Modeling the Skull–Face Overlay Uncertainty Using Fuzzy Sets

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***Abstract*—Craniofacial superimposition (CS) is a forensic process where photographs or video shots of a missing person are compared with the skull that is found. By projecting both photographs on top of each other (or, even better, matching a scanned 3-D skull model against the face photo/video shot), the forensic anthropologist can try to establish whether it is the same person. The whole process is influenced by inherent uncertainty, mainly because two objects of different nature (a skull and a face) are involved. In this paper, we extend our previous evolutionary-algorithm-based method to automatically superimpose the 3-D skull model and the 2-D face photo with the aim to overcome the limitations that are associated with the different sources of uncertainty, which are present in the problem. Two different approaches to handle the imprecision will be proposed: weighted and fuzzy-set-theory-based landmarks. The performance of the new proposal is analyzed, considering five skull–face overlay problem instances that correspond to three real-world cases solved by the Physical Anthropology Laboratory, University of Granada, Granada, Spain. The experimental study that is developed shows how the fuzzy-set-based approach clearly outperforms the previous crisp solution. Finally, the proposed method is validated by the comparison of its outcomes with respect to those manually achieved by the forensic experts in nine skull–face overlay problem instances.**

***Index Terms*—Covariance matrix adaptation evolution strategy, craniofacial superimposition (CS), evolutionary algorithms, forensic identification, fuzzy distances, fuzzy landmarks, genetic fuzzy systems, skull–face overlay (SFO).**

I. Introduction

One of the most prominent disciplines in forensic medicine is human identification. When this task is done studying skeleton remains, we refer to the area of forensic anthropology [1]. Over the past few decades, anthropologists have focused their attention on improving those techniques that allow a more accurate identification. Hence, forensic identification has become a very active research area.

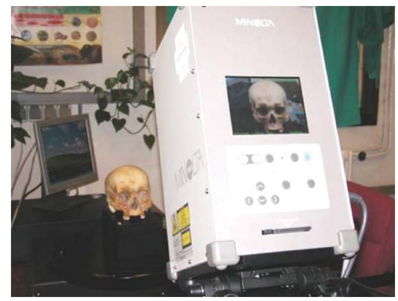

Fig. 1. Acquisition of a skull 3-D partial view by the use of the Konica-Minolta laser range scanner of the Physical Anthropology Laboratory at the University of Granada.

Before making a decision on the identification, there is a need to follow different procedures that let the forensic experts assign a sex, age, human group, and height to the subject from the study of the bones that are found. Once the sample of candidates for identification is constrained by these preliminary studies, a specific identification technique is applied. Among those available in the discipline, *craniofacial superimposition* (CS) [2]–[4] is a forensic process in which photographs or video shots of a missing person are compared with the skull that is found. By projecting both photographs on top of each other (or, even better, matching a scanned 3-D skull model against the face photo/series of video shots), the forensic anthropologist can try to establish whether is it the same person. This *skull–face overlay* (SFO) process is usually done by some corresponding anthropometrical landmarks matching on the skull and the face.

The SFO is known to be one of the most time-consuming tasks for the forensic experts [5]. (It takes up to 24 h in many real-world situations.) In addition, there is no systematic methodology for CS, but every expert usually applies a particular process. Therefore, there is a strong interest in designing automatic methods to support the forensic anthropologist to put it into effect [6].

In particular, the design of computer-aided CS methods has experienced a boom over the past 20 years [7]. The most recent ones consider the use of laser range scanners to achieve a digital model of the human skull that is found (see Fig. 1) by means of a manual or automatic 3-D reconstruction procedure [8], [9], as is the case in the current contribution.

There are other works on the area of 3-D face processing [10], [11], which could seem to have some relation with CS. Specifically, the face modeling topic, where 3-D-face-processing methods deal with the very complex task to properly turn a 3-D

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object (the subject face) into a 2-D image. To obtain a skull 3-D model is feasible—as well as very useful to improve the identification process—due to the availability of the physical object in the forensic anthropology laboratory. Nevertheless, the existing powerful methods in 3-D face modeling, such as [12], cannot be applied on this framework since CS deals with the identification of deceased people. Hence, it is usually difficult for the forensic anthropologist to get significant data (i.e., photographs) under real conditions to apply the latter techniques.

The SFO process is influenced by inherent uncertainty since two objects of different nature are involved (a skull and a face) [13]. In this paper, we aim to overcome most of the limitations associated with the different sources of uncertainty in the problem. In particular, the difficult task to invariantly locate anthropometric landmarks, the precise location of cephalometric landmarks in digital photographs with a poor quality, and the inability to locate a large set of (noncoplanar) landmarks due to occlusions will be considered. To do so, we have incorporated two different approaches to handle the imprecision in landmark location to our previous evolutionary-based SFO procedure [14]: weighted and fuzzy-set theory-based landmarks. Specifically, fuzzy sets have largely demonstrated their capability to deal with vagueness and imprecise information [15], and they have been successfully hybridized with evolutionary algorithms over the last two decades that results in the wide genetic fuzzy systems research area [16].

The novel proposal is tested on five SFO problem instances that are derived from three real-world identification cases that are solved by the Physical Anthropology Laboratory, University of Granada, Granada, Spain, showing an outstanding performance. The current research constitutes an innovative application of fuzzy set theory, such as the following: 1) To the best of our knowledge, it is the first time that it has been used for the CS forensic identification technique, and 2) it outperforms the existing crisp solution, which allows us to properly design an automatic, quick, and accurate SFO procedure to support the forensic anthropologist in the CS task.

The paper is organized as follows. In Section II, we describe the SFO problem and our previous evolutionary-algorithm-based method to deal with it. Then, we study, in detail, the sources of uncertainty that is associated with the SFO task in Sections III-A and B, and introduce our proposal to deal with them in Section III-C. In Section IV, we test the new proposal on five problem instances, benchmarking it with the previous crisp-based one under the supervision of the forensic experts. Then, in Section V, we validate our fuzzy-evolutionary-based approach against forensic anthropologist performance in nine SFO problem instances. Finally, we present some concluding remarks and future work in Section VI.

II. Skull–Face Overlay in Craniofacial Superimposition

The success of the SFO process requires to position the skull in the same pose of the face as seen in the given photograph. The orientation process is a very challenging and time-consuming part of the CS technique [5].

Fig. 2. Main craniometric landmarks: lateral (left) and frontal (right) views.

Fig. 3. Main facial landmarks: lateral (left) and frontal (right) views.

Most of the existing SFO methods are guided by a number of anthropometrical landmarks that are located in both the skull and the photograph of the missing person (see Figs. 2 and 3, respectively). The selected landmarks are placed in those parts, where the thickness of the soft tissue is small. The goal is to ease their location when the anthropologist must deal with changes in age, weight, and facial expressions.

Once these landmarks are available, the SFO procedure is based on searching for the skull orientation leading to the best matching of the two sets of landmarks.

In view of the task to be performed, the relation of the desired procedure with the image registration (IR) problem in computer vision [17] can be clearly identified. Following a 3-D–2-D IR approach, we aim to properly align the 3-D skull model and the 2-D face photograph in a common coordinate frame. The required perspective transformation that is to be applied on the skull was modeled in [14] as a set of geometric operations involving 12 parameters/unknowns, which are encoded in a real-coded vector to represent a superimposition solution.

Formally, the SFO can be formulated as follows. Given two sets of 2-D facial and 3-D cranial landmarks F and C, respectively, both comprising N landmarks:

$$F = \begin{bmatrix} x_{f_1} & y_{f_1} & 1 & 1 \\ x_{f_2} & y_{f_2} & 1 & 1 \\ \vdots & \vdots & \vdots & \vdots \\ x_{f_N} & y_{f_N} & 1 & 1 \end{bmatrix}, \qquad C = \begin{bmatrix} x_{c_1} & y_{c_1} & z_{c_1} & 1 \\ x_{c_2} & y_{c_2} & z_{c_2} & 1 \\ \vdots & \vdots & \vdots & \vdots \\ x_{c_N} & y_{c_N} & z_{c_N} & 1 \end{bmatrix}$$

the overlay procedure aims to solve the following system of equations with the following 12 unknowns: a rotation represented by an axis (d_x, d_y, d_z) and angle θ, a center of mass (r_x, r_y, r_z), a translation vector (t_x, t_y, t_z), a uniform scaling s, and a 3-D–2-D projection function that is given by a field of view ϕ. These 12 parameters determine the geometric transformation f, which projects every cranial landmark cl^i in the skull 3-D model onto its corresponding facial landmark fl^i in the photograph as follows:

$$F = f(C) = C \cdot (A \cdot D_1 \cdot D_2 \cdot R_\theta \cdot D_2^{-1} \cdot D_1^{-1} \cdot A^{-1}) \cdot S \cdot T \cdot P \tag{1}$$

where $R = (A \cdot D_1 \cdot D_2 \cdot R_\theta \cdot D_2^{-1} \cdot D_1^{-1} \cdot A^{-1})$ represents a rotation matrix to orient the skull in the same pose of the photograph. Such a rotation involves a number of geometric transformations $(A \cdot D_1 \cdot D_2 \cdot R_\theta)$ that aim to do the following.

1) Translate the skull to align the origin of coordinates with the rotation axis A.
2) Reorient the skull so that the rotation axis coincides with one of the Cartesian axes D_1 and D_2.
3) Perform the rotation given by R_θ.
4) Use the inverse rotation matrices in reverse order in order to leave the rotation axis in its original orientation, i.e., D_2^{-1}, D_1^{-1}, and A^{-1}.
5) Apply the inverse translation matrix to leave the rotated skull in its original location.

S, T, and P are uniform scaling, translation, and perspective projection matrices, respectively. See [18] for a detailed description of the matrices in (1) and their relation with the 12 unknowns of the problem, as well as see [14] for a deeper explanation.

Different definitions of the fitness function were studied, and the one that achieves the best results was the mean error ME[1]

$$\text{ME} = \frac{\sum_{i=1}^{N} \|f(cl^i) - fl^i\|}{N} \tag{2}$$

where $\|\cdot\|$ is the 2-D Euclidean distance, N is the number of considered landmarks (provided by the forensic experts), cl^i corresponds to every 3-D craniometric landmark, fl^i refers to every 2-D facial landmark, f is the function that defines the geometric 3-D–2-D projective transformation, and $f(cl^i)$ represents the projected skull 3-D landmark cl^i in the image/photo plane.

Solving the SFO problem in the latter fashion results in a really complex optimization task, with a highly multimodal landscape, and forensic experts demand very robust and accurate results. This complex landscape led us to tackle the problem considering robust evolutionary algorithms to search for the optimal values of the 12 registration transformation parameters. In [14], CMA-ES [19] and different real-coded genetic algorithms [20] were applied, achieving very promising results in some problem instances in a short run time.

III. Analysis of the Skull–Face Overlay Uncertainty and its Modeling Using Fuzzy Sets

The whole CS process is influenced by the uncertainty. In particular, the SFO is affected by two sources of uncertainty of different nature. On the one hand, there is an inherent uncertainty that is associated with the two different kinds of objects that are involved in the process, i.e., a skull and a face. On the other hand, there is also an uncertainty that is associated with the 3-D–2-D overlay process that tries to superimpose a 3-D model over a 2-D image. In Sections III-A and B, both sources of uncertainty are studied in detail. Finally, in Section III-C, two imprecise approaches are presented to overcome most of the limitations that are associated with the latter sources of uncertainty.

[1]The mean-square error is not used because of its negative effect when image ranges are normalized in [0, [1].

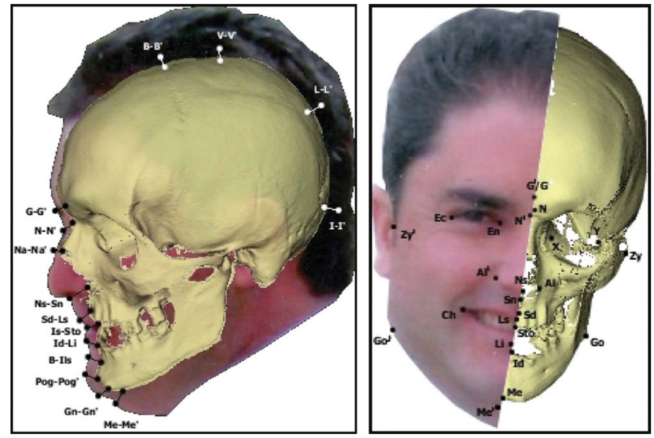

Fig. 4. Correspondences between facial and craniometric landmarks: lateral (left) and frontal (right) views.

A. Uncertainty Inherently Associated With the Objects Under Study

We have identified two inherent sources of uncertainty regarding the handled objects (i.e., a skull and a face) and their relationship. On the one hand, the *landmark location uncertainty* is related to the extremely difficult task to locate the points in an invariable place since the definition of any anthropometric landmark is imprecise in its own. As an example, the Ectocanthion is defined as the point at the outer commissure of the palpebral fissure just medial to the malar tubercle to which the lateral palpebral ligaments are attached. Indeed, every forensic anthropologist is prone to locate the landmarks in a slightly different position [21], regardless of the means that are used to represent the involved objects (a skull and a face), i.e., 3-D model, 2-D photo, video shot, etc. The left images of Fig. 5 show some examples of this situation.

On the other hand, the *landmark matching uncertainty* refers to the imprecision that is involved in the matching of two sets of landmarks corresponding to two different objects: a face and a skull. As shown in Fig. 4, there is a clear partial matching situation. The correspondence between facial and cranial anthropometric landmarks is not always symmetrical and perpendicular; some landmarks are located in a higher position in the alive person face than in the skull, and some others do not have a directly related landmark in the other set [3]. Besides, the facial soft tissue depth varies for each cephalometric landmark, as well as for different person groups (based on age, race, and gender). Many works have been done in order to study distances between each pair of anthropometric landmarks for different groups of study. See [22] and [23] for a deep review. In addition, in the case of SFO, considerations of how these distances are affected by the pose of the face in the image have to be taken into account as well.

B. Uncertainty Associated With the 3-D-Skull-Model–2-D-Face-Photo Overlay Process

The uncertainty associated with the 3-D-skull–2-D-face overlay is not inherent to the object themselves but to our approach, where we try to overlay a 3-D model and a 2-D image. As done in Section III-A, we can also distinguish between landmark matching and landmark location uncertainty. However, the nature of these two sources of uncertainty is different in the current case.

On the one hand, the landmark location uncertainty refers to the difficulty to locate landmarks with the accuracy required for the automatic overlay of a 3-D skull model and a 2-D face photo. The ambiguity may arise from reasons such as variation in shade distribution depending on light condition during photographing, unsuitable camera focusing, poor image quality, face pose in the photograph, partial or whole landmark occlusion, etc.

Of course, the location uncertainty may affect any of the landmarks involved in the SFO process, regardless if they belong to the face photograph or the skull model. Nevertheless, it has a stronger influence on the cephalometric (i.e., facial) ones because of the typical high resolution of the 3-D skull models carrying the craniometric landmarks. In addition, 3-D models do not suffer from occlusions which are originated by the projection as 2-D photographs do.

Forensic experts are prone to locate only those landmarks, which can be unquestionably identified in the skull and in the face. Different reasons, such as the pose of the missing person, the quality of the image, or partial occlusions of landmark regions, make this task especially difficult for the case of the face photographs. Therefore, forensic anthropologists are usually only able to locate a reduced set of all the available cephalometric landmarks.

On the other hand, the matching uncertainty refers to the negative influence of a small number of landmarks with an unsuitable spatial distribution in the quality of the SFO results. This effect happens when the landmarks guiding the optimization method are coplanar or near-coplanar.

Landmark coplanarity is a common problem in many 3-D–2-D overlay processes in computer vision. In particular, in our 3-D-skull–2-D-face overlay procedure, it becomes a very usual situation for two main reasons: 1) Most of the facial landmarks are located in the same plane (see the profile image in Fig. 3), and 2) forensic experts usually prefer those case studies in which the pose of the face is frontal or near-frontal because they can both analyze the symmetries of the face easily and select a higher number of landmarks. Hence, the forensic anthropologists can unquestionably identify landmarks in the face photo that are likely to be coplanar, while the remaining usually unidentified landmarks are those located in different planes.

This landmark coplanarity makes the equation system (the objective function of the IR procedure) undetermined (or near-undetermined), i.e., there is an uncertainty (there is not enough information or it is imprecise) regarding which of the possible solutions is the best. As a consequence, it is not possible to numerically distinguish among the different resulting (after a search process) sets of projection parameters, which originate different SFO results.

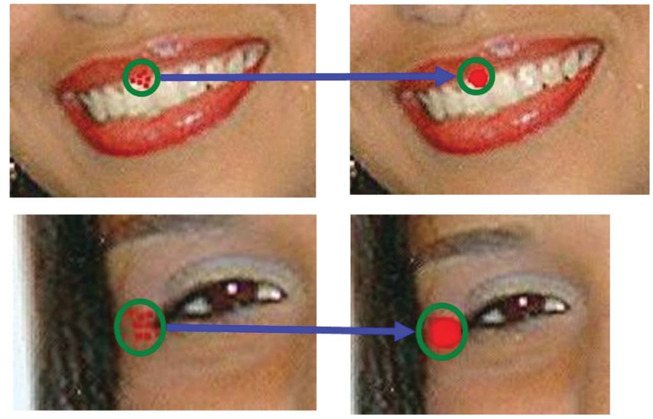

Fig. 5. Examples of precise landmark location (each red spot) by different forensic anthropologists (left) and imprecise ones (right). Labiale superius (upper images) and right Ectocanthion (lower images) landmarks.

In [24], we experimentally demonstrated the strong negative impact of coplanar landmarks in the quality of the SFO results that are derived by our automatic procedure. Having a reasonable number of anthropometrical landmarks that are located in different planes becomes a real need for the good performance of the method.

C. Imprecise Approach to Jointly Tackle Landmark Location and Coplanarity in Automatic Skull–Face Overlay

In this section, we will propose a framework and two different models to deal with the analyzed SFO uncertainty sources. Our approach will be based on to allow the forensic anthropologist to perform an *imprecise location of cephalometric landmarks*. By the usage of *imprecise landmarks*, (s)he can locate the landmark as a region instead of as a crisp point as usual. The size of the region that is defined by the forensic expert will become a measure of the landmark uncertainty (the broader the region is, the higher the uncertainty is in the location of that landmark). Of course, (s)he can both define crisp and imprecise cephalometric landmarks in a face photo, thus keeping the chance to properly locate the unquestionably identified ones.

Notice that, by marking landmarks in an imprecise way, we will manage to solve the problems that are related to three of the four uncertainty sources that are analyzed at the same time. First, the inherent uncertainty of the landmark location in the missing person photograph (see the first part of Section III-A) can be properly tackled, as shown in Fig. 5. The same way, the forensic experts would be able to deal with the location of landmarks whose position cannot be determined accurately due to the photograph conditions (see the first part of Section III-B) with the proper level of confidence (using imprecise regions of different sizes). As a consequence, we will allow them to increase the number of selected landmarks. As explained, those additional landmarks are essential to the coplanarity problem in the automatic deal with search of the best SFO (see the second part of Section III-B). Only the landmark matching uncertainty (see the second part of Section III-A) will be left for future works.

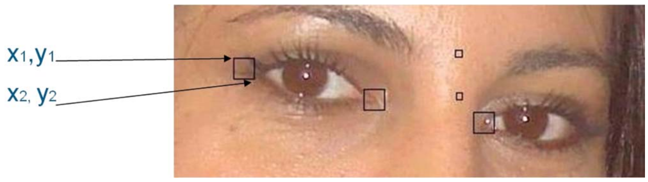

Fig. 6. Example of weighted landmarks.

The imprecise landmark location approach is implemented through two alternative models of imprecise landmarks: weighted and fuzzy ones. The following is devoted to introduce them.

1) Weighted Landmarks: Based on the work by Sinha [25], we consider modeling the cephalometric landmarks as rectangular zones. We will refer to these rectangular zones as weighted landmarks because they contribute to the optimization process depending on their size.[2] Every weighted landmark is given by a rectangular array of pixels defined by diagonally opposite corners (x_1, y_1) and (x_2, y_2) (say $x_2 > x_1$ and $y_2 > y_1$). Hence, a bigger rectangle means a higher uncertainty associated with the landmark (see Fig. 6).

Sinha introduced the latter concept to provide more robustness and tolerance to a neural network that is designed to match 2-D facial images. In that work, crisp points were substituted by rectangles to avoid human error due to image ambiguity. Each rectangular landmark was then temporarily "defuzzied" by taking the centroid as a crisp target feature. Those crisp features were used to learn the preliminary weights of the neural network. Then, there was a later stage, where the rectangle landmarks were adapted (reduced), considering the neural-network responses.

In contrast to Sinha's work, we will consider these rectangular zones to allow the forensic anthropologist to locate the facial landmarks in an imprecise way, and we will not adapt their size during the optimization stage. Hence, they will be internally used by our evolutionary-algorithm-based SFO procedure to avoid local minima by prioritizing some landmarks (more precisely located) rather than others (imprecisely located). Proceeding that way, we establish an order of importance between the different landmarks that are selected by the forensic expert. While those showing a lower uncertainty have a higher influence to guide the search, those which are less precisely located are also considered, although to a lower degree. Therefore, we have modified the previous definition of the fitness function [see (2)] as follows:

$$\text{Weighted}_{\text{ME}} = \frac{\sum_{i=1}^{N} \sqrt{[u_i(x'_{cl^i} - x_{fl^i})]^2 + [v_i(y'_{cl^i} - y_{fl^i})]^2}}{N} \tag{3}$$

where x'_{cl^i} and y'_{cl^i} are, respectively, the coordinates of the transformed 3-D craniometric landmark cl^i in the projection plane; x_{fl^i} and y_{fl^i} are the coordinates of the centroid of the weighted landmark of every 2-D cephalometric landmark; and N is the number of considered landmarks. The terms u_i and v_i are used to represent the uncertainty around each landmark. Their value depends on the size of the rectangular zone, such that [25]

$$u_i = \frac{1}{1 + |x_2 - x_1|}, \quad v_i = \frac{1}{1 + |y_2 - y_1|}.$$

In this formulation, $(x_2 - x_1)$ and $(y_2 - y_1)$ are, respectively, the measures of *X*- and *Y*-axis uncertainty. According to it, when the rectangle that define the weighted landmark is bigger (i.e., it shows a lower value of u_i and/or v_i), the corresponding weight in the fitness function (i.e., the landmark influence to guide the search) will be lower. Thus, a more imprecise location of a landmark implies a less important landmark for the optimization procedure, as desired.

2) Fuzzy Landmarks: We think that the weighted landmarks approach is a too simple way to represent the uncertainty underlying the SFO since all the possible crisp points in the rectangle are equally likely to be the actual location of the landmark, which is not so realistic. Besides, in the weighted approach, the Euclidean distances between craniometric and cephalometric landmarks are computed by the use of the centroid of the rectangles that are associated with the latter ones. Thus, once the centroids of the imprecise cephalometric landmarks are considered, the problem of computing distances between a set of imprecise landmarks and a set of crisp ones becomes the problem of measuring a set of Euclidean distances between different pairs of crisp landmarks.

In summary, this first approach to model the location uncertainty does not take into account the inherent uncertainty that is involved when we are measuring distances between imprecise and crisp points. In this section, we will introduce a new imprecise landmark approach, which will tackle better the real conditions of our work environment. It is based on allowing the forensic experts to locate the cephalometric landmarks using ellipses and on considering fuzzy sets to model the uncertainty that is related to them. Besides, we will also consider fuzzy distances to model the distance between each pair of craniometric and cephalometric landmarks.

Following the idea of fuzzy plane geometry in [26] and of metric spaces in [27], we will define a fuzzy landmark as a fuzzy convex set of points having a nonempty core and a bounded support. That is, all its α-levels are nonempty bounded and convex sets. In our case, since we are dealing with 2-D photographs with an $x \times y$ resolution, we can define the fuzzy landmarks as 2-D masks that are represented as a matrix M with $m_x \times m_y$ points (i.e., a discrete fuzzy set of pixels). Each fuzzy landmark will have a different size, depending on the imprecision on its localization, but at least one pixel (i.e., crisp point that is related to a matrix cell) will have membership with degree 1.

These masks are easily built starting from two triangular fuzzy sets $\widetilde{V}$ and $\widetilde{H}$. They model the approximate vertical and horizontal position of the ellipse representing the location of the landmark. Thus, they become 2-D fuzzy sets, where each triangular fuzzy set $\widetilde{A}$ is defined by its center c and its offsets l and

[2]Despite Sinha naming them fuzzy landmarks, we found that terminology incorrect since they are not based on fuzzy set theory at all.

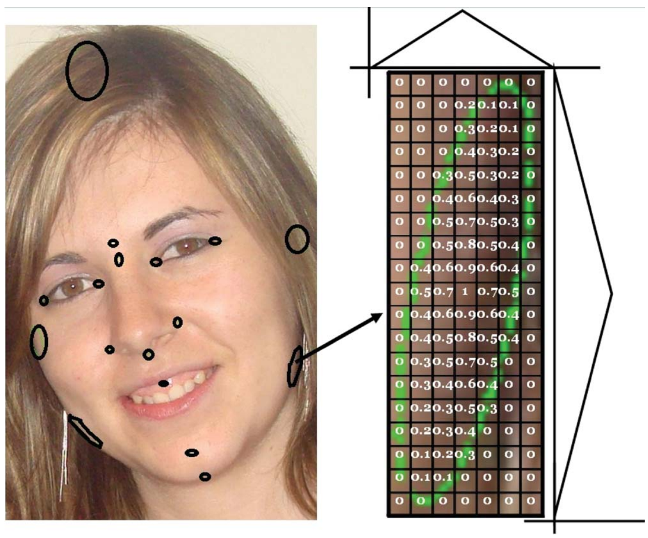

Fig. 7. Example of fuzzy location of cephalometric landmarks (left) and representation of an imprecise landmark using fuzzy sets (right).

r as follows:

$$\widetilde{A}(x) = \begin{cases} 1 - \dfrac{|x-c|}{c-l}, & \text{if } l \le x \le c \\ 1 - \dfrac{|x-c|}{r-c}, & \text{if } c < x \le r \\ 0, & \text{otherwise} \end{cases}$$

and the membership functions of the fuzzy landmarks $\widetilde{F}$ are calculated using the product t-norm by

$$\mu_{\widetilde{F}}(i,j) = \mu_{\widetilde{V}}(i) \cdot \mu_{\widetilde{H}}(j).$$

An example of these fuzzy cephalometric landmarks is given in Fig. 7, where the corresponding membership values of the pixels of one of those landmarks are depicted on the right.

Now, we can calculate the distance between a point (which will be the pixel that constitutes the projection of a 3-D craniometric landmark on the 2-D face photo) and a fuzzy landmark (the discrete fuzzy set of pixels that represent the imprecise position of the cephalometric landmark). To facilitate the comprehension of our fuzzy distance formulation to the reader, we will first review some required basic concepts from classical and fuzzy sets theory [15] as follows:

Distance between a point and a set of points: Given a point x of $\mathbb{R}^n$ and a nonempty subset A of $\mathbb{R}^n$, we can define a distance $d : \mathbb{R}^n \times \mathbb{P}(\mathbb{R}^n) \to \mathbb{R}^+$ by

$$d(x, A) = \inf\{\|x - a\|; a \in A\}$$

for a certain norm $\|.\|$ on $\mathbb{R}^n$. Thus, $d(x, A) \geq 0$, and $d(x, A) = 0 \Rightarrow x \in A$.

Distance between a point and a fuzzy set of points: Now, we can define the distance between a point x of $\mathbb{R}^n$ an a fuzzy set of points $\widetilde{A} : \mathbb{R}^n \to [0, 1]$ by

$$d^*(x, \widetilde{A}) = \int_0^1 d(x, \widetilde{A}_\alpha) d\alpha$$

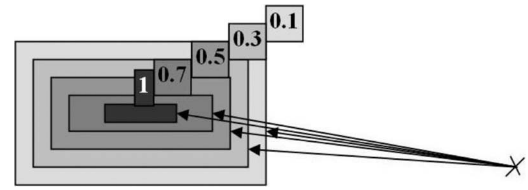

Fig. 8. Distance between a crisp point and a fuzzy point.

where $\widetilde{A}_\alpha$ is the α-level set (α-cut) of $\widetilde{A}, \alpha \in [0, 1]$.

Lemma 3.1: The distance from the point x to the fuzzy set $\widetilde{A}$ is lesser or equal to the distance to the core of $\widetilde{A}$ and greater or equal to the distance to the support of $\widetilde{A}_0$. That is

$$d(x, \widetilde{A}_1) \leq d^*(x, \widetilde{A}) \leq d(x, \widetilde{A}_0).$$

The proof is straightforward.

If we denote the distance from point x to the α-level set $\widetilde{F}_{\alpha_i}$ as $d_i = d(x, \widetilde{F}_{\alpha_i})$, then the distance from the point to the fuzzy landmark $\widetilde{F}$ can be expressed by

$$d^*(x, \widetilde{F}) = \frac{\sum_{i=1}^m d_i \cdot \alpha_i}{\sum_{i=1}^m \alpha_i}.$$

In the example of Fig. 8, taking $\{\alpha_1 = 0.1, \alpha_2 = 0.3, \alpha_3 = 0.5, \alpha_4 = 0.7, \alpha_5 = 1\}$ and assuming $\{d_1 = 4.5, d_2 = 5.4, d_3 = 6.3, d_4 = 7.3, d_5 = 9\}$, we calculate the distance as

$$d^*(x, \widetilde{F}) = \frac{d_1 \cdot \alpha_1 + \cdots + d_5 \cdot \alpha_5}{\alpha_1 + \cdots + \alpha_5} = \frac{19.33}{2.6} = 7.43.$$

Note that the implemented distance between a point and a fuzzy set of points is quite similar to that defined in [28]. In fact, it has been already used in other image-processing applications in [29].

Therefore, we have modified the previous definition of our evolutionary-algorithm-based SFO technique's fitness function as follows:

$$\text{fuzzy ME} = \frac{\sum_{i=1}^N d^*(f(cl^i), \widetilde{F}^i)}{N} \tag{4}$$

where N is the number of considered landmarks; cl^i corresponds to every 3-D craniometric landmark; f is the function that defines the geometric 3-D–2-D transformation; $f(cl^i)$ represents the position of the transformed skull 3-D landmark cl^i in the projection plane, that is to say, a crisp point; $\widetilde{F}^i$ represents the fuzzy set of points of each 2-D cephalometric landmark; and finally, $d^*(f(C_i), \widetilde{F}^i)$ is the distance between a point and a fuzzy set of points.

IV. Experiments

Our experimental study will involve five different SFO problem instances corresponding to three real-world cases previously addressed by the staff of the Physical Anthropology Laboratory in collaboration with the Spanish Scientific Police. They were selected as the most representative among the available cases of the study due to their specific characteristics: poor quality face photograph and/or coplanar/nearcoplanar-corresponding landmark sets.

All those identification cases were positively solved following a computer-supported but manual approach for the SFO. We will consider the available 2-D photographs of the missing people and their respective 3-D skull models that are acquired at the laboratory by the use of its Konica-Minolta 3-D Laserscanner VI-910.

The experiments that are developed in this section are devoted to study the performance of the proposed approaches to model the imprecise location of cephalometric landmarks within our SFO method in comparison with the classical crisp location method. With this aim, we first show the considered parameter setting. Then, we introduce each of the five selected real-world SFO problems to be tackled together with the obtained results and their analysis.

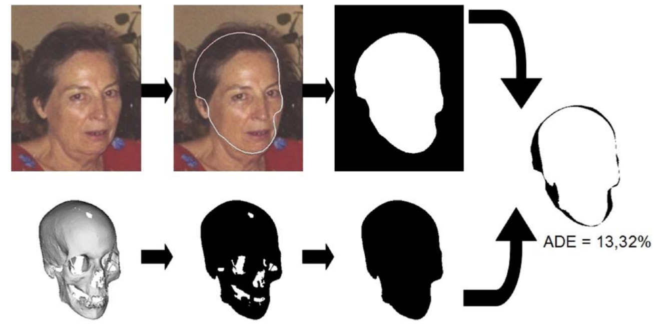

Fig. 9. Example of the ADE procedure. From left to right, original photographs (top) and projected skull (bottom), intermediate images with the head boundary (top) and binary skull (bottom), and final XOR image (rightmost) with the corresponding ADE value below the image.

A. Experimental Design

For all the experiments, we used CMA-ES[3] as the evolutionary algorithm in the SFO procedure [14] that is guided by the corresponding objective functions, (2) for crisp landmarks, (3) for weighted landmarks, and (4) for fuzzy ones. Thirty independent runs were performed for each case with the following set of parameters:

$$\text{initial } \theta \text{ (mutation distribution variance)} = 0.1$$

$$\lambda \text{ (population size, offspring number)} = 100$$

$$\mu \text{ (number of parents/points for recombination)} = 15.$$

Each run involves the development of 500 000 evaluations. The restart operator [30], which does not increase the population size, is used every 25 000 evaluations to avoid the convergence of the algorithm to local minima. The rest of the parameters are the default ones, which are reported in [31].

Two different types of landmark sets were provided by the forensic experts for each available subject photograph in each case study. The first type is the one that is classically used in the manual overlay process, i.e., those the forensic anthropologist is able to precisely locate in a unquestionable single pixel. We named them crisp landmarks. The second one is a set of imprecise landmarks, that is to say, a region for each landmark, where the precise location of the landmark is to be contained. As said, in this second set, the forensic expert could place more landmarks than in the other, due to the possibility of drawing bigger (in size) square- or ellipse-shaped areas of different sizes that are associated with weighted regions or fuzzy sets of points.

We compare the results of the CMA-ES-based SFO method by the use of a crisp set of landmarks with those reached by the use of imprecise locations of cephalometric landmarks (weighted and fuzzy landmarks). In order to perform a significant and fair comparison between the crisp and the imprecise approaches, we considered the following experimental design concerning the number of landmarks: Two different sets of each kind of imprecise landmarks (weighted and fuzzy) are used, one with the same cardinal number (and, of course, the same specific landmarks) as the crisp set and another that includes the additional landmarks identified thanks to the use of the imprecise location approach.

We should note that, as in any SFO process, the evaluation of the quality of the outcomes that are obtained by each considered approach involves a subjective task. To do so, an experienced forensic anthropologist must analyze the obtained skull–face superimpositions to determine their accuracy from a qualitative viewpoint. For this assessment, we collaborate with the forensic experts from the Physical Anthropology Laboratory, which originally solved the tackled cases.

Nevertheless, we would also like to have a quantitative measure allowing us to benchmark the achieved outcomes. Unfortunately, the ME values that are obtained by each approach are not significant to perform a comparison because of the different objective functions that are to be minimized and the different number of landmarks to be considered. Besides, if we analyze the results that are presented in Table II (see Section IV-E) and the visual representations of the corresponding SFOs that are collected in Figs. 11, 13, and 15, then using an imprecise landmark set can lead to a higher ME value, even when the final overlay shows to be more accurate for the forensic expert. Despite that, we will report the ME numerical results as complementary information.

Because of the latter reasons, we adopted an alternative, specifically designed image-processing scheme to evaluate the performance of every SFO approach. First, the forensic experts approximately extracted the head boundary of the missing person in the photograph. (They did so for all the cases of the study.) Next, we obtained a binary image of both the head boundary and the projected skull. Then, the XOR logic operator was applied considering both images. Finally, the error was computed as a percentage of the head boundary that is not covered by the area of the projected skull. Fig. 9 shows an example of the application of this evaluation procedure, which is named "area deviation error (ADE)." Notice that this quantitative measure is so generic that can help in other forensic identification studies by CS, as will be shown in Section V.

In our opinion, this is definitely a more appropriate error estimator for the SFO problem since it is more in concordance

[3]An experimental study using different evolutionary approaches to solve the SFO problem was carried out in [14], where CMA-ES is demonstrated to be the most accurate and robust approach. Hence, that study is out of the scope of the current contribution.

Fig. 10. Case study 1: photograph of the missing person with two different sets of 7 crisp (left) and 15 fuzzy (right) landmarks.

Fig. 11. *Case study 1*. Best SFO results. In the first row, from left to right, results by the use of seven crisp, seven weighted, and seven fuzzy landmarks. In the second row, from left to right, results by the use of 15 weighted and 15 fuzzy landmarks.

with the visual results that are achieved than the ME. Even so, it fails to measure how inner parts of the skull (set of teeth, eye cavity, and so on) fit to the corresponding ones in the face. In addition, it is based on an imprecise extraction of the boundary of the head since it is done by the use of the provided missing people face photographs, where, in most of the cases, there is hair occluding in some parts of the head boundary. Nevertheless, regardless the latter drawbacks, it can successfully provide us with a fair numerical index to compare the obtained SFOs in an objective way, which properly complements the qualitative forensic anthropologists' assessment.

B. Case Study 1

The first case of the study happened in Málaga, Spain. The facial photograph of this missing lady was provided by the family and the final identification done by CS has been confirmed. The forensic experts manually selected a set of seven 2-D cephalometric landmarks on the face that is present in the photo, following a crisp approach, and 15 weighted and fuzzy landmarks, following an imprecise approach (see Fig. 10).

Regarding visual results, Fig. 11 presents the best SFO results corresponding to the crisp, the weighted, and the fuzzy approaches to allow for a visual comparison. The fact that the overlays that are achieved are much more accurate when using a larger number of imprecise landmarks can be clearly identified. Between the two imprecise location approaches, the fuzzy one achieves the best overlay, as confirmed by the forensic anthropologists and as can be clearly recognized even by a nonexpert reader.

These conclusions regarding the SFO visual results are also supported by the ADE, which are presented in Table I. The best results were achieved following an imprecise location approach with the larger number of landmarks (15), using either fuzzy landmarks (13.32%) or weighted ones (15.32%). They both clearly outperform the results that are achieved by the use of a crisp set of landmarks (58.18%). Notice that, considering the same number of landmarks (7), there is also an improvement when they are imprecise (35.30% and 37.53% for weighted and fuzzy landmarks, respectively). Both the usual visual results and these ADE differences directly justify the need of an imprecise location because of the inherent imprecise definition of the anthropometric landmarks. They clearly show the performance advantage of the usage of the imprecise landmarks and, especially, the fuzzy ones.

C. Case Study 2

The second real-world case that is considered corresponds to a Moroccan woman whose corpse was found in the South of Spain. There is a single available photograph that corresponds to that one in the alleged passport. Notice that passport photographs usually include an undulating watermark that makes the accurate location of cephalometric landmarks even more difficult. Therefore, the use of imprecise landmarks can help the forensic expert in the recognition of a higher number of facial reference points in this low-quality photograph. In particular, the selection of noncoplanar landmarks is, thus, eased. In this case of the study, the forensic experts identified six and 16 cephalometric landmarks following a crisp and a imprecise approach, respectively (see Fig. 12).

In Fig. 13, it can be clearly seen how the two overlays that are associated with the two imprecise approaches with the large landmark sets show the best quality, with the fuzzy approach being slightly better. The ADE values given in Table I corroborate the best performance of the imprecise location approach (and, specifically, of the fuzzy one) in comparison with the precise one, achieving much better values (11.92% against 32.63%).

D. Case Study 3

The third case of the study happened in Cádiz, Spain. The three different photographs that are shown in Fig. 14 are available. They were provided by the relatives, which acquired them at different moments and in different poses and conditions. Hence, this case study consists of three distinct SFO problem instances. Notice that these three images have a frontal or near-frontal pose of the face, and/or the corresponding craniometric set of landmarks are coplanar or near-coplanar.

The forensic experts were able to locate nine, 11, and 12 landmarks following a crisp (precise) approach and 14, 16, and 15 using imprecise landmarks for poses 1, 2, and 3, respectively

TABLE I
AREA-DEVIATION-ERROR VALUES IN THE BEST SKULL–FACE OVERLAY ESTIMATIONS OF EVERY APPROACH

Approach	case 1		case 2		case 3, pose 1		case 3, pose 2		case 3, pose 3	
	$\#land$	ADE	$\#land$	ADE	$\#land$	ADE	$\#land$	ADE	$\#land$	ADE
Crisp	7	58.18%	6	32.63%	9	50.28%	11	42.84%	12	53.85%
Weighted	7	35.30	6	33.17%	9	49.84%	11	42.67%	12	54.97%
Fuzzy	7	37.53%	6	32.88	9	51.60%	11	41.54%	12	54.84%
Weighted	15	15.32%	16	16.66%	14	34.34%	16	27.88%	15	23.82%
Fuzzy	15	**13.32%**	16	**11.92%**	14	**27.97%**	16	**21.27%**	15	**18.94%**

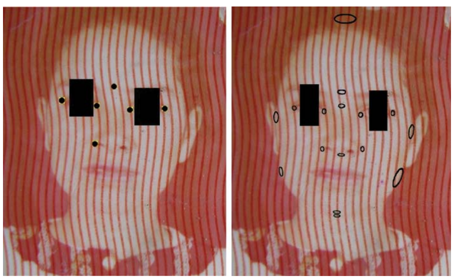

Fig. 12. Case study 2: photograph of the missing person with two different sets of six crisp (left) and 16 fuzzy (right) landmarks.

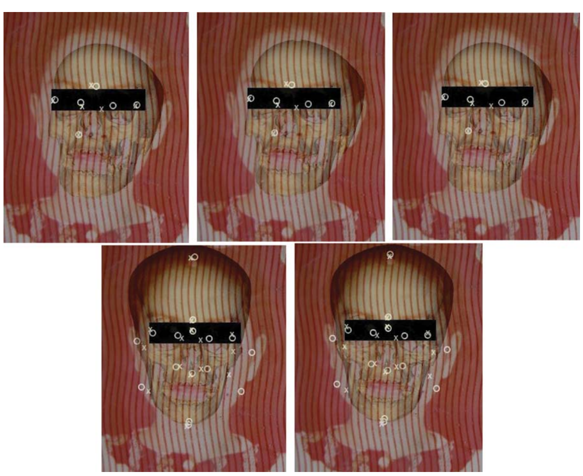

Fig. 13. *Case study 2*. Best SFO results. In the first row, from left to right, results by the use of six crisp, six weighted, and six fuzzy landmarks. In the second row, from left to right, results by the use of 16 weighted and 16 fuzzy landmarks.

(see Fig. 14). As in the other cases, these additional landmarks will play an essential role in order to tackle the coplanarity problem. A clear example is the landmark on the top of the head, named *vertex*, which is never used by the forensic anthropologists because it is normally occluded by hair (and, thus, they are not able to precisely locate it), although it is very useful for the automatic overlay process since it lies in a complete different plane.

The following is devoted to present and analyze the experimental results that are obtained for each of the three cases.

1) Pose 1: The SFO results (see Fig. 15, left column) show again the best performance that is achieved when an imprecise location approach is followed. By the use of the large imprecise landmark sets, the obtained overlays are more accurate, especially in the fuzzy approach, as confirmed by the forensic anthropologists. In Table I, the ADE values for all the approaches corroborating the latter two conclusions are given. The best performance (27.97%) is again achieved by the use of fuzzy landmarks.

Fig. 14. Case study 3 (left to right): photographs of the missing person corresponding to poses 1, 2, and 3. Pictures in the top row show the used crisp landmarks sets, which are composed of nine, 11, and 12 crisp landmarks, respectively. Pictures in the bottom row show the used imprecise landmarks sets, which are composed of 14, 16, and 15 landmarks, respectively.

2) Pose 2: Once again, the bad performance that is obtained by the use of a small set of crisp landmarks is easily identified, with ADE values that range from 41.54% to 42.84% (see Table I). These values are clearly outperformed when an imprecise location approach is properly followed (21.27% and 27.88%), as seen in the corresponding overlays' quality (see Fig. 15, center column).

3) Pose 3: As in the previous cases, the overlays that are achieved (see Fig. 15, right column) are much more accurate when using the large imprecise landmark sets. Among the imprecise location approaches, the fuzzy one achieves the best overlay one more time. These conclusions are also supported by the ADE values, which are presented in Table I. The best results were achieved following an imprecise location approach with the large number of landmarks (15), using fuzzy landmarks (18.94%) or weighted ones (23.82%). They both clearly outperform the results achieved by the use of a crisp set of landmarks (53.85%). Notice that the consideration of the same number of landmarks, even of an imprecise nature, is not enough to derive a good performance due to the coplanarity problem.

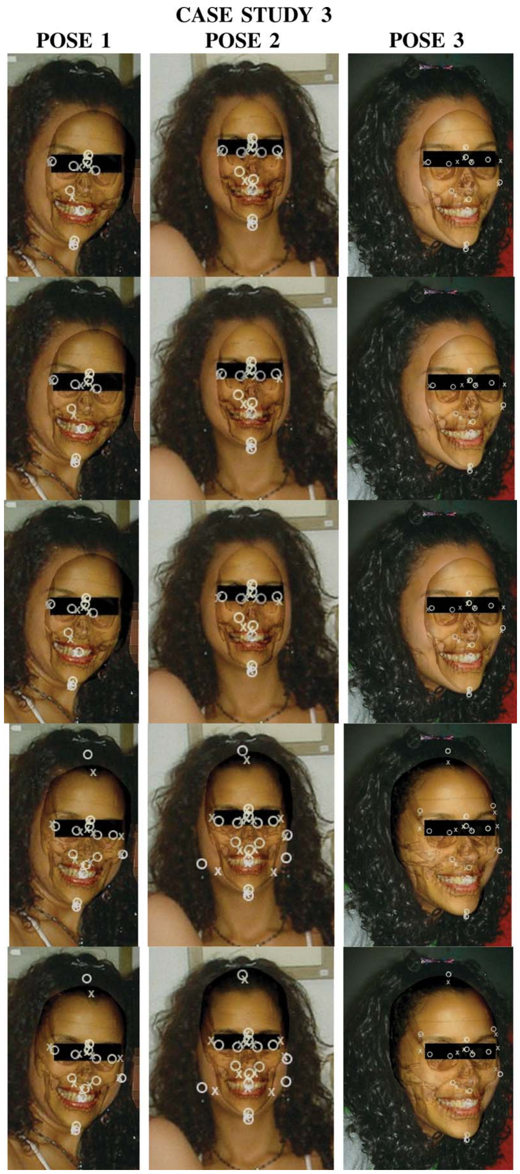

Fig. 15. Case study 3. In columns 1–3, best SFO results that correspond to poses 1, 2, and 3, respectively, are shown. In the first row, results by the use a crisp set of landmarks (nine, 11, and 12 landmarks, respectively) are shown. In the second and third rows, results by the use of the same set of landmarks but following a weighted and a fuzzy approach, respectively, are shown. In the fourth row, results by the use of a larger set of weighted landmarks (14, 16, and 15 landmarks, respectively) are shown. In the fifth row, results by the use of the latter set of landmarks but considering a fuzzy approach are shown.

TABLE II
SKULL–FACE-OVERLAY RESULTS OF CASE STUDIES 1, 2, AND 3 CORRESPONDING TO POSES 1, 2, AND 3

Case	Landmark set	ME			
		m	M	ϖ	σ
1	7 crisp l.	0.0232	0.0262	0.0243	0.0006
1	7 weighted l.	0.0227	0.0282	0.0240	0.0018
1	7 fuzzy l.	0.0273	0.0325	0.0282	0.0011
1	15 weighted l. (ME over 7)	0.0326	0.0372	0.0364	0.0010
1	15 fuzzy l. (ME over 7)	0.0348	0.0546	0.0375	0.0055
2	6 crisp l.	0.0153	0.0154	0.0153	0.0000
2	6 weighted l.	0.0154	0.0155	0.0154	0.0000
2	6 fuzzy l.	0.0155	0.0158	0.0157	0.0000
2	16 weighted l. (ME over 6)	0.0221	0.0230	0.0224	0.0001
2	16 fuzzy l. (ME over 6)	0.0214	0.0225	0.0219	0.0002
3, 1	9 crisp l.	0.0083	0.0084	0.0083	0.0000
3, 1	9 weighted l.	0.0083	0.0088	0.0084	0.0000
3, 1	9 fuzzy l.	0.0084	0.0085	0.0084	0.0000
3, 1	14 weighted l. (ME over 9)	0.0094	0.0095	0.0094	0.0000
3, 1	14 fuzzy l. (ME over 9)	0.0100	0.0102	0.0101	0.0000
3, 2	11 crisp l.	0.0096	0.0097	0.0096	0.0000
3, 2	11 weighted l.	0.0096	0.0141	0.0098	0.0008
3, 2	11 fuzzy l.	0.0092	0.0094	0.0092	0.0000
3, 2	16 weighted l. (ME over 11)	0.0126	0.0128	0.0127	0.0000
3, 2	16 fuzzy l. (ME over 11)	0.0133	0.0134	0.0133	0.0000
3, 3	12 crisp l.	0.0220	0.0222	0.0220	0.0000
3, 3	12 weighted l.	0.0220	0.0222	0.0220	0.0000
3, 3	12 fuzzy l.	0.0217	0.0219	0.0218	0.0000
3, 3	15 weighted l. (ME over 12)	0.0251	0.0258	0.0254	0.0001
3, 3	15 fuzzy l. (ME over 12)	0.0269	0.0274	0.0271	0.0001

SFO results.

E. Mean-Error Analysis

Table II presents the ME values for the obtained SFOs in the previous five cases, distinguishing between crisp, weighted, and fuzzy locations. The minimum (m), maximum (M), mean (ϖ), and standard deviation (σ) values of the 30 runs that are performed are shown for each case. We should recall that results are not fully comparable since the overlay processes by the use of weighted and fuzzy landmarks do not minimize the ME but a different function [see (3) and (4)].

Conclusions are quite similar for all the cases. As was expected, ME values are higher when more landmarks are taken into account (imprecise location) since we are minimizing distances among a bigger number of corresponding landmarks but calculating the ME over the same smaller set of landmarks.

Finally, from the observation of the resulting mean (in general, quite similar to the minimum value) and standard deviation values (close to 0 for all the cases), corresponding to 30 different runs, the strong robustness of the method is demonstrated.

V. GLOBAL VALIDATION

Once we have presented our proposal and analyzed its performance, we will validate its applicability for daily work on a forensic anthropology laboratory. Since we are dealing with a real-world application, we aim to compare our results with those manually achieved by the forensic experts in a time-consuming trial-and-error SFO procedure. This study comprises the previous five SFO problems in Section IV and four new SFO problems that correspond to a new pose of case study 3, and two additional real identification cases of two missing persons in Granada: case study 4 (one photograph) and case study 5 (two photographs).

On the one hand, Fig. 16 depicts the best manual outcomes that are achieved by the forensic experts of the Physical Anthropology Laboratory, as well as the corresponding best superim-

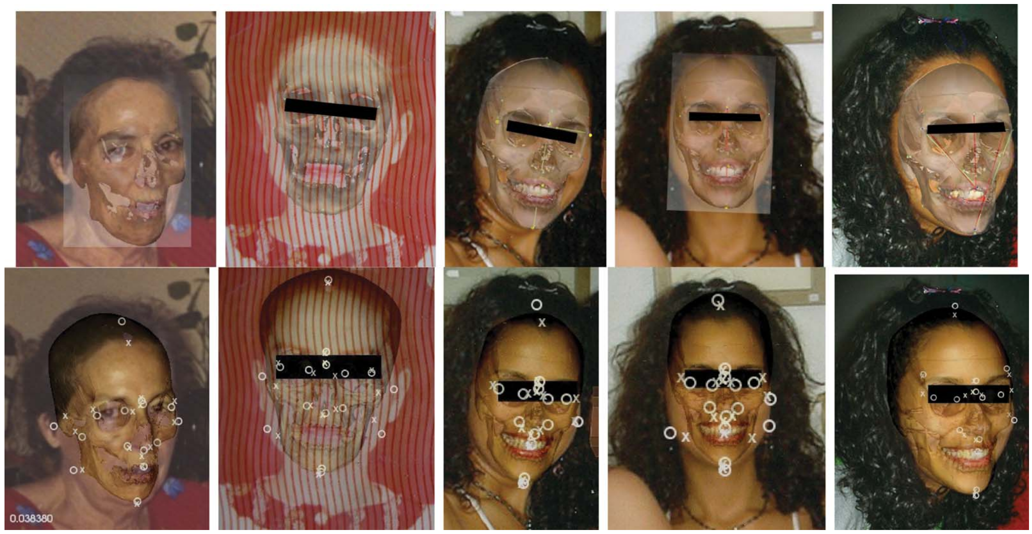

Fig. 16. Best superimposition that is obtained by the forensic experts (first row) and the manual ones that are achieved by our automatic fuzzy-evolutionary method (second row). From left to right, case studies 1, 2, and 3 (poses 1–3).

Fig. 17. Face photographs of the missing people (first column), together with the manual superimposition that is obtained by the forensic experts (second column) and the best ones that are achieved by our automatic fuzzy-evolutionary method (third column). From top to bottom. Case studies 3 (pose 4), 4, and 5 (pose 1 and 2).

positions that are achieved by our automatic fuzzy-evolutionary method for the already seen SFO problems. On the other hand, Fig. 17 consists of three columns: the first one presents the photographs of the missing persons of the four new SFO problems, the second one depicts the best manual outcomes that are performed by the forensic experts, and the third one shows the best overlays that are achieved by our automatic method. Our comparison will rely on two different evaluation procedures: a visual analysis (which is developed by the forensic anthropologists) and a numerical analysis (which is based on the ADE).

Regarding the visual assessment, our approach generally achieves a better fit of the top of the head. When we provided the forensic experts with our superimpositions, they recognized the defects of their own overlays, which were due to the limitations of the commercial software that is used to project the 3-D skull into a 2-D image. Instead, our method properly models the perspective transformation.

The group of photographs with a lateral pose [case studies 1 and 3 (poses 2 and 3), and 5 (pose 1)] represents a particularly difficult set of SFO problems for the forensic anthropologists. They had to deal with significant perspective deformations causing a lower confidence on the extracted landmarks (as already mentioned in Section III). In general, they were able to fit the frontal axis (see the proper alignment of the jaw and the eye caves). Nevertheless, the skulls are clearly downsized, and they do not match the top and lateral parts of the face properly. This is again a consequence of the shortcomings of the commercial software that is used. Therefore, experts made a positive identification decision for those cases based on just the frontal poses.

On the contrary, our approach performs better in this kind of scenarios. Not only the frontal axis but also the outer parts of the face (the forehead and the right or left cheek) are properly overlayed, thanks to the said better handling of the perspective projection that is provided by our automatic method. Actually, *the forensic experts were positively impressed by the quality of those superimpositions*.

Finally, the automatic overlays in case studies 3 (pose 2) and 5 (pose 2) (see Figs. 16 and 17, respectively) demonstrate some difficulties of the fuzzy-evolutionary-based SFO method when dealing with some frontal images. Automatic results are worse on both sides of the face since the projected skull is too narrow.

TABLE III
AREA DEVIATION ERROR OF THE BEST SKULL–FACE OVERLAYS MANUALLY OBTAINED BY THE FORENSIC EXPERTS AND THE AUTOMATIC ONES ACHIEVED BY OUR AUTOMATIC FUZZY-EVOLUTIONARY METHOD

Approach	**ADE**								
	case 1	**case 2**	**case 3, 1**	**case 3, 2**	**case 3, 3**	**case 3, 4**	**case 4**	**case 5, 1**	**case 5, 2**
Manual	34.70%	31.73%	31.84%	31.58%	38.22%	32.64%	13.81%	28.26%	37.54%
Automatic	13.23%	11.96%	21.26%	27.96%	18.95%	15.84%	4.73%	21.79%	21.04%

We think that these problems can be solved once the matching uncertainty is considered. Nevertheless, the superimpositions that are achieved by the forensic experts in these complex problems also need important improvements. They fit the chin better than the automatic method, but they are not able to properly match both sides of the jaw. In addition, they have problems with the perspective again to properly project the skull in the area covered by hair.

On the other hand, in Table III, the ADE values for all the considered case studies are given, distinguishing between the overlays that are manually achieved by the forensic experts and those that are automatically obtained by the use of our fuzzy-evolutionary-based approach. The first issue that the results show up is the lower ADE values of the automatic approach for all the case studies. Moreover, most of the these values are approximately half of the corresponding manual ones. In addition, they are really small, i.e., usually below 20%, and some of them are especially good, like those in case studies 2 (11.96%) and 4 (4.73%). All these errors are closely related with the visual assessments that are shown in Figs. 16 and 17.

As said, the ADE provides a measure of the SFO quality focused on the outer skull contour. Therefore, we can conclude that manual overlays are worse according to this characteristic.

In summary, in view of both the visual inspection and the ADE values of the obtained overlays, our automatic fuzzy-evolutionary method is competitive with the manual results by the forensic anthropologists.

VI. CONCLUDING REMARKS AND FUTURE WORKS

In this paper, we have identified and studied the sources of uncertainty that are related with the SFO process and procedure used in forensic identification by CS. We have distinguished between the uncertainty inherent to the objects under study and that associated with the overlay process.

Two different approaches, weighted and fuzzy landmarks, have been proposed to deal jointly with the imprecise landmark location and the coplanarity problem. Summarizing the results, it is clear that a larger number of imprecise landmarks results in more accurate overlays. Hence, the imprecise location of landmarks is a promising approach to improve the performance of any SFO method.

After looking at the two error measures that are used in the developed experimental study and comparing them with the achieved visual results, we can conclude that the ADE provides a more reliable error indicator. By the use of this error function as a reference measure, the fuzzy landmark approach is clearly better than the weighted one as a way to model the imprecise location of cephalometric landmarks. This assumption was supported by the forensic team of the Physical Anthropology Laboratory.

Based on nine complex real-world identification cases, we can recognize that all the overlays that are achieved by our technique are competitive with the manual ones that are performed by the forensic experts and they are better in some cases. Besides, our automatic method properly manages to get a good overall alignment of the skull and the face objects according to the ADE.

Despite the new proposed method that is based on the use of imprecise landmarks provides very accurate results and still behaves robustly, we should note that it implies more computational operations with the consequent increment in the run time required. From 20 s/run using crisp landmarks, the CMA-ES-based SFO method increases its run time to 2–4 min when using fuzzy landmarks. However, it is still a significantly short time if we compare it with the usual time needed by the forensic anthropologists to perform a manual superimposition (up to 24 h in many cases).

We consider some extensions of our proposal that will be developed as future works. First, we aim to tackle a higher number of real-world identification cases provided and solved by the Physical Anthropology Laboratory. Our results will thus be validated through a more extensive study once legal issues allow us to do so.

We also plan to make an online survey among different forensic experts, asking them to locate the cephalometric landmarks over a set of photographs. We aim to study some aspects, such as the variations in the locations of the same landmarks, how the location procedure is affected by the quality of the image, what landmarks are more difficult to be located, and how the pose of the face in the photograph influences the location procedure. This survey will also be helpful to define the most appropriate shapes and sizes for the fuzzy landmarks in several face photographs corresponding to solve real-world identification cases.

Finally, we are planning to tackle the inherent matching uncertainty regarding each pair of cephalometric–craniometric landmarks (see the second part of Section III-A). With the support of the forensic anthropologists collaborating with us and starting from Stephan and Simpson's works [22], [23], we aim to deal with this partial matching situation by the usage of fuzzy sets and fuzzy distance measures.

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