Invited Paper: People Identification and Tracking through Fusion of Facial and Gait Features

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Abstract. This paper reviews the contemporary (face, gait, and fusion) computational approaches for automatic human identification at a distance. For remote identification, there may exist large intra-class variations that can affect the performance of face/gait systems substantially. First, we review the face recognition algorithms in light of factors, such as illumination, resolution, blur, occlusion, and pose. Then we introduce several popular gait feature templates, and the algorithms against factors such as shoe, carrying condition, camera view, walking surface, elapsed time, and clothing. The motivation of fusing face and gait, is that, gait is less sensitive to the factors that may affect face (e.g., low resolution, illumination, facial occlusion, etc.), while face is robust to the factors that may affect gait (walking surface, clothing, etc.). We review several most recent face and gait fusion methods with different strategies, and the significant performance gains suggest these two modality are complementary for human identification at a distance.

1 Introduction

Human identity recognition is fundamental to human life, and the technology of human identification and tracking from a distance may play an important role in crime prevention, law enforcement, search for missing people (e.g., missing children or people with dementia), etc. Nowadays, CCTV cameras are widely installed in public places such as airports, government buildings, streets and shopping malls for the afore-mentioned purposes. In 2013, the British Security Industry Authority (BSIA) estimated there are up to 5.9 million CCTV cameras nationwide, and that is around 1 every 11 people [11]. Because of the need for sufficient manpower to supervise such a large number of CCTVs, the need for automatic human identification systems is acute.

Out of various biometric traits (e.g., fingerprint, iris, palmprint, voice, face, gait, etc.), face recognition is deemed as one of the most popular one, which can be performed at a distance without subject's cooperation. CCTV footage or images containing face information are often released to the public for the identification of the perpetrators. For example, in June 2014, British Transport Police (BTP) released CCTV in hunt for angle-grinder gang, who broke the ticket machines at railway stations in UK, as shown

(a) (b)

Fig. 1. (a) CCTV images of the angle-grinder gang, released by BTP [4] (b) CCTV images of the two perpetrators in Boston Marathon bombings, released by FBI [69]

(a) (b)

Fig. 2. (a) CCTV images for the robbery case in Denmark [57], left: the perpetrator, right: the suspect; (b) CCTV images for the burglary case in UK [34], left: the perpetrator, right: the suspect.

in Fig. 1(a). In April 2013, Federal Bureau of Investigation (FBI) released the face images of the two perpetrators in Boston Marathon bombings [69], as shown in Fig.1(b). However, for automatic systems, factors like illumination, resolution, blur, occlusion (e.g., sunglasses), or pose may make the recognition unreliable.

Recently, a number of reports (e.g.,[57][34]) suggested that behavioral biometrics, gait recognition, can be used for human identification from CCTV footage. In [57], based on a checklist for forensic gait analysis, Larsen et al. managed to identify a bank robber in Denmark by matching surveillance footage, as illustrated in Fig. 2(a). Fig. 2(b) shows a gait recognition scenario in UK where a burglar was identified through gait analysis from a podiatrist [34]. These pieces of gait-based evidences proved their usefulness by providing incriminating evidence, leading to convictions in a court of law. However, similar to automatic face recognition, covariate factors like camera viewpoint, carrying condition, clothing, etc. may limit the performance of the automatic gait recognition systems.

It was shown that combining multiple biometric traits may reduce the error rate effectively[36], [59], [74]. In the context of automatic human identification at a distance, it is natural to fuse gait and face, which can be acquired from the same camera. They may be complementary traits for recognition since gait is less sensitive to the factors that affect face recognition, such as low resolution, illumination, etc. while face is robust to covariates that affect gait recognition, e.g., carrying condition, walking surface, clothing, etc. Although there are various face/gait recognition algorithms, research on gait and face fusion is still at its early stage, which will be reviewed in this paper. The rest of this paper is organized as follows. In section 2 and 3, we introduce automatic remote face/gait recognition and the limitations. In section 4, we review several gait and face fusion strategies and analyze their performance. Summary and further research directions on gait+face fusion will be provided in section 5.

2 Automatic Face Recognition

Automatic face recognition is one of the most active research topics in computer vision and pattern recognition. Over the past decades, major advances occurred in automatic face recognition, yet the recognition accuracy of faces captured at a distance is still unsatisfactory. It is challenging due to the large intra-class variations caused by 1) less controlled environment, e.g., with factors like low resolution, blur, illumination, etc.; 2) non-cooperative subjects, e.g., with factors like pose, occlusion (e.g., sunglasses, scarf, hat, veil), etc.

2.1 Face Recognition Algorithms

A gamut of face recognition algorithms were proposed to tackle the effect of the aforementioned factors.

Low resolution. There are two directions to handle the problem of low resolution. 1) *super-resolution (SR) based methods* [24],[38],[27],[28],[32], which reconstruct high-resolution images from low resolution images for visual enhancement. After applying SR, a higher resolution image can be obtained and used for recognition. One major drawback of SR is that significant reconstruction artifacts may be introduced, thus hampering the recognition accuracy. 2) *Non-SR based methods*, which include support vector data description (SVDD) [46], coupled mappings (CMs) [47], multi-dimensional scaling [8], class specific dictionary learning [63], etc.

Image blur. There are two classes of blur that affect face images: focus blur and motion blur. A focus is the point where lights originating from a point on the object converge. When the light reflected by an object diverges, a out-of-focus image will be generated by the sensor, resulting in the blur effect. The work in [31] analyzed the impact of out-of-focus blur on face recognition performance. Motion blur, however, occurs when exposure time is not brief enough due to the rapid object moving or camera shaking. There are two main categories of approaches for improving the quality of the blurred face images: 1) *blurred image modelling* using methods such as subspace analysis [55] or sparse representation [82], and 2) *blur-tolerant descriptor based methods* which attempt to extract blur insensitive features such as Local Phase Quantization (LPQ) [1],[25].

Illumination variations. There are three categories of approaches to handle illumination variations: 1) *illumination normalization* [12],[62],[9] which seeks to suppress the illumination variations either by image transformations or by synthesising an unaffected image, 2) *illumination invariant representation* [14],[2],[71] which attempts to extract features invariant to illumination changes, and 3) *illumination variation modelling*[16],[58],[3] which is based on the theoretical principle that the set of images of a convex Lambertian object [45]obtained under a wide variety of illumination conditions, can be approximated by a low-dimensional linear subspace, in which the recognition can be performed [5].

Pose variations. Early approaches [85] include: 1) *multi-view method* [7] which is an extension of the conventional frontal face recognition where a set of images depicting the object from multiple angles are required, 2) *pose variation modelling* [6] which assumes that the 3D shape of an object can be represented by a linear combination of prototypical objects, and 3) *linear subspace method* [56] which represents each person in the gallery by a parametric linear subspace model. Recently, with the development of novel 3D sensors, 3D-based approaches achieve successful performance when addressing pose variations [84].

Occlusion. There are three main categories of approaches for occlusion handling: 1) *reconstruction-based approaches*, that formulate the recognition of occluded faces as a reconstruction problem [37],[79],[54],[83],[76]. An occluded query face is reconstructed by a linear combination of gallery images before being assigned to the class with the minimal reconstruction error. 2) *local matching based approaches* [52],[67], [66], [48], [77], [78], [75] that extract features from the local areas of a face (e.g., patches), such that the affected and unaffected parts of the face can be analyzed separately. To minimize matching errors of the occluded parts, several strategies can be used such as local space learning [66],[52],[67], multi-task sparse representation learning [48] or voting [75]. 3) *occlusion-insensitive feature based approaches* [10],[70],[88] that utilize features such as line segments [10], image gradient orientation (IGO) difference [70] and the Gabor phase (GP) difference [88] which were shown to be robust to occlusion.

2.2 Open Issues in Face Recognition

As afore-introduced, a plethora of algorithms for handling different types of factors have been proposed. However, in real-world face recognition scenarios, these factors can be coupled. For example, low resolution and blur effects are often coupled with other uncontrolled variations such as pose, illumination or occlusion, making the tasks of automatic face recognition difficult. When a face is fully occluded (e.g., Fig. 2(a)) or at a long distance, most of the afore-mentioned methods would become useless. In this case, the behaviorial biometric trait, such as gait, may be of great aide.

3 Automatic Gait Recognition

Existing gait recognition algorithms can be roughly divided into two categories: model-based and appearance-based approaches. Model-based methods (e.g.,[17]) aim to model the human body structure for recognition, while appearance-based approaches can perform classification regardless of the underlying body structure. Although model-based methods may perform well in some challenging cases (e.g., when the view change is large [17]), they generally have lower performance than appearance-based methods.

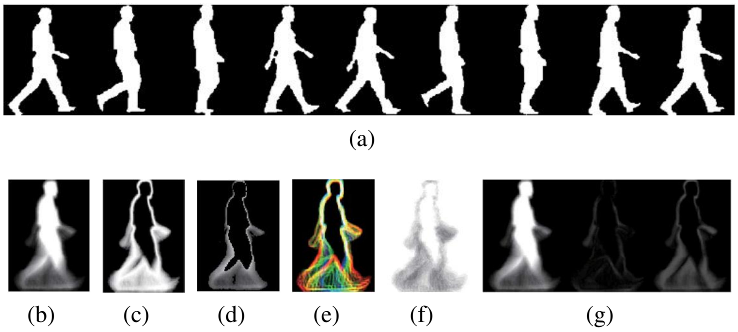

Fig. 3. Gait representations for a subject on the OU-ISIR-LP dataset [35], (a) the original gait silhouettes (b)-(g) the 6 period-based feature templates from left to right: GEI [26], GEnI [39], MGEI [40], CGI [72], GFI [64], and FDF (with 0, 1, and 2 times frequency elements)[51]

One major reason is that when affected by self-occlusion, low resolution or other factors, it is often difficult to estimate the body structure features precisely, and in this case they only provide limited information for recognition. As such we focus on introducing appearance-based methods in this paper.

3.1 Gait Feature Templates

In early works, researchers formulated gait recognition as a three dimensional video classification problem, based on the preprocessed gait data after background substraction, silhouette binarization and alignment, etc. For example, Sarkar et al. proposed the gait recognition baseline method, which applies spatial-temporal correlation on the gait silhouettes [60]. Wang et al. used spatial-temporal correlation on the gait features extracted through PCA [73]. These algorithms often require significant computational complexity, and tend to be less robust to segmentation errors.

To deal with these dilemmas, period-based gait feature templates were proposed in recent works that encode the information of the frames from a gait cycle into a single image and formulate gait recognition as a two dimensional image classification problem. On the OU-ISIR-LP dataset, consisting of more than 3000 subjects, Iwama et al. [35] conducted a study on six popular period-based feature templates including Gait Energy Image (GEI)[26], Gait Entropy Image (GEnI) [39], Masked GEI based on GEnI (MGEI) [40], Chrono-Gait Image (CGI) [72], Gait Flow Image (GFI)[64], and Frequency-Domain Feature (FDF) [51] (as shown in Fig. 3). The results showed that when there are no covariates, GEI-based template can generally yield the best performance. However, when the walking condition changes, directly applying GEI matching makes the classification prone to errors. Fig. 4 shows some GEIs of one subject in walking conditions with different covariates, from the USF gait dataset [60]. It follows that covariates may significantly change the human appearance, thus giving rise to recognition difficulties. It is important to extract covariate-insensitive features for robust gait recognition.

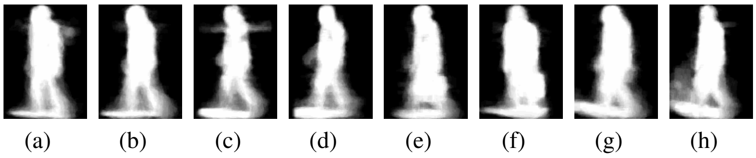

Fig. 4. GEIs of one subject walking in different walking conditions from the USF gait dataset [60]. (a) is the GEI in normal condition. (b)-(h) are the GEIs under the influences of (b) viewpoint, (c) walking surface, (d) viewpoint and walking surface, (e) carrying condition, (f) carrying condition and viewpoint, (g) elapsed time, shoe type, and clothing, (h) elapsed time, shoe type, clothing, and walking surface.

3.2 Gait Feature Extraction and Classification

Covariates can be roughly divided into three categories: 1) subject-related, e.g., shoe type, carrying condition, speed, clothing, etc., and 2) environmental, e.g., walking surface, elapsed time, etc. 3) camera viewpoint. To reduce such effects, various feature extraction and classification methods have been proposed.

Shoe, (small changes in) view, and carrying condition. Based on concatenated GEIs, Han and Bhanu utilized PCA and LDA for feature extraction [26]. By using two subspace learning methods, coupled subspaces analysis (CSA) and discriminant analysis with tensor representation (DATER), Xu et al. extract features directly from GEIs[81]. Both methods demonstrate their effectiveness against several simple covariates such as shoe, and (small changes in) camera viewpoint. In [68], Gabor-filtered GEIs were used as the gait feature template, and general tensor discriminant analysis (GTDA) was proposed for feature extraction. The extracted Gabor features demonstrated their robustness in tackling the carrying condition covariate.

Walking speed. In order to handle variations in walking speed, the feature template head and torso image (HTI) was proposed, which removes the unstable leg parts from silhouettes [65]. Kusakunniran et al. proposed higher-order derivative shape configuration (HSC) to extract speed-invariant gait features from the procrustes shape analysis (PSA) descriptors [42]. Based on the HSC framework, a differential composition model (DCM) was proposed, which can adaptively assign weights to different body parts [43]. Although it was claimed that DCM is insensitive to large speed changes, it requires an additional training data that covers all the possible speeds.

Walking surface. By using a "cutting and fitting" scheme, Han and Bhanu [26] generated synthetic GEIs to simulate the walking surface effect. By claiming that walking surface may cause spatial misalignment, Image-to-Class distance was utilized in [33] to allow feature matching to be carried out within a spatial neighborhood. By using the techniques of universal background model (UBM) learning and maximum a posteriori (MAP) adaptation, Xu et al. proposed the Gabor-based patch distribution feature (Gabor-PDF) [80]. Significant performance gain can be achieved against walking surface by these methods [26],[33],[80].

Elapsed time and clothing. Most existing algorithms perform unsatisfactorily when elapsed time is taken into consideration, as elapsed time potentially also includes the changes of clothing, walking conditions, etc. In [53], by fusing gait features, Matovski et al. studied the effect of elapsed time on a small gait dataset and found that short term elapsed time does not affect the recognition significantly. They claimed that clothing may be the most challenging covariate [53]. Based on a newly constructed gait dataset consisting of 32 different clothes combinations, Hossain et al. proposed an adaptive scheme for weighting different body parts to reduce the effect of clothing [50]. However, this method requires an additional training data that covers all the possible clothes types, which is less practical in real-world applications.

General covaraite-invariant gait recognition. From the perspective of effect, Guan and Li contended that most of the covariates only affect parts of human silhouettes (with unknown locations)[20]. They proposed an effective framework based on the concept of the random subspace method (RSM) [29]. From the perspective of learning-based methods, they claimed that overfitting the less representative training data is the major problem in gait recognition [21]. They combined a large number of RSM-based weak classifiers to reduce the generalization errors [21]. Experimental results suggest that RSM is robust to a large number of covariates such as shoe, (small changes in) camera viewpoint, carrying condition[21], clothing[22], speed[20], frame-rate[18],[19], etc.

3.3 Open Issues in Gait Recognition

As introduced above, a large number of algorithms have been proposed to tackle different types of covariates. However, gait is a relatively weak trait and the performance can be limited when intra-class variations are extremely large [36]. With gaits taken from the lateral view, the recognition accuracies are still low when facing covariates like elapsed time, walking surface, etc. For cross-view gait recognition, it is challenging when the view difference (between gallery and probe) is large (e.g., greater than 36°)[44], which can change the gait appearance significantly.

4 Fusing Gait and Face

When performing human identification at a distance without the subject's cooperation, large intra-class variations can affect the performance of gait/face recognition systems substantially. Large intra-class gait variations may be attributed to walking surface, clothing, etc., while face recognition may suffer from low resolution, facial occlusion, etc. Multimodal fusion is a solution to reduce the error rate, and it has been widely applied to the biometrics field [36], e.g., face+fingerprint[59], face+iris[74].

Compared with remote human identification based on gait or face recognition, the technology of fusing gait and face is still at the early stage. We will introduce several recent works on fusing these two modalities. In [61], after applying canonical view rendering technique (CVRT), face and gait information from multiple camera views were fused at the score level. Performance improvement is significant by fusing these two modalities in a multiple camera environment. In [41], Kale et al. showed that even in single camera environment, directly combining the scores of face and gait can boost the overall performance. Based on population Hidden Markov model (pHMM), Liu and Sarkar selected gait stances for recognition in the outdoor environment [49]. Extensive experimental results were reported on handling variations in the walking surface

Table 1. The performance of gait and face fusion algorithms

Algorithm	Condition	Gait	Face	Fusion	Type	Δ	#Subjects
CVRT[61]	Multi-cameras	68%	72%	89%	score-level	23.6%	26
View-invariant[41]	Outdoor+C1	60%	94%	100%	score-level	6.3%	30
Distance-driven[15]	view 0°	82.5%	58.8%	90.0%	score-level	9.1%	20
	view 45°	82.5%	77.5%	95.0%	score-level	15.2%	20
	view 90°	80.0%	70.0%	90.0%	score-level	12.5%	20
pHMM[49]	Outdoor+C2	39%	40%	71%	score-level	77.5%	70
	Outdoor+C3	30%	40%	50%	score-level	25%	70
OSFI+GEI [87]	C4	82.2%	64.4%	82.2%	score-level	0%	45
ESFI+GEI [87]	C4	82.2%	80.0%	88.9%	score-level	8.2%	45
OSFI+GEI [86]	C4	82.2%	64.4%	86.7%	feature-level	5.5%	45
ESFI+GEI [86]	C4	82.2%	80.0%	91.1%	feature-level	10.8%	45
AMP [30]	Outdoor+C5	53.6%	54.6%	65.2%	score-level	19.4%	122
Multimodal-RSM[23]	C6	88.2%	74.0%	95.6%	score-level & decision-level	8.4%	155

Δ denotes the performance improvement. C1-C6: Covariate factors. C1: (small changes in) view; C2: walking surface; C3: elapsed time; C4: clothing; C5: (small changes in) view, shoe, carrying condition, walking surface, elapsed time, and clothing; C6: shoe, carrying condition, elapsed time, and clothing.

and elapsed time covariates, based on different fusion strategies. They found performance is higher when fusing gait and face than intra-model fusion (i.e., face+face or gait+gait) [49]. By claiming that the reliability of face and gait varies with different subject-camera distances, Geng et al. proposed an adaptive score-level fusion scheme [15]. The weights of the face score and gait score are distance-driven. It was experimentally shown to outperform score-level fusion with fixed weights in the multi-view environment. In [87], Zhou and Bhanu performed a score-level fusion of gait and the enhanced side face image(ESFI). Compared with original side face image (OSFI), they found that improving face image quality can further enhance the fusion performance. They further applied feature-level fusion by concatenating the ESFI and gait [86]. In [30], alpha matte preprocessing (AMP) was used by Hofmann et al. to segment gait and face images with improved qualities, before score-level fusion. Recently, Guan et al. proposed the multimodal-RSM framework [23]. In RSM systems, weak classifiers with lower dimensionality tend to have better generalization ability [29]. However, they encounter the underfitting problem if the dimensionality is too low. In [23], face was used as ancillary information to strengthen the gait-based weak classifiers, before the majority voting was carried out among these updated classifiers. Significant performance gains are achieved in tackling the most challenging elapsed time covariate, which also includes the changes of clothing, carrying condition, shoe, etc.

We report the performance of the afore-mentioned fusion algorithms in Table 1. For multiple results based on different fusion rules, only the best ones are reported. As listed in Table 1, fusing gait and face can yield significant performance improvement, given by $\Delta = (Fusion - max(Face, Gait))/max(Face, Gait)$. We find that: 1) Feature-level fusion yields higher Δ than score-level fusion, although more experiments on larger dataset have to be conducted to support the final conclusion. 2) Fusing gait and face can effectively tackle difficult covariates (e.g.,[49],[30],[23]) like clothing, walking surface, elapsed time, etc. However, to the best of our knowledge, without a multi-view gallery to facilitate in-depth investigations, how (large changes in) camera viewpoint covariate should be handled remains an open question. 3) Generally, Δ is higher when gait and face have similar accuracies (e.g.,23.6% for [61], 77.5% for [49],19.4% for [30]), and vice versa (e.g., 6.3% for [41], 0% for [87], 5.5% for [86]). To improve the overall fusion performance, it is important to improve the performance of relatively weak modality (e.g., [87],[86]), or employ an adaptive mechanism (e.g., [15]).

5 Summary and Further Research Directions

In this paper, we review the contemporary (face, gait, and fusion) algorithms for human identification at a distance. Significant performance gain can be achieved when gait and face modalities are combined to tackle the hard problems in less controlled environments. Research on fusing these two modalities is in its infancy, and we propose the following possible lines of investigation. 1) *Fusion strategy*: Most existing works are based on score-level fusion, and it is desirable to explore the effectiveness of other fusion strategies such as feature-level fusion, decision-level fusion, rank-level fusion, etc. 2) *Adaptive mechanism*: the work in [15] used an adaptive weighting scheme based on different subject-camera distances. In the future, one can extend this scheme to a quality-driven one. For example, gait will have a high weight when face is occluded (e.g., Fig. 2(a)), while face will have a high weight when gait information is unavailable (e.g., Fig. 1(b)). Moreover, before the fusion, different face/gait algorithms should be adaptively chosen for the most suitable scenarios. 3) *Segmentation quality*: the quality for gait or face is important. The works in [86],[87] suggest that the performance of fusion can be improved on higher quality face images. In [30], alpha mattes segmentation is used for higher gait quality. In the future, more advanced segmentation methods (e.g.,the superpixels-based method [13]) will be of great aide.

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