Facial Profiles Recognition Using Comparative Facial Soft Biometrics

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Abstract: This study extends previous advances in soft biometrics and describes to what extent soft biometrics can be used for facial profile recognition. The purpose of this research is to explore human recognition based on facial profiles in a comparative setting based on soft biometrics. Moreover, in this work, we describe and use a ranking system to determine the recognition rate. The Elo rating system is employed to rank subjects by using their face profiles in a comparative setting. The crucial features responsible for providing useful information describing facial profiles have been identified by using relative methods. Experiments based on a subset of the XM2VTSDB database demonstrate a 96% for recognition rate using 33 features over 50 subjects.

Keywords: Comparative Soft Biometrics, Profile Face Recognition, Profile Facial Attributes, Ranking.

1 Introduction

Due to increasing security threats around the world, there is an urgent need for more advanced technologies in the field of biometrics, particularly in facial recognition. Popular authentication methods in diverse security systems involve identity verification based on the identity card of an individual and identification based on biometric measurements. In their 2018 survey, Abdelwhab et al. explain that unlike other methods, biometrics are unique for each individual; cannot be easily transferred; are readily available; and cannot be easily borrowed, forgotten, shared, stolen, or observed [AV18].

The soft biometric provides extra knowledge for higher recognition by using comparative description based on eyewitness testimonies from a scene of a crime. Soft biometrics are dynamic features of an individual such as age, skin colour, height, ethnicity, and face dimensions, which provide additional information provided by eyewitnesses to improve the accuracy and reliability of traditional biometrics or to perform recognition for cases where there is no recoding system in the scene of the crime and there are only eyewitness testimonies to describe the criminal. Although traditional biometrics play a primary role in recognition and detection, recent research shows that the use of soft biometrics has significant potential in different applications such as identification, and identity verification. For instance, Klare et al. utilized hand-drawn sketches and compared them with facial components using two experimental methods for identifying suspects in criminal investigations

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[Kl14]. The approach was relatively successful for enhancing the recognition/identification of individuals through verbal description, particularly by victims of criminal activities.

Various studies have assessed the efficacy of profile face images. For instance, in [YEE19], authors show how the profile face images can affect the accuracies and they found that age and gender classification can achieve high accuracies by combining ear and profile face images which contain a valuable information. Moreover, [BU17] and [ZW11] demonstrate that estimating ages from ear and side-view of face images leads to a promising performance in recognition rate.

Although there are many research studies on facial profile attribute analysis, only a few are concerned with the analysis of facial profile attributes for biometric purposes. Facial recognition remains significantly affected by the wide variations of pose. The pose problem makes the training of face retrieval algorithms challenging. In fact, effective recognition requires the capture of numerous face images at different angles for the same person. The existing systems in the literature do not provide a large volume of annotated side view faces. Our main contribution in this work is to propose facial profiles as a viable biometric system in a soft biometric framework. In summary, the contributions of our work are listed in more details as:

- It establishes a soft biometric system with face profiles to highlight the significance of profile (or side view) in biometric recognition.
- It proposes a new set of semantic profile facial attributes along with their comparative labels.
- It identifies the important attributes that enable efficient recognition of an individual using the profile face.

The remainder of the paper is organized as follows: Section 2 explains the research approaches and the use of a ranking system with semantic attributes and labels. Section 3 is a description of the experimental platform and discusses the results. Finally, Section 4 draws some conclusions which outlines our research and discusses the future work.

2 Methodology

2.1 Attributes Definition

In this paper, we analyse profile face attributes based on approaches used in previous studies. In our method a new set of facial profile attributes are proposed for comparative soft biometrics for recognition and identification. We also use some existing soft biometric features previously proposed in, [ANH16a], [ANH16b], [ANH17], which describe the important traits of a human face, e.g. shape of an eyebrow, eye and nose and allow the definition of 26 attributes relevant for extracting the identity of each face. Our proposed new attributes are nostril size, nose tip, face profile height, face profile width, ear-to-head ratio, ear-to-nose distance and ear-to-chin distance, because they can, intuitively, describe or be associated with a facial profile.

2.2 Profile Facial Dataset

We used the XM2VTSDB dataset for this research. This dataset is established and maintained by the University of Surrey. The multimodal database hosts numerous speech recordings, video sequences, and facial images from 295 subjects [Me99]. The recordings of images in XM2VTSDB spanned an extended period, involving four sessions, to allow significant variation in the appearance of the subjects. For instance, the recordings preserved in the resources are likely to have individuals with variances in shape, facial hair, and hairstyles. Fig.1 shows example images in XM2VTSDB face profile dataset.

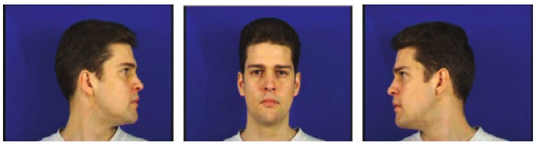

Fig. 1: Example images in facial profiles in the sample XM2VTSDB dataset

2.3 Relative Rating of Attributes from Comparative Labels

In this paper, we have used a comparative scheme to rank subjects based on their attributes. These comparative labels allow systems and individuals to compare relative features among various subjects to avoid data biases and human (labelers) errors in comparison with a categorical framework. Consequently, the soft biometrics features are generated based on this comparative scheme for our soft biometric system [ANH17].

This study utilized a 4-point bipolar scale for the comparative labels associated with attributes (see Tab. 1). The label values are 1 for ”More A,” 0 for “Same,” -1 for More B/Less A,” and -2 for “Cannot see”.

2.4 Data Acquisition Through Crowdsourcing

Effective labelling of a dataset is of critical importance to the research process in a soft biometric framework. As a result, a significant portion of the existing literature on soft biometrics utilizes a crowdsourcing platform for labelling the datasets. Such an approach provides a reliable method for the analysis of traits and labels [ANH16a], [ANH17]. Thus, the construction and monitoring of crowdsourcing annotations involves the use of the Appen platform in the collection of labels. This platform guarantees high-quality annotations by spreading analyses and encouraging customers to use a range of answers. It also identifies and rejects dishonest responses. A total of 50 subjects with four profile samples obtained from the XM2VTSDB dataset are used for this experiment. Tab. 2 presents an overview on the crowdsourcing of comparative labels.

No.	Soft Traits	Comparative Labels			
		1	**0**	**-1**	**-2**
1	Eyebrow length	More Long	Same	More Short	Cannot see
2	Eyebrow shape	More Raised	Same	More Low	Cannot see
3	Eyebrow thickness	More Thick	Same	More Thin	Cannot see
4	Spectacles	More Covered	Same	Less Covered	Cannot see
5	Eye-to-eyebrow distance	More Large	Same	More Small	Cannot see
6	Eye lashes	More Long	Same	More Short	Cannot see
7	Eye size	More Large	Same	More Small	Cannot see
8	Nose-to-mouth distance	More Long	Same	More Short	Cannot see
9	Nostril size	More Wide	Same	More Narrow	Cannot see
10	Nose tip	More Pointed Down	Same	Less Pointed Down	Cannot see
11	Nose size	More Large	Same	More Small	Cannot see
12	Lips thickness	More Thick	Same	More Thin	Cannot see
13	Face profile height	More Long	Same	More Short	Cannot see
14	Face profile width	More Wide	Same	More Narrow	Cannot see
15	Skin smoothness	More Smooth	Same	Less Smooth	Cannot see
16	Skin condition	More Clear	Same	More Pimples	Cannot see
17	Forehead hair	More Forehead Hair	Same	Less Forehead Hair	Cannot see
18	Ear size	More Large	Same	More Small	Cannot see
19	Ear orientation with respect to head	More Further from head	Same	More Close to head	Cannot see
20	Ear-to-head ratio	More Large	Same	More Small	Cannot see
21	Ear-to-chin distance	More Further	Same	More Close	Cannot see
22	Ear-to-nose distance	More Large	Same	More Small	Cannot see
23	Cheek shape	More Flat	Same	More Prominent	Cannot see
24	Cheek size	More Large	Same	More Small	Cannot see
25	Chin and jaw shape	More Receding	Same	More Protruding	Cannot see
26	Double chin	More Large	Same	More Small	Cannot see
27	Chin height	More Large	Same	More Small	Cannot see
28	Neck length	More Long	Same	More Short	Cannot see
29	Neck thickness	More Thick	Same	More Thin	Cannot see
30	Age	More Old	Same	More Young	Cannot see
31	Gender	More Masculine	Same	More Feminine	Cannot see
32	Skin colour	More Dark	Same	More Light	Cannot see
33	Figure (shape)	More Fat	Same	More Thin	Cannot see

Tab. 1: Soft profile face biometric attributes and comparative labels

2.5 Ranking by Relative Profile Face Attributes

The Elo rating system is a popular algorithm for ranking players in chess. The system ranks players by using variances between the actual results in a game and expectations. The effectiveness of the scale is making it popular in other fields, such as soft biometrics recognition [RNS13]. The biometric signatures which are feature vectors composed of the relative strength of attributes based on comparative labels, will be generated by Elo rating system. Almudhahka et al. uses the Elo system in their study to evaluate the comparative rates between features from biometric signatures and comparative labels [ANH17].

Total number of labelers per question	15
Total traits comparison per subject	3.960
Total number of images	200
Average number of comparison per subject	2
Total trusted judgment	198.000

Tab. 2: The statistics of crowd-sourcing task for XM2VTSDB dataset

The use of comparative soft biometrics involves distinct processes and activities. The systematic process begins with the construction of a dataset based on the Appen platform. The next step is the conversion of comparisons made by labelers into ranks using Elo rating system. Such ranks then provide a set of feature vectors for profile faces for each image. Finally, the k-NN classifier is used to calculate the recognition rate.

3 Experiments

3.1 Correlation Analysis

Pearson's correlation r, helps spot linear dependencies between the attributes. Equation (1) shows how Pearson's correlation r between variables x and y is measured [To15]:

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (1)$$

where x and y are independent variables, used to describe traits on the facial profiles, in this regard, x_i and y_i are two distinct labels, representing i^{th} annotation of a given subject.

The collected profile face comparisons in the study have significant correlations, as illustrated in Fig. 2 Dark brown color on the cells represents traits with high positive correlation; and dark green color corresponds to a strong negative correlation; and white/light cells show the absence of a linear correlation. A positive or negative correlation between features and labels expresses dependencies between two traits. Features with negative relationships are highly reliable for distinguishing individuals from others. Fig. 2 shows a positive correlation between age and profile face width. Gender and eyebrow thicknesses also have a positive correlation. Moreover, there is a significant relationship between ear size and age. However, age and eyebrow length have a negative correlation.

3.2 Discriminative Power of Facial Profiles

The improvement of efficiency and accuracy requires a reduction in the number of non-useful features. In this study, feature analysis and orderings facilitated feature set selection through mutual information (MI) and sequential floating forward selection (SFFS)[SSZ13].

Mutual Information (MI)

Mutual information (MI) measurement is used to assess the significance of the contribution of a profile attribute and MI is defined as:

$$MI = I(X,Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \ln \left(\frac{p(x,y)}{p(x)p(y)} \right) \tag{2}$$

Where X is a variable representing an attribute, and Y is an attribute representing a label. The computation of MI using the two traits with p(x, y) is the probability density function for X and Y. In this regard, p(x) and p(y) are marginal probability density functions.

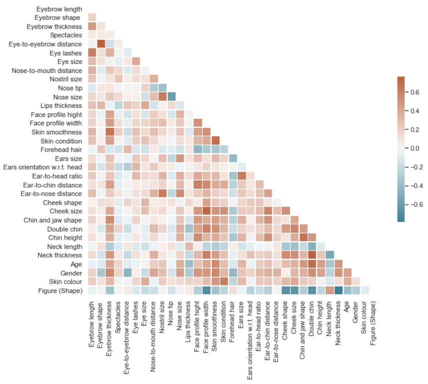

Fig. 2: The correlation matrix between the profile face attributes

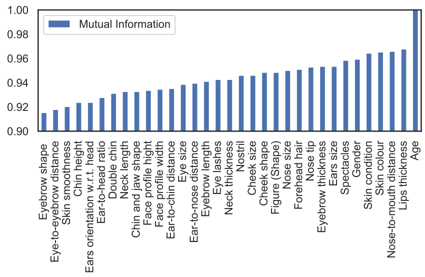

Fig. 3: Normalized MI for each of the 33 attributes with the target variable (label)

MI is used to evaluate the discriminative power of the 33 profile attributes by computing its value for each attribute jointly with the label. Fig. 3 illustrates that skin colour, nose-to-mouth distance, lips thickness, and age have high scores compared to eyebrow shape and eye-to-eyebrow distance, which have low MI scores.

Sequential Floating Forward Selection (SFFS) Algorithm

The SFFS algorithm helps rapidly identify the best set of features which contribute in the recognition. The SFFS algorithm begins with an empty set (d=0). For each iteration, it tries to find the best attribute that can be added to improve the recognition rate. Then, in the same iteration, it tries to remove a feature that was selected in past iterations in order to further improve the recognition. The algorithm repeats the steps in each iteration until no improvement can be realized. In our experiments, SFFS identified 17 attributes among the 33 features (3,4,7,9,11,12,13,15,16,17,18,24,29,30,31,32,33) (see Tab. 1). The features selected by this algorithm has led to a final value of 98% accuracy for recognition rate.

3.3 Recognition Performance of Facial Profiles

To measure the recognition rate, a Leave-One-Out Cross Validation (LOOCV) strategy is employed in this paper. We have employed k-NN as a basic classifier. In this study, by using all the attributes proposed in Tab. 1, an accuracy of 96% for the recognition rate is achieved, as illustrated in Fig. 4. The dataset in this study contained 50 subjects with four images per subject. There are therefore 200 face profile images in our dataset. As a result, there are almost 1000 questions per image. One image in the dataset was used as a testing image and the remaining ones as the training set. The k-NN classifier used a training split described by 1-vs-rest.

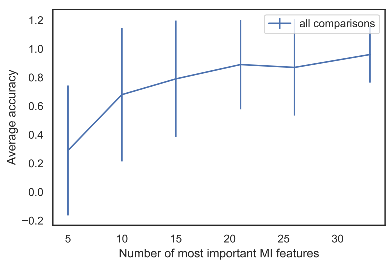

Fig. 4: The results of the accuracy with ($\approx$ 1000) comparisons per subject

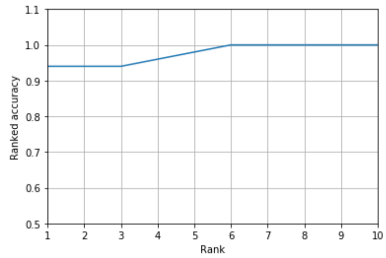

Fig. 5: Recognition via CMC performance of this study for the 33 attributes and 25% test samples

In our study, we have achieved 96% recognition rate with 50 subjects. This is comparable to Nawaf et al. study where 100 subjects with front view faces were considered and 100% recognition rate was achieved [ANH16a]. Obviously a lower recognition rate is expected with face profiles (side view faces), since less information is available to labelers with face profiles. However our recognition rate of 96% indicates face profiles carry enough information to be considered as an important biometric modality. In fact, since we use Elo rating system, it seems that the subjects preserve their ranks independently of the view point. Future works will address the learning of a latent feature space, that is adapted for view independent face recognition, based on soft biometrics.

The CMC curve is a crucial tool for assessing retrieval performance [DR13]. The metric encapsulates recognition accuracy by employing the k-NN method. Fig. 5 depicts the recognition performance by facial profile traits using soft facial traits. In this curve, the first candidate has 96% accuracy, which increases with the improvement of the number of candidates to 100% at rank-6.

4 Conclusions and Future Work

This paper proposes a novel biometric system based on facial profiles in a soft biometric framework. The study proposes and evaluates a list of semantic human facial profile attributes, and it also introduces comparative labels to facilitate the assessment of comparative soft biometrics. Our numerical analysis in this paper demonstrates that face profiles can be considered as an important biometric modality.

Future work will focus on increasing the number of subjects in XM2VTSDB dataset. We also plan to find corresponding features by using computer vision techniques in a traditional biometric framework to allow profile face identification to show that the traits proposed in this paper are important in both the soft biometric and the traditional biometric.

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