Applied Soft Computing 46 (2016) 596–612

Contents lists available at ScienceDirect

Applied Soft Computing

journal homepage: www.elsevier.com/locate/asoc

Design of criteria to assess craniofacial correspondence in forensic identification based on computer vision and fuzzy integrals

Carmen Campomanes-Alvarez [a,*], Oscar Ibáñez [a], Oscar Cordón [a,b]

[a] Department of Computer Science and Artificial Intelligent, University of Granada, C/ Daniel Saucedo Aranda, s/n, 18071 Granada, Spain
[b] European Centre for Soft Computing, C/ Gonzalo Gutierrez Quirós, s/n, 33600 Mieres, Asturias, Spain

ARTICLE INFO

Article history:
Received 5 June 2015
Received in revised form 28 October 2015
Accepted 2 November 2015
Available online 14 November 2015

Keywords:
Forensic identification
Craniofacial superimposition
Decision making
Computer vision
Spatial relations
Sugeno integral

ABSTRACT

Craniofacial superimposition is one of the most relevant skeleton-based identification techniques. Within this process, the skull-face overlay stage focuses on achieving the best possible overlay of a skull found and an *ante mortem* image of a candidate person. In previous work, we proposed an automatic skull-face overlay method, based on evolutionary algorithms and fuzzy sets. The following stage, decision making, consists of determining the degree of support of being the same person or not. This decision is based on the analysis of some criteria assessing the skull-face morphological correspondence through the resulting skull-face overlay. In this work, we take a first step to design a decision support system for craniofacial superimposition. To do so, we consider the modeling of two of the most discriminative criteria for assessing craniofacial correspondence: the morphological and spatial relationship between the bony and facial chin, and the relative position of the orbits and the eyeballs. For each criterion, different computer vision-based approaches have been studied. The accuracy of each method has been calculated as its capability to discriminate in a cross-comparison identification scenario. Sugeno integral has been used to aggregate the results of the different methods taking into account the corresponding individual accuracy index. This allows us to provide a single global output specifying the matching of each criterion while combining the capabilities of different methods. Finally, the performance of the designed criteria and methods have been tested on 172 skull-face overlay problem instances of positive and negative cases to illustrate the discriminative power of each criterion. It has been shown that thanks to the use of Sugeno integral for aggregating different methods, a more robust measurement output is achieved.

1. Introduction

Skeleton-based identification methods have been under continuous investigation within the forensic anthropology and odontology communities [1]. Craniofacial superimposition (CFS) [2], one of the approaches in craniofacial identification [3,4], is a representative technique of this kind. It involves superimposing a skull onto a number of ante-mortem (AM) images of a missing person and the analysis of their morphological correspondence to determine if they belong to the same subject.

Three consecutive stages have been distinguished for the whole CFS process in [5]. The first stage involves the acquisition and processing of the skull (or skull 3D model) and the AM facial images, followed by the location of the craniometric and facial landmark. The second stage is the skull-face overlay (SFO), which focuses on achieving the best possible superimposition of the skull and a single AM image of the missing person. This process is repeated for each available photograph, obtaining different overlays. Thus, SFO corresponds to what traditionally has been known as the adjustment of the skull size and its orientation with respect to the facial photograph [2,6]. Finally, the resulting superimpositions are analyzed in a third stage for decision making. It consists of determining the degree of support of being the same person or not (exclusion) by considering the different criteria studying the anatomical relationship (spatial and morphological) between the skull and the face. These criteria can vary depending on the region and the pose [7].

There is a strong interest in designing automatic methods to support the forensic anthropologist to put CFS into effect. In particular, the design of computer-aided CFS methods has experienced a boom over the past twenty years [8]. The most recent approaches use skull 3D models, which are employed in this contribution as well.

The works developed by authors such as [9–14] serve as examples of how computer algorithms, specially computer vision [15] and soft computing techniques [16], can automate SFO and accommodate the uncertainty/fuzziness of some facial landmarks [17] and of the soft tissues [18]. These methods represent a clear step forward since they have managed to reduce time and subjectivity inherent to manual approaches applied by forensic anthropologists. However, the quality of the obtained overlays is influenced by several sources of uncertainty, as well as by partial and incomplete knowledge about skull-face anatomical correspondence. Thus, reaching an optimal accuracy is still an open field of research and manual refinement of SFO results is currently needed for such a purpose.

Once one or several appropriate skull-face overlays are obtained, forensic experts evaluate spatial and morphological skull-face relationships in the third stage. To do so, they focus on certain regions that demonstrated to be more discriminative. The final decision is provided in terms of strong, moderate or limited support to the assertion that the skull and the facial image belong to the same person or not [7]. This is a subjective process that relies on the forensic expert's skills

* Corresponding author. Tel.: +34 686602750.
E-mail addresses: carmen.campomanes@decsai.ugr.es (C. Campomanes-Alvarez), oscar.ibanez@decsai.ugr.es (O. Ibáñez), ocordon@decsai.ugr.es (O. Cordón).

http://dx.doi.org/10.1016/j.asoc.2015.11.006
1568-4946/

and the quantity and quality of the used materials. Hence, a decision support system (DSS) is desirable to take their decision in a faster and more objective way. It would also open the door to the application of CFS to identification scenarios involving multiple comparisons. Our long-term, very complex goal is to design such a DSS based on the evaluation of the said spatial and morphological relations. This system will provide a numeric index as output, aiming to support to forensic anthropologist to take the CFS final decision.

Computational methods in the fields of computer vision (CV) and soft computing (SC) can be extremely useful for this aim. CV includes techniques for processing, analyzing, segmenting and registering image data in an automatic way [15]. Meanwhile, SC is aimed for the design of intelligent systems to process uncertain, imprecise and incomplete information [16]. SC methods applied to real-world problems often offer more robust and tractable solutions than those obtained by more conventional mathematical techniques. Two of the main SC techniques are fuzzy set theory and fuzzy logic. They extend classical logic to provide a conceptual framework for knowledge representation under imprecision and the consequent uncertainty [19]. Fuzzy integrals, in general, and Sugeno integrals, in particular, are well known to be one of the most powerful and flexible aggregation operators. They permit the aggregation of information under different assumptions on the independence of the information sources [20].

In this work, we take a first step to design a DSS for CFS. To do this, we model two of the most discriminative criteria for assessing craniofacial correspondence. Namely, the morphological and spatial relationship between the bony and facial chin, and the relative position of the orbits and the eyeballs. To model the former criterion, we have implemented some CV methods aimed to measure how the chin facial shape follows the skull shape given the delineation of these regions in a particular overlay. That process involves the proper extraction of the two chin curves (from the region given at hand) and the subsequent analysis of the relationship between them. Similarly, we have developed two methods to measure the relative position between the orbit and the center of the eyeball for the latter criterion. We have also implemented an adapted version of the state of the art methods in order to compare them with our proposal's performance.

Regardless the criterion type, we have performed a study to analyze different ways to aggregate the outputs of the measurement methods. The accuracy of each method is calculated as its capability to discriminate in the decision making process (ranking positive and identification negative cases). Sugeno integral [21] has been used to aggregate combinations of the different methods taking into account the corresponding individual accuracy index. Thus, it serves to provide a global output specifying the matching of each criterion in the specific skull-face overlay. Finally, we have tested these methods on 172 skull-face overlay problem instances of positive and negative cases to illustrate the discrimination power of each criterion.

Notice that, the combination of the proposed DSS for the third CFS stage make up a complete hybrid intelligent system to support the forensic anthropology in the automation of the CFS task. It is based on the use of fuzzy integrals [21] and the two existing methods employed for the first and the second stages are based on evolutionary algorithms [29] and fuzzy sets [19].

The structure of this paper is organized as follows: in Section 2, we review previous proposals dealing with forensic anthropology based on CV and SC and introduce our automatic SFO approach. Section 3 outlines the main issues related to the final decision making stage in the CFS process. In Section 4, we explain our general methodological proposal for the development of a CFS DSS. In Section 5, we introduce the experimental setup, the corresponding results and their analysis. Finally, in Section 6 we remark the conclusions and the related future works.

2. Preliminaries

2.1. Computer vision and soft computing techniques in forensic anthropology

Computational methods as CV and SC can be extremely useful for the automation of the CFS decision making process. The guiding principle of these methods is perfectly adapted to the way in which reasoning and deduction have to be performed in forensic science. In fact, several successful applications of these techniques in forensic anthropology have been developed so far. They include age estimation [22], skull 3D modeling [23], facial soft thickness prediction [24], facial identification [25] and skull 3D model simplification [26]. Specifically, fuzzy integrals have been used for face recognition [27] and estimation of skeletal age-at-death [28]. Within CFS, evolutionary algorithms (EAs) [29] and fuzzy sets [19] have being used to tackle SFO in an automatic way [9–12]. The following Section 2.2 summarizes the previous SFO system since the overlays analyzed in this work have been obtained using it.

2.2. Automatic skull-face overlay

The SFO process requires positioning the skull in the same pose as the face in the photograph. From a CV point of view, the AM image 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 field of view in a given pose [30].

The most natural way to deal with the SFO problem is to replicate that 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 [31]. The goal is to adjust its size and its orientation with respect to the head in the photograph [2]. In addition, the specific characteristics of the camera must also be replicated to reproduce the original situation as much as possible [30]. To do this, the skull 3D model is positioned in the camera coordinate system through geometric transformations, i.e. translation, rotation and scaling. The goal is to adjust the skull size and its orientation to be at the same angle as the face in the image [2]. Then, a perspective projection of the skull 3D model is performed onto the facial photograph.

Hence, a 3D–2D image registration process (IR) [32] 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 [9,30].

In our automatic SFO procedure, the 3D–2D IR approach is guided by a set of cranial and facial landmarks previously located by a forensic expert on both the skull 3D model and the facial photograph (see Fig. 1). Once the location of these landmarks is provided by the forensic anthropologist, the SFO procedure is based on automatically searching for the skull orientation leading to the best matching of the two sets of landmarks. We aim to properly align the skull 3D model and the 2D facial photograph in a common coordinate frame system following a 3D–2D IR approach. The required perspective transformation to be applied on the skull was modeled in [9] as a set of geometric operations. These operations involve 12 parameters/unknowns which are encoded in a real-coded vector to represent a superimposition solution.

Hence, given two sets of cranial and facial landmarks, $C=\{cl^1, \ldots, cl^n\}$ and $F=\{fl^1, \ldots, fl^n\}$, the overlay procedure aims to solve a system of equations with the following 12 unknowns: the direction of the rotation axis $\vec{d}=(d_x, d_y, d_z)$, the location of the rotation axis with respect to the center of coordinates $\vec{r}=(r_x, r_y, r_z)$, the rotation angle θ, the factor s that scales the skull 3D model as the face in the photograph, the translation $\vec{t}=(t_x, t_y, t_z)$ that places the origin of the skull 3D model in front of the camera to replicate the moment of the photograph, and the camera's angle of view ϕ. These 12 parameters determine the geometric transformation f which projects every cranial landmark cl^i in the skull 3D model onto its corresponding facial landmark fl^i of the photograph as follows:

$$F = C \cdot R \cdot S \cdot T \cdot P \tag{1}$$

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 [9]. A complete description of the matrices of Eq. (1) is detailed in [33].

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 following mean error (ME) fitness function [9]:

$$ME = \frac{\sum_{i=1}^{N} d(f(cl^i), fl^i)}{N}, \tag{2}$$