Craniofacial Superimposition

Seminar Report

Submitted in partial fulfillment for the award of the degree
of
BACHELOR OF TECHNOLOGY
IN
ELECTRONICS AND COMMUNICATION ENGINEERING

Submitted by

Abraham Joseph
MDL15EC005

Department of Electronics
Govt. Model Engineering College
Thrikkakara, Cochin - 682 021
APJ Abdul Kalam Technological University

November 2018

Bonafide Certificate

MODEL ENGINEERING COLLEGE

THRIKKAKARA, KOCHI-21

DEPARTMENT OF ELECTRONICS AND COMMUNICATION

APJ ABDUL KALAM TECHNOLOGICAL UNIVERSITY

Bonafide Certificate
This is to Certify that the Seminar Report entitled

Craniofacial Superimposition

Submitted by

Abraham Joseph

is a bonafide account of his work done under our supervision.

Seminar Co-ordinator
Smt. Sheeba P S
Associate Professor
Dept. of Electronics and
Communication Engineering

Seminar Guide
Mr.Vasanth Kumar
Assistant Professor
Dept. of Electronics and
Communication Engineering

Abstract

Craniofacial superimposition involves the process of overlaying a skull with a number of ante-mortem images of an individual and the analysis of their morphological correspondence. Within the craniofacial superimposition process, the skull-face overlay stage focuses on achieving the best possible overlay of the skull and a single ante-mortem image of a missing person. This technique has been commonly applied following a nonautomatic trial-and-error approach. Automatic skull-face overlay methods have been developed obtaining promising results. This paper presents two new variants that are an extension of existing 3-D–2-D methods to automatically superimpose a skull 3-D model on a facial photograph. It has modeled the imprecision related to the facial soft tissue depth between corresponding pairs of cranial and facial landmarks which typically guide the automatic approaches. As an illustration of the model's performance, the soft tissue distances associated to studies for Mediterranean population have been considered for dealing with this landmark matching uncertainty. Hence, it directly incorporates the corresponding landmark spatial relationships within the automatic skull-face overlay procedure. It has tested the performance of our proposal on 18 skull-face overlay instances from a ground truth data set obtaining valuable results. The current proposal is thus the first automatic skull-face overlay method evaluated in a reliable and unbiased way.

keyword- Forensic anthropology, craniofacial identification, craniofacial superimposition, 3D-2D skull-face overlay, soft tissues, fuzzy sets and distances.

Table of Contents

List of Figures

List of Equations

Acknowledgement

On the recollection of so many great favors and blessings, I offer my sincere thanks to the Almighty, the Creator and Preserver.

I express my heartfelt gratitude to Principal **Prof. (Dr.) Vinu Thomas**, and **Prof. (Dr.) Laila D**, HOD of Electronics and Communication Engineering, Govt. Model Engineering College, Thrikkakara for providing me with excellent library facilities.

I sincerely thank my seminar guide **Mr. Vasanth Kumar s**, Assistant Professor of Department of Electronics and Communication Engineering, for her timely advice and suggestions.

I am thankful to my seminar coordinator **Smt. Sheeba P S**, Assistant Professor, Department of Electronics and Communication Engineering for the full-fledged support and guidance.

Last but not the least I am thankful to one and all of the Department of Electronics and Communication Engineering and the whole library staff for their co-operation and active involvement. I also thank my colleagues for their support.

Chapter 1

Introduction

The techniques used to identify a missing person from skeletal information have been under continuous investigation within forensic anthropology. Craniofacial superimposition (CFS), one of the approaches in craniofacial identification, involves superimposing a skull onto a number of ante-mortem images of an individual and the analysis of their morphological correspondence. Three consecutive stages for the whole CFS process have been distinguished in : 1) Acquisition and processing of the skull and the ante-mortem facial photographs, together with the location of anatomical landmarks on the skull and the face; 2) Skull-face overlay (SFO), which focuses on achieving the best possible superimposition of a skull (or a skull 3D model) and a single ante-mortem image of a missing person. This process is iteratively repeated for each available photograph, obtaining different overlays. Skull-face overlay thus refers to what traditionally has been known as the adjustment of the skull size and its orientation with respect to the facial photograph . It is the most time consuming stage of the whole CFS procedure. 3) Decision making where the degree of support shows that the skull and the available photograph belong to the same person or not (exclusion). This task requires a thorough analysis of the face/skull correspondence provided by SFO (second stage) to determine if the skull and the face actually belong to the same person. Currently, decision making in CFS must be manually taken by the human expert, a forensic anthropologist. This decision is guided by different criteria involving the relationship between the skull and the face: the morphological correlation, the matching between the corresponding landmarks according to the soft tissue depth and the consistency between asymmetries. An important limitation of the CFS technique is the absence of a commonly accepted methodology.1 Experts try to solve the CFS problem by applying a specific strategy which uses their knowledge and the available technologies. During the SFO stage, the focus of this contribution, most forensic anthropologists follow a trial-and-error approach until they attain a good enough superimposition. The appropriate projection of the skull onto the facial photograph is a very challenging and time-consuming part of the CFS technique. This task involves the estimation of the best correspondence and it can take hours to arrive at the best possible fit. In addition, an inherent uncertainty exists because of overlaying two different "objects" (a skull and a face) . Hence, a systematic and automatic SFO method is a real need in forensic anthropology. Computational methods in the fields of computer vision (CV) and soft computing (SC) can be extremely useful of this proposal. Computer vision includes techniques for processing, analyzing, segmenting and registering image data in an automatic way. Within CV, image registration (IR) aims to find a geometric transformation that overlays two images taken under different conditions (at different times, from different viewpoints, and/or by different sensors). Meanwhile, SC aims to design intelligent systems that process uncertain, imprecise and incomplete information. Two of the main SC techniques are fuzzy logic (FL) and evolutionary algorithms (EAs). The former extends classical logic to provide a conceptual framework of knowledge representation under imprecision and the consequent uncertainty. The latter combines powerful bio-inspired search and optimization tools to automate problem solving in areas such as modeling, simulation or global optimization. Specifically, fuzzy sets have largely demonstrated their capability to deal with vagueness and imprecise information. The previous work tackles SFO automatically using EAs and fuzzy sets. These approaches are based on overlaying a skull 3D model on a facial photograph by minimizing the distance among pairs of landmarks as well as handling the imprecision due to the facial landmarks' location. This minimization process involves the search for the specific projection of the skull 3D model that reduces all the distances between every pair of corresponding landmarks as much as possible. This is a good approximation to deal with the problem, which provides reasonable results but it is not anatomically correct. In fact, the anatomical distance between a cranial landmark and its corresponding facial point (soft tissue depth) is not considered. In reality, the thickness of the facial soft tissue differs for each corresponding pair of landmarks, varies among individuals and produces a mismatch among cranial and facial landmarks. Furthermore, another drawback of this proposals is that they have only been validated in a subjective way, based on the visual evaluation of the superimposition results by forensic experts. This is due to the lack of an objective assessment methodology in the area. In this contribution, our proposal deals with the automation of the SFO task that is focused on the projection of a 3D skull model over a 2D photograph. It presents an automatic 3D-2D SFO method which considers the imprecision related to the matching of landmarks in the skull and face. Thanks to fuzzy sets, it has modeled the soft tissue thickness between pairs of cranial and facial landmarks. This novel proposal uses the same optimization mechanism employed before but it changes the formulation of the problem to directly incorporate the spatial relationships between corresponding landmarks. Unlike traditional SFO approaches locating tissue depth markers on the physical or the 3D model skull this proposal allows us to incorporate any soft tissue study easily. In addition, it has performed an objective and quantitative evaluation of the SFO results. We included the soft tissue depth measurements of specific studies within the SFO task. It has tested the performance of this approach on 18 SFO problem instances that belong to the first and unique ground truth dataset. This allows to evaluate this automatic SFO method following an unbiased and reliable procedure. To my knowledge, the current proposal is the first automatic SFO procedure that incorporates forensic studies of inter-landmark distances and considers a ground truth dataset to validate the results. The paper is organized as follows.

Chapter 2

Background

2.1 Craniofacial Superimposition

Craniofacial superimposition is one of the approaches in craniofacial identification. It involves the superimposition of a skull with a number of ante-mortem images of an individual and the analysis of their morphological correspondence. Since the first documented use of CFS for identification purposes, the technique has been under continuous improvement. Although the foundations of the CFS method were laid at the end of the ninetieth century the associated procedures evolved as new technology became available. Therefore, three different main approaches have been developed: photographic superimposition (developed in the mid 1930s), video superimposition (widely used since the second half of the 1970s) and computer-aided superimposition (introduced in the second half of the 1980s). The role of computerized systems in CFS is very important nowadays. Thus, special attention has been given to them in the more recent surveys in the field. In particular, they highlight the importance of stating the difference between non automatic and automatic computer-aided methods. Among the latter group, a reduced number of proposals deal with the same problem tackled in this manuscript: the SFO task. They obtain unbiased results and drastically reduce the time taken for SFO. These proposals are based either on photograph to photograph comparison or on skull 3D model to photograph comparison.

2.2 Skull-Face overlay as a computer vision problem

Skull-face overlay requires positioning the skull in the same pose as the face in the photograph. From a purely CV point of view, the ante-mortem photograph is the result of the 2D projection of a real (3D) scene that was acquired by a particular (unknown) camera. In such a scene, the living person was somewhere inside the camera's field of view in a given pose. The most natural way to deal with the SFO problem is to replicate this original scenario. To do so, a 3D model of the skull must be used. Current 3D scanners provide skull 3D models with a precision of less than one millimeter in a few minutes. These models can be properly handled using the computer, making the automation of the SFO task easier. Once the skull 3D model has been obtained, the goal is to adjust its size and its orientation with respect to the head in the photograph. In addition, the specific characteristics of the camera must also be replicated to reproduce the original situation as much as possible. First, the skull 3D model is positioned in the camera coordinate system through geometric transformations, i.e., translation, rotation and scaling, which corresponds to the adjustment of the skull size and its orientation at the same angle as the face in the photograph. Then a perspective projection of the skull 3D model is placed onto the facial photograph. Hence, a 3D-2D IR process where these unknown parameters are estimated seems to be the most appropriate formulation to automate SFO. In fact, that process directly replicates the original scenario in which the photograph was taken.

2.3 Automatic Skull-Face Overlay Procedure

The 3D-2D IR approach is guided by the cranial and facial landmarks previously assigned by a forensic expert to the skull 3D model and the facial photograph. Hence, given two sets of cranial and facial landmarks, the process has to solve a system of equations with 12 unknowns [15]: the direction of the rotation axis

$$d = (d_x, d_y, d_z), \tag{2.1}$$

the location of the rotation axis with respect to the center of coordinates.

$$r = (r_x, r_y, r_z), \tag{2.2}$$

the rotation angle , the factor s that scales the skull 3D model using the face in the photograph, the translation

$$t = (t_x, t_y, t_z) \tag{2.3}$$

that places the origin of the skull 3D model in front of the camera to replicate the moment of the photograph and the angle of view . These parameters determine the geometric transformation f that projects every cranial landmark

$$cl^i \tag{2.4}$$

of the skull 3D model onto its corresponding facial landmark

$$fl^i \tag{2.5}$$

of the photograph:

$$F = C * R * S * T * P \tag{2.6}$$

The rotation matrix R turns the skull to the same pose as the head in the photograph. S, T, and P are scaling, translation and perspective projection matrices respectively. A complete description of the matrices of the above equation is detailed in. Using the cranial and facial landmarks, an EA iteratively searches for the best geometric transformation f, i.e., the optimal combination of the 12 parameters that minimizes the mean error (ME) fitness function:

$$ME = (\sum_{i=1}^{i=N} d(f(cl^i), fl^i))/N \tag{2.7}$$

where

$$cl^i \tag{2.8}$$

is the 3D cranial landmark,

$$fl^i \tag{2.9}$$

is the 2D facial landmark, f is the geometric transformation, f(cli) represents the 2D position of the 3D cranial landmark when projected onto the photograph, d is the 2D Euclidean distance, and N is the number of landmarks placed by the expert.

2.4 Modeling the Uncertainty Related to the Location of Facial Landmarks

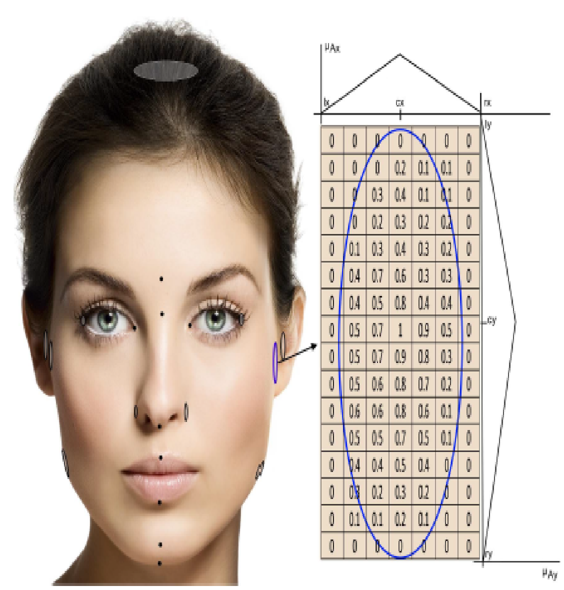

Figure 2.1: Imprecise location of facial landmarks (left) and representation of a fuzzy landmark with fuzzy sets (right).[1]

The uncertainty related to the location of facial landmarks refers to the difficult task of placing landmarks on a photograph. Among other reasons, the definition of many anthropometric landmarks is imprecise in nature. Using precise landmarks, forensic anthropologists can only place the facial landmarks that they clearly identify in the facial photograph. The fuzzy approach developed in [9] allows experts to enclose a region where the facial landmark is placed without any doubt by using variable-size ellipses (fuzzy landmarks) instead of locating a precise point as usual. The number of landmarks placed by the expert can thus increase when these landmarks are employed. This leads to a better description of the skull-face correspondence thanks to the new pairs of cranial points and fuzzy landmarks in the face. The performance of the automatic SFO method is thus improved. As a consequence of handling these fuzzy landmarks, modeled as bi-dimensional fuzzy sets the computation of the distances between the corresponding cranial and facial landmarks in equation of ME is affected as follows:

$$d'(x, F) = (\sum_{k=1}^{i=m} d(x, F_k) * a_k) / \sum_{k=1}^{k=m} a_k \tag{2.10}$$

where x is a precise point, Fk is the kth element (pixel) of the fuzzy landmark F , d is the 2D Euclidean distance, k is the membership value of Fk, and m is the number of elements of the fuzzy landmark F . The interested reader is referred to for a more in-depth explanation and an example of the calculation of the distance between a point and a fuzzy landmark.

Considering this latter distance , the definition of the EA fitness function is modified as follows:

$$fuzzyME = (\sum_{i=1}^{i=N} d'(f(cl^i), F^i))/N \tag{2.11}$$

where f(cli) represents the 2D position of the 3D cranial landmark when projected onto the photograph, F i represents the fuzzy landmark, and d(f (cli), F i) is the distance between a point and a fuzzy landmark, and the remaining parameters

Chapter 3

Incorporating facial soft tissue modelling to the skull face overlay method

Facial soft tissue depth varies for each landmark correspondence and for different groups of people. Some facial and cranial landmarks show a very close relationship as glabella, dacryon and frontotemporale. Meanwhile, others do not exactly overlap because of varying thicknesses in the soft tissue between them, e.g. gnathion, zygion and alare . This variability has been widely studied in many populations and considering different age and gender subgroups . The proposal goes beyond the use of tissue depth markers as it directly incorporates the corresponding landmark spatial relationships and distances within the automatic SFO procedure . To do this, model the minimum (min), mean (mean) and maximum (max) distances between a pair of cranial and facial landmarks using fuzzy sets (what is defined as landmark matching uncertainty). These distances are obtained from any study looking at the specific population group considered. In this section, presents two alternative approaches that deal with the landmark matching imprecision in SFO.

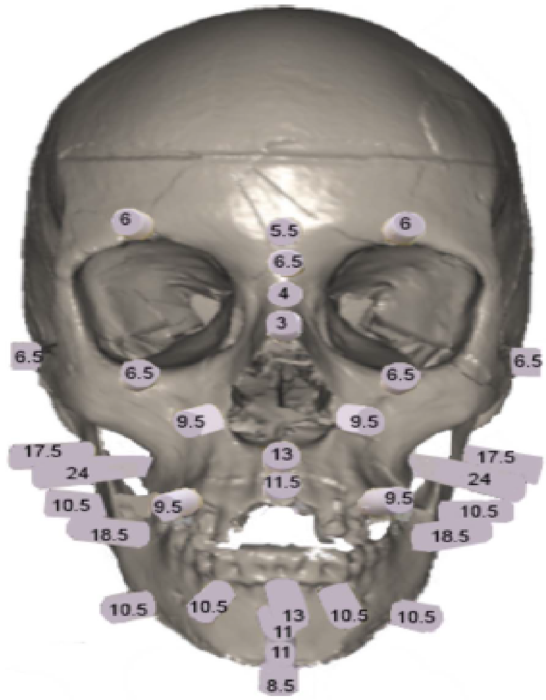

Figure 3.1: Mean soft tissue depths (in mm) and spatial relationship between cranial and facial landmarks[1]

3.1 Modeling the Landmark Matching Uncertainty Using Spheres

The first approach consists of building a fuzzy set whose center is the 3D cranial landmark with a membership degree of zero. The rest of the points are calculated adding the positive and negative values of the min, mean and max

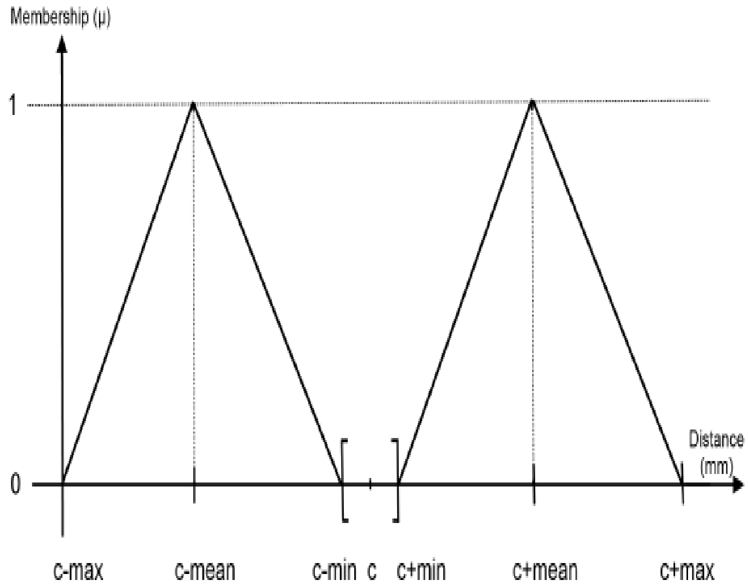

Figure 3.2: Graphical representation of one of the dimensions of the 3D fuzzy set ˜Bp for modeling the landmark matching uncertainty using a sphere. The other two dimensions are modeled in a homologous way.[1]

distances to the 3D cranial landmark position along the three axes (X, Y and Z). We thus define a 3D volume (sphere) in the space where each facial landmark is expected to be located according to a particular soft tissue depth study. A triangular fuzzy set is chosen to define the masks for handling the landmark matching uncertainty. This choice is motivated by the large amount of literature available on the topic. Although different membership function shapes can be considered, both piece-wise (e.g. trapezoidal-shaped) and continuous (e.g. Gaussian), piece-wise triangular fuzzy membership functions are simpler and easier to handle. In addition, some works have proven that a linear piecewise fuzzy membership function can approximate a continuous function to the desired degree, achieving similar results. Formally, this handles the landmark matching uncertainty using 3D masks represented as a matrix M with mx my mz points. These masks are defined by three triangular fuzzy sets ˜B x , ˜By, and B z , which model the approximate vertical, horizontal, and depth position of the sphere that represents the place of each facial landmark in relation with its cranial counterpart. They thus become 3D fuzzy sets, where each triangular fuzzy set ˜B p, with p x, y, z, is defined by its center c cx , cy , cz (the 3D coordinates of the cranial landmark) and the min, mean, and max distances as follows:

$$B_p = 1 - (|p - c + mean|)/(max - mean), ifc - max <= p < c - mean \tag{3.1}$$

$$B_p = 1 - (|p - c + mean|)/(mean - min), ifc - mean <= p < c - min \tag{3.2}$$

$$B_p = 1 - (|p - c - mean|)/(max - mean), ifc + mean <= p < c + max \tag{3.3}$$

$$B_p = 1 - (|p - c - mean|)/(mean - min), if c + min <= p < c + mean \tag{3.4}$$

In the case that p = x, the point would be c = cx . Hence, the calculated fuzzy set corresponds to Bx. If p = y then c = cy . Using this value, the defined fuzzy set is B y. Finally, if p = z implies that c = cz . The resulting fuzzy set is Bz. The 3D fuzzy set Bxyz, which defines the whole sphere, is the result of applying the product t-norm of the latter three 1D fuzzy sets B xyz = Bx · By · B z . Its membership function is determined as

$$\mu_B = \mu_{Bx}.\mu_{By}.\mu_{Bz} \tag{3.5}$$

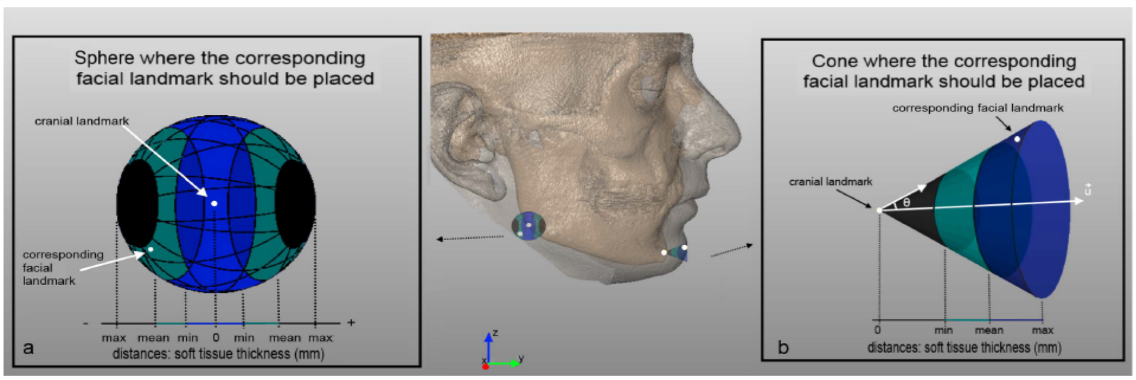

Figure 3.3: Facial landmark position from a cranial landmark using a sphere (a) and a cone (b). min, mean, and max are the soft tissue depths. For the cone, u is the normal vector at the cranial landmark in the skull, is the rotation angle of u.[1]

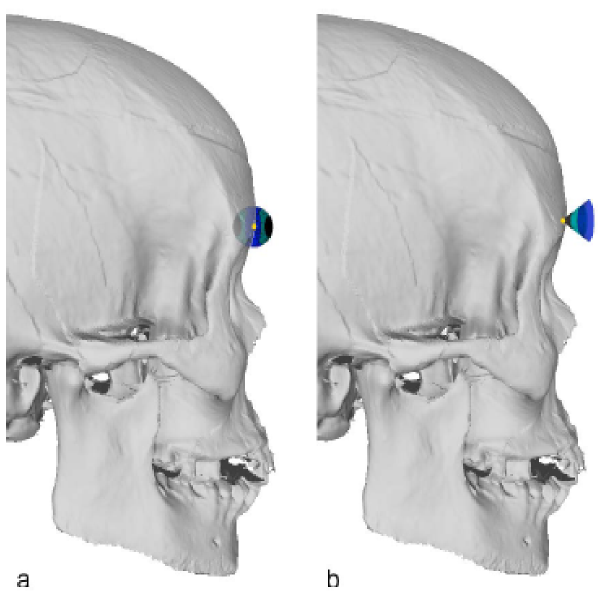

Figure 3.4: Facial landmark position from a cranial landmark using a sphere (a) and a cone (b).[1]

3.2 Modeling the Landmark Matching Uncertainty Using Cones

The previous approach is a good solution to tackle this SFO problem of modeling the facial soft tissue thickness with the available studies. However, it produces inconsistent anatomical solutions because it does not model the positional relationships between pairs of landmarks. For example, facial landmarks located inside the skull are considered to be correctly positioned. A variation of the previous method is proposed as follows: instead of modeling the soft tissue depth using a sphere with the cranial landmark in the center, a cone is defined whose vertex is the cranial landmark. Each facial landmark is supposed to be located inside the cone. Using a cone, we closely specify a narrower region where the facial landmark should be located. We refine the search of the facial landmarks placement to a specific region. It assumes a certain degree of perpendicularity between cranial and facial landmarks as most soft tissue studies do. To do this, it considers the normal vector 2 on the surface of the skull 3D model at each cranial landmark: v = (xn, yn, zn). The unit vector of v, which has the same direction,but a magnitude of the unit, has been determined below:

$$u = (x_n/|v|, y_n/|v|, z_n/|v|) = (u_x, u_y, u_z) \tag{3.6}$$

$$v = \sqrt{x_n^2 + y_n^2 + z_n^2} \tag{3.7}$$

In order to estimate the position of the facial landmarks, u coordinates (ux, uy, uz) are multiplied by the specific distance (min, mean, or max). Since the correspondence between a pair of cranial-facial landmarks is not always perpendicular, different inclination angles are applied to the unit vector u in order to define the volume in which the facial landmark is likely to be located. The amplitude of this area can be defined by a rotation equal to

$$+ \ or - \theta \tag{3.8}$$

along the three axes X, Y and Z. The 3D rotation of the unit vector u consists of three different rotations, i.e., a rotation of an angle along the X, Y and Z axes. The expressions for each axis rotation are the following: x-axis rotation

$$x' = u_x \tag{3.9}$$

$$y' = u_y cos\theta - u_z sin\theta \tag{3.10}$$

$$z' = -u_y sin\theta + u_z cos\theta \tag{3.11}$$

y-axis rotation

$$x' = u_x cos\theta + u_z sin\theta \tag{3.12}$$

$$y' = u_y \tag{3.13}$$

$$z' = -u_x sin\theta + u_z cos\theta \tag{3.14}$$

z-axis rotation

$$x' = u_x cos\theta - u_y sin\theta \tag{3.15}$$

$$y' = u_x sin\theta + u_y cos\theta \tag{3.16}$$

$$z' = -u_z \tag{3.17}$$

Likewise, a fuzzy set is defined whose center is the 3D cranial landmark with a membership degree of zero. The rest of the points are calculated by multiplying the coordinates of the unit vector u by the values of the different distances min, mean, and max. Thus, a 3D cone is defined where each facial landmark is expected to be located according to a particular soft tissue depth study. The landmark matching uncertainty is defined using 3D masks in the same fashion as the spheres. Hence, a fuzzy set ˜B p with p element of x, y, z is determined by its center c element of cx , cy , cz (the 3D coordinates of the cranial landmark), the normal vector coordinates u element of (ux , uy , uz), and the min, mean, and max soft tissue distances:

$$\begin{aligned}\bar{B}_p &= 1 - \frac{|p - c - u.mean|}{u(mean - min)},\ if\ c + u.min \leq p \leq c + u.mean \\ &= 1 - \frac{|p - c - u.mean|}{u(max - mean)},\ if\ c + u.mean \leq p \leq c + u.max \\ &= 0,\ otherwise\end{aligned} \tag{3.18}$$

In the case that p = x, the points would be c = cx and u = ux . Hence, the calculated fuzzy set corresponds to ˜Bx. If p = y then c = cy and u = uy. Using these values, the defined fuzzy set is ˜By. If p = z it implies that c = cz and u = uz , with the resulting fuzzy set being ˜Bz . The 3D fuzzy set ˜Bxyz, which defines the whole 3D cone, is the product t-norm of the previous three, one-dimensional fuzzy sets ˜B xyz = ˜Bx · ˜By · ˜Bz . Its membership function is determined by the product t-norm of the membership functions of each fuzzy set:

$$\mu_B = \mu_{Bx} * \mu_{By} * \mu_{Bz} \tag{3.19}$$

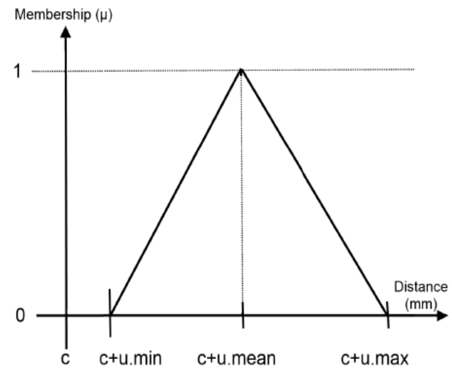

Figure 3.5: Graphical representation of one of the dimensions of the 3D fuzzy set B p for modeling the landmark matching uncertainty with a cone. The other two dimensions are modeled in a homologous way.[1]

3.3 Distance Between Two Fuzzy Sets and Fitness Function Definition

Our proposal allows experts to mark both precise and imprecise (fuzzy) facial landmarks. These latter landmarks can be used by forensic anthropologists as necessary. With the modeling of the landmark matching uncertainty proposed in the previous subsection, the need to compute the distance between two fuzzy sets arises. One of these two fuzzy sets is the projection of the 3D cranial landmark on the facial photograph, which is composed of the precise 3D cranial landmark (called cli in the two previous sections) and the fuzzy set that models the landmark matching uncertainty. The other fuzzy set would be the fuzzy facial landmark of the photograph representing the imprecise position of a facial landmark. The distance between two fuzzy sets ˜F and ˜G can be stated by:

$$d''(F,G) = \frac{\sum_{k=1}^{k=m}\sum_{l=1}^{l=n}(d(F_k,G_l).min[\alpha_k,\beta_l])}{\sum_{k=1}^{k=m}\sum_{l=1}^{l=n}min[\alpha_k,\beta_l]} \tag{3.20}$$

where ˜Fk is the kth element of the fuzzy set ˜F , ˜G l is the lth element of the fuzzy set G˜ , d is the 2D Euclidean distance, k is the membership value of ˜Fk , l is the membership value of ˜Gl , m is the number of elements of the fuzzy set ˜F , and n is the number of elements of the fuzzy set G˜ . Therefore, the fitness function Fuzzy Mean Error (FME) for the current automatic 3D-2D SFO task has been formulated by taking into account the latter fuzzy distances:

$$FME = \frac{\sum_{i=1}^{i=Ncrisp}(d'(x_i,f(C^i))) + \sum_{j=1}^{j=Nfuzzy}(d''(F^j,f(C^i)))}{N} \tag{3.21}$$

where Ncrisp is the number of 2D facial landmarks precisely located (crisp points), Nfuzzy is the number of 2D facial landmarks imprecisely located and defined as bi-dimensional fuzzy sets, N is the total number of landmarks considered (N = Ncrisp + Nfuzzy), xi corresponds to a 2D facial landmark defined as a crisp point (xi in F), ˜C i and ˜C j are fuzzy sets modeling each 3D cranial landmark and the soft tissue distance to the corresponding 3D facial landmark i or j; f is the function that determines the 3D-2D perspective transformation that properly projects every 3D skull point onto the 2D photograph; f(˜C i) and f(˜C j) are two fuzzy sets, corresponding to the result of applying the perspective transformation f to the 3D volume (either sphere or cone), which model the landmark matching uncertainty; ˜F j represents the fuzzy set of points of the imprecise 2D facial landmark; d (xi , f (˜C i)) is the distance between a point and a fuzzy set of points, and d (˜F j , f (˜C j)) is the distance between two fuzzy sets. Solving the SFO problem results in an extremely complex optimization task with a highly multimodal landscape. This scenario led us to face the problem of considering robust EAs to search for the optimal values of the 12 registration transformation parameters, as discussed in.

Chapter 4

Conclusion

The SFO process is a repetitive and tedious task in CFS. It requires several hours to overlay a skull on a facial photograph. The design of unbiased, systematic, automatic and quantifiable methods to perform SFO is a real need in forensic anthropology. So if this method is implemented, then we will get an easy, fast and efficient method for identification in forensics.

Bibliography

[1] Modeling Facial Soft Tissue Thickness for Automatic Skull-Face Overlay,IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, VOL. 10

[2] K. R. Burns, Forensic Anthropology Training Manual, 3rd ed. Upper Saddle River, NJ, USA: Pearson Education

[3] M. Yoshino, “Craniofacial superimposition,” in Craniofacial Identification, C. Wilkinson and C. Rynn, Eds. Cambridge, U.K.: Cambridge Univ. Press

[4] C. N. Stephan, “Craniofacial identification: Techniques of facial approximation and craniofacial superimposition,” in Handbook of Forensic Anthropology and Archaeology, vol. 25, S. Blau and D. Ubelaker, Eds. Walnut Creek, CA, USA: Left Coast Press