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Face and Gait Fusion Methods: A Survey

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***Abstract*— Biometric authentication of a person is highly challenging and complex problem. Face and gait identifications in video have received significant attention. Consequently, their identification problems have challenges due to their large varying appearances and high complex pattern distributions. However, the complementary properties of these two biometrics suggest fusion of them. Face identification is more reliable when the person is close to the camera. On the other hand, gait is a suitable Biometric trait for human identification at a distance. In this paper we have discussed multimodal biometrics to increase the security level. With the fusion of multiple biometrics we can minimize the system error rates, Moreover, we have mentioned some of the most recent algorithms developed for this purpose and attempts to give an idea of the state of the art of face and gait recognition technology and a brief overview of Biometric methods, both unimodal and multimodal, and their advantages and disadvantages, will be presented.**

***Index Terms*— Face Recognition, Gait Recognition, Fusion Levels and Biometric Authenticatio**n

I. INTRODUCTION

BIOMETRIC-BASED technologies include identification based on physiological characteristics (such as face, fingerprints, finger geometry, hand geometry, hand veins, palm, iris, retina, ear and voice) and behavioral traits (such as gait, signature and keystroke dynamics) [1].

Face recognition is a task so common to humans, that the individual does not even notice the extensive number of times it is performed every day. Although research in automated face recognition has been conducted since the 1960's, it has only recently caught the attention of the scientific community. Many face analysis and face modeling techniques have progressed significantly in the last decade [2]. However, the reliability of face recognition schemes still poses a great challenge to the scientific community [3]. Facial recognition holds several advantages over other Biometric techniques. It is natural, non-intrusive and easy to use. The basic face information consists of: *Landmarks* set is a set of x and y coordinates that describes features (here facial features) like eyes, ears, noses, and mouth corners. *Geometric* information is the distinct information of an object's shape, usually extracted by annotating the object with landmarks.

Photometric information is the distinct information of the image, i.e., the pixel intensities of the image. Moreover, *Shape* is all the geometrical information that remain when location, scale and rotational effects are filtered out from an object [2].

Gait is a behavioral barometric that is superior in person's authentication. Thus, utilizing gait as identification criteria identifies certain distinct phases or stances. Study of human gait and its mathematical modeling has implications for different areas like surveillance, medical diagnosis, entertainment industry, video communications, etc. The attractiveness of gait as a Biometric arises from the fact that it is nonintrusive and can be detected and measured even in low resolution video. Gait as a Biometric method has some advantages such as being difficult to hide, steal, or fake. Furthermore, gait can be recognizable from distance. However, most other biometrics can be captured only by physical contact or at a close distance from the recording probe. Moreover, users do not need to unveil additional information about them other than already available. Despite the advantages enjoyed by gait, it faces many challenges that the existing gait identification methods are sensitive to such as: Type of clothes, person's speed, illumination changes and person's directions [4-7].

In recent years, multimodal fusion has gained much attention of many researchers due to the benefit it provides for various multiple biometric analysis tasks. Multimodal Biometric systems can be designed to operate in five integration scenarios: 1) multiple sensors, 2) multiple biometrics, 3) multiple units of the same biometric, 4) multiple snapshots of the same biometric, 5) multiple representations and matching algorithms for the same Biometric [8-9]. It is interesting to notice that in case of face recognition, there is more information in the frontal face than that in the side face. Thus, recognition of the frontal face is generally easier than that of the side face. However, the situation happens to be the reverse in case of gait. Usually it is easier to recognize the side view gait than the frontal view gait due to the fact that there are more motion characteristics in the side view of a walking person. Up to the present, most reported experiments are performed on the side view gaits [10]. However, it is not realistic to expect only side view gait in real applications. These complementary properties of face and gait inspire fusion of them to get more accurate results. What biological measurements qualify to be a biometric? Any human physiological and/or behavioral characteristic can be used as a Biometric characteristic as long as it satisfies the following requirements [11]: *Universality*, *Distinctiveness*, *Permanence and Collect ability*. However, in a practical Biometric system (i.e., a system that employs biometrics for personal recognition), there are a number of other issues that should be considered, including [11]: *Performance*, *Acceptability*, *Circumvention*, *Exception handling and System Cost*.

Some limitations, related to the properties described above, have been noticed when only a unique modality is used in Biometric systems [12]: *Acquisition of noisy data*, *Intra-class variability*, *Distinctiveness*, *Non-universality*, *Spoof attacks*. A practical Biometric system should meet the specified recognition accuracy, speed, resource requirements, users' safety, intended population's acceptability, and be sufficiently robust to various fraudulent methods and attacks to the system. This paper is organized as follows: Section 2 describes the Biometric systems, and explains the advantages and disadvantages of biometrics. Section 3 introduces the comparison of face and gait biometrics. Applications of Biometric systems are presented in section 4. Section 5 explains the multimodal Biometric systems. Section 6 contains the related work in face authentication. Section 7 contains the related work in gait authentication. Section 8 contains the related work in face and gait fusion techniques for human authentication. Finally section 9 concludes the chapter.

II. BIOMETRIC SYSTEMS

A Biometric system is a pattern recognition system that operates by acquiring Biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template set [13-16].

Enrolment: A user is added to the Biometric system. A certain number of Biometric presentation of a particular user are acquired, preprocessed, transformed into features, and post-processed, then used to train a user model and adapt (retrain) the world model if necessary. The user model along with impostor presentations may be used to obtain a threshold for that user. The new model is then stored, along with the threshold for that user if needed [17], as shown in Figure (1.a).

Verification: The claim to a user's identity causes the presented Biometric data to be compared against the claimed user's model. Thus, the Biometric data is acquired, preprocessed, transformed into features, and post-processed, before being matched with the claimed user's model and the resulting score being compared with the stored threshold computed for the claimed user or a generic threshold value [17], as shown in Figure (1.b).

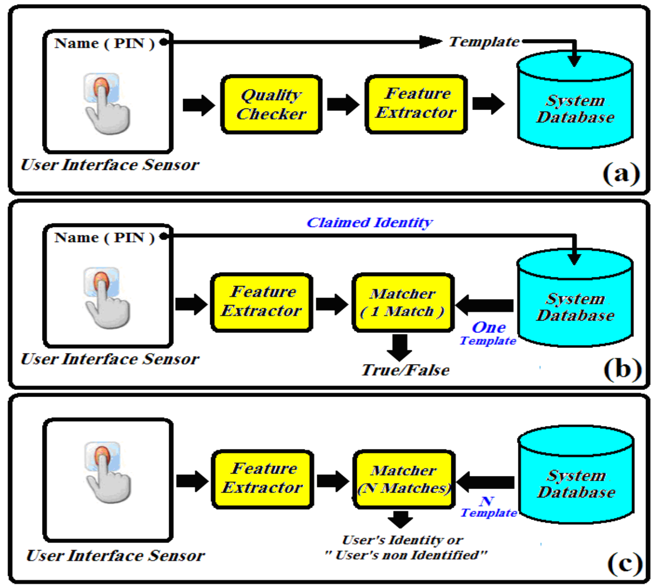

Fig. 1: Block diagrams of Biometric system

Identification: A database of user models is searched for the most likely source of the Biometric presentation. Thus, the Biometric data is acquired, pre-processed, transformed into features, and post-processed, before being matched with all the user models of interest. The user model that obtains the highest score with respect to the presentation is suggested to be the source of the presentation [17], as shown in Figure (1.c).

The advantages of biometrics are (uniqueness, no need to remember password or carry tokens, biometrics cannot be lost, stolen or forgotten, more secure than along password, and not susceptible to traditional dictionary attacks).The disadvantages of biometrics are (violation of privacy, often requires significant computational resources, and it cannot be changed: Once forget,……).

III. COMPARISON OF VARIOUS BIOMETRICS

Topology of biometrics methods can be divided into two main groups: behavioral and physiological biometrics [18-31]. A brief introduction of the commonly used biometrics is given below:

• *Face:* Face recognition is a non-intrusive method, and facial images are probably the most common Biometric characteristic used by humans to make a personal recognition. The applications of facial recognition range from a static, controlled verification to a dynamic, uncontrolled face identification in a cluttered background (e.g., airport).The most popular approaches to face recognition are based on either (i) the location and shape of facial attributes, such as the eyes, eyebrows, nose, lips, and chin and their spatial relationships, or (ii) the overall (global) analysis of the face image that represents a face as a weighted combination of a number of canonical faces. While the verification performance of the face recognition systems that are commercially available is reasonable [20], they impose a number of restrictions on how the facial images are obtained, sometimes requiring a fixed and simple background or special illumination. These systems also have difficulty in recognizing a face from images captured from two drastically different views and under different illumination conditions. It is questionable whether the face itself, without any contextual information, is a sufficient basis for recognizing a person from a large number of identities with an extremely high level of confidence [21]. In order that a facial recognition system works well in practice, it should automatically *(i)* detect whether a face is present in the acquired image; *(ii)* locate the face if there is one; and *(iii)* recognize the face from a general viewpoint (i.e., from any pose).

• *Gait:* Gait is a peculiar way and a complex biometric. Gait is not supposed to be very distinctive, but is sufficiently discriminatory to allow verification in some low-security applications. Gait is a behavioral Biometric and may not remain invariant, especially over a long period of time, due to fluctuations in body weight, major injuries involving joints or brain, or due to inebriety. Acquisition of Gait is similar to acquiring a facial picture and, hence, may be an acceptable biometric. Since Gait-based systems use the video-sequence footage of a walking person to measure several different movements of each articulate joint, it is an input intensive and computationally expensive [11].

IV. APPLICATIONS OF BIOMETRIC SYSTEMS

The applications of biometrics can be divided into the following three main groups [11]:

• *Commercial* applications such as computer network login, electronic data security, Internet access, credit card, physical access control, cellular phone, medical records management, distance learning, etc…

• *Government* applications such as national ID card, correctional facility, driver's license, social security, welfare-disbursement, border control, passport control, etc.

• *Forensic* applications such as corpse identification, criminal investigation, terrorist identification, parenthood determination, missing children, etc….

V. MULTIMODAL BIOMETRIC SYSTEMS

In recent times, multimodal fusion has gained much attention of many researchers due to the benefit it provides for various multiBiometric analyses tasks. The integration of multimodal biometric, their associated features, or the intermediate decisions in order to perform an analysis task is referred to as multimodal fusion. Multimodal Biometric data used for these tasks could be sensory (such as audio, video, image) as well as non-sensory (such as WWW resources, database). These Biometrics and related features are fused together for the accomplishment of various analysis tasks. Multimodal Biometric systems can be designed to operate in five integration scenarios:

1) Multiple sensors: The information obtained from different sensors for the same Biometric are combined. For example, optical, solid-state, and ultrasound based sensors are available to capture fingerprints.

2) Multiple biometrics: Multiple Biometric characteristics such as fingerprint and face are combined. These systems will necessarily contain more than one sensor with each sensor sensing a different Biometric characteristic. In a verification system, the multiple biometrics are typically used to improve system accuracy, while in an identification system the matching speed can also be improved with a proper combination scheme (e.g., face matching which is typically fast but not very accurate and then fingerprint matching which is slower but more accurate can be used for making the final identification decision).

3) Multiple units of the same biometric: Fingerprints from two or more fingers of a person may be combined or one image each from the two irises of a person may be combined.

4) Multiple snapshots of the same biometric: More than one instance of the same Biometric is used for the enrollment and/or recognition.

5) Multiple representations and matching algorithms for the same biometric: This involves combining different approaches to feature extraction and matching of the Biometric characteristic. This could be used in two cases. Firstly, verification or an identification system can use such a combination scheme to make a recognition decision. Secondly, an identification system may use such a combination scheme for indexing.

The fusion of multiple modalities can provide complementary information and increase the accuracy of the overall decision making process. The benefit of multimodal fusion comes with a certain cost and complexity in the analysis process [32]. Data fusion techniques can be grouped in five hierarchical levels in: i) Data in-Data out, ii) Data in-Feature out, iii) Feature in-Feature out, iv) Feature in-Decision out, v) Decision in-Decision out [33].

5.1 Modes of operation:

A multimodal Biometric system can operate in one of three different modes: serial mode, parallel mode, or hierarchical mode. In the serial mode of operation, the output of one Biometric trait is typically used to narrow down the number of possible identities before the next trait is used. This serves as an indexing scheme in an identification system. This is in contrast to a parallel mode of operation where information from multiple traits is used simultaneously to perform recognition. In the cascade operational mode, the various Biometric characteristics do not have to be acquired simultaneously. In the hierarchical scheme, individual classifiers are combined in a treelike structure [11].

5.2 Levels of fusion:

The literature shows that four possible levels of fusion are used for integrating data from two or more Biometric systems [34-37]. These are the sensor level, the feature level, the matching score level, and the decision level. The sensor level and the feature level are referred to as pre-mapping fusion (early fusion [32]) while the matching score level and the decision level are referred to as post-mapping fusion (late fusion [32]) [38]. In pre-mapping fusion, the data is integrated

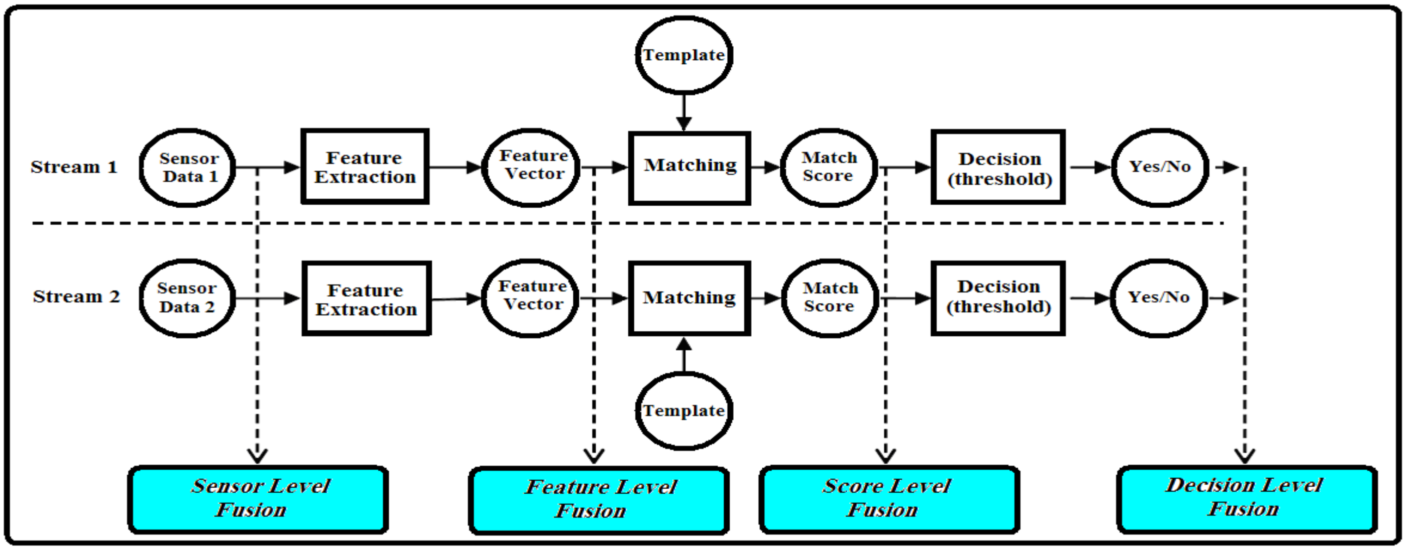

Fig. 2: Fusion levels in multimodal Biometric fusion [39]

before any use of classifiers, while in post-mapping fusion; the data is integrated after mapping into matching score/ decision space. Figure (2) shows the four possible fusion levels [39].

5.2.1 Pre-mapping fusion (early fusion)

The early fusion consist of fusion at the sensor level and fusion at the feature level, this fusion type stands for immediate data integration at the beginning of the processing chain [40].

5.2.1.1 Fusion at the sensor level: witch acquires the Biometric data [41]. The raw data, acquired from sensing the same Biometric characteristic with two or more sensors, is combined. Although fusion at such a level is expected to enhance the Biometric recognition accuracy [36, 42], it can not be used for multimodal biometrics because of the incompatibility of data from different modalities [36].

5.2.1.2 Fusion at the feature level: where the acquired data is processed to extract feature vectors [41]. Fusion at this level can be applied to the extraction of different features from the same modality or different multimodalities [36]. It is stated in [36, 42] that fusion at the feature level is expected to perform better in comparison with fusion at the score level and decision level. The main reason is that the feature level contains richer information about the raw Biometric data. However, such a fusion type is not always feasible [36, 42]. For example, in many cases the given features might not be compatible due to differences in the nature of modalities. Also such concatenation may lead to a feature vector with a very high dimensionality. This increases the computational load. It is reported that a significantly more complex classifier design might be needed to operate on the concatenated data set at the feature level space [36].

5.2.2 Post-mapping fusion (late fusion)

The late fusion consist of fusion at the matching score level and fusion at the decision level, this fusion type represents late integration at the end of the process [40].

5.2.2.1 Fusion at the matching score level: where feature vectors are compared against those in the template [41]. At this level, it is possible to combine scores obtained from the same Biometric characteristic or different ones. Such scores are obtained, The overall score is then sent to the decision module [43-44]. Currently, this appears to be the most useful fusion level because of its good performance and simplicity [45-46]. Fusion is normally at the score level. This is because the individual modalities provide different raw data types, and involve different classification methods for discrimination. To date, a number of score-level fusion techniques have been developed for this task [38-39]. This fusion level can be divided into two categories: *combination* and *classification*. In the former approach, a scalar fused score is obtained by normalizing the input matching scores into the same range and then combining such normalized scores. In the latter approach, the input matching scores are considered as input features for a second level pattern classification problem between the two classes of client and the Impostor [47].

The score level fusion techniques are divided into two main categories of *fixed rules* (rule-based) (AND, OR, Majority, Maximum, Minimum, Sum, Product and Arithmetic rules) Trained rules (learning-based) (Weighted Sum, Weighted Product, Fisher Linear Discriminate, Quadratic Discriminate, Logistic Regression, Support Vector Machine, Multi-Layer Perceptrons and Bayesian classifier) [48-49]. The fixed rules are also referred to as the nonparametric rules while the trained rules are referred to as the parametric rules [50].

5.2.2.2 Fusion at the decision level: In which the user's identity is established or a claimed identity is accepted or rejected [41]. In this approach separate decision is taken for each Biometric type at a very late stage. Other wise, When each matcher outputs its own class label (i.e., accept or reject in verification system, or the identity of a user in an identification system) [51-52].

VI. Past And Present Techniques For Face Recognition

Face recognition techniques can be broadly divided into three categories: methods that operate on intensity images, those that deal with video sequences and those that require other sensory data such as 3D information or infra-red imagery [53].

6.1 Face recognition methods for intensity images: consist of two main categories feature-based and holistic:

- *Feature-based approaches* first process the input image to identify and extract (and measure) distinctive facial features such as the eyes, mouth, nose, etc., and then compute the geometric relationships among those facial points, thus reducing the input facial image to a vector of geometric features.
- *Holistic approaches* attempt to identify faces using global representations, i.e., descriptions based on the entire image rather than on local features of the face. These schemes can be subdivided into two groups: *statistical, AI approaches, and Multiple Classifier Systems* [53].

6.2 Face recognition from video sequences: Since one of the major applications of face recognition is surveillance for security purposes, which involves real time recognition of faces from an image sequence captured by a video camera, a significant amount of research has been directed towards this area in recent years. A video-based face recognition system typically consists of three modules: one for detecting the face; a second one for tracking it; and a third one for recognizing it [54].

6.3 Face recognition from other sensory inputs: Though the bulk of the research on face recognition has been focused on identifying individuals from 2D intensity images, in recent years some attention has nevertheless been directed towards exploiting other sensing modalities, such as 3D or range data and infra-red imagery, for this purpose [55-56].

VII. Past And Present Techniques For Gait Recognition

Gait has played an important role in Biometric authentication due to its unique characteristics compared with other biometrics. Gait can be captured at a distance and without requiring the prior consent of the observed subject. Most other biometrics can be captured only by physical contact or at a close distance from the recording probe. Gait also has the advantages of being difficult to hide, steal, or fake. The techniques used for gait recognition can be divided into two categories: model-based methods and motion-based methods [57]. Model-based methods aim to explicitly model human body or motion, and they usually perform model matching in each frame of a walking sequence so that the parameters such as trajectories are measured on the model. The effectiveness of model-based methods, especially in body structure/motion modeling and parameter recovery from a walking video, is still limited allowing for current imperfect vision techniques (e.g., tracking and localizing human body accurately in 2D or 3D space has been a long-term challenging and unsolved problem). Further, the computational cost of model-based methods is relatively high [58-67]. However, motion-based approaches can be further divided into two main classes: The first class called the state space methods. These methods considered gait motion to be composed of a sequence of static body poses and recognized it by considering temporal variations of observations with respect to those static poses. The second class called the spatiotemporal methods. These methods generally characterized the spatiotemporal distribution generated by gait motion in its continuum [68-78].

VIII. Past And Present Techniques For Face And Gait Fusion

There are several previous works on fusion of face and gait Biometric. For example, *Shakhnarovich and Darrell* [79], develop a probabilistic approach to combining visual cues for human recognition, as well as for using multiple instances of face classifications, and demonstrated its performance on the example of integrated face and gait recognition. *Shakhnarovich et al.* [80], develop a view-normalization approach to multi-view face and gait recognition. An image-based visual hull (IBVH) is computed from a set of monocular views and used to render virtual views for tracking and recognition. For optimal face recognition, virtual cameras are placed to capture frontal face appearance, for gait recognition virtual cameras placed to capture a side-view of the person. Multiple cameras can be rendered simultaneously, and camera position is dynamically updated as the person moves through the workspace. *Kale et al.* [81] present a fusion of face and gait cues for the single camera. A view invariant gait recognition algorithm was employed for gait recognition.

A sequential importance sampling based algorithm was used for probabilistic face recognition from video. Decision fusion was employed to combine the results of proposed gait recognition algorithm and the proposed face recognition algorithm. *Geng et al.* [82] have proposed an adaptive multi-Biometric fusion, which dynamically adjusts the fusion rules to suit the real-time external conditions. *Zhou and Bhanu* [83] introduce a new video-based recognition method to recognize non cooperating individuals at a distance in video who expose side views to the camera. Information from two biometrics sources, side face and gait, was utilized and integrated for recognition. For side face, an enhanced side-face image (ESFI). For gait, the gait energy image (GEI).

Zhou and Bhanu [84] [85] present a new approach that utilizes and integrates information from side face and gait at the feature level. *Zhou and Bhanu* [86] introduce a new video based recognition method to recognize non-cooperating individuals at a distance in video, who expose side views to the camera. Information from two Biometric sources, side face and gait, is utilized and integrated for recognition. *Liu and Sarkar* [87] explore the possibility for using both face and gait in enhancing human recognition at a distance performance in outdoor conditions. *Lee et al.* [88] describe a method to recognize people using face and gait features in a novel yet natural way, using a single camera.

Table 1: Previous Works on fusion of face and gait Biometric

Work	**Biometrics**	**Data**	**Fusion Rules**
Shakhnarovich and Darrell [79] [80]	Frontal face and gait silhouette	12 subjects and 6 sequences per person [80]	Weighted SUM [80].
	frontal face and side gait from a 3D model	26 subjects and 14 sequences per person [79]	SUM, PRODUCT, MIN, MAX [79].
Kale et al. [81]	Frontal face and 'inverted Σ' gait	30 person	SUM, PRODUCT, Hierarchical method.
Geng et al. [82]	Face and gait in 5 view angles		Adaptive fusion
Zhou et al. [98] [83] [84] [85] [86]	Face profile and gait silhouette [98]	14 people (2 outdoor video sequences each)	SUM, PRODUCT, Hierarchical method
	Side face and gait silhouette [83] [84] [85]	45 people (2 to 3 video sequenceseach)	SUM, MAX, PRODUCT [83] Feature fusion [84] [85]
	Side face and gait [86]	46 people (2 video sequences each)	SUM, MAX, PRODUCT
Liu et al. [87]	Frontal face and side gait	70 people (6 video sequences each, 6 static face images each)	SUM, Bayesian, Confidence weighted Score SUM, Rank
Lee et al. [88]	Frontal face and trajectories of gait defining points on body	12 people (2 video sequences each)	Hierarchical method
Yazdanpanah et al. [89]	Frontal face and gait silhouette	360 images corresponding to 120 subjects from three databases including ORL face, USTB ear, CASIA gait databases	weighted (SUM and PRODUCT)
Zhang et al. [90]	Frontal face and gait in 8 view angles	60 volunteers in all including 32 male and 28 female subjects aged between [22-28]	SUM rule
Hou et al. [91]	Frontal face and side gait silhouette	31 individuals	SUM, MIN, MAX, PRODUCT
Hossain et al. [92]	Side face and gait	100 video sequences for 25 People. [19 males and 6 females]	Feature fusion
Shen et al. [93]	Side face and gait in 11 view angles	CASIA-B database (124 person)	Feature fusion
Huang et al. [94]	Frontal face and side gait	40 different subjects	Feature fusion
Shan et al . [95]	Frontal face and gait in 11 view angles	CASIA-B database (124 person)	Feature fusion
Lu et al. [99]	Frontal face and side gait silhouette	PIE and FERET face databases. USF gait database	Multilinear principal component analysis feature extractors
Huang et al. [96]	Frontal face and side gait silhouette	CMU, PIE, FERET, FRGC face databases, and USF gait database	image-to-class distance

Yazdanpanah et al. [89] propos a novel multimodal Biometric recognition system using three modalities including face, ear and gait, based on Gabor and PCA feature extraction method with fusion at matching score level. *Zhang and Wang* [90] consider the combination of face and gait biometrics from the same walking sequence to carry out gender recognition. *Hou and Li* [91] propos and use a new approach in which fusion of face and gait for human recognition at a distance in video sequences. Hidden Markov Models (HMM) and Fisherfaces method were primarily applied for face and gait classifier, respectively. And then, the results obtained from the two classifiers are utilized and integrated at match score level. *Hossain and Chetty* [92] propos a novel approach for ascertaining human identity based on fusion of profile face and gait Biometric cues the identification approach based on feature learning in PCA-LDA subspace, and classification using multivariate Bayesian classifiers allows significant improvement in recognition accuracy for low resolution surveillance video scenarios. *Shen et al.* [93] combine face and gait using Two-Direction Image Matrix based Principal Component Analysis (2DIMPCA) and Multiple Discriminant Analysis (MDA), a new approach for human recognition was presented based on integrating information from Gait and side face at the feature level. *Huang et al.* [94] demonstrate Eigenspace transformation(EST) based on Principal Component Analysis to be a potent metric in automatic face recognition and gait analysis.

Shan et al. [95] investigate a gender classification from human gaits in image sequences, a relatively understudied problem. Moreover, *Huang and Xu* [96] propose a new distance measure for face recognition and human gait recognition. Table 1 and Table 2 represent a comparative study among different techniques fusion for face and gait biometric.

IX. Summary

The fusion of Face and Gait is promising in real world application because of their individual characteristics. Compared with gait, face images are readily interpretable by humans, which allows people to confirm whether a biometrics

Table 2: represent comparative accuracy among previous different fusion techniques

Work	Fusion Rules			Accuracy: Face	Accuracy: Gait	Accuracy: Fusion
Shakhnarovich and Darrell [79] [80]	Faces integrated with PRODUCT rule[79]		MIN	0.72	0.67	0.8
			MAX			0.75
			MEAN			0.87
			PRUDUCT			0.87
	Faces integrated with MIN rule[79]		MIN	0.57	0.68	0.67
			MAX			0.72
			MEAN			0.84
			PRUDUCT			0.84
	No VH[80]		MAX	0.31	0.52	0.44
	VH[80]		MAX	0.8	0.87	0.91
Kale et al. [81]	Holistic Fusion		SUM	-	-	1
			PRUDUCT			1
	Hierarchical Fusion					0.97
Geng et al. [82]	Adaptive fusion			0.6167	0.65	0.8667
Zhou et al. [98] [83] [84] [85] [86]						
	SUM [83]			OSFI 0.733 / ESFI 0.911	GEI 0.933	0.933
	PRUDUCT[83]					0.956
	MAX[83]					0.933
	OSFI & *GEI* [84] [85]			OSFI 0.733 / ESFI 0.911	GEI 0.933	0.978
	ESFI & *GEI* [84] [85]					1
	OSFI & *GEI* [86]		SUM	OSFI 0.717 / ESFI 0.848	GEI 0.87	0.891
			PRUDUCT			0.848
			MAX			0.848
	ESFI & *GEI* [86]		SUM			0.913
			PRUDUCT			0.848
			MAX			0.848
Liu et al. [87]	inter-model combination		Rank SUM	0.68	0.81	0.85
			Weighted SUM	0.75	0.70	0.8
			Score SUM	0.70	0.75	0.92
			Bayesian Rule	0.70	0.76	0.88
	intra-model combination		Rank SUM	0.50	0.55	0.69
			Weighted SUM	0.59	0.52	0.72
			Score SUM	0.50	0.52	0.75
			Bayesian Rule	0.51	0.52	0.74
Liu et al. [89]	Min-max normalization		Weighted SUM	0.65 (Ear 0.825)	0.725	0.925
			Weighted PRUDUCT			0.9416
	Median-MAD normalization		Weighted SUM			0.8916
			Weighted PRUDUCT			0.9083
	z-score normalization		Weighted SUM			0.9583
			Weighted PRUDUCT			0.975
Zhang et al. [90]	SUM			0.9	0.9	0.9333
Shen et al. [91]	SUM			0.89	0.726	0.965
	PRODUCT					0.931
	MAX					0.91
	MIN					0.704
Hossain et al. [92]	*PCA* with Bayesian and 1-NN Classifier	Partial Gait	1-NN	0.9	0.55	0.7
			Bayesian-linear	0.8	0.4	0.7
			Bayesian-quadratic	0.9	0.65	0.7
		Full Gait	1-NN	0.9	0.7	0.85
			Bayesian-linear	0.8	0.6	0.6
			Bayesian-quadratic	0.9	0.65	0.9
	LDA with Bayesian and 1-NN Classifier	Partial Gait	1-NN	0.95	0.8	0.95
			Bayesian-linear	0.95	0.9	1
			Bayesian-quadratic	0.95	0.95	1
		Full Gait	1-NN	0.95	0.85	1
			Bayesian-linear	0.95	0.9	1
			Bayesian-quadratic	0.95	0.9	1
Shen et al. [93]	*GEI and OSFI Fusion*			0.9059	0.7366	0.9597
	GEI and ESFI Fusion			0.9059	0.7984	0.9785
Huang et al. [94]	EST+CST			0.925 (EST only) 0.9125 (CST only) 0.95 (EST+CST)	1 (EST only) 1 (EST+CST)	-------
Shan et al. [95]	SVM (Linear/Polynomial) classifier		Direct Feature Fusion	0.875	0.942	0.956
			CCA Feature Fusion			0.969
			PCA Feature Fusion			0.923
			PCA+LDA Feature Fusion			0.956
	SVM(RBF) classifier		Direct Feature Fusion	0.904	0.935	0.945
			CCA Feature Fusion			0.972
			PCA Feature Fusion			0.925
			PCA+LDA Feature Fusion			0.956
Huang et al. [96]	Image - To - Class			0.904 (CMU PIE) 0.9 (FERET) 0.71 (FRGC)	0.7917 (USF)	---------

system is functioning correctly, but the appearance of a face depends on many factors: incident illumination, head pose, facial expressions, moustache/beard, eyeglasses, cosmetics, hair style, weight gain/loss, aging, and so forth. Although gait images can be easily acquired from a distance, the gait recognition is affected by clothes, shoes, carrying status and specific physical condition of an individual. Biometric technology adds a new layer of security by ensuring secure identification and authentication. But biometric authentication systems like any other technology are also vulnerable to attacks such as transmission, replay and spoofing. There are many proposed methodologies that are used to defeat them. Multimodal biometric system is a major approach to defeat spoofing attacks. Various fusion levels and scenarios of multimodal systems are discussed. The fusion system is relatively more robust compared with the system that uses only one biometrics.

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