Face Profile Biometric Enhanced by Eyewitness Testimonies

Malak Alamri, Sasan Mahmoodi
Department of Electronics and Computer Science
University of Southampton
Southampton, United Kingdom
Email: ma6n19@soton.ac.uk, sm3y07@soton.ac.uk

***Abstract*—Continuous development in surveillance systems is increasingly motivating research in biometrics to articulate unconstrained recognition of human faces. Comparative soft biometric has recently been employed to characterize eyewitness testimonies for use in a biometric system to improve the recognition accuracies of the traditional biometric systems. In this paper, we present a face profile recognition system by fusing features extracted in a traditional face recognition system and eyewitness testimonies processed in a soft biometric system to improve recognition accuracies. Here we have also demonstrated an association between our traditional face profile biometric system and the soft biometric system by numerically mapping the features extracted from a face profile to its soft biometric attributes. Our experiments on 230 subjects in XM2VTSDB dataset demonstrate 84% accuracy for traditional biometrics. The recognition rate is further improved to 98% accuracy when soft and traditional biometrics are fused.**

I. Introduction

Closed-circuit television (CCTV) systems are highly dynamic amid advancing technology. Nonetheless, organizations and security entities are facing significant challenges identifying individuals under diverse surveillance conditions, such as low resolution, unconstrained pose, and adjusting illumination. The phenomenon has increased interest in physical and behavioral soft biometric traits for semantically defining humans. Conventionally, security entities deploy traditional biometric systems to identify and recognize individuals and objects when cameras recording images and videos are available. On the other hand, on some occasions, only eyewitness testimonies from a crime scene are available without captured images or videos. In this regard, soft biometric is highly crucial for converting eyewitness testimonies into a set of features that can recognize objects and individuals. More so, instances with both images/videos and eyewitness testimonies require the fusion of soft biometric and traditional biometric.

Because of its ability to bridge the semantic gap between human descriptions and traditional biometrics features, soft biometric systems are gradually growing and dominating the security and identity areas. To allow searching and identification of a specific individual from a large population, the algorithms use attributes that are comprehensible by humans, such as gender and hair color. Soft biometrics can be used to search for people using eyewitness descriptions from surveillance films and databases [1]. In a soft biometric system, attributes could be expresses categorically where a person's attributes are assigned to specific classes (such as a class of people as tall as 180 cm to 200 cm or a group of people as tall as 160 cm to 180 cm), or comparatively, where the attributes are classified relative to those of another person (such as Subject A having a larger nose size than Subject B). In this context, numerous studies acknowledge the critical role of comparative attributes on recognition [2], [3], [4]. As a result, soft biometrics approaches can consider non-facial factors including body shape [5] and clothes [6], while others continue to focus on facial traits [6], [2].

Previously, researchers have evaluated the use of comparison labels from photos or video footages using humanoid comparative labels, such as crowdsourcing [7], [8]. In this context, this work evaluates facial soft biometric in the literature, specifically the profile face, because facial profiles are receiving minimal considerations despite exhibiting good accuracy. Face profiles could play crucial roles in various occasions, mainly when only side faces are observed in images/videos captured by surveillance and security cameras. In such cases, the existing face recognition algorithms are ineffective necessitating development of recognition systems based on face profiles.

Our work evaluates how our traditional face-profile biometric system relates to the soft biometric system by numerically mapping the features extracted from a face profile images to the comparative soft biometric attributes, where 230 subjects from the XM2VTSDB dataset are used [9]. Furthermore, the study examines the impact of combining traditional biometric systems with soft biometric systems on recognition performance. By illustrating the implications of traditional and soft biometrics on profile face recognition performance, this work makes a significant contribution to research on face profile biometric. We therefore use both human and machine annotation to annotate the dataset.

Obviously, the facial profile presents limited information for recognition compared to front face. In this regard, recognition requires introduction of several facial profile attributes, including length of facial profile, ear-to-chin distance, and philtrum size [10]. Any face profile recognition system is vulnerable to challenges emanating from changes in pose, hindering recognition. The following are the main contributions of this paper:

- This research demonstrates the importance of using soft

biometrics for face profile recognition in large datasets.
- In this work, we have bridged the gap between human descriptions and the computer vision descriptions by mapping the features extracted from face profiles to the space of human descriptions of face profiles.
- This research also suggests combining tradition biometric with soft biometric of comparative profile face labels using profile images to create a unified framework for a face profile recognition system.
- This work further creates a dataset of 885600 crowd-sourced comparisons that describe 230 subjects from XM2VTSDB, based on 31 traits. This dataset will be publicly accessible.
- This study proposes some techniques to adapt a state-of-the-art pose estimation method for fast landmark prediction to locate landmark locations on profile face images [11].

The second section of this paper describes how comparative profile face soft biometric are produced from the dataset employed in the trials. The extraction of face profile features from the images and how to numerically map those features into the space of soft biometric attributes are demonstrated in the third section. Furthermore, the experimental design, recognition performance, and discussions are presented in the fourth section. Lastly, section V draws conclusions from the previous sections and highlights the study's implications.

II. Crowdsourcing of Comparative Facial Profile Traits

In this section, we will discuss the human annotations process. The comparison of two or more objects in the real world is relatively a natural process. Intuitively, individuals find it easy to describe one person as taller than another, but labelling or estimating people's height in absolute terms without effective tools is relatively difficult. Subsequently, this work exploits the ease of making comparisons to generate reliable and robust descriptions.

The development of comparative soft biometrics based on subject comparisons is reported by Reid and Nixon [12]. The method improved the accuracy and reliability of recognition systems. Biometric signatures for recognizing and identifying subjects are provided by comparative soft biometrics for surveillance and security systems. Using eyewitness testimonies and soft biometric evidence, comparative descriptions are an effective and reliable approach for human descriptions [4]. People can also be described using comparative soft biometrics, which allows for the recording of distinctions and accurate representations of traits for effective recognition.

A. Attribute Definition

Using methodologies developed in prior studies [8], this study analyses facial features. Our study uses comparative face profile soft biometrics to identify individuals and the existing soft biometric features, which describe important traits of a human face, such as brow, eye, and nose shape, and proposes the definition of 23 attributes relevant for extracting the identity of each face [8], [6], [13]. Other commonly used eight features include nostril, nose tip, face profile length, face profile width, and ear-to-chin distance, are illustrated in Table I [10].

TABLE I
Soft facial profile biometric attributes and possible associated response labels.

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

B. Dataset and labelling

The XM2VTSDB database is a research resource established and maintained by the University of Surrey (see [9] for details), and it is an extend version of the M2VTS database. XM2VTSDB is thus larger than M2VTS, with more recordings taken for each subject during each session. XM2VTSDB involved four sessions and was produced over a significant period of time, allowing for wide variations of appearances in individual subjects. The individuals documented, for example, were likely to have different face shapes, facial hair, haircuts, and whether or not they wore glasses, making it a difficult dataset to recognize. This dataset contains both left and right profile photos (samples) per individual per session, totaling 2,360 images. However, after inspecting the dataset, 230 of the 295 subjects were found to meet our criteria and could be used in the analysis. Our rational to choose this dataset for this research study is that only face profile of subjects is visible to both the biometric system and the eyewitnesses in this dataset and no other part of the face is revealed to the system or the eyewitnesses. However, in other face datasets such as LFW, some part of the other side of the face profiles is also visible which makes LFW dataset less challenging than XM2VTSDB dataset.

The labeling of a dataset is an important part of the research process. As a result, the existing literature on soft biometrics employs crowdsourcing platforms to define dataset labeling, allowing for credible trait and label analysis [6], [8]. In this regard, the building and monitoring of crowdsourced annotations in this work necessitates the use of the Appen platform for label collection [14]. Appen platform collects the response of human annotators for later numerical analysis and processing. Dishonest responses are likewise detected and rejected by the platform.

Contemporary systems that interpret biometric data use a paradigm similar to how humans make descriptions. Persons and systems can use these comparative labels to compare relative features across individuals. As a result, the properties of soft biometrics should be linked to a pre-existing comparable label [7]. To generate comparative human labels and annotations related to the attributes tabulated in Table I, this study uses a 4-point bipolar scale. 1 indicates "More A," 0 indicates "Same," -1 indicates "More B/Less A," and -2 indicates "Cannot see."

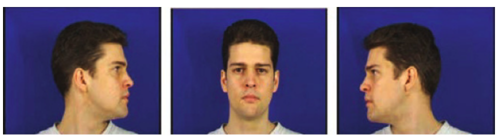

Fig. 1. Example images of XM2VTSDB face profile dataset [9].

The platform had a collection of image pairs that could be compared based on a single facial profile trait. To optimize response speed and help respondents to complete the questions, the answers in a form of options were collected using radio buttons. A ranking system is then used to turn the pairwise comparisons into scores linked with images. The set of created ranks for each characteristic is used to build a traits vector for each image, with each component representing the intensity of the relevant trait in the image.

C. Relative Rating of Attributes from Comparative Labels

Due to its role in assessing objects relative to others using specified criteria and establishing a matching order for the objects, ranking is a key action in practical situations. In this context, the ELO rating system is a widely used ranking system among chess players. The system assigns points to players based on variations that take into account both expected and actual game outcomes. Because the scale is so effective, it can be used in other sectors as well, such as soft biometrics recognition [4], [8], [10]. The ELO rating system will generate biometric signatures for each comparison label, which is a vector formed of the relative strength of each attribute. the ELO system is employed in [7] to compare the rates of features from comparative labels.

ELO is an iterative technique which can briefly be described as follows. Subject A's characteristics are described using its strength against Subject B in the ELO rating system. The comparative formula used in the system is listed below.

$$\overline{R}_A = R_A + K(S_A - E_A) \tag{1}$$

$$\overline{R}_B = R_B + K(S_B - E_B) \tag{2}$$

Equations 1 and 2 describe a unique ranking where R_A and R_B are the default rating, S_A and S_B are actual analysis score (-1 for less and 1 for more), and K represents score's alteration element. Meanwhile, E_A and E_B of the subjects in the current ratings entails the listed formula:

$$E_A = \frac{1}{Q_A} \tag{3}$$

$$E_B = \frac{1}{Q_B} \tag{4}$$

In equations 3 and 4, Q_A and Q_B are subjects' current ratings and addition of constant U allows the description of the respondents' current ratings to affect the outcomes.

$$Q_A = 1 + 10^{\frac{R_A - R_B}{U}} \tag{5}$$

$$Q_B = 1 + 10^{\frac{R_B - R_A}{U}} \tag{6}$$

For each evaluation of labels collected from the sample dataset, ELO is employed to produce the soft biometric features.

D. Attribute Analysis

The identification of an attribute's importance provides a good understanding of its strength as a semantic descriptor as well as its contribution to the attainment of effective identification and recognition. In this subsection, we are analysing our traits with two different views:

1) Mutual Information (MI): The relevance of an attribute is determined by determining its strength as a semantic descriptor and its contribution to the achievement of effective identification and recognition. Each trait is treated as a random variable in MI. MI [15] is computed as follows:

$$MI = I(X,Y) = \sum_{y\in Y}\sum_{x\in X} p(x,y)\ln\left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{7}$$

Where, X is a variable representing an attribute, and Y is an attribute representing a label. The MI analysis based on the ELO rating system reveals discriminative power of each attribute, and Figure 2 describes the findings, where some fascinating results are achieved. As observed from Figure 2, skin and nose traits (i.e. nose size, and nostril size) have high discriminative power, possibly because it would be visible on the profile face. Another pertinent fact is that the gender trait has a high discriminative power due to its binary structure. Finally, some ear and eye characteristics have a lower discriminative potential in general, which might be attributed to occlusion in those areas.

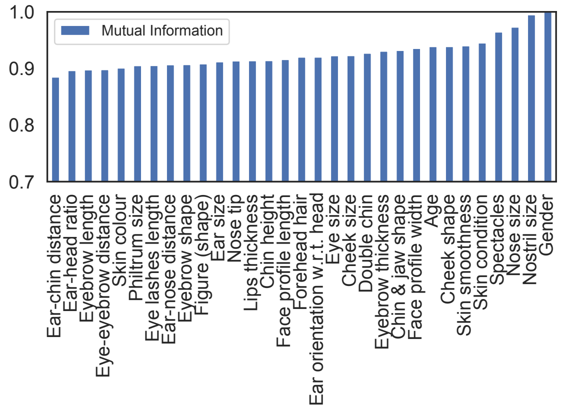

Fig. 2. Normalized MI for each of the 31 attributes with the target variable (label).

2) Pearson's correlation: The Pearson's r correlation analysis allowed for the assessment of linear linkages between qualities and the discovery of variable dependencies. Pearson correlation between variables X and Y is calculated as follows [16]:

$$r = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{8}$$

Where X and Y are independent variables representing facial profile feature, and two different labels that represent i^{th} annotation of a certain person in this scenario. Figure 3 depicts that there is a low correlation between the traits, indicating that the attributes employed in this work are mostly independent. It is worth mentioning that ear size and age have a correlation, which supports the findings of some early research [17].

III. Approach

The present study on profile face recognition using comparative soft biometrics is mostly focused on evaluating recognition in a human features utilizing human supplied annotations

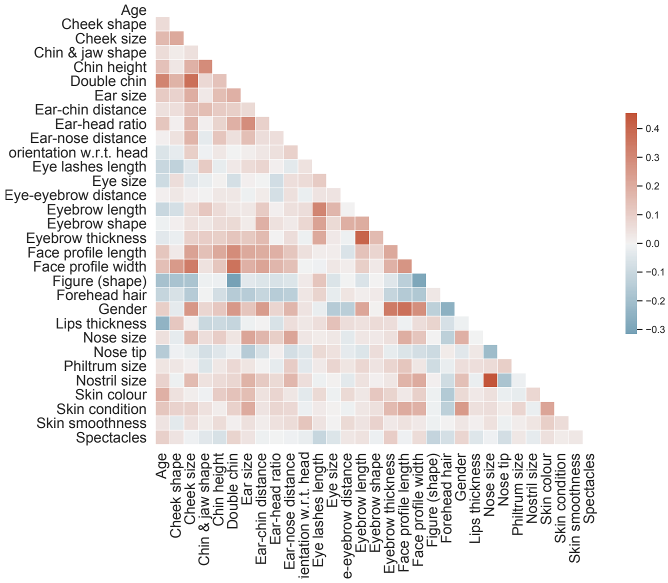

Fig. 3. The correlation matrix between the profile face attributes.

[10]. The fundamental unresolved challenge is to what extend is the association between traditional and soft face profile biometric system and can we numerically find a mapping of the features extracted from a face profile into the space of its soft biometric attributes? A related question is: to what degree can comparative soft biometrics assist traditional biometric performance when combined? These problems are addressed in this study by looking into recognition utilizing a variety of scenarios, including human-labelled profile face traits (soft biometric), automatically extracted attributes (traditional biometric), and a combination of both kind of biometrics systems. The main source of inspiration is the method used in [8] for assessing comparative face labels and constructing biometric signatures made up of the relative rates of the traits. The procedure is divided into two steps: (1) Detecting the face profile landmarks; and (2) Mapping traditional face profile features to their corresponding soft biometric attributes.

A. Detection of face profile landmarks

This section will cover the dataset's machine annotation. This stage has a purpose of segmenting the face profile components to allow automatic generation of features corresponding to each trait in Table I by using the pose estimation method presented in [11]. Our approach in this stage is focused on detecting the bounding box of a face profile for all photos in the dataset and then designating the essential landmarks within the bounding box. A pre-trained HOG with Linear SVM (Support Vector Machine) object detector is used here for face profile detection; as presented in [11]. The automatic detection of landmark locations on face profile images is possible thanks to Kazemi and Sullivan's 2014 work [18], which is state of the art in fast landmark prediction and regression-based methods that employ tree-based regressors.

On a specific face, the system uses a total of 57 landmarks. Despite this, the technique required manual training and testing to deal with missing landmarks, which involves manually by locating 10 ear and 6 neck landmarks before adding them to the model for automatic recognition. The next step is to segment face profile components, and twelve parts in face profiles are therefore used. Eight parts out of the twelve as examples are shown in Figure 4.

After segmenting the principal face profile components, GIST features are used to create a visual descriptor vector for each face profile component [19]. The intensity normalization of the face profile component image is followed by a succession of Gabor filters in four scales and eight orientations per scale to extract GIST features. To build a set of features, 32 orientation maps are separated into 44 grids and the mean intensity for each block in the grid is calculated. For each face profile component, this generates a vector of 512 features. As mentioned later in this section, these features are employed to train a model that generate comparative face profile labels. From the generated features, the association between our traditional face profile biometric system and the soft biometric system can be studied by numerically mapping the features extracted from a face profile to its soft biometric attributes.

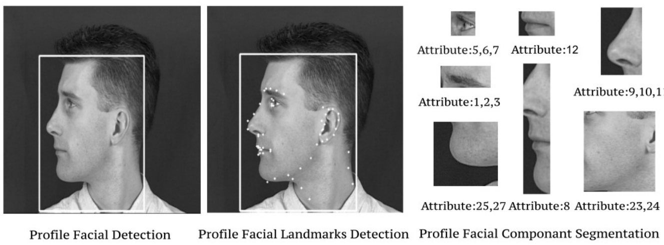

Fig. 4. Face profile landmarks detection and face profile components segmentation alongside their corresponding traits.

B. *Mapping traditional face profile features into soft biometric attributes*

As discussed in the second section, the GIST features extracted from images are related to comparative labels that represents the difference between two subjects as Less or More, which corresponds to -1 or 1. To find the comparative labels from the images, we train 31 multiples linear regressors, in which visual elements are considered independent variables that are used to predict a dependent variable (i.e. a comparative label). Because it explicitly incorporates order, linear regression is utilized to generate comparative labels. The goal of the regressors' training is to build a direct correlation between visual characteristics mined with the GIST descriptors and comparative label values (-1 or 1) for the 31 face profile traits (see Table I). The dataset is partitioned into four groups (each group contains 230 image samples) at random, with three groups containing m comparisons each being used to train the regressors and the fourth group containing n comparisons being used for testing, resulting in a total of $m+n$ comparisons for each attribute. The following model can be used to describe the relationship between the visual aspects of each attribute and the comparative labels:

$$y_c^t = \beta_0 + \beta_1 x_{c1}^t + \beta_2 x_{c2}^t + ... + \beta_p x_{cp}^t + \epsilon_t \tag{9}$$

The comparison index represented by $1 \leq c \leq m$, y_c^t is the comparative label value for $y \in -1, 1$ of the comparison c for the attribute t, x_{ci}^t is the difference in the i^{th} GIST feature between the two individuals composing the appraisal c for the trait t, while $1 \leq i \leq p$ describes the GIST feature index, and ϵ_t represents the error term. The purpose of the training is to identify the weight coefficients' vector $\hat{\beta} = \beta_0, \beta_1, ..., \beta_p$ to ensure the summation of squared residuals is as small as possible:

$$minimize \left(\frac{1}{m} \sum_{c=1}^{m} \left(y_c^t - \hat{y}_c^t \right)^2 \right) \tag{10}$$

The value of the expected comparable label from soft biometric is represented by y_c^t, and the comparative label predicted by equation (9) is represented by $\hat{y}_c^t$. The projected comparative label b for trait t flanked by individuals (i, j) constituting a comparison in the testing group is derived as follows once the weight coefficients vector $\hat{\beta}$ is generated:

$$b_d^t(i, j) = \begin{cases} -1 & \text{if } \hat{y}_d^t < 0 \\ 1 & \text{if } \hat{y}_d^t \geq 0 \end{cases} \tag{11}$$

The comparison's index in the testing group is represented by $1 \leq d \leq n$ and as explained in section II, the anticipated comparison labels are utilized to derive comparative rates for the 31 traits through the ELO rating. The relative rates are utilized to create biometric signatures for all the subjects, which are made up of 31 relative rates constituting soft biometrics used for subject recognition. After comparative labels is predicted from the images, we find the associated rating for each attribute using ELO.

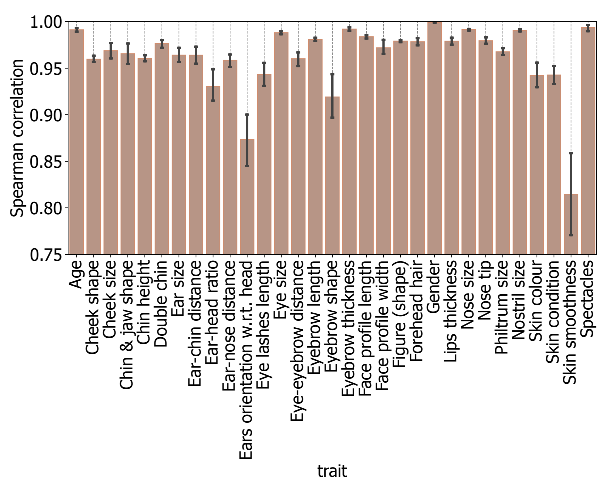

Fig. 5. Spearman's correlation coefficient is used here to average and to quantify the correspondence between soft and traditional generated labels.

Figure 5 shows the relationship and the Spearman's correlation between soft and traditional comparative face profile biometrics features, as evaluated by equations (9) and (10). The discriminative power analysis by MI (Figure 2) and the correspondence analysis have a substantial relationship, as shown in Figure 5. The strongest relationship is between binary-like attribute (e.g., gender), followed by nose size and nostril size. While the majority of eye and ear characteristics have the least, but still substantial, correspondence. The ability of soft biometric face profile features to discriminate has a significant impact on traditional biometrics, as can be seen in Figure 5, highlighting the need for the soft biometrics and traditional biometrics systems to be combined.

IV. Face profile recognition Performance

A. Feature Construction

In our experiments, we develop and test three different sorts of features: human-labeled, automatically-labeled, and fusion features. The human features (soft biometric) are created by comparing image pairs on a particular attribute using a platform that contains a set of image pairs (facial profile trait). A ranking system is then used to turn the pairwise comparisons into scores linked with images. The set of created ranks for each attribute is used to build a feature vector for each image. Subsequently, each subject has a biometric signature. The automatic features (traditional biometric) are built using trained regressors to automatically generate comparative labels for each subject based on visual GIST features, and for each participant in the dataset, a biometric signature is created. The regressors are trained using comparisons (i.e. pairings of face profile images). The fused features are where human and automatic features are combined, and each image has a features vector extracting from both the human and the machine together. Finally, after extracting feature vectors for both annotation systems, a fusion vector is formed by concatenating the feature vectors into a single feature vector for each image.

B. Face Profile Recognition

In this paper, a Leave-One-Out Cross Validation (LOOCV) technique is used to calculate the recognition rate. With Recursive Feature Elimination (RFE) [20], we used XGBoost [21] as a classifier. In this investigation, employing all of the features listed in Table I, an average recognition rate of 97% is attained with soft biometric feature vectors, while 84% an average recognition rate is achieved with the GIST related features. The fused feature vectors achieve an average recognition rate accuracy of 98%. This result demonstrates how significant the contribution of the eyewitness testimonies (soft biometric) is to improve the performance of the traditional biometric by 14%.

24 comparative attributes are used in [7], and identification was evaluated with 430 subjects from the LFW dataset. The study achieved a 98.37% retrieval rate at rank-5 from the human features and a 90.93% retrieval rate at rank-10 for the automatic features. In comparison with [7], we achieve a promising accuracy using profile face. In the case of face profiles, it is expected that the recognition rate will be lower since only half of the face is exposed and not all face information is available to observers. Our experimental results of 98% recognition rate for our face profile recognition system indicates, however, that face profiles are sufficient to qualify as a separate biometric modality.

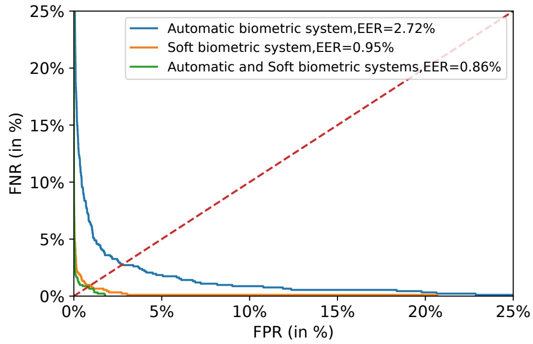

Fig. 6. DET Curve for each of the three biometric systems.

The trade-off between false positive rate (FPR) and false negative rate (FNR) was demonstrated and represented by the DET curve to evaluate the system performance. As shown in Figure 6, the system fusing features from eyewitnesses' testimonies and features from face profile images can achieve an Equal Error Rate (EER) of 0.86%, compared to 0.95% and 2.72% for the soft biometric and traditional biomteric systems respectively. Overall, our findings show that fusing soft and traditional comparative face profile systems can improve recognition accuracy significantly. Furthermore, the findings suggest that combining eyewitness testimonies and computer vision techniques can result in a biometric system with higher performance.

V. Conclusions and Future works

The importance of face profile in biometric systems for security and surveillance is discussed in this study. In addition to examining the impact of human comparative labels on face profile recognition performance, this research investigates the improvement of the biometrics systems of face profile recognition by fusing comparative soft biometrics with the traditional biometrics. For automatically determining comparative face profile labels, we use a method that combines computer vision and human description. Furthermore, utilizing a subset of the XM2VTSDB dataset, we investigate three biometric systems and found that when combined with automatic biometric system, comparative facial soft biometrics in humans can lead to significant recognition accuracy.

These discoveries broaden the possibilities for bridging the semantic divide between people and machines, as well as providing a foundation for future research. Bilateral symmetry is a topic which can be used as our future work. As another topic for future research, we are interest to find out if it is possible for a face profile recognition system to recognize subjects with full face images. Future work will also be focused on testing our method on larger and more challenging datasets.

REFERENCES

[1] D. A. Reid, S. Samangooei, C. Chen, M. S. Nixon, and A. Ross, "Soft biometrics for surveillance: an overview," in *Handbook of statistics*. Elsevier, 2013, vol. 31, pp. 327–352.

[2] D. A. Reid and M. S. Nixon, "Human identification using facial comparative descriptions," in *2013 International Conference on Biometrics (ICB)*. IEEE, 2013, pp. 1–7.

[3] S. Samangooei, B. Guo, and M. S. Nixon, "The use of semantic human description as a soft biometric," in *2008 IEEE Second International Conference on Biometrics: Theory, Applications and Systems*. IEEE, 2008, pp. 1–7.

[4] D. A. Reid, M. S. Nixon, and S. V. Stevenage, "Soft biometrics; human identification using comparative descriptions," *IEEE Transactions on pattern analysis and machine intelligence*, vol. 36, no. 6, pp. 1216–1228, 2013.

[5] D. Martinho-Corbishley, M. S. Nixon, and J. N. Carter, "Soft biometric recognition from comparative crowdsourced annotations," 2015.

[6] N. Almudhahka, M. Nixon, and J. Hare, "Human face identification via comparative soft biometrics," in *2016 IEEE International Conference on Identity, Security and Behavior Analysis (ISBA)*. IEEE, 2016, pp. 1–6.

[7] N. Y. Almudhahka, M. S. Nixon, and J. S. Hare, "Semantic face signatures: Recognizing and retrieving faces by verbal descriptions," *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 3, pp. 706–716, 2017.

[8] N. Almudhahka, M. Nixon, and J. Hare, "Automatic semantic face recognition," in *2017 12th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2017)*. IEEE, 2017, pp. 180–185.

[9] K. Messer, J. Matas, J. Kittler, J. Luettin, and G. Maitre, "Xm2vtsdb: The extended m2vts database," in *Second international conference on audio and video-based biometric person authentication*, vol. 964, 1999, pp. 965–966.

[10] M. Alamri and S. Mahmoodi, "Facial profiles recognition using comparative facial soft biometrics," in *2020 International Conference of the Biometrics Special Interest Group (BIOSIG)*. IEEE, 2020, pp. 1–4.

[11] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," in *2005 IEEE computer society conference on computer vision and pattern recognition (CVPR'05)*, vol. 1. Ieee, 2005, pp. 886–893.

[12] D. A. Reid and M. S. Nixon, "Imputing human descriptions in semantic biometrics," in *Proceedings of the 2nd ACM workshop on Multimedia in forensics, security and intelligence*, 2010, pp. 25–30.

[13] N. Y. Almudhahka, M. S. Nixon, and J. S. Hare, "Unconstrained human identification using comparative facial soft biometrics," in *2016 IEEE 8th International Conference on Biometrics Theory, Applications and Systems (BTAS)*. IEEE, 2016, pp. 1–6.

[14] A. S. Center. Appen center. (Accessed: 20.12.2020). [Online]. Available: https://success.appen.com/hc/en-us

[15] B. Guo and M. S. Nixon, "Gait feature subset selection by mutual information," *IEEE Transactions on Systems, MAN, and Cybernetics-part a: Systems and Humans*, vol. 39, no. 1, pp. 36–46, 2008.

[16] P. Tome, R. Vera-Rodriguez, J. Fierrez, and J. Ortega-Garcia, "Facial soft biometric features for forensic face recognition," *Forensic science international*, vol. 257, pp. 271–284, 2015.

[17] R. Tan, V. Osman, and G. Tan, "Ear size as a predictor of chronological age," *Archives of gerontology and geriatrics*, vol. 25, no. 2, pp. 187–191, 1997.

[18] V. Kazemi and J. Sullivan, "One millisecond face alignment with an ensemble of regression trees," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2014, pp. 1867–1874.

[19] A. Oliva and A. Torralba, "Modeling the shape of the scene: A holistic representation of the spatial envelope," *International journal of computer vision*, vol. 42, no. 3, pp. 145–175, 2001.

[20] I. Guyon, J. Weston, S. Barnhill, and V. Vapnik, "Gene selection for cancer classification using support vector machines," *Machine learning*, vol. 46, no. 1, pp. 389–422, 2002.

[21] T. Chen and C. Guestrin, "Xgboost: A scalable tree boosting system," in *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, 2016, pp. 785–794.