Title: A first approach to a fuzzy classification system for age estimation based on the pubic bone

Authors: P. Villar, I. Alemán, L. Castillo, S. Damas, O. Cordón

Event: IEEE International Conference on Fuzzy Systems 2017 (FuzzIEEE 2017), Naples (Italy), July 9-12, 2017.

DOI: 10.1109/FUZZ-IEEE.2017.8015760

A first approach to a fuzzy classification system for age estimation based on the pubic bone

P. Villar[a], I. Alemán[b], L. Castillo[b], S. Damas[a], O. Cordón [c]

[a]Dept. of Software Engineering; University of Granada
18071 - Granada, Spain. e-mail: pvillarc,sdamas@ugr.es

[b]Dept. of Legal Medicine, Toxicology and Physical Anthropology;
University of Granada, 18071 - Granada, Spain. e-mail: ialeman@ugr.es

[c]Dept. of Computer Science and A.I.; University of Granada,
18071 - Granada, Spain. e-mail: ocordon@decsai.ugr.es

Abstract

The study of human remains suffers from a lack of information for determining a reliable estimation of the age of an individual. One of the most extended methods for this task was proposed in the twenties of the past century and is based on the analysis of the pubic bone. The method describes some age changes occurring in the pubic bone and establishes ten different age ranges with a description of the morphological aspect of the bone in each one of them. These descriptions are sometimes vague and there is not a systematic way for using the method. In this contribution we propose two different preliminary fuzzy rule-based classification system designs for age estimation from the pubic bone that consider the main morphological characteristics of the bone as independent and linguistic variables. So, we have identified the problem variables and we have defined the corresponding linguistic labels making use of forensic expert knowledge, that is also considered to design a decision support fuzzy system. A brief collection of pubic bones labeled by forensic anthropologists has been used for learning the second fuzzy rule-based classification system by means of a fuzzy decision tree. The experiments developed report a best performance of the latter approach.

1 Introduction

Forensic anthropology is best conceptualized more broadly as a field of forensic assessment of human remains, mostly skeletonized, and their environments [1]. Assessing age from skeletal remains is a complex task and there are different methods to be applied depending on the individual's development stage. In general, the problem is easier in young individuals since the bone changes are less systematized as the subject is still under development [2]. At the adult age (after age 25), changes are related to the bone maturing and later with the starting and development of degenerative processes. They can be identified in several structures as the skull sutures, symphysis pubis, and the external rib extremity. Variations in bone morphology are well known but they do not happen at the same time in different individuals as they are subjected to genetic and environmental conditions.

In forensic anthropology, it is well known that certain bone areas adjacent to joints show definite sequence of modification strictly associated with age. In the twenties of the last century, W. Todd proposed an age estimation method based on the analysis of the symphysis pubis [3][4] which has been extensively used in the area. According to the author, the symphysis pubis is a good choice for age estimation: "*once symphysis pubis changing features are properly understood, forms one of the most stable and satisfactory guides to the age of the individual*".

In [3], Todd defined ten age categories and he also provided a really thorough description of the morphological aspects of the symphysis pubis in each of them. However, the descriptions are sometimes imprecise and can lead to confusion between age groups, specially for new practitioners. There are some main characteristics that concentrates the most clear changes in the bone but they are not clearly established.

In this contribution, we aim to solve these shortcomings by proposing a fuzzy decision support system for age estimation that can be easily interpreted. We just focus our study on the main characteristics used in the age group descriptions in [3]. Considering the osteological collection of the Physical Anthropology Laboratory at the University of Granada, Spain, the forensic anthropology experts of that laboratory have established a set of nine morphological aspects (together with their possible stages), that are crucial for age estimation based on symphysis pubis. So, the proposed fuzzy system includes nine linguistic variables with their corresponding label sets.

Two different approaches are considered to design our fuzzy decision support system, that takes the structure of a fuzzy rule-based classification system (FRBCS) [5][6]. In the first approach, the FRBCS is designed from expert knowledge directly provided by the forensic anthropologists. In the second approach, knowledge is automatically obtained by a machine learning scheme, i.e., fuzzy rules are derived using examples from the referred osteological collection at the University of Granada by using a fuzzy decision tree derivation method [7].

The rest of this contribution is organized as follows. Section 2 reviews the use of computational intelligence approaches to tackle age estimation. Todd's age estimation method proposed in [3] is introduced in Section 3. In Section 4 we present our proposal, including the structure of our fuzzy model (linguistic variables and label sets), the instance set generation process and the two fuzzy models proposed for age estimation. Finally, some conclusions and future work are suggested in Section 5.

2 Age estimation based on computational intelligence

In the last few years, several studies have been published applying computational intelligence to different fields of forensic anthropology, such as skull 3D modeling [8], skull-face overlay [9][10], facial soft thickness prediction [11], and craniofacial correspondence [12][13]. A review of papers focused on forensic identification by craniofacial superimposition can be found in [14], including different manuscripts based on computational intelligence.

In forensic anthropology, some studies use the fuzzy integral for age estimation from skeletal adults [15][16]. These methods consider the manual application of different age assessment methods based on different bones: Todd's method using the symphysis pubis and other two using the auricular surface and the cranial suture closure. The three independent estimations are combined by a fuzzy integral in order to obtain a more accurate estimation.

Beyond forensic anthropology, there are several contributions for age estimation using computational intelligence. Some of those proposals are related to pediatric radiology [17][18][19], in order to evaluate growth disorder, growth potential and monitor the therapy effects of growth. Some diseases affecting growth are related to a significant difference between skeletal age and chronological age. These methods use hand radiographs of living individuals as knowledge source for training the classifiers. In [17], a computing with words-based classifier for skeletal maturity assessment is proposed, using a fuzzy ID3 decision tree. Meanwhile, the method proposed in [18] is based on a neural network classifier and a fuzzy filter output. In [19], a fuzzy inference system is used for age assessment.

3 Todd's age estimation method

In [3], the author performed a thorough study of the morphological aspects of the symphysis pubis belonging to 306 male individuals with known death age. From this study, Todd established ten age groups and described the bone aspect in each one of them, emphasizing the changes associated with age. A brief summary of the age groups is shown as follows ([4]):

- *"Age 18-19. Phase 1: Typical adolescent ridge and furrow formation with no sign of margins and no ventral bevelling".*
- *"Age 20-21. Phase 2: Foresliadowing of ventral bevelling with slight indication of dorsal margin".*
- *"Age 22-24. Phase 3: Progressive obliteration of ridge and furrow system with increasing definition of dorsal margin and commencement of ventral rarefaction (bevelling)".*
- *"Age 25-26. Phase 4: Completion of definite dorsal margin, rapid increase of ventral rarefaction and commencing delimitation of lower extremity".*

- *“Age 27-30. Phase 5: Commencing formation of upper extremity with increasing definition of lower extremity and possibly sporadic attempts at formation of ventral rampart”.*
- *“Age 30-35. Phase 6: Development and practical completion of ventral rampart with increasing definition of extremities”.*
- *“Age 35-39. Phase 7: Changes in symphysial face and ventral aspect of pubis consequent upon diminishing activity, accompanied by bony outgrowths into pelvic attachments of tendons and ligaments”.*
- *“Age 39-44. Phase 8: Smoothness and inactivity of symphysial face and ventral aspect of pubis. Oval outline and extremities clearly defined but no rim formation or lipping”.*
- *“Age 45-50. Phase 9: Development of rim on symphysial face with lipping of dorsal and ventral margins”.*
- *“Age 50 and upwards. Phase 10: Erosion of and erratic, possibly pathological osteophytic growth on symphysial face with breaking down of ventral margin”.*

In [3], the author also included several pictures for showing the real aspect of the symphysis pubis in the different age groups. In order to apply the method, the bone must be observed and it is classified finding in which of the ten descriptions fit better.

4 Fuzzy Rule-Based Classification System for age estimation

Although the descriptions provided by Todd [3] seem exhaustive, the method is difficult to apply even for experienced practitioners, due to certain vagueness in some explanations. There is no clear specification of the main characteristics that are changing with age. Moreover, there is no systematic way to apply the method. The practitioner is supposed to know the Todd’s studies in depth and look for the phase that best fits the symphysis pubis under study. The complexity and extension of the studies make difficult the daily use of the method by non-expert physical and forensic anthropologists.

Our main objective is to systematize and simplify Todd’s method application. To do so, we characterize the main aspects of the symphysis pubis that are likely to change at different ages, using the information provided in [3] and knowledge extracted from forensic anthropologists of the Physical Anthropology Laboratory at the University of Granada.

Therefore, we consider these characteristics as the input variables of our fuzzy model for age estimation. The experts in forensic anthropology also identify all the possible “stages” of each variable that can be observed in the symphysis pubis of an individual. These stages constitute the linguistic label set of the variable. Of course, the variables can vary on the size of the label set and on the name of the labels. The ten age groups established by Todd (see Section 3) will be the classes of the output variable (<u>Estimated age</u>).

The proposed FRBCSs for age estimation consider the use of Mamdani-type fuzzy rules with a class in the consequent (the most extended fuzzy classification rule structure [5][6]). The minimum is used as conjunction operator and the winner rule as fuzzy reasoning method. Strong fuzzy partitions in interval $[0, 1]$ are used and the membership functions of the linguistic labels are triangular-shaped. We consider two approaches for deriving the rule base of the FRBCS:

- By extracting expert knowledge of the forensic anthropologists experts and representing it in the form of fuzzy classification rules.
- By deriving the rules using an automatic learning method based on examples.

Labeled data is required for the second way and it is also helpful to measure the quality of the FRBCS obtained in both approaches. Therefore, a dataset of labeled data was built using symphysis pubis from the osteological collection of the Physical Anthropology Laboratory at the University of Granada.

Next, we detail the input variables, the dataset generation process, the quality measure and, for both alternatives of deriving the rule base, the rule generation process and the final FRBCS, together with the results obtained.

4.1 Structure of the fuzzy model

Below, we enumerate the linguistic variables considered and its labels, joint with a brief description of them:

- Variable 1: <u>Articular face</u>:
  - *regular porosity*: ordered pores can be observed, following well defined direction.
  - *ridges and grooves*: well defined ridges and grooves.
  - *grooves shallow*: there are some ridges and the grooves are shallow.
  - *grooves rest*: plain articular face with slight trace of some grooves.
  - *no grooves*: completely plain articular face (no rest of ridges and/or grooves).
- Variable 2: <u>Irregular porosity</u>:
  - *absence*: no irregular porosity.
  - *medium*: some pores randomly distributed.

- *much*: surface with pores with different sizes and irregular disposition.

- Variable 3: Upper symphysial extremity:
  - *not defined*: no margin delimiting the upper border.
  - *defined*: upper symphysial extremity clearly defined.

- Variable 4: Bony nodule:
  - *absent*: even though the margin of the pubis symphysis might be already defined, there is no bony nodule.
  - *present*: bony nodule clearly defined.

- Variable 5: Lower symphysial extremity:
  - *not defined*: no margin delimiting the lower border.
  - *defined*: clearly defined lower symphysial extremity.

- Variable 6: Dorsal margin:
  - *not defined*: no margin delimiting the dorsal border. If there are differences they are marked by texture.
  - *defined*: clearly defined dorsal margin.

- Variable 7: Dorsal plateau:
  - *absent*: no texture difference between the dorsal half and the ventral half.
  - *present*: significant texture difference between the dorsal half and the ventral half.

- Variable 8: Ventral bevel:
  - *absent*: even though the margin of the pubis symphysis might be already defined, there is no elevation in ventral zone.
  - *in process*: a part of the ventral zone begins to elevate.
  - *present*: significant elevation of the ventral zone irregular disposition.

- Variable 9: Ventral margin:

– *absent*: no margin delimiting the ventral border. If there are differences they are marked by texture.

– *partially formed*: ventral margin in formation phase.

– *formed without rarefactions*: ventral border clearly defined without recesses and protrusions (rarefactions).

– *formed with few rarefactions*: ventral border clearly defined with some recesses and protrusions.

– *formed with many rarefactions*: ventral border clearly defined with a lot of recesses and protrusions.

4.2 Dataset generation process

We used the left symphysis pubis of 74 individuals with known age of death. A PhD student of the Physical Anthropology Laboratory examined every bone, and assigned a value to the nine variables selected without knowing the death age. For each input variable, the student chose the most appropriate label.

With the aim of clarifying the process and assisting the task of labeling the bones, a tagging guide was designed previously by an expert forensic anthropologist and it was provided to the student. The guide included a brief description of all the labels together with a photograph of a real symphysis pubis in which such an attribute can be easily recognized. Figure 1 shows a part of the tagging guide.

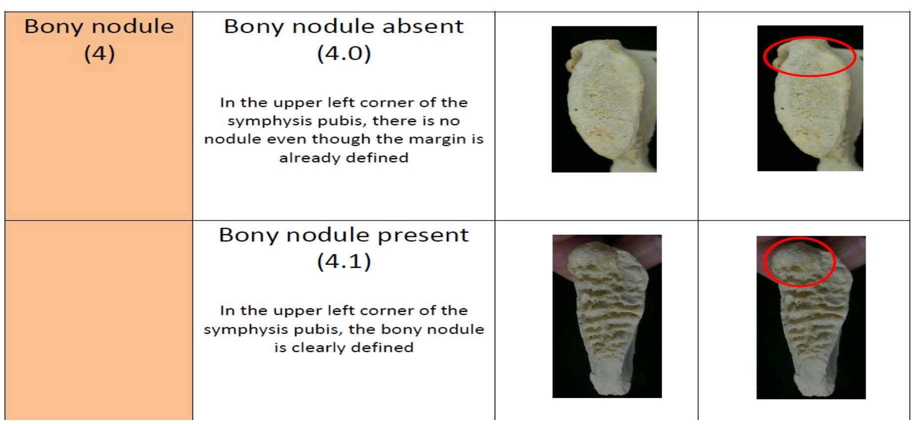

Figure 1: Tagging guide (variable 4: Bony nodule)

After this process, the known age of death was incorporated to the input data as the actual class of the example, obtaining 74 labeled data pairs. We are aware of the limitations of the dataset currently available. As we are constrained to the symphysis pubis of the osteological collection considered, there are classes with just a few examples and even one of the classes (Phase 2) is not represented in the dataset. The class distribution is shown in Table 1. Beyond these shortcomings, the dataset is big enough to perform our study and draw some preliminary but important conclusions.

Table 1: Class distribution of the dataset

Class (Phase)	1	2	3	4	5	6	7	8	9	10
Number of examples	8	0	3	4	6	5	8	9	13	18

4.3 Quality metric

In our classification system, age estimation can be considered an ordinal classification problem as the output labels (i.e., the classes) exhibit an ordering relation. Therefore, a performance metric for this type of problems should be considered. The Mean Absolute Error (MAE) is an example of a metric that includes the order information. MAE is the average mean in absolute value of the difference between the predicted rank (Y_i') from the true one (Y_i):

$$MAE = \frac{1}{N}\sum_{i=N}^{N} |Y_i - Y_i'| \quad (1)$$

where N is the number of examples and $MAE \in [0, C-1]$, being C the number of classes. In our study, $MAE \in [0, 9]$.

4.4 FRBCS with rules derived from expert knwoledge

In this first approach, a forensic anthropologist expert was asked to derive a single fuzzy rule for each of the ten age groups considered. This task is not very difficult as the expert is only required to choose the most appropriate label for each variable defined in Section 4. When there is a doubt between two labels, both corresponding rules are generated.

In principle, the number of rules obtained was relatively high (32), due to the high dimensionality of the input space. A preliminary test of this FRBCS with the dataset led to very bad results. They were mainly related to the high number of unclassified examples (42 examples unclassified, that is, 56.7% of the whole dataset). When all these examples are classified in class 5.5, the reported MAE is 2.04. This situation is due to the large size of the input space (with nine variables and nearly three labels mean). Probably, some of the variables are irrelevant in certain age groups but these situations are difficult to be recognized for the experts, as they usually consider all the variables. This problem also arises in Todd's method, that includes a detailed description of the morphological aspects, although some of them are probably not very relevant for age estimation.

4.5 FRBCS with rules derived from data

Given the previous results, we followed an alternative approach. In particular, we derived the rules by an automatic learning process that considers feature selection in order to simplify the model and achieve better prediction results.

We have derived the rules by means of a Fuzzy Decision Tree (FDT), the one proposed in [7], which implicitly includes feature selection. We used the FDT implementation provided by a fuzzy modeling open source software called GUAJE (Generating Understandable and Accurate fuzzy models in a Java Environment) [20][21][22].

We follow a ten k-fold cross-validation scheme for testing the FRBCS performance. Table 2 shows the MAE values for training and test datasets together with the number of rules in the different fuzzy classification rule bases derived ($\#rules$).

Table 2: Ten k-fold cross-validation results obtained

Fold	MAE_{tra}	MAE_{test}	$\#rules$
0	0.86	1.75	19
1	0.97	1.37	17
2	1.03	1.25	20
3	0.88	2.00	19
4	0.89	2.42	17
5	0.73	2.14	17
6	0.94	1.71	19
7	1.00	0.71	19
8	1.00	1.42	19
9	0.97	2.00	20
Mean	0.93	1.68	18.6

As it can be observed, the MAE obtained over the test data set shows a somehow good value as $MAE \in [0, 9]$. However, these results may be influenced by the randomly selected distribution of training and test examples, due to the small size of the dataset and the few examples available for some classes.

In order to avoid any possible distribution bias, we divided the dataset into training and test data three times, with different partition sizes. The splitting was not performed completely at random since we tried that the distribution of classes was similar in both sets. For each class, the distribution of each particular example into either the training or the test data set was performed randomly.

The results obtained are reported in Table 3, where $\#tra$ and $\#test$ are the number of examples for training and test, respectively. The last row of Table 3 also includes the performance of the FRBCS obtained considering the whole dataset as the training data set. It can be observed that the MAE value remains close to 1, this represents a reasonable generalization capability. In average, the predicted value is one of the adjacent classes. That it is a good performance, having in mind the high number of classes.

The rules learned by the FDT considering the whole dataset as training examples are shown in Figure 2. There are three classes not considered in the consequent of any rule. As we already mentioned, class 2 is not represented in the dataset and it is thus not included in any of the obtained fuzzy rules.

Table 3: MAE results obtained

Sampling	$\#tra$	$\#test$	MAE_{tra}	MAE_{test}	$\#rules$
1	55	19	1.0	1.36	18
2	60	14	1.03	1.21	17
3	63	11	1.08	1.18	17
dataset	74	0	1.07	–	18

R1: **IF** Articular face **is** regular_porosity **THEN** Estimated age **is** phase 1

R2: **IF** Articular face **is** ridges_and_grooves **THEN** Estimated age **is** phase 1

R3: **IF** Articular face **is** grooves_shallow **and** Ventral margin **is** absent **THEN** Estimated age **is** phase 3

R4: **IF** Articular face **is** grooves_shallow **and** Ventral margin **is** partially_formed **THEN** Estimated age **is** phase 4

R5: **IF** Articular face **is** grooves_rest **and** Irregular porosity **is** absent **and** Ventral bevel **is** in_process **and** Ventral margin **is** partially_formed **THEN** Estimated age **is** phase 5

R6: **IF** Articular face **is** grooves_rest **and** Irregular porosity **is** medium **and** Bony nodule **is** present **THEN** Estimated age **is** phase 5

R7: **IF** Articular face **is** no_grooves **and** Irregular porosity **is** absent **and** Ventral bevel **is** absent **and** Ventral margin **is** formed_without_rarefactions **THEN** Estimated age **is** phase 8

R8: **IF** Articular face **is** grooves_rest **and** Irregular porosity **is** absent **and** Ventral bevel **is** in_process **and** Ventral margin **is** formed_without_rarefactions **THEN** Estimated age **is** phase 9

R9,R10: **IF** Articular face **is** grooves_rest **and** Irregular porosity **is** absent **and** Ventral bevel **is** absent **and** Ventral margin **is** partially_formed **or** formed_without_rarefactions **THEN** Estimated age **is** phase 9

R11: **IF** Articular face **is** no_grooves **and** Irregular porosity **is** absent **and** Ventral bevel **is** in_process **and** Ventral margin **is** formed_without_rarefactions **THEN** Estimated age **is** phase 9

R12: **IF** Articular face **is** grooves_shallow **and** Ventral margin **is** formed_without_rarefactions **THEN** Estimated age **is** phase 10

R13,R14,R15: **IF** Articular face **is** grooves_rest **and** Irregular porosity **is** medium **and** Bony nodule **is** absent **and** Ventral margin **is** partially_formed **or** formed_without_rarefactions **or** formed_with_few_rarefactions **THEN** Estimated age **is** phase 10

R16,R17: **IF** Articular face **is** no_grooves **and** Ventral margin **is** partially_formed **or** formed_with_few_rarefactions **THEN** Estimated age **is** phase 10

R18: **IF** Articular face **is** no_grooves **and** Irregular porosity **is** medium **and** Ventral margin **is** formed_without_rarefactions **THEN** Estimated age **is** phase 10

Figure 2: Fuzzy rules derived from the whole dataset

Regarding classes 6 and 7 (not covered by the fuzzy rules obtained), we also need more examples. The initial design of variables and labels is good but more instances are needed (specially in the less represented classes) in order to improve the performance of this preliminary FRBCS. After this, a learning process for adjusting the fuzzy partitions can obtain more accurate classification results.

In order to analyze the performance of our proposal, we also used a classical decision tree, the C4.5 algorithm [23]. The model obtained by C4.5 applied to the whole dataset achieved slightly worse results ($MAE = 1.12$), than our FRBCS ($MAE = 1.07$). Since there are no examples of class 2, neither C4.5 nor any other machine learning method cover it. Besides the previously uncovered classes by FDT (6,7), C4.5 does not cover two more classes (5,8). Therefore, C4.5 is not able to generate rules for four classes (5,6,7,8) as a consequence of using crisp borders. On the contrary, the soft borders of the FDT allow to cover two more classes (5,8). Therefore, our fuzzy approach overcomes a classical method in this age estimation problem. Table 4 shows the MAE results for each class.

Table 4: MAE values for each class (whole dataset)

Class	1	2	3	4	5	6	7	8	9	10
FDT	0.0	-	2.33	1.75	2.16	2.4	2.0	1.11	0.38	0.5
C4.5	0.0	-	0.33	1.25	3.66	2.8	2.12	1.44	0.15	0.5

It is important to remark the interpretability of the obtained fuzzy model. The rule base is compact, with few rules, and each rule is very simple as it does not use many of the variables in the antecedent. In fact, some variables do not appear in any rule. One might think that these variables are not relevant in age estimation and they could be neglected in order to make the process simpler. However, before making a decision, a wider experimental study including a bigger dataset must be performed.

On the other hand, our method is simpler than Todd's method as it does not require as much time of assimilation as required by the application of Todds method, just a bit of knowledge to be able to understand the tagging guide and label a new symphysis pubis. We should remember that the input values of the dataset were labeled by a PhD student.

5 Concluding remarks

This contribution introduces a preliminary FRBCS for age estimation of skeletal remains in forensic anthropology. Our proposal is based in the symphysis pubis, following Todd's method, that it is purely descriptive. Our aim is to systematize and simplify the process, detecting the main characteristics of the problem and learning a compact FRBCS for classifying new cases according to such characteristics. We have generated a labeled dataset and the results obtained for this preliminary model are very promising.

In future work, we will improve the model incorporating new instances and adjusting the fuzzy partitions. We are also interested in analyzing the behavior of the model considering the right symphysis pubis and learning different models depending on the gender of the individual.

Acknowledgments

This work is supported by Spanish Ministerio de Economía y Competitividad under the NEWSOCO project (ref. TIN2015-67661-P) and the Andalusian Department of Innovación, Ciencia y Empresa under project TIC2011-7745, both including European Development Regional Funds (EDRF). The authors would like to thank Dr. Jose María Alonso for his help in the use of the GUAJE software tool to derive the fuzzy rule bases.

References

[1] M.Y. Iscan, *Integral forensic anthropology*, Practicing Anthropology 3(4): 21–30, 1981.

[2] L. Scheuer and S. Black, *The Juvenile Skeleton*. Elsevier Academic Press, 2000.

[3] W. Todd, *Age changes in the pubic bone (Part I)*, American Journal of Physical Antropology 3(3): 285-339, 1920.

[4] W. Todd, *Age changes in the pubic bone (Part II)*, American Journal of Physical Antropology 4(1): 1-77, 1921.

[5] H. Ishibuchi, T. Nakashima and M. Nii, *Classification and Modeling with Linguistic Information Granules. Advanced Approaches to Linguistic Data Mining*. Springer, 2005.

[6] O. Cordón, M.J. del Jesus, F. Herrera, *A Proposal on Reasoning Methods in Fuzzy Rule-Based Classification Systems*, International Journal of Approximate Reasoning 20: 21–45, 1999.

[7] H. Ichihashi, T. Shirai, K. Nagasaka, and T. Miyoshi, *Neuro-fuzzy id3: a method of inducing fuzzy decision trees with linear programming for maximizing entropy and an algebraic method for incremental learning*, Fuzzy Sets and Systems 81: 157–167, 1996.

[8] J. Santamaría, O. Cordón, S. Damas, J.M. García-Torres and A. Quirin, *Performance evaluation of memetic approaches in 3D reconstruction of forensic objects*, Soft Computing 13(8): 883-904, 2009.

[9] O. Ibáñez, O. Cordón, S. Damas and J. Santamaría, *Modeling the skullface overlay uncertainty using fuzzy sets*, IEEE Transactions on Fuzzy Systems 16(5): 946-959, 2011.

[10] B. Rosario Campomanes-Álvarez, O. Ibáñez, F. Navarro, I. Alemán , M. Botella, S. Damas and O. Cordón, *Computer vision and soft computing for automatic skullface overlay in craniofacial superimposition*, Forensic Science International 245: 77-86, 2014.

[11] Q.H. Dinh, T.C. Ma, T.D. Bui, T.T. Nguyen and D.T. Nguyen, *Facial soft tissue thickness prediction using anthropometric distances*, in: N.T. Nguyen, B. Trawinski, J.J. Jung (Eds.), New Challenges for Intelligent Information and Database Systems in Computational Intelligence, 351, Springer, 117-126, 2011.

[12] C. Campomanes-Alvarez, O. Ibáñez and O. Cordón, *Design of criteria to assess craniofacial correspondence in forensic identification based on computer vision and fuzzy integrals*. Applied Soft Computing 46: 596–612, 2016.

[13] C. Campomanes-Alvarez, O. Ibáñez and O. Cordón, *Experimental study of different aggregation functions for modeling craniofacial correspondence in craniofacial superimposition.* Proceedings IEEE International Conference on Fuzzy Systems: 437–44, 2016.

[14] S. Damas, O. Cordón, O. Ibáñez, J. Santamaría, I. Alemán, M. Botella and F. Navarro, *Forensic identification by computer-aided craniofacial superimposition: a survey*, ACM Computing Surveys (CSUR) 43(4): 27, 2011.

[15] M. Anderson, D. T. Anderson and D. Wescott, *Estimation of adult skeletal age-at-death using the sugeno fuzzy integral*, American Journal of Physical Anthropology 142: 30–41, 2010.

[16] D. T. Anderson, M. Anderson, J. M. Keller and D. Wescott, *Linguistic description of adult skeletal age-at-death estimations from fuzzy integral acquired fuzzy sets*, Proceedings IEEE International Conference on Fuzzy Systems: 2274-2281, 2011.

[17] S. Aja-Fernández, R. Luis-García, M.A. Martín-Fernández and C. Alberola-López, *A computational TW3 classifier for skeletal maturity assessment. A computing with Words approach*, Journal of Biomedical Informatics 37(2): 99-107, 2004.

[18] C-W. Hsieh, T-L. Jong and C-M. Tiu, *Bone age estimation based on phalanx information with fuzzy constrain of carpals*, Medical & Biological Engineering & Computing 45: 283–295, 2007

[19] M. Mansourvar, A. Asemi, R.G. Raj, S.A. Kareem, C.D. Antony, N. Idris and M.S. Baba, *A Fuzzy Inference System for Skeletal Age Assessment in Living Individual*, International journal of Fuzzy Systems, 2016. doi:10.1007/s40815-016-0232-7

[20] D. P. Pancho, J. M. Alonso, and L. Magdalena, *Quest for interpretability-accuracy trade-off supported by Fingrams into the fuzzy modeling tool GUAJE*, International Journal of Computational Intelligence Systems, 6(sup1): 46–60, 2013.

[21] J. M. Alonso and L. Magdalena, *Generating understandable and accurate fuzzy rule-based systems in a java environment*, Lecture Notes in Artificial Intelligence - 9th International Workshop on Fuzzy Logic and Applications, LNAI 6857: 212–219, 2011.

[22] J. M. Alonso and L. Magdalena, *HILK++: an interpretability-guided fuzzy modeling methodology for learning readable and comprehensible fuzzy rule-based classifiers*, Soft Computing, 15(10): 1959–1980, 2011.

[23] J. R. Quinlan, C4.5: *Programs for Machine Learning.* San Mateo, California: Morgan Kaufmann Publishers, 1993.