Exploratory Factor Analysis of Gait Recognition

Imed Bouchrika & Mark S. Nixon
Department of Electronics and Computer Science
University of Southampton, SO17 1BJ, UK
{ib04r, msn}@ecs.soton.ac.uk

Abstract

Many studies have now shown that it is possible to recognize people by the way they walk. As yet there has been little formal study of the effects of covariates on the recognition process. We show how these factors can separately affect the walking pattern. Further we assess the contribution and discriminatory significance of the gait dynamics used for recognition. Based on a covariate-based probe dataset of 440 samples, a high recognition rate of 73.4% is achieved using the KNN classifier. This is to confirm that people identification using dynamic gait features is still perceivable with better recognition rate even under the different covariate factors.

1. Introduction

Surveillance technology is of increasing us in modern society. This is largely due to the vital need to provide a safer environment. Because of the rapid growth of security cameras and need for automated analysis, the deployment of biometric technologies becomes important for the development of automated visual surveillance systems. The suitability of gait recognition for surveillance systems emerges from the fact that gait can be perceived from a distance as well as its non-invasive nature. Although gait recognition is still a new biometric and is not sufficiently mature to be deployed in real world applications such as visual surveillance, it overcomes most of the limitations that other biometrics suffer from such as face, fingerprints and iris recognition which can be obscured in most situations where serious crimes are involved.

Gait is a new biometric with a number of benefits arising from its non-intrusive nature and the possibility of use at a distance [21, 3, 7, 9, 10] . Hence, the analysis of the different covariate factors becomes essential to quantify the intrusiveness of gait recognition which will be the focus of this paper. The covariate factors can be related either to the subject as for the case when a subject smiles for face recognition, or related to the environmental conditions such as lighting, nature of the ground or camera setup. Gait is also affected by different covariate factors including footwear, clothing, injuries, age, walking speed, and much more akin with other biometrics. In fact, the effects of the different covariates for gait analysis and recognition have not been investigated much by medical and other researchers [10], This is mainly due to the lack of availability for databases, as well as the availability of automated systems which would help for the extraction of gait features. Moreover, the complexity of earlier model-based approaches has precluded their deployment for this analysis.

The effects of covariate factors on the performance of gait recognition using computer vision methods have been investigated by only one recent major research study by Sarkar *et al.* [15]. Sarker described a baseline algorithm for gait recognition based on the temporal correlation of silhouette data. The algorithm is evaluated on a set of twelve experiments in order to examine the effects of the different covariates including viewpoint, footwear, walking surface, time and carrying conditions. However, their work lacks exploratory analysis of the different gait features under covariate data due to the use of the silhouette approach. In this research, a full investigation is carried out to explore the covariate effects on gait recognition using dynamic-related features derived via model-based method. The covariate factors includes footwear, clothing, carrying conditions and walking speed. Furthermore, we assess the contribution and discriminatory significance of the different dynamic (gait-related) features used for gait recognition. The previous covariate studies [15] have used the NIST data which combines covariates. We now study the independent effect of covariates using the SOTON covariate database where only one covariate is changed between sequences (except time which affects all sequences equally).

2. Data Acquisition for Covariate Analysis

In order to study the exploratory effects of covariate factors on gait recognition, a gallery dataset of 160 video sequences is taken from the SOTON gait database. The galley consists of 20 different walking subjects with 8 sequences for every individual recorded without covariate effects. Further, a probe dataset of 440 video sequences is collected from the Southampton Covariate Database. The dataset consists of ten different walking subjects with eight males and two females. Each subject is recorded from the sagittal view walking at eleven different scenarios, including normal walking. Four video sequences are taken for each situation. The different recorded scenarios are aimed to investigate the following factors:

- ***Footwear:*** flip-flop, trainer, bare-feet, boots.
- ***Clothing:*** coat, trench coat.
- ***Carrying Conditions:*** barrel bag, handbag.
- ***Walking Speed:*** normal, quick and slow walking.

To extract the gait features of walking subjects from the covariate dataset, we applied the model-based method described in [4] to automate the extraction process of the joint trajectories. Spatial motion templates describing the motion of the joints are derived by manual gait analysis and used to aid the markerless extraction of the joint positions. A recursive evidence gathering algorithm is employed for the extraction process whereby spatial model templates for the human motion are presented in a parameterized form using the Elliptic Fourier Descriptors described in equation (1):

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} cos(\alpha) & -sin(\alpha) \\ sin(\alpha) & cos(\alpha) \end{bmatrix} \begin{bmatrix} F_x(t) * s_x \\ F_y(t) * s_y \end{bmatrix} \tag{1}$$

where α is the rotation angle, s_x and s_y are the scaling factors across the horizontal and vertical axes respectively. a_0 and b_0 define the position of the shape's centre. $F_x(t)$ and $F_y(t)$ are computed using equation :

$$\begin{aligned} F_x(t) &= \sum_{k=1}^{n} a_{x_k} cos(kt) + b_{x_k} sin(kt) \\ F_y(t) &= \sum_{k=1}^{n} a_{y_k} cos(kt) + b_{y_k} sin(kt) \end{aligned} \tag{2}$$

where a_{x_k},a_{y_k}, b_{x_k} and b_{y_k} are the set of the elliptic coffecients which can be computed by a Riemann summation [1]. Gait knowledge is exploited via heel strike extraction to reduce the the parameter space dimensionality and therefore reduce the computational load of the evidence gathering algorithm being used in the extraction process.

In order to identify a subject by their gait, we derive the angular measurements as well as the trunk spatial displacement which best describe the gait kinematics. The use of angular motion is very common in gait analysis and recognition. The angles of the joints including the hip and the knee; are considered the most important kinematics of the lower limbs. Feature selection is employed to derive as many discriminative cues as possible whilst removing the redundant and irrelevant gait features which may degrade the recognition rate. It is practically infeasible to run an exhaustive search for all the possible combinations of features in order to obtain the optimal subset for recognition due to the high dimensionality of the feature space. For this reason, we employed the Adaptive Sequential Forward Floating Selection (ASFFS) search algorithm [16]. The algorithm uses a validation-based evaluation criterion which is proposed to find the subset of features that minimises the classification errors as well as ensure good separability between the different classes. In contrast to the voting scheme used in the KNN, the evaluation function uses different weights w to signify the importance of the most nearest neighbours. The probability score for a sample s_c to belong to class c is expressed in the following equation (3):

$$f(s_c) = \frac{\sum_{i=1}^{N_c-1} z_i w_i}{\sum_{i=1}^{N_c-1} w_i} \tag{3}$$

where N_c is the number of instances in class c, and the weight w_i for the i^{th} nearest instance is inversely related to proximity as:

$$w_i = (N_c - i)^2 \tag{4}$$

The value of z_i is defined as:

$$z_i = \begin{cases} 1 & \text{if } nearest(s_c, i) \in c \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

such that the $nearest(s_c, i)$ function returns the i^{th} nearest instance to the sample s_c. The Euclidean distance metric is employed to find the nearest neighbours.

3. Covariate Analysis for Gait Recognition

In order to quantity the covariate effects on the performance of gait recognition, the Correct Classification Rate (CCR) is computed using the K-nearest neighbour (KNN) classifier with the Leave-one-out cross-validation rule. Based on the subset of features derived using the Feature Selection algorithm, we have achieved a high recognition rate of 95.75% for the value of $k = 5$ using the set of 160 video sequences from the covariate-free dataset. This is achieved using solely features describing purely the dynamics of the locomotion process. Furthermore, we have probed 440 samples from the covariate dataset against the gallery database. A recognition rate of 73.4% is achieved for all the covariate factors including footwear, clothing, load carriage and walking speed which is higher when compared to the low recognition rates reported by Phillips *et al.* [15] using the silhouette-based method.

The Cumulative Match Score curves showing the comparative results are shown in Figure (3). Phillips reported a CCR of 57% for Data (I) with load carriage and footwear covariates whilst a CCR of 3% is achieved for Data (II)

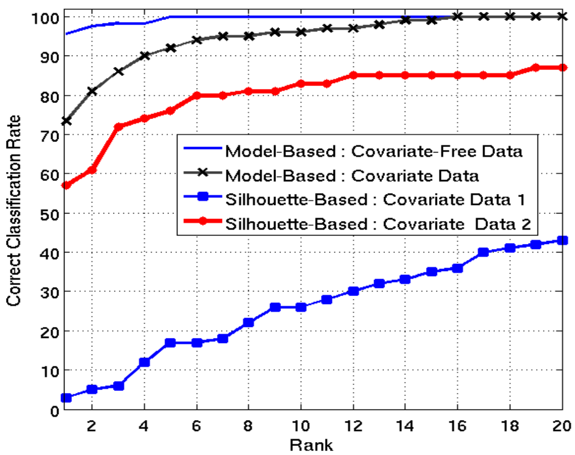

Figure 1. The Cumulative Match Score Curves for the Classification Results.

with the following covariates : time, footwear, and clothing. Time has been shown [15, 19] to play a major part in reducing recognition capability by gait. Using a silhouette based approach Veres showed that this could be redressed by fusing those parts of the gait signature which are invariant with time. In this way the overall CCR could be improved from 23 to 27% [20]. By modelling the change in feature space (by using linear interpolation) the recognition rate with variation in time was improved from 23% to 65% [19]. Both of these are considerably improved over the 3% achieved by Phillips et al [15]. Given the limited data on time, Veres' study and the depth of her results, the time factor is included implicitly and not considered further here.

3.1. The Footwear Effects

The gait pattern is affected by the different footwear as people are observed to walk differently when wearing trainers as to when wearing flip flops. This has been confirmed by research carried out by Dobbs *et al.* [5]. Based on their experimental results, it was reported that the stride and cadence parameters of the walking pattern are affected by footwear as opposed to walking with barefeet. Moreover, recent studies [11] showed that changing the footwear texture causes changes in the gait pattern. In the studies carried out by Phillips *et al.* [15] to investigate the footwear effects on the performance of gait recognition, a high recognition rate of 78% is reported using a silhouette-based method. This is because of the fact that body-related or silhouette-based features are almost invariant to the different footwear.

In order to explore the effects of footwear on the performance of people identification using dynamic gait features, a number of experiments are carried out for subjects wearing a variety of different footwear including flip flop, boots and normal shoes. In addition, subjects are also recorded walking with barefeet. For each of the footwear-related factors, 40 video sequences are processed to derive gait signatures based on the dynamic gait features. To assess the classification performance, subjects are validated against the gallery dataset which consists of 160 gait signatures for 20 different subjects recorded with no covariate effects.

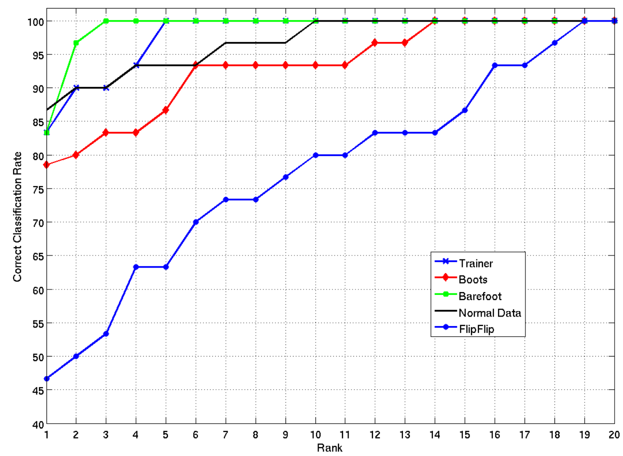

Figure 2. Classification Results for the Footwear Covariates.

The classification results for the footwear covariates are expressed using the cumulative match score as shown in Figure (2). The recognition rates for the trainer and boots cases are observed to be almost the same as the normal case with achieved rates of 78%, 83.33% and 86.67% for the boots, trainer and normal shoe cases respectively. When subjects are assessed walking with barefeet, the same gait recognition rate is achieved as the other footwear factors including trainers, boots and normal shoes with a reported CCR of 83.33%. This suggests that the dynamic gait features for people identification are not affected largely with the different footwear. However, the human gait is observed to vary much when people walk with flip flops as the recognition rate drops largely to 46%. This is likely due to the comfortability issue with flip flops which are not commonly to worn in the UK, and the mode grip differs in that the pillar in the flip flop is clenched between the big toe and its neighbour. Further, there is no rear part of the shoe so this must be compensated when walking.

3.2. The Clothing Effects

The clothing effects on human gait as well as the posture and balance can be considerably important. In [13], Punakallio *et al* showed that suits wore by fire-fighters have significantly impaired their postural and functional balance. In another study by Egan *et al* [6], it was revealed that clothing properties such as weight can be another factor which have effects on balance and gait of people. Furthermore, Rahmatalla *et al* [14] concluded that restrictive clothing can impose constraints on the relative joint angle limits of the walking subject and therefore affect their gait pattern. In the study carried out by Phillips *et al.* [15] for gait recognition using the silhouette-based approach, the recognition rate dropped sharply to 3% for the following combined covariate factors: time, footwear and clothing.

(a) (b) (c)

Figure 3. Clothing Covariate Factors: (a) Normal Clothing (b) Coat (c) Trench Coat

In order to investigate the effects of clothing on the human gait and people identification using gait, we have performed a number of experiments on people wearing different clothing including coat, trench coat and their normal clothing as depicted in Figure (3.2). For each of the clothing-related factors, the gait signature is derived from the dynamic features for 10 subjects with 4 sequences for every individual. The classification performance is assessed as the same way as the footwear case by matching the probe set against the gallery dataset. Figure (4) shows the cumulative match score curves for the gait classification experiments. The correct classification rate for the coat is almost the same as the normal case with reported rates of 83.33% and 86.67% respectively. However for the case of the trench coat, the recognition decreases largely to 60%. This is mainly due to nature of the clothing which is distracting the gait dynamics as well as the occlusion of the knee and hip joints faced during the extraction of gait features. This does not occur with the trousers which adhere to the front of the leg, but could equally occur with the female clothing (eg. a chardor).

3.3. Load Carriage

The impact of load carried on human gait and body posture has been extensively investigated for different purposes including medical, training and military [8] use but rarely for the purpose of gait recognition. In [12], Pascoe *et al* carried out a number of experiments to examine the effects of carrying bags on gait kinematics for youth people. Pascoe reported that the stride length decreases whilst the gait

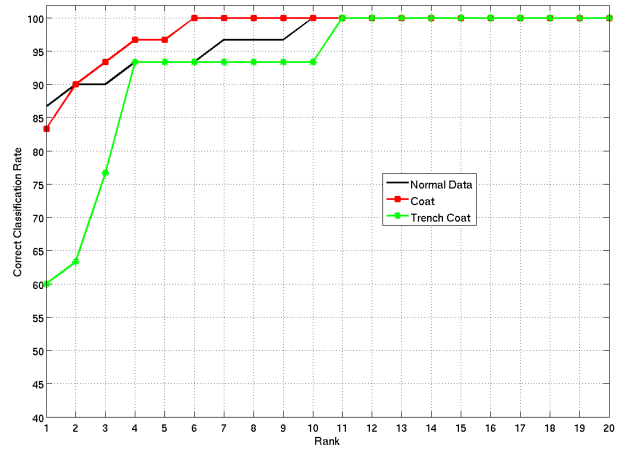

Figure 4. Classification Results for the Clothing Covariates.

cadence increases in response to the weight of the load. The same results were also confirmed by the work of Attwells *et al* [2] and Wang [22]. Attwells observed from experiments carried out on military personnel that the gait angular data including the knee and femur angles are significantly affected with the increase of carriage load. For the effects of carrying conditions on the performance of gait recognition, Phillips *et al.* [15] reported a correct classification rate of 61% using KNN for $k = 1$ employing a silhouette-based method for people carrying a briefcase.

(a) (b) (c)

Figure 5. Load Carriage Covariate Factors: (a) Normal Walking (b) Handbag (c) Barrel Bag

To investigate the impact of load carriage on the performance of gait recognition using the model-based method for the extraction of dynamic gait features, three different covariate cases related to carrying conditions are used to construct the probe dataset. The cases include people carrying handbags and barrel bags besides the normal walking without carriage as illustrated in Figure (5). The probe set consists of 120 video sequences for 10 different subjects with 4 trials for every case. People in the probe set are matched against the same gallery dataset which is used for the evaluation of previous covariate factors. The classification results for gait recognition are detailed using the CMS curves shown in Figure (7).

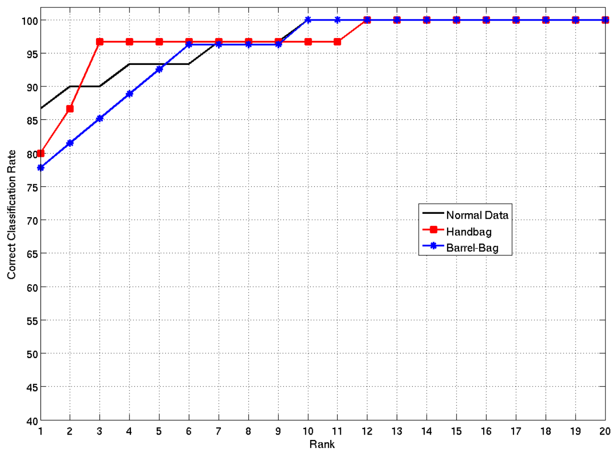

Figure 6. Classification Results for the Load Carriage.

The achieved recognition rate for people carrying a handbag is almost the same as the normal case with a reported CCR of 80%. This is because of the lightness of the handbag which does not affect the gait pattern. For the case of the barrel bag which is covering the mid part of the human body, the recognition rate drops slightly to 77%. However, such results may not express the real impact of the carriage load on the performance of gait recognition. This is because the duration of load carriage was brief, as the responses and effects of load may change with the duration of carriage as a result of exacerbated fatigue. This was not possible to study in this research due to the limitation of the gait database.

3.4. The Speed Effects

There is currently not much work that investigates the effects of speed on the performance of gait recognition methods and the relationship between the gait features and the varying walking speed [18]. Based on a model-based method for feature extraction, Yam [23] reported the possible existence of an individual mapping between the walking and running gait patterns. In [17], Bobick *et al* observed that appearance-based features derived from silhouette of walking people are speed-dependent and therefore, a preprocessing stage for feature adjustment is suggested to improve the recognition performance. To study the impact of speed variation on gait recognition, a probe dataset is constructed consisting of 10 subjects recorded at different walking speed: slow, normal and quick with 4 trials for every case. The recognition rate for both slow and quick walking drops largely to 60% and 50% respectively compared

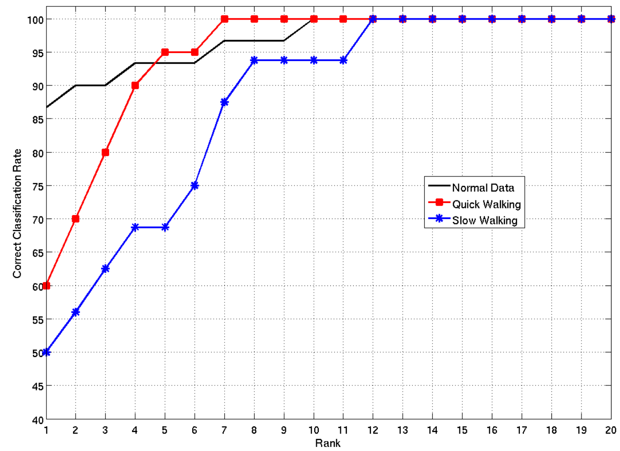

Figure 7. Classification Results for the Walking Speed Covariates.

to the achieved CCR of %86 for the normal walking case leading to the conclusion that dynamic gait features are also dependent on speed.

4. Covariate Factor Analysis of Gait Features

Feature analysis is performed to quantify the footwear effects on the different dynamic gait components employed for recognition. For each of the gait angular signature components (i.e. knee, ankle and hip), the correct recognition rate is computed using leave-one-out validation and a KNN classifier with $k = 5$ for the different covariate factors. The overall results are summarised in Table (1) which shows the means and standard deviations of the recognition rates for the various gait dynamic features. The knee is observed to have the highest average CCR whilst it is the most component susceptible to the different covariates with a standard deviation of 14.1%. The ankle has the lowest standard deviation among the angular features. the vertical tipping motion of the trunk (Y displacement) is observed as the most stable features with high average CCR and almost low standard deviation.

Table 1. Statistical Analysis of Gait Features.

	Mean CCR	Std. Deviation
Hip	25	12.1
Knee	27.9	14.1
Ankle	24.1	9.6
X Displacement	15.9	7.2
Y Displacement	23.3	7.3

5. Conclusions

In this chapter, we have investigated the impact of the different covariate factors on the performance of gait recognition using kinematic-related features. Four different covariates are analysed including footwear, load carriage, clothing and walking speed. Based on a covariate-based probe dataset of 440 samples, a high recognition rate of 73.4% is achieved using the KNN classifier with $k = 5$. This is to conclude that people identification using dynamic gait features is still perceivable with better recognition rate even under the different covariate factors. The footwear, clothing and load carriage covariates are observed to have almost no effects on the performance of gait recognition with similar results when walking with barefeet or without carrying bags. However, the gait recognition drops largely when walking with flip flops or wearing a trench coat due the difficulties encountered during the extraction of dynamic gait features using the model-based method.

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