_loading rate Z	0	1	0	0	0	20

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.953	0.983	0.962	0.963	0.946	**0.961**

Sequential floating backward selection (sfbs)

Las variables seleccionadas junto con precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	1	1	1	1	1	100
Hip Angle Y	1	1	1	0	0	60
Hip Angle Z	1	1	1	1	1	100
Knee Angle X	1	1	1	1	1	100
Knee Angle Y	1	1	0	1	1	80
Knee Angle Z	0	1	1	1	1	80
Ankle Angle X	1	1	0	1	1	80
Ankle Angle Y	1	1	1	1	1	100
Ankle Angle Z	1	1	1	1	1	100
Hip Vel_Ang X	1	1	1	1	1	100
Hip Vel_Ang Y	1	1	1	1	1	100
Hip Vel_Ang Z	0	0	1	0	1	40
Knee Vel_Ang X	0	1	1	1	0	60
Knee Vel_Ang Y	1	1	1	1	1	100
Knee Vel_Ang Z	1	1	0	0	1	60
Ankle Vel_Ang X	0	1	1	1	1	80
Ankle Vel_Ang Y	1	0	0	1	1	60
Ankle Vel_Ang Z	1	1	1	1	1	100
Hip Mom X	1	0	1	1	1	80
Hip Mom Y	1	1	1	1	1	100
Hip Mom Z	0	1	1	1	1	80
Knee Mom X	0	0	1	1	1	60
Knee Mom Y	1	0	1	0	0	40
Knee Mom Z	0	0	1	1	1	60
Ankle Mom X	1	1	1	1	1	100
Ankle Mom Y	1	1	1	1	1	100
Ankle Mom Z	1	1	1	1	1	100
Hip Pow X	1	1	0	1	1	80
Knee Pow X	1	1	1	1	1	100
Ankle Pow X	1	1	1	1	1	100
FP Z	1	0	1	1	1	80
FP_loading rate Z	1	1	0	1	1	80

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.970	1	0.983	0.983	0.979	**0.983**

Genetic algorithm (ga)

Las variables seleccionadas junto con la precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	0	0	1	0	0	20
Hip Angle Y	0	0	0	1	0	20
Hip Angle Z	1	0	1	1	1	80
Knee Angle X	1	0	1	0	1	60
Knee Angle Y	1	1	1	1	1	100
Knee Angle Z	1	1	0	1	1	80
Ankle Angle X	1	1	1	0	1	80
Ankle Angle Y	1	1	1	1	1	100
Ankle Angle Z	1	0	1	1	1	80
Hip Vel_Ang X	1	0	1	1	0	60
Hip Vel_Ang Y	0	1	0	0	1	40
Hip Vel_Ang Z	0	1	0	0	1	40
Knee Vel_Ang X	1	0	1	1	1	80
Knee Vel_Ang Y	0	0	0	1	1	40
Knee Vel_Ang Z	0	1	1	0	0	40
Ankle Vel_Ang X	1	1	1	1	0	80
Ankle Vel_Ang Y	0	1	1	1	0	60
Ankle Vel_Ang Z	1	0	0	1	1	60
Hip Mom X	0	0	0	0	1	20
Hip Mom Y	0	1	1	0	0	40
Hip Mom Z	0	1	1	0	0	40
Knee Mom X	0	1	0	1	0	40
Knee Mom Y	0	0	0	0	1	20
Knee Mom Z	0	1	1	1	1	80
Ankle Mom X	1	1	1	1	1	100
Ankle Mom Y	1	1	1	1	1	100
Ankle Mom Z	1	1	0	1	0	60
Hip Pow X	1	0	1	0	0	40
Knee Pow X	1	1	0	0	1	60
Ankle Pow X	1	1	1	1	0	80
FP Z	1	1	1	1	1	100
FP_loading rate Z	0	1	0	0	0	20

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.983	0.995	0.983	0.983	0.979	**0.985**

Whale optimization algorihm (woa)

Las variables seleccionadas junto con la precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	1	0	0	0	1	40
Hip Angle Y	1	0	0	1	0	40
Hip Angle Z	0	1	1	1	0	60
Knee Angle X	0	1	1	1	0	60
Knee Angle Y	0	0	1	0	0	20
Knee Angle Z	1	1	0	0	1	60
Ankle Angle X	0	1	1	0	1	60
Ankle Angle Y	1	1	0	1	1	80
Ankle Angle Z	1	0	1	0	1	60
Hip Vel_Ang X	0	0	1	0	1	40
Hip Vel_Ang Y	0	1	1	1	0	60
Hip Vel_Ang Z	0	1	1	0	0	40
Knee Vel_Ang X	1	0	1	1	1	80
Knee Vel_Ang Y	1	1	1	1	1	100
Knee Vel_Ang Z	1	0	0	1	1	60
Ankle Vel_Ang X	1	1	1	1	1	100
Ankle Vel_Ang Y	0	1	0	0	1	40
Ankle Vel_Ang Z	1	0	1	1	0	60
Hip Mom X	1	0	1	1	1	80
Hip Mom Y	0	0	0	0	1	20
Hip Mom Z	1	1	0	0	0	40
Knee Mom X	1	1	1	0	0	60
Knee Mom Y	1	1	1	0	1	80
Knee Mom Z	1	1	0	1	1	80
Ankle Mom X	1	1	1	0	1	80
Ankle Mom Y	1	1	1	1	1	100
Ankle Mom Z	1	1	1	1	0	80
Hip Pow X	1	0	0	1	0	40
Knee Pow X	1	1	1	0	0	60
Ankle Pow X	1	0	0	0	0	20
FP Z	1	0	1	0	0	40
FP_loading rate Z	0	0	1	1	1	60

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.975	0.992	0.984	0.978	0.983	**0.982**

Ant colony optimization (coa)

Las variables seleccionadas junto con la precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	0	0	0	0	0	0
Hip Angle Y	0	0	0	0	1	20
Hip Angle Z	1	1	1	0	0	60
Knee Angle X	0	0	0	0	0	0
Knee Angle Y	0	0	0	0	0	0
Knee Angle Z	0	0	0	0	0	0
Ankle Angle X	1	0	0	1	0	40
Ankle Angle Y	0	0	0	0	0	0
Ankle Angle Z	0	0	1	1	1	60
Hip Vel_Ang X	0	0	0	0	0	0
Hip Vel_Ang Y	0	0	1	0	0	20
Hip Vel_Ang Z	0	0	0	0	1	20
Knee Vel_Ang X	0	1	0	0	0	20
Knee Vel_Ang Y	1	1	1	1	1	100
Knee Vel_Ang Z	1	1	1	1	1	100
Ankle Vel_Ang X	0	0	0	0	0	0
Ankle Vel_Ang Y	1	1	1	1	1	100
Ankle Vel_Ang Z	1	1	1	1	1	100
Hip Mom X	0	0	0	0	0	0
Hip Mom Y	0	0	0	0	0	0
Hip Mom Z	0	1	0	1	1	60
Knee Mom X	0	0	0	0	0	0
Knee Mom Y	0	0	0	0	0	0
Knee Mom Z	1	0	1	0	0	40
Ankle Mom X	1	0	1	0	0	40
Ankle Mom Y	1	0	0	0	0	20
Ankle Mom Z	1	0	0	0	0	20
Hip Pow X	0	0	0	0	0	0
Knee Pow X	1	0	0	0	1	40
Ankle Pow X	0	0	0	0	0	0
FP Z	0	0	1	0	0	20
FP_loading rate Z	0	0	1	0	1	40

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.967	0.945	0.962	0.941	0.946	**0.952**

Simulated annealing (sa)

Las variables seleccionadas junto con la precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	0	1	0	1	1	60
Hip Angle Y	0	1	0	0	0	20
Hip Angle Z	0	1	0	1	0	40
Knee Angle X	0	0	1	1	1	60
Knee Angle Y	1	1	0	0	1	60
Knee Angle Z	1	0	1	0	1	60
Ankle Angle X	0	1	0	1	1	60
Ankle Angle Y	1	1	1	1	0	80
Ankle Angle Z	1	0	0	1	1	60
Hip Vel_Ang X	1	0	0	1	1	60
Hip Vel_Ang Y	0	1	1	0	1	60
Hip Vel_Ang Z	1	1	0	1	1	80
Knee Vel_Ang X	1	1	1	1	0	80
Knee Vel_Ang Y	1	1	1	1	1	100
Knee Vel_Ang Z	0	0	1	0	0	20
Ankle Vel_Ang X	0	0	0	1	1	40
Ankle Vel_Ang Y	0	0	0	0	1	20
Ankle Vel_Ang Z	1	1	1	0	1	80
Hip Mom X	0	0	0	0	0	0
Hip Mom Y	1	1	1	0	0	60
Hip Mom Z	1	0	1	1	0	60
Knee Mom X	0	1	0	0	1	40
Knee Mom Y	0	1	1	1	1	80
Knee Mom Z	0	1	0	0	0	20
Ankle Mom X	1	0	1	0	1	60
Ankle Mom Y	1	1	0	0	1	60
Ankle Mom Z	0	1	0	1	1	60
Hip Pow X	0	0	1	0	1	40
Knee Pow X	1	0	0	1	0	40
Ankle Pow X	0	0	1	0	1	40
FP Z	1	1	1	1	1	100
FP_loading rate Z	0	1	0	0	1	40

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.966	0.983	0.950	0.921	0.970	**0.958**

Taboo Search (TS)

Las variables seleccionadas junto con precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	0	0	1	0	0	20
Hip Angle Y	1	0	1	1	1	80
Hip Angle Z	1	0	1	1	1	80
Knee Angle X	1	0	0	0	0	20
Knee Angle Y	1	1	1	1	1	100
Knee Angle Z	1	1	1	0	1	80
Ankle Angle X	1	1	0	0	1	60
Ankle Angle Y	0	1	1	1	1	80
Ankle Angle Z	0	0	1	1	1	60
Hip Vel_Ang X	1	1	1	1	1	100
Hip Vel_Ang Y	0	1	0	0	1	40
Hip Vel_Ang Z	0	0	0	0	0	0
Knee Vel_Ang X	1	1	1	1	1	100
Knee Vel_Ang Y	1	0	0	1	1	60
Knee Vel_Ang Z	0	1	1	0	0	40
Ankle Vel_Ang X	0	0	1	1	1	60
Ankle Vel_Ang Y	0	0	0	1	0	20
Ankle Vel_Ang Z	1	1	1	0	1	80
Hip Mom X	1	0	0	1	0	40
Hip Mom Y	0	0	1	1	0	40
Hip Mom Z	0	1	1	0	0	40
Knee Mom X	0	0	1	1	0	40
Knee Mom Y	0	1	0	1	0	40
Knee Mom Z	0	1	1	0	0	40
Ankle Mom X	1	1	1	0	1	80
Ankle Mom Y	0	1	0	0	0	20
Ankle Mom Z	1	1	1	1	1	100
Hip Pow X	0	0	1	1	0	40
Knee Pow X	1	1	0	0	0	40
Ankle Pow X	0	0	1	1	1	60
FP Z	1	0	1	1	1	80
FP_loading rate Z	0	1	0	1	1	60

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.991	0.996	0.992	0.988	0.991	**0.992**

Las Vegas (lvw)

Las variables seleccionadas junto con la precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	0	0	1	0	1	40
Hip Angle Y	0	0	1	1	0	40
Hip Angle Z	0	1	0	0	1	40
Knee Angle X	0	0	1	1	1	60
Knee Angle Y	1	0	1	1	1	80
Knee Angle Z	0	0	1	0	1	40
Ankle Angle X	1	1	0	0	1	60
Ankle Angle Y	1	1	1	1	1	100
Ankle Angle Z	0	1	0	1	0	40
Hip Vel_Ang X	1	1	0	0	0	40
Hip Vel_Ang Y	0	0	0	1	1	40
Hip Vel_Ang Z	0	0	0	1	1	40
Knee Vel_Ang X	1	0	1	1	1	80
Knee Vel_Ang Y	0	1	1	1	1	80
Knee Vel_Ang Z	1	1	1	1	1	100
Ankle Vel_Ang X	1	1	1	1	1	100
Ankle Vel_Ang Y	0	1	0	1	1	60
Ankle Vel_Ang Z	1	0	1	1	0	60
Hip Mom X	0	1	1	1	1	80
Hip Mom Y	0	1	1	1	1	80
Hip Mom Z	0	1	0	0	1	40
Knee Mom X	0	1	0	1	0	40
Knee Mom Y	1	0	0	1	1	60
Knee Mom Z	0	0	1	1	1	60
Ankle Mom X	1	0	0	1	0	40
Ankle Mom Y	1	1	1	1	1	100
Ankle Mom Z	1	1	1	1	1	100
Hip Pow X	1	0	0	0	0	20
Knee Pow X	0	1	0	0	0	20
Ankle Pow X	0	1	1	0	0	40
FP Z	0	0	1	0	1	40
FP_loading rate Z	1	1	1	1	0	80

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.967	0.963	0.974	0.966	0.967	**0.967**

Hill-Climbing (hc)

Las variables seleccionadas junto con la precisión promedia obtenidas han sido:

	Iter1	Iter2	Iter3	Iter4	Iter5	Promedio %
Hip Angle X	1	0	0	0	1	40
Hip Angle Y	0	0	1	0	1	40
Hip Angle Z	1	1	0	1	1	80
Knee Angle X	1	0	1	0	1	60
Knee Angle Y	0	0	1	1	0	40
Knee Angle Z	1	1	0	1	0	60
Ankle Angle X	0	1	1	0	0	40
Ankle Angle Y	1	1	0	1	1	80
Ankle Angle Z	0	1	0	0	1	40
Hip Vel_Ang X	1	0	1	1	0	60
Hip Vel_Ang Y	1	0	0	0	1	40
Hip Vel_Ang Z	0	0	0	1	0	20
Knee Vel_Ang X	1	0	1	1	0	60
Knee Vel_Ang Y	1	1	1	0	1	80
Knee Vel_Ang Z	1	0	0	0	1	40
Ankle Vel_Ang X	0	1	1	1	1	80
Ankle Vel_Ang Y	0	1	0	0	0	20
Ankle Vel_Ang Z	1	0	1	1	1	80
Hip Mom X	1	0	0	0	1	40
Hip Mom Y	1	1	1	1	0	80
Hip Mom Z	1	0	0	0	1	40
Knee Mom X	0	1	0	0	1	40
Knee Mom Y	1	0	0	0	1	40
Knee Mom Z	1	0	1	1	0	60
Ankle Mom X	1	1	1	0	0	60
Ankle Mom Y	1	1	1	1	1	100
Ankle Mom Z	0	1	1	1	1	80
Hip Pow X	0	0	1	0	0	20
Knee Pow X	0	1	1	1	1	80
Ankle Pow X	1	1	1	1	0	80
FP Z	0	1	0	1	0	40
FP_loading rate Z	0	0	1	1	0	40

Los resultados obtenidos junto con las variables seleccionadas en cada iteración son:

Iter1	Iter2	Iter3	Iter4	Iter5	**Average**
0.975	0.996	0.975	0.983	0.967	**0.979**

Annexe VI. Example of Taboo Search for the Question 3 and 4

As a pre-processing step ahead of the actual model building, a feature selection was carried out. A wrapper approach guided by Taboo search (TS) was used. This performed a feature selection, by discarding input variables that were not useful or were less relevant to compute the output. Features found to be meaningful are those variables used in all iterations with [80-100] % average. Therefore, we were able to discern which variables had greater influence on the movement strategy for each limb in each role position when moving to the dominant and non-dominant direction. **Table 8**, displays which variables had greater influence for the question 3: "which differences exist between dominant and non-dominant limb when both are performing the lead role".

It was considered that significant differences existed between the dominant and non-dominant direction movement strategies when both are performing the lead role. **Table 8**, showed which variables had more influence in the lead limbs strategy. It seems that the hip and knee angular velocity in the sagittal plane, knee angle in the coronal plane and ankle moment in the transverse plane had the most critical influence in the differentiation between the lead limbs. Additionally, in 80% of the iteractions, hip and ankle angles in the coronal plane, hip and knee rotations angles and ankle rotation angular velocity in transverse plane, ankle dorsiflexion moment in sagittal plane and VGRF also had an importante relevance in the strategy. Thus, we can observe that angles, angular velocities and joint moments in all planes had a higher impact to classify the model.

Table 8. *Cross-validation with Taboo Search (TS) for Feature Selection when we compared between the dominant and non-dominant direction in limbs when both are performing the lead role position.*

Variables	Iter1	Iter2	Iter3	Iter4	Iter5	Average %
Hip angle X	0	0	1	0	0	20
Hip angle Y	1	0	1	1	1	80
Hip angle Z	1	0	1	1	1	80
Knee angle X	1	0	0	0	0	20
Knee angle Y	1	1	1	1	1	**100**

Knee angle Z	1	1	1	0	1	80
Ankle angle X	1	1	0	0	1	60
Ankle angle Y	0	1	1	1	1	80
Ankle angle Z	0	0	1	1	1	60
Hip Ang_Vel X	1	1	1	1	1	**100**
Hip Ang_Vel Y	0	1	0	0	1	40
Hip Ang_Vel Z	0	0	0	0	0	0
Knee Ang_Vel X	1	1	1	1	1	**100**
Knee Ang_Vel Y	1	0	0	1	1	60
Knee Ang_Vel Z	0	1	1	0	0	40
Ankle Ang_Vel X	0	0	1	1	1	60
Ankle Ang_Vel Y	0	0	0	1	0	20
Ankle Ang_Vel Z	1	1	1	0	1	80
Hip Moment X	1	0	0	1	0	40
Hip Moment Y	0	0	1	1	0	40
Hip Moment Z	0	1	1	0	0	40
Knee Moment X	0	0	1	1	0	40
Knee Moment Y	0	1	0	1	0	40
Knee Moment Z	0	1	1	0	0	40
Ankle Moment X	1	1	1	0	1	80
Ankle Moment Y	0	1	0	0	0	20
Ankle Moment Z	1	1	1	1	1	**100**
Hip Power X	0	0	1	1	0	40
Knee Power X	1	1	0	0	0	40
Ankle Power X	0	0	1	1	1	60
VGRF	1	0	1	1	1	80
VGRF loading rate	0	1	0	1	1	60
Average iterations	**0.9916**	**0.996**	**0.992**	**0.988**	**0.9918**	**99.19**

In the **Table 9**, we were able to discern which variables had greater influence for the question 4: "which differences exist between dominant and non-dominant limb when both are performing the trail role?".

When considering if differences exist between the dominant and non-dominant limb movement strategies when both are performing the trail role, we observed a predictive accuracy of > 93% for both models, indicating a difference in landing strategy between the dominant and non-dominant limbs. **Table 9**, showed which variables had more influence in the trail limbs strategy. It seems that the most critical variables to differentiate between trail limbs were: for the hip, rotation angles in the coronal plane and abduction angular velocities in the transverse plane; for the knee, abduction moments in the coronal plane; and for the ankle, dorsiflexion moments in the sagittal plane and rotation angular velocities in the transverse plane. Additionally, in 80% of the iteractions, hip abduction moments and ankle abduction and rotation moments in the coronal and transverse planes also had an important relevance in the strategy. Similarly to the lead limbs, we can observe that angles, angular velocities and joint moments in all planes had a higher impact in the model classification. However, for the trail limb, ankle eversion/inversion moments had a principal importance to discern between the dominant and non-dominant limbs.

Table 9. *Cross-validation with Taboo Search (TS) for Feature Selection when we compared between the dominant and non-dominant direction in limbs when both are performing the trail role position*

Variables	Iter1	Iter2	Iter3	Iter4	Iter5	Average %
Hip angle X	1	0	0	1	0	40
Hip angle Y	0	0	0	1	0	20
Hip angle Z	1	1	1	1	1	**100**
Knee angle X	0	0	0	0	1	20
Knee angle Y	0	0	1	0	1	40
Knee angle Z	1	0	0	0	0	20
Ankle angle X	0	0	0	0	0	0
Ankle angle Y	0	0	0	0	0	0
Ankle angle Z	0	0	1	0	0	20
Hip Ang_Vel X	1	1	0	1	0	60
Hip Ang_Vel Y	1	1	1	1	1	**100**
Hip Ang_Vel Z	1	0	0	0	1	40
Knee Ang_Vel X	0	1	1	1	0	60
Knee Ang_Vel Y	1	1	0	0	1	60
Knee Ang_Vel Z	0	0	0	1	0	20
Ankle Ang_Vel X	1	0	1	1	0	60

Ankle Ang_Vel Y	0	0	0	0	0	0
Ankle Ang_Vel Z	1	1	1	1	1	100
Hip Moment X	0	0	1	0	0	20
Hip Moment Y	1	1	1	0	1	80
Hip Moment Z	1	0	0	1	0	60
Knee Moment X	0	0	0	0	0	0
Knee Moment Y	1	1	1	1	1	**100**
Knee Moment Z	0	0	1	1	0	40
Ankle Moment X	1	1	1	1	1	**100**
Ankle Moment Y	0	1	1	1	1	80
Ankle Moment Z	1	1	1	0	1	80
Hip Power X	0	0	1	0	0	20
Knee Power X	0	0	0	0	0	0
Ankle Power X	0	0	1	0	0	20
VGRF	1	0	1	0	1	60
VGRF loading rate	0	0	0	1	1	40
Average iterations	**1**	**0.9918**	**0.9875**	**0.9918**	**0.9918**	**99.26**

Agradecimientos / Acknowledgements

Parece que fue ayer cuando a la "Elia recién graduada" le propusieron la aventura de meterse en ese mundillo llamado investigación. Su vocación y su espíritu curioso le hicieron querer llegar con mayor profundidad a todo conocimiento que le hiciera aprender. Parecía divertida la aventura de ser "100tifik", porque sonaba a que iba a tener todo el conocimiento del mundo, y porque la bata le hacía parecer más interesante. Al final, esa Elia motivada y un poco alocada empezó a darse cuenta de que por mucho que todo le gustase, había temas que no le apasionaban del todo. Eso le hizo tratar diferentes áreas y temáticas: "que si se ponía horas y horas a analizar transiciones casi sin pestañear, que si calculaba el centroide, que si usaba plantillas instrumentalizadas, que si ahora se hacía biomecánica y trasteaba los juguetitos, que si metía Inteligencia Artificial que mola y es el futuro, que si selección de características o árboles de decisión…" pero fue precisamente en esa búsqueda un poco desorganizada y caótica, dónde pudo dejarse llevar por su propia curiosidad y descubrir lo que le permitió desarrollar esta idea de proyecto de tesis doctoral, mediante la guía de sus directores.

Hablé en pasado porque, aunque "la Elia de la que hablaba" y la "Elia que está escribiendo ahora" sean la misma, hay muchas cosas que han cambiado. Todo el que me conoce sabe que sigo siendo una motivada empedernida y que también mantengo mi puntito de alocada, porque es algo que me caracteriza. Sin embargo, lo que realmente ha cambiado es que en todo este proceso de maduración, he podido aprender lo que es la resiliencia y la proactividad, lo que es frustrarse pero recomponerse, lo que es sentir satisfacción personal por haber puesto todo de tu parte, lo que es el seguir adelante a pesar de que no siempre todo sea justo, pero sobretodo he aprendido lo que es valorar el apoyo de tu familia y de muchas personas que te quieren y que creen en ti. El hacer una tesis doctoral sin mayor incentivo que hacerla por plena vocación no es fácil, pero como siempre me han dicho mis padres "es de bien nacido ser agradecido", y gracias a todas estas personas esta tesis doctoral de 5 años ha sido posible.

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soy, y que me acompaña en mi proceso constante de conocerme a mí misma. Gracias por tanto y por estar siempre ahí. Nos queda aún una vida de conocernos compañero.

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Curriculum Vitae

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Aurelio Ureña	Professor at University of Granada. Ex-couch National volleyball team. aurena@ugr.es
José Manuel Benítez	Professor at University of Granada. Department of Computer Science and Artificial Intelligence, DICITS, DASCI, IMUDS. J.M.Benitez@decsai.ugr.es

EDUCATION

2016-present	PhD in Biomedicine, University of Granada, Spain
2015-2016	Master's Degree in Teaching Compulsory and Pre-University Secondary Education, Vocational Training and Language Teaching. Specializing in Physical Education. University of Granada, Spain
2014-2015	Master's Degree in Research in Sports and Physical Activity. Specializing in performance sports. University of Granada, Spain
2010-2014	Degree in Physical Activity and Sport Sciences, University of Granada, Spain

INTERNSHIPS

2012-2013 10 months exchange Erasmus Program at University of Tallinn in Estonia

2015-2015. 3 months International internship as teacher assistant in Bradford College (UK).

2018-2018 3 months international internship for the Ph.D. in Allied Health Research Unit at the University of Central Lancashire in Preston (UK).

RESEARCH / INTERESTS

My research activities focus on performance sports and motion capture as a tool to improve performance and avoid injuries in lower limbs. My Ph.D. has been mainly centred on semi-professional female volleyball players and analysing kinetic and kinematic variables which were used to differentiate movement strategies between legs carried out through Machine Learning methods. Therefore, my team and I were able to detect which variables were relevant to discern the strategies and may provide a better understanding of lower limb injury risks.

Additionally, I have worked with other sports including; football, handball, tennis, and amateur running as well. In addition, I have worked with military groups and people with back pain and neck pain. I have also worked in a European project at University of Central Lancashire in Preston (UK) where I was testing products for different enterprises. Moreover, my areas of interest include the study of biomechanics variables across diverse populations in the assessment of performance and efficiency of movement.

PROFESSIONAL POSITIONS

2018-2019 Research assistant in "Mobility Equipment Testing" in the Allied Health Research Unit - September 2018 – April 2019 - University of Central Lancashire (UK).

2017-2018 Research Assistant at the University of Granada's Sport and Health Institute (IMUDS). Department of Physical Education and Sport, Faculty of Sport Sciences, University of Granada, Granada, Spain.

2016-2017 Project Research staff. Department of Physical Activity and Sports, School of Sport Sciences, University of Granada, Spain.

2015-2016 ECTS Fellow. Grant-assisted student. Department of Physical Activity and Sports, School of Sport Sciences, University of Granada, Spain.

2015-present Ph.D. part-time in Biomedicine at the University of Granada, Spain.

PARTICIPATION IN RESEARCH PROJECTS

2016-present SAVIA project". Analysis of sport specific tasks in volleyball and their relationship with injury prevention. ***Principal researcher.***

2018-present "FEDER project". Analysis and modeling of time series with Deep and Machine Learning techniques. Application in prevention of sports injuries. ***Researcher.***

2018-2019 "Mobility Equipment Testing" University of Central Lancashire's £2.4 million European Regional Development Fund project. During this time I collaborated with several companies on different projects as a ***Research assistant***:

- "Cervical pillow project". Exploring the use of neck pain management strategies and cervical pillows.
- "Back Care Chairs project". Exploring the effect of office seating design elements to determine the ideal seating solution.
- "Massage device project". Exploring the efficacy and effectiveness of a new massage device.
- "Tap dance project". Exploring the effect of a new design of tap shoe through drop rig testing and product evaluation questionnaires.
- "Index project". Exploring the potential use of various Index Therapeutic prototypes.
- "Foam testing project". Exploring the use of effect of new mattresses.
- "Mattress project". Exploring the effect of several mattresses and pillows.

- "Lymphology project". Exploring if the use of a new compression garment can improve tissue health.
- "Aspirator dentist". Exploring the effect of a new design of dental aspirator tip.
- "Posture Care project". Exploring the effect of a postural care system on pressure and stability.
- "Seating project". Exploring the effect of seat design elements through biomechanical factors.
- "Yoga for breast cancer project". Exploring the potential use of a yoga class for Breast-cancer related lymphedema patients.

2018-2019 "Uruguay project". Determining factors of impulse and its relationship with power capacity in Squat Jumps controlled by assisted mechanical dynamometry. ***Researcher.***

2017-2019 "AVÏSAME project": Monitoring and promotion of healthy habits, through a platform based on portable sensors and virtual advisors, for the promotion of active aging in the elderly population. ***Researcher.***

2017-2019 Exolimb", "Exosoldier" and "ExoLimb3D": 3 projects to develop a prototype of passive exoskeleton adapted to technical boot, for the optimization of human locomotion, valid for the military and civil environment. ***Researcher***

2017-2018 "eINJURIES project": Protocol for the detection of biomechanical risks of knee injury. ***Researcher and practical tutor.***

2017-2018 "eTEAMsports": Service to help sports people practicing team sports through optimization of performance, prevention of injuries and promotion of health. ***Technician***

2017-2018 "eRUNNING project". Development of a comprehensive technological system for the biomechanical assessment of the running techniques, its optimization and the development of programs for the prevention of muscle-skeletal injuries. ***Researcher***

2015-2016 "Centroid project". New method for measuring the availability of the middle attacker in volleyball. ***Principal researcher***

2015-2016 "Talent Project": Project for the development of human talent in an integral, multidisciplinary and transversal way in childhood. ***Technician***

PUBLICATIONS

1. **Mercado-Palomino E.,** Richards, J., Molina-Molina, A., Benítez JM., Ureña A. (2020). Can kinematic and kinetic differences between planned and unplanned volleyball block jump-landings be associated with injury risk factors? Gait & Posture, 79, 71-79. *Accepted* *https://doi.org/10.1016/j.gaitpost.2020.04.005*.

2. **Mercado-Palomino E.,** Millán-Sánchez, A.; Parra-Royón, M.J.; Benítez, J.M.; Ureña Espa, A. (202x) Setter's Action Range As a Performance Indicator in Male Volleyball. Revista Internacional de Medicina y Ciencias de la Actividad Física y el Deporte vol. X (X) pp. xx. Http://cdeporte.rediris.es/revista. *Accepted, In Press.*

3. Haworth, L. A., Sumner, S. C., **Mercado-Palomino, E**., Mbuli, A. M., Stockley, R. C., & Chohan, A. (2019). Postural management system for bedbound patients. PRM+, 2(2), 24-28. *Accepted*.

4. Fábrica C.G., González, A., **Mercado-Palomino, E**., Molina A., Chirosa I. (2019). Differences in utilization of lower limb muscles power in squat jump with positive and negative load. Frontiers in Physiology. *Accepted. In press*

5. **Mercado-Palomino E.,** Aragón-Royón, F., Richards, J., Benítez JM., Ureña A. (2019). Which kinematic and kinetic variables are most relevant when comparing different movement strategies between the lead and trail limb in block jump-landing in volleyball? Sports Biomechanics. *Submitted.*

6. **Mercado-Palomino E.,** Aragón-Royón, F., Richards, J., Benítez JM., Ureña A. (2019). Are there differences between moving to the dominant and non-dominant directions during block jump-landings in volleyball? Journal of Human Kinetics. *Submitted.*

7. **Mercado-Palomino, E**., Molina-Molina, A., Delgado-García, G, Aragón-Royón. F, Richards, J, Benítez, JM., Ureña, A., (2019). Are there differences between the lead limbs during block jump-landing in different directions? Work presented in 24th annual Congress of the European College of Sport Science. Prague. *Accepted.*

8. Fábrica C.G., González, A., **Mercado-Palomino, E**., Molina A., Chirosa L. J. (2019). Power-velocity and Force–velocity relationships are consistent with the Maximum Dynamic Output Hypothesis when are obtained with effective force in Squat Jump. Journal of Strength and Conditioning Research. *Submitted.*

9. **Mercado-Palomino, E**., Morante, J.C., Parra, M., Benítez, J.M., Ureña, A., (2016). A new method for measuring the availability of the middle attacker in volleyball. Work presented in 21st annual Congress of the European College of Sport Science. Vienna. ISSN: 978-3-00-053383-9. *Accepted.*

10. Millán A., Sanchez J., **Mercado-Palomino, E**., Ureña, A. (2016). Probabilidad de error en ataque en voleibol masculino de alto nivel. Revista internacional de Deportes colectivos 74-76. ISSN: 1989-841X. *Accepted.*

11. **Mercado-Palomino E.,** Benítez JM., Ureña A. (2015) Effect of the available area between setter and middle-attacker in elite men Volleyball. Digibug. Repositorio Institucional de la Universidad de Granada http://hdl.handle.net/10481/39628. *Accepted*.

CONTRIBUTION TO INTERNATIONAL AND NATIONAL CONGRESSES

- **Elia Mercado Palomino;** Alejandro Molina Molina; Delgado García Gabriel, Aragón Royón Francisco, Jim Richards, Jose Manuel Benítez Sánchez, Aurelio Ureña Espá (2019). Are there differences between the lead limbs during block jump-landing in different directions? 24st annual Congress of the European College of Sport Science. Prague (Czech Republic). *International Congress*.

- Haworth, L. A., Sumner, S. C., Olivier, M., **Mercado-Palomino, E**., & Chohan, A. (2019). A potential new solution for postural management of bedbound patients? Posture and Mobility Group Conference. Telford (UK). *International Congress*.

- Bermudez, G., **Mercado-Palomino, E.,** González, L., Chirosa, L. and Fábrica, G. (2019). Coordination and power during Squat Jumps with loads controlled by an electromechanical dynamometer. 22 Congreso de Bioingeniería, Uruguay.

- Molina-Molina, A., **Mercado-Palomino, E**., Delgado-García, G., Latorre-Román, P.A., Soto-Hermoso, VM (2019). Effect of two different retraining programs on popular long-distance runners in terms of postural balance. 24st annual Congress of the European College of Sport Science. Prague (Czech Republic). *International Congress*.

- Gabriel Delgado García; Emilio José Ruiz Malagón; Alejandro Molina Molina; **Elia Mercado-Palomino**; Victor Manuel Soto Hermoso (2018). Validación de Wearables para el análisis técnico de tenistas. XLI Congreso de la sociedad ibérica de biomecánica y biomateriales. Madrid (Spain). *National Congress.*
- Gabriel Delgado García; Jose María Chicano Gutiérrez; **Elia Mercado-Palomino**; Alejandro Molina Molina; Emilio José Ruiz Malagón; Francisco Javier Rojas Ruiz (2018). Análisis de la trayectoria de la raqueta de tenistas ATP en competición mediante un sistema fotogramétrico 3D lowcost. XLI Congreso de la sociedad ibérica de biomecánica y biomateriales. Madrid (Spain). *National Congress.*

- Gabriel Delgado García; **Elia Mercado-Palomino**; Alejandro Molina Molina; Victor Manuel Soto Hermoso (2017). Sistema de evaluación de corredores basado en sensores inerciales.

XL Congreso de la sociedad ibérica de biomecánica y biomateriales. Barcelona (Spain). *National Congress.*

- Gabriel Delgado García; Muñoz-García, Alejandro; **Elia Mercado-Palomino**; Alejandro Molina Molina; Victor Manuel Soto Hermoso (2017). Test específico de evaluación biomecánica de jugadores de tenis basado en sensores inerciales. XL Congreso de la sociedad ibérica de biomecánica y biomateriales. Barcelona (Spain). *National Congress.*

- Alejandro Molina Molina; **Elia Mercado-Palomino**; Gabriel Delgado García; Gálvez-carmona, Juan José; Ramos-Muñoz, Jose Luis; Roldán-aranda, Andrés; Victor Manuel Soto Hermoso (2017). Desarrollo de un prototipo de exoesqueleto para la mejora de la eficiencia y la salud en gestos de locomoción del soldado de tierra (estudio piloto). XL Congreso de la sociedad ibérica de biomecánica y biomateriales. Barcelona (Spain). *National Congress.*

- **Elia Mercado-Palomino**; Alejandro Molina Molina; Gabriel Delgado García; Victor Manuel Soto Hermoso; Aurelio Ureña Espa (2017). Differences between centre of mass in control and a random block jump in volleyball players. International Congress Interdisciplinary Physical Prevention & Rehabilitation. Granada (Spain). *International Congress.*

- Alejandro Molina Molina; **Elia Mercado-Palomino**; Gabriel Delgado García; Richards, Jim; Victor Manuel Soto Hermoso (2017). The acute effect of the kinematic alterations produced in the increase of pace in endurance runners. International Congress Interdisciplinary Physical Prevention & Rehabilitation. Granada (Spain). *International Congress.*

- Gabriel Delgado García; Tójar-Molina, Miguel; **Elia Mercado-Palomino**; Victor Manuel Soto Hermoso (2017). International Congress Interdisciplinary Physical Prevention & Rehabilitation. Granada (Spain). *International Congress.*

- Alejandro Molina Molina; **Elia Mercado-Palomino**; Gabriel Delgado García; Antonio Millán Sánchez; Aurelio Ureña Espa; Victor Manuel Soto Hermoso (2017). Concurrent validity of lower limb kinematics between markerless and marker-basedmotion capture systems in gait and running. 35th International Conference on Biomechanics in Sport. Colonia (Germany). *International Congress.*

- Manuel Jesús Parra Royón; **Elia Mercado-Palomino**; Aurelio Ureña Espa; Jose Manuel Benitez Sanchez (2017). Análisis inteligente del rendimiento de jugadas de voleibol. II Jornadas de Investigadores en Formación: fomentando la interdisciplinariedad. Granada (Spain*). National Congress.*

- Gabriel Delgado García; Alfonso Mañas Bastidas; **Elia Mercado-Palomino**; Molina-Molina, Alejandro; Victor Manuel Soto Hermoso (2017). Physical and health related variables testing battery for paddle players. XIII Congreso Internacional de Ciencias del Deporte y Salud. A Coruña (Spain). *International Congress.*

- **Elia Mercado-Palomino**; Juan Carlos Morante Rábago; Parra -Royón,Manuel; Jose Manuel Benitez Sanchez; Aurelio Ureña Espa (2016). A new method for measuring the availability of the middle attacker in volleyball. 21st annual Congress of the European College of Sport Science. Vienna (Austria). *International Congress*.

- Antonio Millán Sánchez; Joaquín Sánchez Moreno; **Elia Mercado-Palomino**; Aurelio Ureña Espa (2016). Probability of error in the attack in elite men's volleyball. IV Congreso Internacional de Actividad Física y Deportes. Zaragoza (Spain). *International Congress*.

TEACHING EXPERIENCE

2018	Teacher collaborator in the III Edition of the "Master of Optimization of Sports Physical Training and Re-adaptation".
2018	Practical tutor of bachelor students at University of Granada.
2017	Teacher assistant at "Appleton Academy" in Bradford (UK).
2017	Teacher assistant at "I.E.S Fray Luis" high school in Granada (Spain).

PREVIOUS STAYS IN OTHER CENTERS

2018-2019	Allied Health Research Unit, University of Central Lancashire, Preston, UK.
2016	Department of Teacher Education, Bradford College, Bradford, UK.
2014-present	Department of Physical Activity and Sports, Faculty of Sport Sciences, University of Granada.
2012-2013	Tallinn University, School of Natural Sciences and Health, Tallinn (Estonia).

SCIENTIFIC JOURNAL REVIEWER

2019	The Knee (Q1).

SPECIFIC SOFTWARE OR TECHNOLOGIES USED PREVIOUSLY

- Qualisys Track Manager (QTM)
- Optitrack
- Simi
- EMG network adquisition and analysis
- Delsys

- mDurance
- Kwon
- Visual 3D
- SPSS
- Nexgen
- Kistler
- Bertec
- AMTI
- Bioware
- Tekscan
- Conformat

The overall aim of the present International Doctoral Thesis is to analyse the landing technique during a volleyball three-step block approach simulating natural game situations. Therefore, the dominance direction, limb role and planned and unplanned situations were studied to determine how limb movement strategies were affected.

Repeated measures analysis of variance (ANOVA) tests and Machine Learning methods were used to generate the models from the dataset. The results showed statistically significant differences when comparing limb movement strategies between lead and trail (accuracy > 94%), and between directions (accuracy > 96%). The findings also suggest that planned situations may generate more load than unplanned situations.

This Thesis may provide relevant information about how to improve the performance of the players and how to plan the training in order to avoid an overload that could lead to risk of injury. Finally, it also raises questions about the learning models that are being used, if the variables that have been considered so far in science really are the most relevant, and if the application of Machine Learning could change the paradigm in the way of interpreting the risk of injury in sport-specific actions.