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A Comparative Study of Soft Biometric Traits and Fusion Systems for Face-based Person Recognition

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Abstract: Soft biometrics is not a unique trait in itself, but it is valuable in enhancing the performance of unique traits used in biometric recognition systems. In this paper, we perform a comparative analysis of soft biometric traits and fusion schemes for improving face recognition systems. Specifically, we present an analysis of the performance of such systems as a function of the fusion strategy used and the soft biometric feature employed. We outline the strengths and weaknesses of the biometric feature employed in fused face and soft biometric systems. The analysis presented in this work is significantly important and different from existing works as the performance profiles of a wider variety of soft biometric traits are compared over major metrics of permanence, ease of collection and distinctiveness.

Index Terms: Soft biometrics, biometric fusion, face recognition

1. Introduction

Both humans and machines employ the use of face for identification and recognition. Naturally, humans perform face recognition intuitively by making use of a good spread of unique biometric features within the face. Natural face recognition happens through a complex mechanism carried out by the brain and its specialized nerve cells that bring about the combination of the different sources of biometric information – both primary and secondary biometric traits – into a useful mix. The machine-based face recognition system comes alive by mimicking the natural system through the processing of facial traits that possess a fair mix of biometric qualities such as unobtrusiveness, universality, distinctiveness, permanence, acceptability, and ease of accessibility. Facial biometrics is one of the commonest biometrics in use. It has a higher level of acceptability, accessibility but a lower recognition rate when compared with some other primary biometrics like iris [1]. Hence, the human face has received tremendous attention from the biometric research community. Automatic face recognition has continued to receive improvements to perform almost as the natural human face recognition system does. The reason has been attributed to the fusion of different biometric information using improved algorithms [2]. While the fusion of multiple primary biometrics like fingerprint, iris or hand geometry has been the trend, they tend to suffer from high computation time, cost and sometimes poor accuracy [2,3]. Soft biometric features, on the other hand, have been found to not suffer from most of the limiting factors traceable to primary biometric features such as privacy threat, invasion, data collection difficulty, occlusion, lighting variation, low resolution, viewpoint and pose.

Most works in this area employ soft biometric traits as ancillary information for improving the rate and accuracies of the recognition system under different scenarios including the unconstrained, at a distance, and in the wild [4]. Soft biometrics are also used to enable fast retrieval of faces from a large database as well as in making a qualitative description of subjects [5]. However, certain soft biometric traits such as sunglasses and scarf covering have been found to degrade the performance of face recognition systems [6]. On the other hand, the objective of some biometric systems could be the determination of soft biometric information through primary biometric traits. Such works include ethnicity and gender from fingerprint [7], and body weight and height from gait [5], among others.

Figure 1 shows a block diagram of a fused face and soft biometric (hereafter referred to as FFS) authentication system. It comprises of two subsystems namely, the face biometric subsystem and the soft biometric subsystem. The face biometric subsystem processes input face data by extracting a set of facial features, which are matched with the face biometric template in the match module before fusion is done. A similar process takes place in the soft biometric subsystem except that soft biometric features are extracted and matched at the match module with the soft biometrics from the soft biometric template. The two subsystems work independently in a coordinated manner. Fusion of the scores arising from the subsystems takes in the fusion module using appropriate fusion algorithm before being passed to the decision module for a decision. The decision could be accept or a reject.

In this paper, we adopt the survey and discuss methodology by considering the various fusion schemes and algorithms that have been proposed for FFS systems, highlighting their strengths and weaknesses.

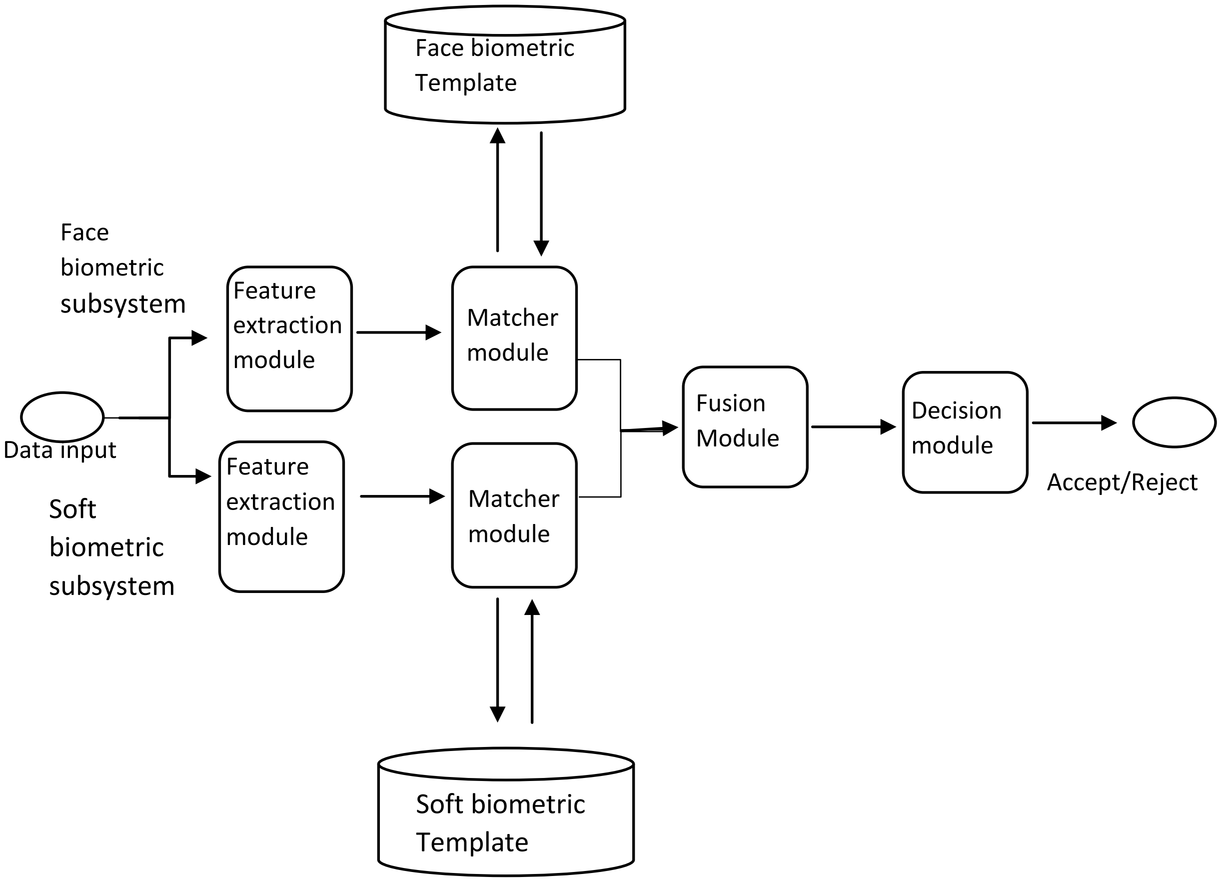

Fig.1. Block Diagram of a Fused Face and Soft Biometric (FFS) System

We also compare the performance of over forty soft biometric traits in terms of distinctiveness, permanence and ease of collection. The analysis performed in this work therefore serves as a reference and guide for the selection of soft biometric traits to be fused with face biometrics for optimal results.

2. Review of Related Works

Several comparative analysis and review researches have been carried out on biometric systems.

M. Ghayoumi [8] reviews eighteen multimodal biometric systems, highlighting the fusion modules and fusion level for each of the works. They present useful information including problems of unimodal biometrics, advantages of multimodal systems, as well as different fusion modalities in existence. A further review of unimodal and multimodal biometric sensing systems was carried out in [9]. They analyse the performance of ten biometric sensing systems against seven factors including ease of use, cost, distinctiveness and their barriers to universality. They also went on to analyse and compare various proposals for multimodal biometric systems with respect to employed algorithm and method of fusion. Other works focus on the survey of facial soft biometrics alone: some focusing on single soft biometric traits [10], others on multiple traits [1,5,11]. On the other hand, the characteristics of different biometric fusion schemes have also been compared. A. Eleyan [12] report an increase in performance when decision or feature level fusion algorithms were employed in comparison to single feature extraction methodology.

Our work analyses both the efficiency of different soft biometric traits, as well as the performance of different fusion algorithms in literature.

The remainder of the paper is organized as follows: In Section 3, we compare and analyse some common soft biometric traits found in literature. Section 4, describes fused face and soft biometric systems. We also discuss fusion scenarios and present a comparative analysis and performance of soft biometric traits used in fusion scenarios. Finally, our conclusion is presented in Section 5.

3. Comparison of Soft Biometric Traits

Soft biometric traits are physical, behavioral, or material accessories, which are associated with an individual and are useful for recognizing the individual. They are attributes that are mainly acquired from primary biometric data, and having the quality of being classifiable in pre-defined human-understandable categories useful for the identification of individuals. In [13], Reid and Nixon describe soft biometric traits as traits concerned with the labels people use to describe each other. Put more strongly, soft biometric traits are said to be a set of discrete features that categorize people into distinct groups [14]. They are considered as ancillary traits possessing inherent human semantic descriptions [13]. Looking at the various definitions, it can be deduced that soft biometrics make use of labels, includes non-classical biometric traits such as accessories, gender, weight, age, etc., and involves measurements and descriptions used for person identification. They are grouped, in most literature, into physical attributes as the global, body, and head features; face, body, and accessories attributes; demographic, anthropometry and geometric; medical, material and behavioral attributes; and as absolute categorical and comparative labels [5, 13, 15, 16]. They are also grouped based on the nature of value as continuous or discrete. It is worthy of note that this grouping of soft biometric traits can easily overlap.

Table 1 shows a list of some of the vast, non-exhaustive number of features that are regarded as soft biometric features/traits as employed in existing biometric recognition systems. We show typical classification of each trait as continuous, multiclass and binary classes. Depending on the requirement of the biometric recognition system, continuous and multiclass traits can be simplified to a binary classification at the expense of distinctiveness. We present an analysis at a glance of these soft biometric traits considering their categorization, description, strengths and weaknesses in terms of the degree of permanence, uniqueness and ease of collection. As expected with soft biometric traits, their recognition can significantly reduce the retrieval time of persons from large databases. For example, black female soldiers corresponding to color of skin, gender and clothing style soft biometric traits respectively, can be filtered from a large database for a finer recognition/persona retrieval using more distinctive primary biometric traits. On the other hand, the presence of certain soft biometric traits can interfere with recognition accuracy, hence the need to identify and remove them. Typical examples are makeup and other low permanence traits.

We categorize the studied soft biometric traits in terms of distinctiveness (a characteristic that makes a person different from every other person), permanence (how the trait can change over time and circumstance) and ease of collection (ease of data collection/identification with little to no user cooperation) [1,17]. For example, hairstyle has a low distinctiveness, as many people can be characterized by the same hairstyle. Generally, soft biometric traits are known to either possess medium or low distinctiveness, hence their use as ancillary information with primary biometrics [17]. From Table 1, we show that traits with measurable/ continuous values or a wide range of classes are indeed able to distinguish between individuals in a group. However, their distinctiveness will always be less than that achieved from primary biometrics like iris and fingerprint.

In terms of permanence, traits are characterized as high, medium or low based on their susceptibility to change over time. For example, face shape and tribal marks are categorized as having high permanence, as they do not change significantly over time, except when altered by makeup, surgery or accident. On the other hand, age and weight have low permanence as they change over time. Finally, a trait is categorized as having high ease of collection if the trait can be identified easily, irrespective of the method of data collection. For example, cloth category has a higher ease of collection as cloth style can be detected from any angle, unlike nose size that requires the cooperation of the subject during data acquisition.

Though soft biometric traits possess known levels of weaknesses as shown in Table 1, new research suggestions show that aggregation of multiple soft biometric traits can produce satisfactory results when used in a stand-alone system for human identification [14,15,18].

Table 1. Categorization and characterization of common soft biometric features that have been investigated in literature

S/N	Soft biometric traits	Category	Description	Strength/Weakness		
				Distinctiveness	*Permanence*	*Ease of Collection*
1.	Scars/Tattoos/Tribal Marks/ Facial Marks [19]	*Body/Face*	Multiclass	Medium	Medium/High	Medium
	Hair Attributes					
2.	Hair length [20]	Face	Multiclass (e.g. bald, short, medium, long fine, long volume)	Low/medium	Low	Medium
3.	Hair colour [1]	Face	Multiclass (e.g. black, blonde, brown etc.)	Low/medium	Low/Medium	Medium
4.	Hairstyle [20]	Face	Multiclass (e.g. bald, short, medium, long fine, long volume)	Low/medium	Low	Medium
	Face attributes/ measurements					

5.	Facial Hair Length [20]	Face	Multiclass (e.g. None, Stubble, Moustache, Goatee, Full Beard)	Low/medium	Low/Medium	Medium
6.	Face length/width [21]	Face	Continuous/ Multiclass (e.g. small, normal, large)	High/Medium	High	Low
7.	Face shape [10,21]	Face	Multiclass (e.g. oblong, heart, diamond, triangle)	Medium	High	Low
8.	Shape of forehead [21]	Face	Multiclass (e.g. flat, protruding, steep)	Medium	High	Low
9.	Ear types [23]	Face	Multiclass (e.g. Long and Narrow, Medium, Short and Broad)	Medium	High	Low
10.	Ear lobe type [23]	Face	Multiclass (e.g. Free, Attached, Absent)	Medium	High	Low
11.	Eye colour [24]	Face	Multiclass (e.g. black, brown, blue, green)	Medium	High	Low
12.	Eye size [21]	Face	Multiclass (e.g. small, normal, large)	Medium	High	Low
13.	Thickness of eyebrow [21]	Face	Multiclass (e.g. thin, normal, thick)	Low	Low/Medium	Low
14.	Eyelashes [25]	Face	Binary (e.g. mascara, no mascara)	Low	Low	Low
15.	Nose shape [26]	Face	Multiclass (e.g. Nubian, Greek, Roman, Snub, Turn-up, Hawk)	Medium	High	Low
16.	Nose size (length, width) [22]	Face	Multiclass (e.g. Normal, Macrorhinic, Microrhinic)	Medium	High	Low
17.	Face adornments (Earring, Nose ring, Glasses) [1,27]	*Accessories*	Binary (Presence or Absence)	Low	Low	Medium
18.	Make-up [28]	Yes	Binary (Presence or Absence)	Low	Low	Medium
	Body attributes/ measurements					
19.	Weight [1,11,29]	Body	Continuous/ Multiclass (e.g. thin, average, fat)	Medium	Low/Medium	Low
20.	Height [11,29]	Body	Continuous/ Multiclass (e.g. short, average, tall)	Medium/Low	Low/Medium	Low
21.	Muscle build [28]	Body	Multiclass (e.g. lean, average, muscular)	Low	Low/Medium	Medium
22.	Skin colour [6,11,29]	Face/Body	Multiclass (e.g. black, white, mixed-race)	Low	Medium/High	Medium
23.	Neck thickness [18, 29]	Body	Multiclass (e.g. Thin, Average, Thick)	Low	Low/Medium	Medium
24.	Chest size	Body	Multiclass (e.g. slim, average, large)	Low	Low/Medium	Low
25.	Shoulder shape	Body	Multiclass (e.g. square, average, round)	Low	Medium	Medium
26.	Arm thickness [13,29]	Body	Continuous / Multiclass (e.g. thin, average, thick)	Low	Low/Medium	Low
27.	Length of Body part (e.g. neck, shoulder, arm, leg) [28]	Body	Continuous / Multiclass (e.g. short, average, long)	Low	Low/Medium	Low
28.	Body fat percentage	Body	Continuous / Multiclass (e.g. low, average, high)	Medium/Low	Low	Low
29.	Hips [28]	Body	Continuous / Multiclass (e.g. narrow, average, broad)	Low	Low/Medium	Low
30.	Leg shape	Body	Multiclass (e.g. straight, average, bow)	Low	Low/Medium	Low
31.	Cloth style [15]	*Accessories*	Multiclass (e.g. chef, soldier, judge)	Low	Low	High
32.	Cloth Color [1,30]	*Accessories*	Multiclass (e.g. white, blue, red etc.)	Low	Low	High
33.	Cloth attributes (e.g. sleeve, length, exposure) [30]	*Accessories*	Multiclass (e.g. short, medium, long)	Low	Low	High
34.	Cloth category [30]	*Accessories*	Multiclass (e.g. shirt, sweater, dress, etc.)	Low	Low	High
35.	Ethnicity [4,14,27]	Face/Body	Multiclass (e.g. Asian, Caucasian, African)	Low	High	Medium
36.	Gender [4,27,31]	Face/Body	Binary (Male, Female)	Low	High	Medium
37.	Age [27,32,33]	Face/Body	Continuous / Multiclass (e.g. infant, adolescent, adult, senior)	Low	Low/Medium	Low/Medium

38.	Sexual Orientation [34]	Face/Body	Binary (Gay, Straight)	Low	Medium	Low
39.	Head clothing [35]	*Accessories*	Multiclass (e.g. none, hat, scarf, cap etc.)	Low	Low	High
40.	Foot clothing [35]	*Accessories*	Multiclass (e.g. flip-flop, heel, boot, trainer etc.)	Low	Low	Medium/High
41.	Handbag [35]	*Accessories*	Multiclass (e.g. side-bad, cross-bag, backpack etc.)	Low	Low	Low/Medium

4. Fused Face and Soft biometric (FFS) systems

The human face possesses different vital information that does not change widely with time, and are harnessed for recognition purposes. The fusion of two or more different biometrics has become the trend of the modern biometric recognition systems for some obvious reasons, namely:

- Improved performance,
- Improved anti-spoof capability, as it is much difficult to cheat two biometrics than one,
- More coverage, since people with various disabilities, may only be able to provide certain biometrics, but not others.
- Increased accessibility, as either of biometric modalities, will be more useful than when the unimodal arrangement is the case etc.

Face biometrics have been fused with other biometric features including fingerprint, iris, gait, gender, age, ethnicity, height, geometric information from mouth, eyebrows, nose, eyes among others. Ghalleb et al. [6] proposed the combination of facial measurements, skin colour and hair colour for the improvement of a face recognition system. In terms of performance improvement, Guo et. al. [36] showed that increasing the number of effective soft biometric traits employed in FFS systems increases the performance improvement accordingly. However, the use of non-facial soft biometric traits for FFS systems has been reported to produce better results as they are complementary to face biometrics [27,31].

4.1 Fusion schemes for FFS systems

In order to fuse complementary or non-complementary pieces of evidence gotten from both the face and the soft biometric subsystems, three major fusion schemes exist: feature level, score level and decision level.

Feature-level fusion combines different features extracted from the same or different modalities into a single representation for a given individual recognition. Here, the features extracted from the inputs to the two subsystems are combined before score values are computed and a decision made. This scheme is rarely used owing to the difficulty of access to features used by most commercial matchers, the cost of feature dimensionality etc. It is known to be rich in information than the other two schemes but its overall performance is less compared to match score level fusion.

The score-level fusion combines match scores generated by different matchers of the different modalities corresponding to the subsystems. This is the most commonly used fusion scheme in the literature owing to the ease of access to match scores in commercial matchers unlike with feature level based schemes. It possesses a fair balanced of qualities, hence, its ease of use. Some of the algorithms used under this scheme are max-score fusion, min-score fusion, or mean-score fusion.

The decision level scheme involves the combination of the decisions arising from different classifiers. It is known to possess less information than the other two schemes. This is suitable for cases where access to features and match scores of commercial systems are difficult to get.

We present an analysis at a glance of some existing works on FFS systems including their fusion schemes in Table 2. Specifically, in [31] a probabilistic approach based on Bayesian framework using score-level fusion scheme was used to integrate faces, fingerprints and soft biometric traits. Experiments conducted on a database of 263 users show significant recognition performance improvement. In [18], three different score level fusion schemes were employed: sum rule, adaptive switch fusion rule and a weighted rule. It achieved considerable performance improvement when scenarios at varying distances were carried out. Djara *et al.* [15], implemented the fusion of face biometrics, contactless fingerprint and facial skin colour using an adapted sequential fusion strategy at the score level. It is based on the probability ratio test carried out successively in the uncertainty zone. They recorded improved recognition performance. Using facial soft biometrics in a primary face biometrics fusion, Ghalleb *et al.* [6] adopted the use of the concatenation approach to fusing the face authentication system with the facial soft biometric traits namely, facial measurement, skin and hair colours to improving facial authentication systems. Arigbabu et al. [11] employ a combined aggregation of body-based soft biometric traits with face-based biometrics in a fuzzy logic fusion strategy under a sequential fusion approach to study the potency of soft biometric traits derived from video clips for the improvement of the commercial face biometric system performance. The result of a comparative experiment carried out using five score fusion techniques namely, sum rule, weighted sum, fuzzy logic, Bayesian, and support vector machine showed fuzzy logic fusion strategy outperformed the other strategies. Jaha [33] considered the use of global face soft biometrics fused with

Gabor-based face biometric feature for the augmentation of the primary face biometrics. Their work is a performance variability evaluation and comparison with the baseline performance of Gabor features in isolation. Gonzalez-Sosa et al. [27] used a deep learning approach to fuse two state-of-the-art face recognition systems with six sets of facial soft biometrics extracted both automatically and manually under unconstrained condition.

4.2. FFS System Fusion Scenarios

Existing FFS systems follow five major design scenarios as discussed below.

a) ***Face biometric with a single soft biometric classifier:*** In this scenario, a single soft biometric attribute is combined with the traditional face biometric system for person recognition/authentication. Example of such systems include the work by Tome et al. [18], where labels extracted manually by human annotators were fused with facial features for person recognition at a distance. Their work uses an adaptive fusion scheme at score level to show the relationship between the distance of a subject from an imaging sensor and the performance of soft biometrics for recognition at a distance. Other examples include the fusion of clothing colour and face feature [37]. Muncaster et. al. [38], used a combination of match scores from face detection and keystroke dynamics and by applying dynamic Bayesian Networks, built a continuous multimodal authentication system.

Table 2. Summary of research works on soft and hard biometric fusion for subject recognition

Authors	Traits	Fusion scheme	Strategy	Strengths	Weaknesses	Performance
Jain *et al.* [31]	Face, fingerprint, ethnicity, gender and height.	Score level.	A probabilistic approach based on Bayesian framework.	1) It employed weights for the soft biometric traits to reflect their various discriminatory powers. 2) The soft biometric weights are small compared to the primary biometric weights to avoid overshadowing.	It is difficult to determine the optimum weighting value.	Significant performance improvement with better recognition accuracy.
Tome *et al.* [18]	Face, global, head and body soft biometrics.	Score level.	Adaptive switch rule and weighted fusion rule.	1) Improved recognition at a distance performance. 2) Robust to failure to acquire and failure to detect errors.	It has no specified scheme to select the optimal soft biometric label for use.	It achieved performance improvement for scenarios at varying distances.
Djara *et al.* [15]	Face, contactless fingerprint and facial skin colour.	Score level.	Adapted score-level sequential fusion algorithm.	Well suited for access control applications areas. It is more efficient than the serial approach.	It is computationally intensive.	Improved performance than comparable feature level fusion approach.
Ghalleb *et al.* [6]	Face, facial measurement, skin colour and hair colour.	Feature level.	Concatenation.	1) Achieves considerable improvement of the face biometrics with an EER of 1.83%. 2) Improved recognition rate.	It is not robust to change in facial appearance as the facial measurement is used as a soft biometric feature.	It increased face recognition rate and decreased the equal error rate. Bring about performance improvement.
Arigbabu et al. [11]	Face and body soft biometric (facial shape, skin colour, height, and weight).	Match score and decision fusion levels.	Sequential attribute combination method using sum rule, weighted sum, fuzzy logic, Bayesian, and support vector machine.	1) Improved face recognition performance even in the unconstrained environment via discarding of attributes that degrades performance.	It assumes the presence of at least a single a subject in the recording scene, which is mostly non-realistic in real life environment.	It achieved considerable improvement in face recognition performance at rank-1 identification rate.
Jaha [33]	Face, gender, ethnicity, age-group, age-level, and skin colour	Feature level.	Concatenation.	1) There is consistent enhancement of identification and verification performance. 2) Robust against changes in facial expression, pose, illumination, and ageing.	It is computationally intensive.	There is notable performance improvement but less than that due to score level approach.
Gonzalez-Sosa et al. [27]	Face, gender, ethnicity, age, glasses, beard and moustache.	Score level.	Equal weighting approach.	40% and 15% recognition rate improvements using manually and automatically extracted soft biometric traits respectively.	Use of single annotator for the manual soft biometric trait extraction.	They recorded performance improvement owing to the score fusion scheme.

Park and Jain [4]	Face, gender, ethnicity and facial marks.	Score level.	Weighted score-sum.	1) Improved face recognition rate even under occluded face 2) Enhanced system performance.	It does not involve off-frontal face mark extraction.	Improved performance due to the fusion approach used.
Abreu et al. [39]	Face, Fingerprint, age and gender.	Score and Decision levels.	Majority vote-based fusion, Sum-based fusion, and Sensitivity-based negotiation fusion methods.	1) The fusion methods resulted in a significant performance gain. 2) The approach addresses identity mode recognition system better.	It is computationally intensive due to the task involve while carrying out intelligent negotiation.	The combination of both score fusion and decision fusion schemes lead to greater performance improvement than earlier recorded.
Zhang et al. [14]	Face, gender, ethnicity, eye color, hair colour and eyebrow.	Score level.	Weighted product rule.	Improved face recognition rate.	It is not robust to change in facial appearance.	Improved recognition performance achieved.

b) ***Face biometric with multiple soft biometric classifiers:*** This involves the fusion of facial features with two or more soft biometric traits. Facial marks such as mole, freckle, scar etc. were combined with face biometric in [40] to improve face recognition matching accuracy and aid fast face image retrieval. Laplacian-of-Gaussian and morphological operators were used to detect facial marks, which were then combined with an active appearance model based facial identity classifier. Lin et al. [41], used a combination of Gabor filter, Adaboost and Support Vector Machine-based classifiers to fuse face biometric trait with gender, age and ethnicity soft biometric for an FFS classifier.

c) ***Face and other primary biometrics with single soft biometric classifiers:*** Here, a single soft biometric trait is combined with a face biometric trait together with yet another unit of a primary biometric trait such as fingerprint from more than one finger or face image at varied input scales. Xiaoguang and Jain in [42] used LDA based scheme for multiscale analysis with different scales of the input grayscale face image in an ensemble framework, to integrate with the LDA analysis for the input face images at varying scales. They combined face biometrics with ethnicity-based soft biometrics for improving the recognition potentials of the face biometric system. This approach is cost-effective while improving system performance as it neither involves multiple sensors nor incorporates additional feature extraction.

d) ***Face and other primary biometrics with multiple soft biometric classifiers:*** This involves the fusion of the outputs of different soft biometric classifiers with that of multiple traditional biometric features, including facial features. The acquisition of the different traditional biometrics. As expected, this fusion scenario is cost-intensive as multiple sensors are required for the setup. However, it is highly desirable when close to perfect retrieval/recognition must be achieved [43].

e) ***Multiple soft biometrics fused together in a soft biometric standalone arrangement:*** In this scenario, multiple soft biometric features are used in establishing a person's identity. As discussed in earlier sections, it is well known that a single soft biometric attribute cannot single-handedly identify subjects due to intra-class variations and inter-class similarities. However, improved performance can be achieved when multiple attributes are fused. Existing works can be found in [1,43].

5. Conclusion

The integration of soft biometric traits with primary biometric traits has become one of the viable ways of improving the recognition performance of classical biometric traits such as fingerprint, iris, voice, face etc. This paper takes on the survey of the fusion of soft biometric traits with face biometrics. We analyzed soft biometric traits as used in biometric recognition with a focus on their strengths and weaknesses. We discussed the benefits of using soft biometrics in a fusion approach with face-based biometric person identification systems and also, considered the various scenarios that are possible in the fusion of soft biometrics and face biometric traits. The analysis performed in this work therefore serves as a reference for the selection of soft biometric traits to be fused with face biometrics for optimal results.

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