Bipolarity in ear biometrics

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Abstract

Identifying people using their biometric data is a problem that is getting increasingly more attention. This paper investigates a method that allows the matching of people in the context of victim identification by using their ear biometric data. A high quality picture (taken professionally) is matched against a set of low quality pictures (family albums). In this paper soft computing methods are used to model different kinds of uncertainty that arise when manually annotating the pictures. More specifically, we study the use of bipolar satisfaction degrees to explicitly handle the bipolar information about the available ear biometrics.

Keywords: Ear biometrics, bipolarity, identification, soft computing

1. Introduction

Person identification has always been an important problem to solve. Most of the applications are situated in the realm of security and law enforcement: verifying the identity of a person to gain access to a restricted area, retrieving the identity of the perpetrator of a crime, identifying victims of an accident... The current identification techniques make use of the biometric characteristics of a person (iris, fingerprints, dental records, DNA...) and have reached a high degree of accuracy. Biometrics are methods that analyse the physical and behavioural properties of human beings in order to uniquely recognise an individual. Most methods rely on having access to the person under consideration: iris scans can only be taken in close proximity while fingerprints and DNA scans require physical contact and processing time respectively. These negative points are compensated by the high precision matching the methods allow.

A number of identification techniques are based on ear recognition. Burge et al. [2] model the ear as an adjacency graph built from the Voronoi diagram of its curve segments. Eigenears, a variation of the technique of eigenfaces (used in face recognition), are also used to compare ears to one another. Chen and Bhanu use an ICP (iterative closest points) approach [4] to match 3D ear models. When the ear is not visible other techniques can help enhance the image, such as thermal imaging [2]. Serrano et al. use soft computing techniques based on modular neural networks and fuzzy integration techniques [14]. Important research has also been performed by Ianarelli, regarding identification by ear biometrics and the uniqueness of ear biometrics. Ianarelli used a grid of lines on which pictures were projected to manually annotate pictures. [3, 12]. A concise overview of what has been done to date can also be found in a publication by Hurley [11]. The above techniques all assume that the ear pictures are of good quality, i.e., more or less have the same ideal perspective and a high resolution.

In this paper we investigate ear biometrics and the application of soft computing methods to achieve a correct match in cases where no ideal, but imperfect pictures are used. Examples are ear pictures that have been extracted from photographs from family albums. Such methods are especially required for victim identification, which is our primary goal.

We will refer to the pictures that were taken before (and after) the person was victimized as antemortem (and postmortem) pictures. The data set we are working with contains both. The antemortem (AM) pictures were retrieved from people's family albums and the postmortem (PM) pictures were taken by a professional under controlled conditions. The entire data set was collected under the auspices of DVI (Disaster and Victim Identification, part of the Federal Police of Belgium). Volunteers had their picture taken and supplied the AM pictures themselves. Ears were cropped from these pictures and the link between AM and PM pictures was noted for use as base truth. A database is used to store all the relevant information: sets of annotated points, metadata, base truth...

We are using soft computing techniques to deal with the different kinds of inaccuracies we encounter in the identification process. Soft computing also allows us to deal with incomplete information as the point sets that are placed upon the pictures by the expert during annotation are by definition imperfect. These sets will always be an (imperfect) approximation of the shape that we wish to contour.

In this paper we detail the proposed method of making a comparison of AM and PM pictures. More specifically we focus on the explicit handling of the bipolarity that is encountered during information gathering and processing. In Section 2 the problem is further explained and examples are given of difficulties with pictures we encounter in practice.

Some preliminaries on bipolarity handling are discussed in Section 3. In Section 4 we detail how the data is annotated and how bipolarity is manifested in this process. Section 5 handles the bipolar comparison technique and describes how the sets of points accompanying the pictures are compared to each other. Aggregation of the resulting values and the other metadata such as gender and race is discussed in Section 6. The next steps we will take using the ideas presented in this work are given in Section 7. Finally, a brief conclusion and acknowledgements can be found in Sections 8 and 9.

2. Problem description

2.1. Picture Quality

The workflow when dealing with victim identification by using ear biometrics consists of two steps. First a picture is taken of the victim's ear(s), which can always be done by a professional in controlled conditions: high resolution, correct angle, uniform lighting, with the ear completely exposed. As these pictures are taken in a postmortem condition we will refer to them as postmortem pictures or PM pictures from now on. In the second step possible candidates (missing persons) for the identification are sought out. A set of pictures is collected from the environment of these candidates on which their ears are reasonably visible. These pictures could be found by addressing the family, checking social networking sites... As they are not taken by a professional with the intent of focusing on the ears they are usually of low quality. We have no control over the conditions in which these pictures are taken, we can only hope to retrieve the best we can. Digital photography is not commonplace in all places of the world so analog photography has to be taken into account as well. An AM picture usually suffers from one or more of the following quality problems (see Figure 1 for examples):

1. The ear is not shown at a perfect angle.
2. Resolution is not good enough to display the ear at full size in high quality. The expert has to be able to confidently place the required annotation points.
3. Lighting is random or very bad.
4. The ear is deformed by glasses or other influences (for example big ear rings stretching the ear vertically).
5. The ear is obscured by hair, accessories or other objects.

2.2. Applications

Identification of people primarily has its use in the law enforcement environment. Different types of source material can be used: pictures taken by the police of people in custody, video streams of private firms, PM pictures taken by forensic experts...

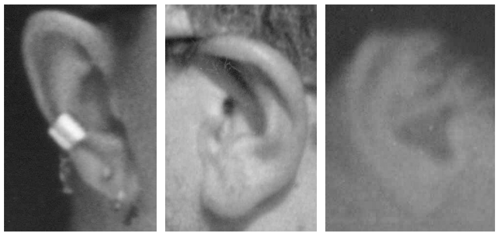

Figure 1: Examples of low quality AM pictures.

The results presented in this paper stem from a project that was started in cooperation with DVI, the Disaster Victim Identification unit of the Federal Belgian police, with the intent of identifying (groups of) victims or missing persons. This could be useful when large scale disasters occur. Use a train crash as an example: when 200 people are on board and the identities of all the travellers are known, the problem of efficiently matching each person to a name in a cheap way becomes a matter of finding AM pictures. PM pictures can be taken in high quality and the knowledge that comes with the limited pool of identities helps with pinpointing the correct matches.

Identifying a found body (as opposed to a disaster victim) is more difficult as there is a bigger pool of possible identities to search through. The researchers must build up a group of likely candidates from their missing persons database and gather AM data (if not already available to the police).

The technique also works in low-tech environments where an abundance of high resolution pictures is simply not available. This makes it usable practically everywhere. The only requirement is a single picture, digital or analog, where the ear is reasonably visible. This should be sufficient to make an initial identification possible.

3. Preliminaries

In this section we explain some concepts and assumptions used in the remainder of the paper.

3.1. Bipolarity issues in ear comparison

When we use the term bipolarity we use it to indicate that information can either be expressed in a positive or a negative way [9, 6, 7]. Typically people indicate how true, desired or preferred a statement is. On the other hand we can also indicate the opposite: how much we dislike a specific statement.

There are different types of bipolarity that differ depending on what kind of information is modelled [10]. Symmetric bipolarity models positive and negative information that complements one another. This ensures that a given statement is always either true or false with absolute certainty. Dual bipolarity is used in possibility theory to model positive and negative information that are measured on different scales. The information is based on the same piece of knowledge. A third type is called heterogeneous bipolarity: two separate origins provide positive and negative information. These are (partially) independent of each other and do not complement one another. For the ear biometrics problem under consideration, heterogeneous bipolarity is assumed.

Retrieving the correct identity of a victim can be seen as a query performed on the data set we have built. A bipolar query can take positive and negative preferences into account [17]: a human can indicate that the satisfaction of one condition makes the result a preferred one or a rejected one. In the presented ear identification approach, AM and PM ear pictures are annotated in a uniform way, resulting for each picture in a set of representative data points (cf. Section 4). Ear comparison is then done by comparing corresponding data points and aggregating the results of individual comparisons in order to obtain an overall comparison result (cf. Sections 5 and 6). Hereby, an individual comparison result is considered as being preferred or rejected, depending on the quality of the points in the comparisons. For the measurement of the quality of a data point, heterogeneous positive an negative aspects are considered.

To compensate for the bad quality of AM pictures, corresponding data points from multiple AM pictures of the same ear are combined. In theory, such points should be relatively similar. Points that do not deviate too much from the norm will be preferred in the comparison. On the other hand, the expert that is annotating the picture can add importance weights [8] to every point. If a certain area of the picture is difficult to see or obviously of bad quality, the points in that area will be rejected in the comparison.

3.2. Bipolar satisfaction degrees

To efficiently deal with heterogeneous bipolarity in the comparison process, bipolar satisfaction degrees are used. The concept bipolar satisfaction degree is closely related to Atanassov intuitionistic fuzzy sets [1] (A-IFS) and originally presented in [13].

Definition 1. *A bipolar satisfaction degree (BSD) is a couple*

$$(s, d) \in [0, 1]^2$$

where s is the satisfaction degree *and d is the* dissatisfaction degree*. Both s and d take their values in the unit interval $[0, 1]$ reflecting to what extent the bipolar representation represents satisfied, resp. dissatisfied. The extreme values are 0 ('not at all'), and 1 ('fully'). The values s and d are independent of each other.*

Three cases are distinguished:

1. If $s+d = 1$, then the BSD is *fully specified.* This situation corresponds to traditional involutive reasoning.
2. If $s + d < 1$, then the BSD is *underspecified.* In this case, the difference $h = 1 - s - d$ denotes the *hesitation* or *indifference* about the criterion being satisfied or not.
3. If $s + d > 1$, then the BSD is *overspecified.* In this case, the difference $c = s + d - 1$ denotes the *conflict* about the criterion satisfaction.

BSDs can be used to express ear comparison results. For each individual comparison result, the associated satisfaction degree s then denotes to what extent the comparison has to be preferred (satisfied) in the overall comparison. Additionally and in an independent way, the dissatisfaction degree d denotes to what extent the comparison has to be rejected (dissatisfied).

The basic operations for conjunction, disjunction and negation of BSDs (s_1, d_1) and (s_2, d_2) are respectively defined as follows [13]:

- $(s_1, d_1) \wedge (s_2, d_2) = (i(s_1, s_2), u(d_1, d_2))$
- $(s_1, d_1) \vee (s_2, d_2) = (u(s_1, s_2), i(d_1, d_2))$
- $\neg(s_1, d_1) = (d_1, s_1)$

where i denotes a t-norm (e.g., min) and u denotes its associated t-conorm (e.g., max).

4. Data annotation

When comparing two ear photographs we use different types of information: annotation data and metadata about the photograph or person on the photograph (gender, name, age when the picture was taken, date of picture...). The metadata will be discussed further in Section 6. The annotation data is the most sensitive part of the data, as the placement of the points is always paired with the introduction of errors. Information like gender is used to make the difficult process of matching points a little easier: females for example will be disregarded automatically when we know that we are looking for males, even if the annotated points resemble each other sufficiently.

Annotation points are manually placed on pictures by experts. Our method is based on the *Ianarelli System* [12]. Ianarelli aligned and normalized pictures of the right ear using a 'Ianarelli Inscribed' enlarging easel. This easel is moved horizontally and vertically until the ear fits in it in a predetermined way. A couple of unique points on the ear are used to determine the exact placement of the easel. After alignment, 12 measured annotation points are determined. These are then used to perform the identification [3]. We use a similar method, but allow for perspective changes and an arbitrary number of annotations. This is done with the following steps:

1. Add three unique reference points, indicated in Figure 3 by the white numbers 1, 2 and 3. Based on the expertise of the DVI-team these three points are determined as follows: the tip

of the tragus (1), the intersection of the helix and antihelix (2) and the intersection (3) of the tangent that is parallel to the line determined by points 1 and 2 and the tangent that is orthogonal to this line.
2. Place a predetermined grid on the picture, and transform this grid using the three reference points.
3. Add extra sets of points. For example, all points on the contour of the concha, all points on the outer contour of the ear, ... (see Figure 4 for a graphical representation).

The data annotation is done using a default square transformation grid (see Figure 2), of which the three corners denoted by $(0, 0)$, $(0, 1)$ and $(1, 1)$ are mapped onto the three unique reference points (with numbers 1, 2 and 3) on the picture. Projecting the mapped transformation grids of two ear pictures, allows us to map one ear picture onto another so that a point-to-point comparison of both pictures can be performed. This projection also helps eliminating problems due to a different perspective, but more research is required to further enhance the accuracy of the mapping. Deviations on the reference points will percolate to the rest of the points as all points are transformed according to their location with respect to these reference points. This will have an impact on the accuracy of the entire comparison process. It is therefore important to consider only pictures on which the reference points (1) and (2) are clearly visible and point (3) can be determined unambiguously.

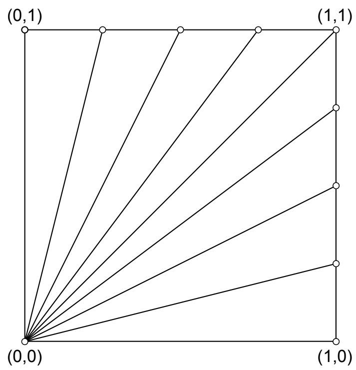

Figure 2: Default transformation grid

After transforming the grid by matching the three reference points with the relevant corners we get the situation as depicted in Figure 3. If necessary, grid lines are extended. We then use the intersections of the grid lines and the outer contour of the helix of the ear to define annotation points. The same is done for the inner contour line of the helix of the ear and the contour line of the concha.

Figure 3 shows the intersection lines for one of the two quadrants we use to annotate the points. The other (bottom) quadrant is constructed in a similar way. This approach merely illustrates a way of defining a list of points on a picture of the ear while

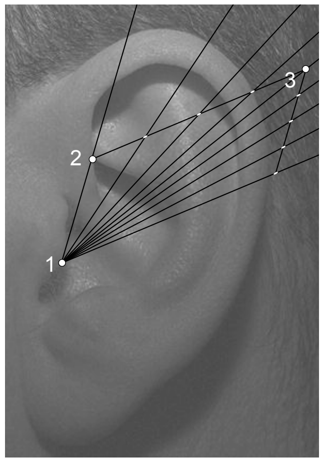

Figure 3: Transformed grid placed on a case picture

making it possible to map the point list of one picture to the point list of another. An example of the annotation that is obtained as described above can be found in Figure 4. The triangles follow the outer contour of the helix, the squares the inner contour of the helix and the circles follow the line that contours the concha area. An alternative method is being implemented that makes it possible to input continuous lines instead of groups of points. Using these lines we can extract arbitrary point sets using different grids or selection criteria. This handles the tedious process of adding points more efficiently.

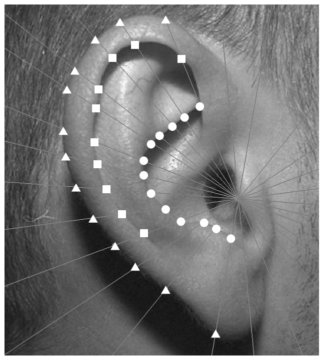

Figure 4: Point annotation

The annotation points suffer from different types of inaccuracies (see Figure 1). A point could be difficult to locate due to the low resolution of the given photo or could be impossible to locate due to the fact that the area of the ear is obscured by hair or other objects such as glasses, piercings, hats... In this case the user could make an educated guess and make the point less relevant (or completely irrelevant) for further comparison. All pictures are contained within a 'case'. This case comprises an identity, known or unknown, that can be compared to another case. These comparisons lead to a ranked list of results. A database has been created to contain all the information needed to perform the identification: data describing the pictures, the cases and the annotation points that were placed on the pictures.

When placing the non-reference points the expert gets the option to specify a weight for every point. It is up to the expert to judge whether a point placement is accurate or not. Some points might be judged to be completely ineffective and some points could be of degraded accuracy. There are two sources of inaccuracy. The first source is the poor quality of most of the AM pictures. When for example the outer contour of the ear is not clearly visible it is hard to pinpoint the exact line on which to place the points. When the ear is (partially) obscured the expert will need to make assumptions as well. The second source of inaccuracy is due to the fact that a given point is not located in the same plane as the reference points (due to deformation or due to a perspective change, an example can be found in the second picture of Figure 1). This illustrates an example where a point is judged to be inaccurate despite the fact that it is clearly visible on the picture. To minimise the deviation that occurs when different experts annotate the same picture, the number of allowed weights the expert can use has been limited. In our current study, the allowed weights are 'accurate', 'inaccurate' and 'ignore point'. The latter two weights are then useful to denote obscured points, points that are not possible to locate accurately or points that are located on deformed parts of the ear.

5. Bipolar comparison

In this section, we explain how we deal with bipolarity (see Section 3.1) in order to augment the available annotation data and to enhance the identification process.

When performing identification using ear biometrics most existing approaches match perfect pictures with each other while allowing for small deviations in perspective, lighting and other parameters. Our approach will focus on user annotated low quality AM pictures. For each picture, annotation points are located and inserted into the database.

In order to keep the comparison of two ear pictures scaling and perspective invariant, the annotation points of both ears are first transformed to the default transformation grid (cf. Section 4) by mapping the three reference point of each ear to the three corners $(0, 0)$, $(0, 1)$ and $(1, 1)$ of the grid and transforming the other points accordingly. After this transformation, the corresponding annotation points of both pictures are compared using soft computing techniques.

We usually have multiple (low quality) AM pictures per case at our disposal and can combine the information of these AM pictures to produce a better match with a (high quality) PM picture. This way, inaccuracies stemming from the annotation process can be partially removed. The comparison of a given PM picture with a set of available AM pictures belonging to the same case is then performed as follows.

Assume that we use n annotation points and have m AM pictures. For each annotation point pm_i, $1 \leq i \leq n$ of the PM picture, we consider the set $AM_i = \{am_{ij} | 1 \leq j \leq m\}$ of corresponding annotation points on the m AM pictures.

Each PM annotation point pm_i is then compared with each AM annotation point $am_{ij} \in AM_i$. The resulting similarity e_{ij} is computed using a 2D-Gaussian distribution with mean pm_i and standard deviations σ_x and σ_y, i.e.,

$$e_{ij} = e^{\frac{(x_{am_{ij}} - x_{pm_i})^2}{-2\sigma_x{}^2}} e^{\frac{(y_{am_{ij}} - y_{pm_i})^2}{-2\sigma_y{}^2}} \qquad (1)$$

where (x_{pm_i}, y_{pm_i}) and $(x_{am_{ij}}, y_{am_{ij}})$ respectively denote the (x, y) coordinates of pm_i and am_{ij}.

Furthermore, a BSD [13] (s_{ij}, d_{ij}) is used to express the 'quality' of the comparison result e_{ij}.

- The satisfaction degree s_{ij} tells us how much the i^{th} annotation point of the j^{th} AM picture can be trusted based on the information available in AM_i. The satisfaction degree is based on dispersion and is calculated using the centre of gravity

$$c_{AM_i} = \left(\frac{\sum_{j=1}^{m} x_{am_{ij}}}{m}, \frac{\sum_{j=1}^{m} y_{am_{ij}}}{m}\right) \qquad (2)$$

  of the set AM_i. The satisfaction degree s_{ij} will be high if am_{ij} lies in close proximity to c_{AM_i}. If am_{ij} is located further from c_{AM_i}, this will lower s_{ij} which results in making am_{ij} less credible. The satisfaction degree can then be computed using a 2D-Gaussian distribution with mean c_{AM_i} and standard deviations σ_x and σ_y as in Eq. (1), i.e.,

$$s_{ij} = e^{\frac{(x_{am_{ij}} - x_{c_{AM_i}})^2}{-2\sigma_x{}^2}} e^{\frac{(y_{am_{ij}} - y_{c_{AM_i}})^2}{-2\sigma_y{}^2}} \qquad (3)$$

  where $(x_{c_{AM_i}}, y_{c_{AM_i}})$ and $(x_{am_{ij}}, y_{am_{ij}})$ respectively denote the (x, y) coordinates of c_{AM_i} and am_{ij}.
- The dissatisfaction degree d_{ij} tells us how much the i^{th} annotation point of the j^{th} AM picture can be trusted based on the opinion of the expert. The weights associated by the expert to non-reference points during annotation are used to determine d_{ij}. The lower the weight w_{ij} of am_{ij}, the larger d_{ij} should be. In the presented approach only three weights w_{ij} are allowed: 'accurate' ($w_{ij} = 1$), 'inaccurate' ($w_{ij} = 0.5$) and 'ignore point' ($w_{ij} = 0$). The dissatisfaction degree d_{ij} related to a point am_{ij} with associated weight w_{ij} is therefore determined by

$$d_{ij} = 1 - w_{ij}. \qquad (4)$$

  The dissatisfaction degree is independent of the satisfaction degree. We can for example have points that are clearly visible but are still dissimilar to the points in the other AM pictures.

The satisfaction degree s_{ij} and dissatisfaction degree d_{ij} can now be used to determine the relevancy of the similarity e_{ij} for the comparison of a PM picture with a set of AM pictures. To do this we need to aggregate all the similarities e_{ij} taking into account their satisfaction and dissatisfaction degrees.

Initial tests indicate that using a Gaussian distribution results in point similarities that produce expected results. However, future testing will also take other means of calculating point similarities into consideration.

6. Aggregation

Each comparison of an AM point am_{ij} with its corresponding PM point pm_i results in a similarity e_{ij} (see Eq. (1)) with an associated BSD (s_{ij}, d_{ij}) (see Eq. (3) and (4)).

In the investigated approach, the next step is to compute the m overall similarities e_j, $1 \leq j \leq m$ resulting from the comparison of the PM picture and each of the m AM pictures that describe the AM case. For that purpose, all n similarities e_{ij}, $1 \leq i \leq n$ are aggregated considering their associated BSD (s_{ij}, d_{ij}). As aggregation operator a weighted mean is chosen, using the satisfaction and dissatisfaction degrees as weights, i.e.,

$$e_j = \frac{\sum_{i=1}^{n} e_{ij} s_{ij}(1 - d_{ij})}{\sum_{i=1}^{n} s_{ij}(1 - d_{ij})}. \tag{5}$$

The resulting similarity e_j then indicates how good the PM picture matches the j^{th} AM picture, based on the considered annotation points. Because the expert might be interested in the 'quality' of the comparison result, the satisfaction degrees s_{ij}, $1 \leq i \leq n$, and dissatisfaction degrees d_{ij}, $1 \leq i \leq n$ that led to this result are also aggregated and communicated as feedback to the user. As all satisfaction and dissatisfaction degrees stem from the same AM picture and we don't want some bad points spoiling the results for an otherwise perfect match, the arithmetic mean operator is used, i.e.,

$$s_j = \frac{\sum_{i=1}^{n} s_{ij}}{n} \tag{6}$$

and

$$d_j = \frac{\sum_{i=1}^{n} d_{ij}}{n}. \tag{7}$$

The comparison of a PM picture with a set of k AM pictures thus results in a set of ordered triples:

$$\{(e_j, s_j, d_j) | 1 \leq j \leq k\}. \tag{8}$$

This set can be ranked according to the user's wishes. The overall similarity or end score of the match between an AM and a PM picture is contained within the similarity e_j. If we have equal results we can differentiate between them by using the satisfaction and dissatisfaction degrees. We can handle this in a number of ways. The following ranking functions give an example of how we could handle results that have an equal end score e_j according to the importance of s_j and d_j [13]. When s_j and d_j are equally important we can use the ranking function r_1:

$$r_1 = s_j - d_j \in [-1, 1] \tag{9}$$

Using just one of the two and the other as a tiebreaker is another example of how to rank according to satisfaction or dissatisfaction. When we want to take them both into account we can for example use the following functions. Ranking function r_2 can be used when favouring s_j over d_j while ranking function r_3 is an example of how to favour d_j over s_j.

$$r_2 = \frac{s_j}{s_j + d_j} \tag{10}$$

$$r_3 = \frac{1 - d_j}{(1 - s_j) + (1 - d_j)} \tag{11}$$

Once we have a ranked list of results for each AM picture, we can additionally consider, compare and aggregate the other registered facts about the PM and AM cases under consideration. A case (a person in our database) contains different kinds of information:

1. Gender of the person.
2. Race of the person.
3. Year of Birth of the person (if known).
4. Description of piercings per ear,
5. Annotated points per ear.

Facts such as gender are easier to interpret than the sets of points. If we get a good match based on the points but notice that the gender (if known for a fact) is wrong we can safely lower the score of the match to zero. These additional metadata help reduce the amount of pictures that need to be taken into account which eliminates a lot of false positives. Most of these aggregations are trivial and some are still under investigation so we won't expand on these in this paper.

7. Future Work

Work on the implementation of the techniques presented in this paper in our existing non-bipolar framework has already been started. A comparison will be made with the current results to determine the impact of the bipolar approach. Hereby, a test database with base truth delivered by DVI will be used.

From a theoretical point of view, new aggregation techniques will be investigated. Furthermore, the use of graphical 3D ear reconstruction techniques is under investigation. Such approaches should further help reduce the inaccuracies with the current point annotation approach and (semi-)automate the annotation process. The 3D models can also be used to construct a testset of synthetic images, which would help quantify the impact of input error and transformations. Whether the various weights have a positive effect also needs to be researched.

8. Conclusion

In this paper we have shown a new way of identifying people using ear biometrics. We use a set of reference points that enables us to compare pictures that are taken in circumstances that are less than ideal for ear identification. These reference points are used to transform the rest of the annotation points that are added by the expert: points that follow certain distinguishable lines on the ear. The concept of bipolarity is used to enrich the data that is inputted by the expert with a 'quality' measure. Bipolarity comprises a bipolar satisfaction degree (BSD) which consists of two values: a membership degree and an independent non-membership degree. The membership degree is calculated by using a set of (when available) AM pictures: if a certain point is visible on all the pictures and is located in more or less the same position we can reasonably assume that this point will be accurate. If it is not it will receive less impact and hence a lower membership degree in the subsequent comparison. The non-membership degree that we use is a measure per point: points that were not perfectly visible will be less relevant in the search than points that are perfectly clear. Ear pictures are compared by comparing corresponding annotation points and aggregating the resulting similarity measures, taking into account the computed BSDs. The presented comparison technique is currently being implemented and will be tested with a real case database provided by the Belgian Federal Police.

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