Parametric Elliptic Fourier Descriptors for Automated Extraction of Gait Features for People Identification

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***Abstract*—The interest in gait as a biometric is strongly motivated by the urgent necessity for automated recognition systems for surveillance applications and forensic analysis. Many studies have now shown that it is possible to recognize people by the way they walk i.e. Gait. As yet there has been little formal study of people recognition using the kinematic-related gait features. In this research study, we have investigated the use of Elliptic Fourier Descriptor for the temporal markerless extraction of human joints. We describe a model-based method whereby spatial model templates for the human motion are described in a parameterized form using the Elliptic Fourier Descriptors accounting for the different variations of scale and rotation. Gait features include the angular measurements of the legs as well as the spatial displacement of the body trunk. To further refine gait features based on their discriminability, a feature selection algorithm which is applied using a proposed validation-criterion based on the proximity of neighbors. Initial experiments have revealed that gait angular measurements derived from the joint motions mainly the ankle, knee and hip angles embed most of the discriminatory potency for gait identification.**

***Keywords*-Elliptic Fourier Descriptor, Gait Recognition, Gait Biometrics**

I. INTRODUCTION

Gait recognition is considered as one of the emerging research area within computer vision and biometrics due to its potential use in a plethora of applications including visual smart surveillance and forensic analysis. Gait, the way we walk is defined as the manner of locomotion characterised by loading and unloading the limbs consecutively. Gait includes running, walking and hopping though the word gait is usually used to refer to the walking pattern. The gait rhythmic pattern is performed in a repeatable and characteristic manner [1]. Meanwhile, gait analysis is the systematic study of human walking [2] concerned with the quantification and understanding of the locomotion process. Such study involves the observation and quantification of body movements, mechanics and muscle activities. Gait analysis is carried out for two basic purposes [2]: The treatment of patients having gait abnormalities in addition to enhance the knowledge and understanding of gait. The study of human gait dates back to the ancient times with Aristotle (384-322 BC) being considered as the pioneer to study the human gait in his work "*De Motu Animalium*".

The suitability of gait as a potential biometrics emerges from the fact that the gait pattern can be captured and perceived from a distance as well as its non-invasive and less-intrusive nature [3], [4], [5]. In fact, early experimental studies conducted by Murray, Cutting and Johansson [6], [7] revealed that the joints motion seen from Moving Light Displays mounted on a walking subject can sufficiently render the gait biometric signature so that an observer can perceive the gender as well as the identity of the person if they are familiar with their walking pattern. For security and forensic cases, there are a number of situations in which gait is the only perceivable trace available from CCTV surveillance footage of a crime scene. As opposed to other biometrics such as face and fingerprint recognition which can be obscured and concealed in most cases. Gait-based forensic analysis overcomes most of the limitations as it is hard to conceal, disguise or alter. In fact, Lynnerup *et al.* [8], [9] from the Department of Forensic Medicine in Copenhagen, affirmed the usefulness of gait analysis for criminal proceedings. The research team was able to identify a bank robber by matching CCTV surveillance video from the crime scene against images of the suspect recorded at the police custody. This evidence was later used for conviction in a court of law stressing the usefulness of gait in forensic analysis.

Because of the dearth of visual marker-less model-based methods that exploit human dynamic gait traits for people identification, we have investigated the use of Elliptic Fourier Descriptor for the temporal markerless extraction of human joints. We describe a model-based method whereby spatial model templates for the human motion are constructed in a parameterized form using the Elliptic Fourier Descriptors in which different variations as scale and rotation are accounted for. A recursive evidence gathering algorithm is employed for the extraction phase in order to derive the parameters for the Elliptic Descriptors. In this way, we have established a baseline analysis which can be deployed in recognition, marker-less analysis and other areas. Further research is carried out to confirm the early psychological experiments reporting that the discriminative features for motion perception and people recognition are planted in gait kinematics. We show that the gait angular measurements derived from the joint motions embed most of the discriminatory power for gait identification.

This paper is organized as follows. The next section outlines the previous approaches for markerless extraction of gait biometric features including mainly model-based methods. The theoretical description of the presented markerless method for extracting and constructing gait-based biometric signature is detailed in Section 3. Subsequently, experimental results are outlined in Section 4.

II. Related Work

Much of the interest in the field of gait analysis has originated from physical therapy, orthopaedics and rehabilitation practitioners for the diagnosis and treatment of patients having walking abnormalities. As gait has recently emerged as an attractive biometric, gait analysis has become a challenging computer vision problem. Many research studies have aimed to propose an automated system capable of overcoming the difficulties imposed by the extraction and tracking of human motion features. Aggarwal *et al.* [10] categorised the different vision-based methods for human motion analysis into two major clasees: non-model based and model-based methods. For the non-model based approach, features extraction is performed via prediction, velocity, shape, texture and colour analysis. For the model-based approach, a prior shape template is established to match real images to this predefined model thus extracting the corresponding features once the best match is obtained.

Gait features can be classified into two major categories, namely static and dynamic-based features. The *static features* concern the geometry-based measurements of the anatomical structure of the human body such as the person's height and length or width of the different body parts. Static features can be derived from the observed gait as the stride length between two heel strikes. The *dynamic features* are the traits which describe the kinematics of the locomotion, such as the angular motion of the lower legs extracted from the joints. As the static cues are less taxing to extract and compute, it would seem straightforward to recognise people using static features as the stride length and body height and so forth. Furthermore, recent research on gait via static features for recognition proved that promising recognition rates can be attained [11]. BenAbdelkader *et al.* [12] reported that gait recognition can be achieved using the subject height and the stride parameters (stride and cadence) as there exists a linear relationship between the two gait variables.

Recently, Zeng *et al.* [13] described a model-based method for human gait recognition from the sagittal plane via deterministic learning. The joint angles for the lower limbs are considered as the main gait features for composing a biometric signature. Identification of people via gait dynamics is performed by using radial basis function neural networks through deterministic learning attaining a recognition rate of 91.9%. Bouchrika *et al* [14], [15] introduced a re-identification system for inter-camera tracking through the use of gait biometrics. The gait signature is derived via extracting the joints positions using Haar-like templates. Bashir *et al* [16] proposed the Gait Entropy Image which encodes into a single image the randomness of pixel values in the silhouette images over a complete gait cycle. Kusakunniran [17], [18] proposed a silhouette-based approach for feature extraction to view-invariant gait biometrics.

III. Proposed Approach

A. Markerless Extraction of Gait Features

In this research study, a model-based method is described for extracting the joints' positions of a single walking person through the use of Elliptic Fourier Descriptors. Although, the Fourier series is considered as the most accurate way for modelling gait motion, numerous methods have adopted simple models [19] to extract gait angular motion via evidence gathering using only a few parameters. This is mainly because of complexity and computational cost of the search space. Grant [20] used the Fourier descriptors to parameterize the templates of moving shapes in a continuous form combined with the temporal evidence gathering method in order to extract the global gait pattern.

The Fourier Transform (FT) has been employed for the analysis and representations of boundaries of shapes as it provides a way for constructing visual descriptors that can be useful for deriving features from images that are central for image understanding. The Fourier descriptors are computed by expanding the parametric representation of a curve in Fourier series. Given f as the function for the closed boundary of any arbitrary shape, f can be expressed via the elliptic Fourier Descriptors [21], where the Fourier series is based on a curve represented by the complex parametric form as shown in Equation (1):

$$f(t) = x(t) + iy(t) \tag{1}$$

where $t \in [0, 2\pi]$. $x(t)$ and $y(t)$ are approximated via the Fourier summation by n terms as shown in equation (2)

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} X_t \\ Y_t \end{bmatrix} \tag{2}$$

where a_0 and b_0 define the centre position of the shape. X_t and Y_t are calculated as defined in equation (3) :

$$\begin{aligned} X_t &= \sum_{k=1}^{n} a_{x_k} cos(kt) + b_{x_k} sin(kt) \\ Y_t &= \sum_{k=1}^{n} a_{y_k} cos(kt) + b_{y_k} sin(kt) \end{aligned} \tag{3}$$

such that a_{x_k},a_{y_k}, b_{x_k} and b_{y_k} are the set of the elliptic phasors which can be estimated using Riemann summation [22] shown as follows:

$$\begin{cases} a_{xk} = \frac{2}{m} \sum_{s=1}^{m} x_s \cos(k_s \frac{2\pi}{m}) \\ a_{yk} = \frac{2}{m} \sum_{s=1}^{m} y_s \cos(k_s \frac{2\pi}{m}) \\ b_{xk} = \frac{2}{m} \sum_{s=1}^{m} x_s \sin(k_s \frac{2\pi}{m}) \\ b_{yk} = \frac{2}{m} \sum_{s=1}^{m} y_s \sin(k_s \frac{2\pi}{m}) \end{cases} \tag{4}$$

where m is the number of points (x_s, y_s) in the shape template. The value of k represents the number of ellipses that construct the shape. According to the Nyquist sampling theorm, k lies between 1 to $m/2$. The larger values of k, the more accurate representation is reconstructed for the boundary.

For a representation invariant to rotation and scaling, f must be written in a parametrized form to account for all the possible graphs or shapes which can be obtained by applying appearance transformation as rotation, translation and scaling. Therefore, the function f can be expressed in the parametric form shown in Equation (5):

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} cos(\alpha) & -sin(\alpha) \\ sin(\alpha) & cos(\alpha) \end{bmatrix} \begin{bmatrix} s_x X_t \\ s_y Y_t \end{bmatrix} \tag{5}$$

such that α is the rotation parameter, s_x and s_y are the horizontal and vertical scaling factors respectively. Equation (5) can be rewritten in its complex form as defined in Equation (6):

$$\begin{cases} f = T + R_\alpha \left(s_x X_t + s_y Y_t i\right) \\ T = a_0 + b_0 i \\ R_\alpha = \cos(\alpha) + \sin(\alpha) i \end{cases} \tag{6}$$

Based on the parametric representation of f expressed in Equation (6), any closed boundary of a given shape can be written using only five parameters which are: a_0, b_0, α, s_x and s_y. X_t and Y_t. This parameters account for the different transformation factors including translation, rotation and scaling. In fact, the number of parameters needed for the Hough Transform is totally independent of the complexity or nature of the shape which is represented using the Elliptic Fourier Descriptors, as the defined parameters are purely related to the appearance transformations covering all possible shapes that can be produced from the original shape.

The Hough Transform is used in order to determine the best set of parameters through a matching procedure of detected low-level points across the whole sequence against the parametric representation. Votes are accumulated for the respective possible set of parameters. The best parameters for the shape to be extracted are taken from the indices of the accumulator space having the largest cast value. For this study, an ancillary phase is performed after the extraction of the global gait motion pattern at a temporal level; an exhaustive local search is done within every frame to determine the joints' positions. The local search process is guided by the global motion pattern derived during the first stage to limit the search space. To accurately obtain the joints positions and restrict the search space, the lower legs pose estimation method uses the anatomical proportions of the human body segments as a filtering process.

To utilize the Hough Transform with a set of predefined templates written using the parametric representation as described in Equation (6), a five-dimensional array is needed for accumulating the cast votes. Thus, the algorithm would be computationally infeasible to implement. In spite of the fact that numerous approaches were described in the literature to address the computational requirements of the Hough Transform [23], the computational cost of such methods does not satisfy the requirements of most vision applications. Instead, gait knowledge is considered to address the computational cost via detecting the heel strikes of a walking subject. The distance between two striking points is employed to reduce the parameter space dimensionality and therefore reduce the computational costs of the evidence gathering algorithm. The Hough Transform is applied infer the remaining free parameters through a matching process of points increasing votes in the accumulator space accordingly. A pseudo-code for the evidence gathering algorithm used for the extraction of the joints' positions of a walking subject is shown in Listing I.

Algorithm III.1: RECREVIDENCEGATHER($model, pts$)

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comment: Global Pattern Extraction

$Acc \leftarrow Array()$
for each $p \in pts$
  do $\begin{cases} parameters \leftarrow HoughTransf(model, p) \\ Acc[parameters] \leftarrow Acc[parameters] + 1 \end{cases}$
$Best \leftarrow indexOfMax(Acc)$
comment: Local Feature Extraction

$Traj \leftarrow Array()$
for each $r \in Frames$
  do $\{Traj[r] \leftarrow SearchLocally(r, Best)$
comment: Recursion

if $Traj \equiv pts$
  then return $(Traj)$
  else $\begin{cases} Traj = RecrEvidenceGather(model, Traj) \\ \textbf{return}\ (Traj) \end{cases}$

B. Extraction of Dynamic Features

The gait biometric vector for each walking person is made by taking the hip, knee and ankle angular measurements of the right and left legs defined as θ_{rh}, θ_{lh}, θ_{rk} θ_{lk}, θ_{ra} and θ_{la}. The symbols: h, k, a, r and l refer to hip, knee, ankle, right and left respectively. As reported in the medical literature [6] that the spatial displacements of the trunk possess some of the discriminative traits reflecting the subject's individuality, the gait vector is constructed such that it includes both the horizontal and vertical spatial motion taken from the hip trajectories. The displacement measurements are normalised to the subject height to account for scale-invariant matching. The angle and displacement values are taken during a single full gait cycle. As preferably, gait features can be taken as the average over different gait cycles, we consider to take only one gait cycle in this paper due to the database limitation.

To derive the most distinctive gait features that capture the relationship for the angular motion between the different legs as well as to improve the identification rates, further gait parameters are produced via fusing together the gait angles for the hip, knee and ankle. The gait feature vector is constructed by the angle between the thighs called θ_H as the sum of the two hip angles. The vector includes additional measures generated by combining the right and left angles of the knee and the ankle. Composition of features is performed via using simple rules including addition, multiplication and subtraction which are denoted as SUM, PRO and DIF generating the following angles: $\theta_s k$, $\theta_p k$, $\theta_d k$, $\theta_s a$, $\theta_p a$ and $\theta_d a$. As the size of the gait vector varies from person to another depending on the duration of the gait cycle ranging between 24 and 31 frames. To ensure consistent representation of the gait feature for all people in the database, the angular vectors are all re-sampled to length of 32 elements by applying cubic spline interpolation.

For a better analysis of the locomotion and derive the characteristic dynamic traits, gait biometric data should be represented using the basic building blocks because of the complex nature of the gait pattern [2]. One such simplification method is employ the Fourier Transform (FT) which transforms complex data into summations of simple sine waves that can simplifying the analysis of gait motion. The FT offers a very compact gait representation as most of the distinctive features is expected to be contained in a few frequencies. For each of the normalised gait raw feature vectors $(\theta_{rh}, \theta_{lh}, \theta_{rk}, \theta_H, \theta_{lk}, \theta_{sk}, \theta_{pk}, \theta_{dk})$ described in this section, we compute the Discrete Fourier Transform (DFT) for the $N/2$ frequencies of interest in N points.

The gait biometric signature of a walking subject is composed from the magnitude and phase of the Fourier components for the angular measurements. The phase data embeds certain degree of discriminatory potency when describing the gait kinematics. This is because the phase information describes when the gait dynamics start to occur. In order to compare or match phase vectors for different persons, all analyses must be synchronized to commence from the same temporal point of the gait cycle. We consider this point as the heel strike of the left leg. Since the magnitude components have been reported to hold poor discriminatory capability even though it enjoys the benefits of translation invariance [24], the product of magnitude to phase is added within the gait vector. Hence, the gait signature is constructed as the concatenation of magnitude and phases features in addition to the element-wise product of phase to magnitude features as illustrated in Equation (7).

$$f = (Magnitudes \quad Phases \quad Magnitudes \times\cdot \; Phases) \tag{7}$$

where $\times\cdot$ denotes the element-wise product of magnitude to phase vectors, which weighs phase by magnitude to retain proportionate discriminativeness potency. The total number of features contained within the gait vector using Fourier analysis reaches 675 elements.

C. Feature Selection and Classification Metrics

Feature selection is considered within this research to derive discriminative features and remove the redundant and irrelevant gait components which may affect the identification rate. It is infeasible to apply an exhaustive search procedure for all possible combinations of feature subsets to derive the optimal feature subset because of the high dimensionality of the feature vector. Instead, the Adaptive Sequential Forward Floating Selection (ASFFS) search algorithm [25] is employed to reduce the number of features.

The feature subset selection method is purely based on an evaluation procedure that examines the discriminativeness of each feature or set of features in order to construct the best subset of features for the recognition process. We describe a validation-based evaluation criterion to choose the subset of features that would minimise the classification errors and ensure good inter-class separability between the different classes. As opposed to the voting paradigm used by the *KNN*, the evaluation criterion employs coefficients w that signify the importance of most nearest neighbours of the same class. The probability score for a candidate s_c to belong to a cluster c is expressed in the following Equation (8):

$$f(s_c) = \frac{\sum_{i=1}^{N_c-1} z_i w_i}{\sum_{i=1}^{N_c-1} w_i} \tag{8}$$

where N_c is the number of instances within cluster c, and the coefficient w_i for the i^{th} nearest instance is inversely related to proximity as given:

$$w_i = (N_c - i)^2 \tag{9}$$

The value of z_i is defined as:

$$z_i = \begin{cases} 1 & \text{if } nearest(s_c, i) \in c \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

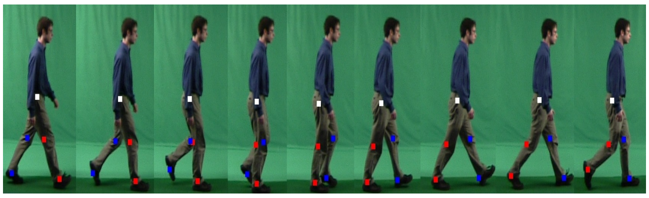
Such that the $nearest(s_c, i)$ function gives the i^{th} nearest instance to the instnance s_c. The Euclidean distance metric is used to deduce the nearest neighbours from the same class. The significance for a subset of features is based on the validation-based metric which is computed using the leave-one-out cross-validation rule. The gait biometric signature is made as the subset of features S among the feature space F attaining the maximum value which is the average sum of f computed across the N instances x as expressed the following equation:

$$Signature = \arg\max_{S \in F} \left(\frac{\sum_{x=1}^{N} f_S(x)}{N} \right) \tag{11}$$

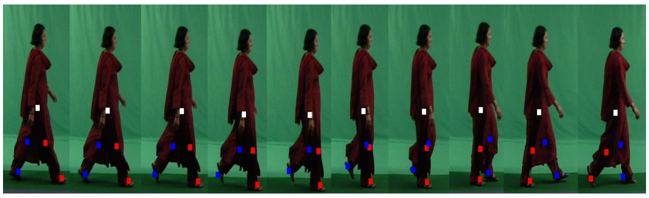
IV. Results

A. Markerless Extraction

For the evaluation of the automated model-based approach proposed for the extraction of the joints' positions for a walking person through the use of Elliptic Fourier Descriptors, the algorithm is tested on a dataset containing 160 video sequences for 20 different subjects with 8 sequences for every person. The videos are taken from the Southampton indoor gait dataset. The extraction results of the ankle, knee and hip joints are considered satisfactory for indoor video sequences with the observation that estimation of the ankle is more accurate than the hip and knee because of the visibility nature of the ankle. The method is further evaluated on outdoor data as well as a woman wearing Indian clothes which is self-occluding her gait dynamics. The joints positions are extracted successfully as shown in Figure (1) which reveals the potency of the proposed method to cope well for the case of occlusion.



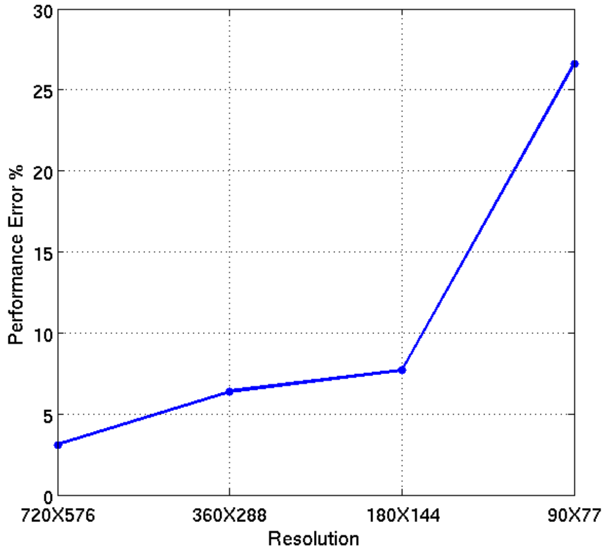
(a) Subject : 009a020s00R. (Indoor Data)



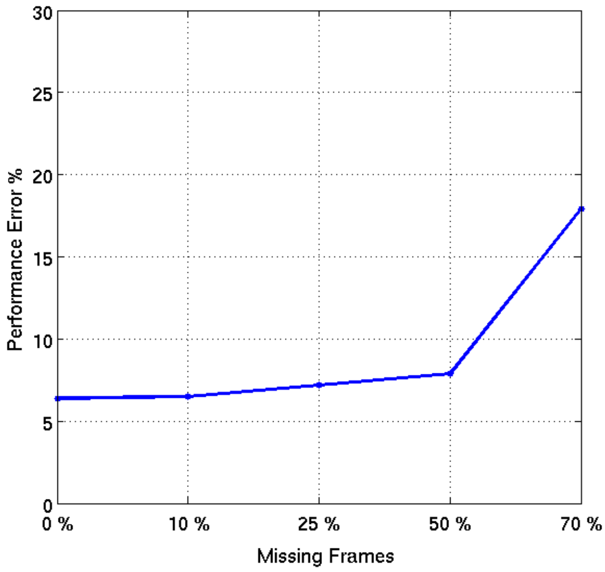
(b) Subject : 012a031s00R. (Data with Self-Occlusion)

(c) Subject : 012a031s00R. (Outdoor Data)

Figure 1. Joints Extraction for Indoor and Outdoor Data.



(a)



(b)

Figure 2. Performance Analysis for The Joint Extraction.

The performance of the model-based approach proposed for extracting the joints' trajectories of a walking person is evaluated on videos set at different resolutions. A set of 10 videos which are manually labelled at the joints position, are taken from the Southampton gait database and used for the evaluation process. Figure (2) depicts the performance error of the method for the automated estimation of the joints at various resolutions. The Euclidean distances between the extracted joints and manually labelled positions (i.e., ground truth data) are used to compute the performance error which is approximated as the average of the distances normalised to the person's height. The mean error for the positions of the extracted joints using the automated approach compared against data of 10 people manually labelled is 3.2% normalised to the height of the subject. The resolution of the image sequences are reduced gradually from an original resolution of 720×576 pixels with the aspect ratio being kept constant. The extraction method is able to derive most of the joints with satisfactory accuracy at a resolution of 144×180 achieving a performance error of 7.7%. However, the algorithm performs poorly when the video size is reduced to 77×90.

Further experiments are carried out using the same video sequences to assess the method potentials for addressing occlusion. For the case of full occlusion, the performance error is estimated by dropping proportionally a certain number of frames from every 30 frames i.e. original frame rate. This is equivalent to decreasing the frame rates. Figure (2) shows the performance error computed by reducing the frame rates of the video resized at a resolution of 360x288. The method performance is observed to be not much affected when dropping 50% of the frames as the extraction predicts the joints trajectories for the dropped frames using the temporal and spatial models represented by the Elliptic Fourier Descriptors. This clearly affirms that one of the merits of automated model-based approaches for their capability of handling occlusion and recovering the missing data.

B. Classification Results & Features Analysis

In order to assess the potency of the model-based approach for people identification by the way they walk, a dataset of 160 sequences is taken from the Southampton indoor gait database. The dataset consists of 20 different people walking from left to right with 8 sequences for every subject. The database serves as a gallery and is employed primarily for training the classifier and subset feature selection. The KNN classifier is applied at the recognition process due to its low complexity and thus fast computation besides the ease of comparison to other exiting approaches. The KNN rule uses the Euclidean distance metric to estimate the distance between a given sample and the enrolled subjects within the defined feature space in order to find the k closest neighbours based on the computed Euclidean distances. From the k closest samples, the class of the test sample is determined based on the class of the closest neighbours with the largest occurrence frequency. A high recognition rate of 95.75% is attained for the value of $k = 5$. This is obtained using features corresponding purely to the dynamics of the gait pattern. To further evaluate the classification performance of the proposed approach for gait identification using dynamic-related traits, a different database which was employed during the training stage is taken from the Southampton gait database and matched against the gallery dataset. The dataset contains 60 videos for 20 people with 3 sequences for every subject. The first gait dataset (I) which is used for the training stage and subset selection of gait features, is regarded as the gallery such that every subject in the gallery has its known class identifier. The second dataset (II) is the probe where every sample does not has class label. For $k = 5$, matching the probe against the gallery achieved a correct classification rate of 86.67% of the 60 videos. The results achieved using this evaluation are encouraging as the probe set has not been used for the derivation gait signature from dynamic features.

In order to conduct an exploratory study for the dynamic gait features and determine what dynamic features are crucial for people recognition, the different components of the gait signature are analysed separately to explore their contribution and discriminatory significance for gait identification. To report accurate and unbiased results, we derived a number of 493 subsets using the validation-based criteria presented in the earlier section for feature analysis. The feature subsets which are of length ranging between 22 and 54 achieve a correct classification rate of 92.15% or over using the KNN rule. The distributions and recognition rates of the features relating to the different components of gait are illustrated in Table (1). The distribution values offer an indication whether such type of feature is important but it does not provide a measure of its discriminatory capability. Instead, the discriminative significance of kinematic-based features is estimated using the correct classification rate.

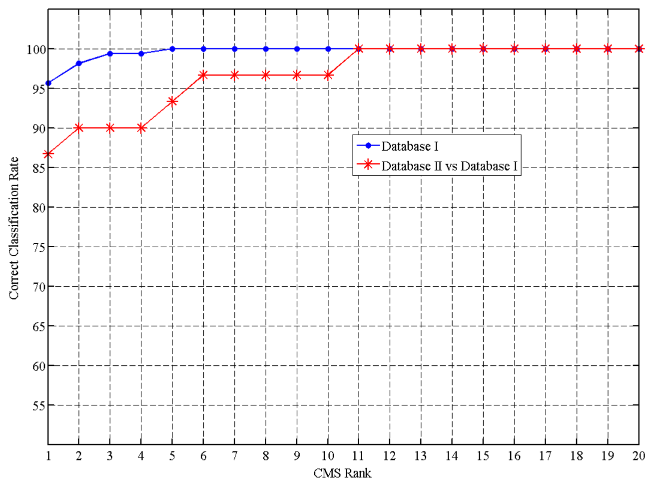


Figure 3. The Cumulative Match Score Curve for the Classificatioh Results

Features	Distribution	Recognition Rate
Angular Data	77%	85%
Displacement data	23%	38.8%
Hip Angle	27%	45%
Knee Angle	29%	52%
Ankle Angle	21%	52.5%
X disp	16%	26%
Y disp	7%	25%

Table I
GAIT RECOGNITION RESULTS USING DYNAMIC CUES

Based on the results described in Table (1), it can be concluded that the angular measurements embed most of the discriminative traits with an average proportion of 77% of the gait biometric signature, whilst only a few features are contained within the displacement motion. The angular data derived from the knee , ankle and hip angles contribute with the proportions of 27%, 29% and 21% respectively. The knee and ankle angular features are observed to be the most distinctive features with an attained classification rates of 52% and 52.5% respectively. However, the potency of the ankle depends mostly on the quality of the extraction process. For example, the extraction of the ankle for subjects walking on the grass is proven to be a difficult task. Further, the discriminatory potency of the angular data versus the displacement features as shown in Table (1) such that the combined angular features attained a classification rate of 85% meanwhile only 38.75% is achieved using the displacement information. These analytical results are consistent with the medical experiments reported in [6] where Murray observed that the ankle rotation, pelvic tipping and spatial displacements of the body trunk bear the subject individuality due to their consistency at different trials. In [26], Wagg confirmed the importance of the angular information for gait identification with a reported classification rate of 77% using dynamic gait features.

V. Conclusions

In these research studies, the reported results confirm further the early psychological theories claiming that the discriminative features for motion perception and people recognition are embedded in gait kinematics. We propose a model-based method whereby spatial model templates for the human motion are described in a parameterized form using the Elliptic Fourier Descriptors accounting for the different variations of scale and rotation. We have shown that the gait angular measurements derived from the joint motions mainly the ankle, knee and hip angles, posses most of the discriminatory potency for gait recognition. As for future work, we aim to investigate the scalability issue of gait recognition and how it performs via increasing the number of subjects in the dataset.

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