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On Evaluating the Scalability Aspect of Gait-Based Biometric Systems for Larger Population

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***Abstract*—The use of biometric technologies becomes ubiquitous in modern society due to the proliferating number of crimes and terror attacks as well as the vital need to provide safer environment. Gait biometrics is considered one of the emerging key research areas due to its potential use in a plethora of applications such as forensics and visual surveillance. As the evaluation of biometric-based evidence in investigation plays a pivotal role for its admissibility in court, we investigate in this research the performance of a model-based approach for people identification over an increasing population. A model-based markerless approach is described to derive the joints positions of walking subjects from uncalibrated single cameras through the use of a haar-like template matching approach. Matching of subjects is performed through posture comparison through a window of frames. Experimental results have shown that increasing the database size, the similarity scores for inter- and intra-class comparisons tend to converge to fixed values that are well separated. This suggests that for larger population, gait analysis can be still deployed and the size of the database should not be a factor impacting on the analysis.**

***Keywords*-Biometrics, Gait Recognition , Gait Biometrics.**

I. Introduction

Because of the proliferating number of crimes and terror attacks as well as the crucial necessity to provide safer environment, the use of biometric technologies have become ubiquitous in modern society. Gait biometrics is considered one of the emerging key research areas due to its potential use in a plethora of applications such as forensic analysis and visual surveillance. Gait, the way we walk is defined as the manner of locomotion characterised by successive cycles of loading and unloading the limbs. Gait includes running, walking and hopping. However the word gait is frequently used to refer to walking. The rhythmic gait pattern is done in a repeatable and characteristic way [1]. Gait analysis is concerned with the systematic study of the human walking [2] in order to quantify and understand of the locomotion process. The study involves the observation of body movements, mechanics and muscle activities. Gait analysis is performed primarily for two reasons [2]: firstly, the treatment of patients with gait abnormalities in addition to enrich our knowledge and understanding about the human gait pattern. The study of the gait pattern dates back to the ancient era with Aristotle (384-322 BC) being considered the pioneer to study the human gait in his book "*De Motu Animalium*".

The use of gait for people recognition for security and surveillance applications has recently gained a lot of interest from the computer vision research community. The suitability of gait as a biometrics emerges from the fact that gait pattern can be acquired and perceived at a distance as well as its non-invasive and less-intrusive merits [3], [4], [5], [6]. Early experimental studies by Murray [7] revealed that gait might be a useful biometrics for people identification. He reported that 20 components of the gait pattern including ankle rotation, spatial displacement and vertical tipping of the body would render uniquely the gait signature for every subject. Furthermore, the studies performed by Johansson [8] on the perception of human motion using Moving Light Displays had confirmed that based on the motion of the joints, an observer can recognise the different types of human activities. Further, the observer can even make a judgement about the gender of the subject, and even recognize the person if they are already familiar with their walking pattern. This leads to the conclusion that gait might be considered as potential biometric for surveillance and forensic systems.

Due to the fact that evaluation of biometric-based evidence in forensic investigation plays a pivotal role for its admissibility in court, we investigate in this research the performance of a model-based approach for people identification over an increasing dataset. In forensic biometrics, one of the key issues is what are the chances that another individual has the biometric measurements. In other words, evidence can be challenged around the certainty that there exists no other people having the same biometric signature as the perpetrator at any one given time on earth. As we are limited and incapable to screen the entire population, the certainty of finding a possible duplicate is supported using statistical probabilities based on research performed on relatively smaller datasets than the whole population. A model-based markerless approach is described to derive the joints positions through the use of a Haar-like template matching approach. Matching of people is performed through posture comparison through a window of frames. Experiments carried out on the CASIA-B dataset confirmed that regardless of the database size, the intra- and inter-class similarity scores tend to converge to fixed values that are well separated. This suggests that for larger population, gait analysis can be deployed and the size of the database should not be a factor impacting on the analysis

This paper is organized as follows. The next section outlines the previous approaches related to gait biometrics. The proposed markerless extraction approach of gait biometric features is detailed in section 3. The gait matching process for people recognition is presented in Section 4. Subsequently, experimental results are reported.

II. Related Work

Much of the interest in the field of gait analysis originated from physical therapy, orthopaedics and rehabilitation for the diagnosis and treatment of people with walking abnormalities. As the gait pattern has emerged as an attractive biometrics, gait analysis has become a challenging computer vision task. Many research studies have aimed to develop a system to overcome the difficulties imposed by the extraction and tracking of human gait features. Aggarwal *et al.* [9] surveyed the different vision-based methods used for human motion analysis classifying them into non-model based and model-based methods. For the non-model based class, feature correspondence between consecutive frames is based upon prediction, velocity, shape, texture and colour. For the model-based methods, a prior template or model is constructed to match real images to this predefined model, and therefore extracting the corresponding features once the best match is acquired.

Gait biometric features can be broadly classified into two main categories, namely static and dynamic cues. The *static features* refers to the geometry-based measurements of the anatomical structure of the body as the subject's height and length or width of the different body segments. Static traits can also be derived from the observed gait such as the length of the stride. The *dynamic features* are the characteristics which describe the kinematics of the walking process, such as the angular motion of the lower legs extracted from the joints trajectories. As the static features are less taxing to extract and estimate, it would seem easy and straightforward to recognise people using static features such as the stride and body height. Furthermore, recent research on gait using static features for people recognition reported that a promising classification rate can be obtained [10]. BenAbdelkader *et al.* [11] affirmed that gait recognition can be performed using the subject height and the stride features (stride length and cadence) as there is a linear relationship between the two stride parameters which can be exploited for recognition.

Recently, Zeng *et al.* [12] proposed 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* [13] described a re-identification system for inter-camera tracking through the use of gait biometrics. The gait signature is constructed via extracting the joints trajectories using Haar-like templates. Bashir *et al* [14] introduced the Gait Entropy Image which encodes into a single image the randomness of pixel values with the silhouette images over a gait cycle. Kusakunniran [15] proposed a silhouette-based approach for feature extraction addressing the view-invariance aspect of gait biometrics.

III. Markerless Extraction of Joints

For the marker-less extraction of gait biometric features, motion models are constructed based on medical data describing the angular motion for both the knee and hip during a complete gait cycle as shown in Figure (1). A gait cycle is defined as the time interval between two consecutive instances of initial foot-to-ground contact of the same leg [16]. Initially, the hip bends by approximately 20° throughout the terminal stance phase and it thereafter extends until it reaches 10° during the stance phase. During the pre-swing and throughout most of swing phase, the hip flexes to reach 20 degrees. Then it starts to extend just before the following initial contact with the floor. As shown in Figure (1), the knee is almost fully extended during the first part of the mid-stance, it begins to flex gradually to its support phase peak which is approximately 20 degrees. The knee extends again almost fully and flexes to about 40 degrees through the pre-swing stage. After toe-off, the knee flexes to reach a peak of 60 to 70 degrees at mid-swing, then it extends again in preparation for the next contact .

As a first step, the proposed method derives the motion map image based on change detection related to the inter-frame difference. Moving pixels of a walking subject across successive frames are detected with the emphasis to acquire better edge data. The motion map M_t for frame t is computed as the absolute difference of two consecutive frames I_t and I_{t+1} as given below:

$$M_t = \|I_t - I_{t+1}\| \tag{1}$$

An example for a motion image is shown in Figure (2) for a walking person recorded using a CCTV surveillance camera at Gatwick airport in the UK.

A *Haar-like* template [17] is introduced for the localization of the gait features due their fast and robust performance for real-time applications from object recognition to pedestrian detection. The template is depicted in Figure (2) which is based on the outlier of the lower part of the human leg. Let p_t^{ankle} is the possible position of the ankle at t^{th} frame. To estimate the ankle position, numerous templates are made to account for the different possible appearance transformations as rotations and translation defined by kinematical knowledge. The Haar-templates are superimposed against the motion map at the candidate point p computing the match value S as given in Equation (2). The similarity score determines how well is the generated template is superimposed on the motion map. It is estimated as the sum of larger values inside the superimposed region divided by the accumulated lower values inside the area that are less than a defined threshold which is experimentally set as $\tau = 20$.

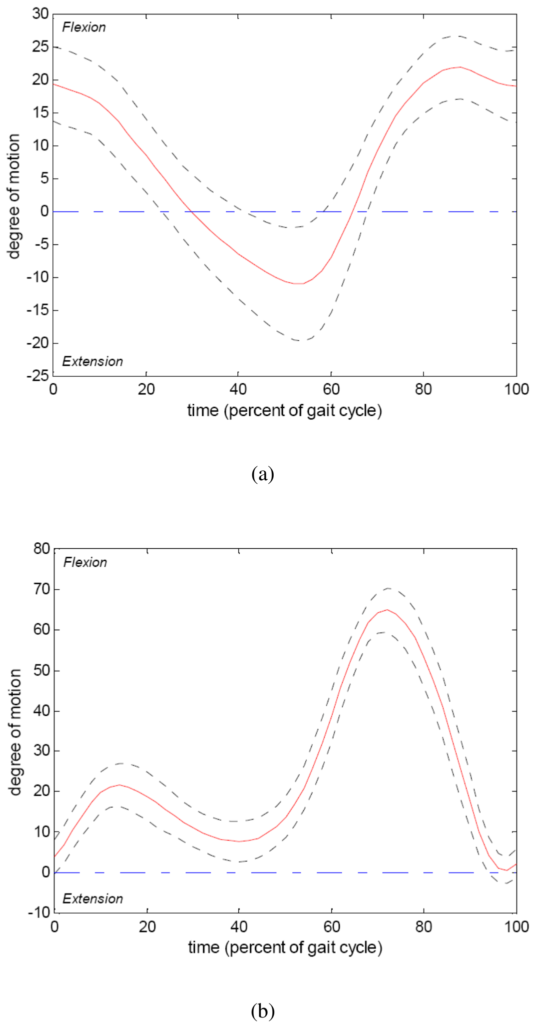
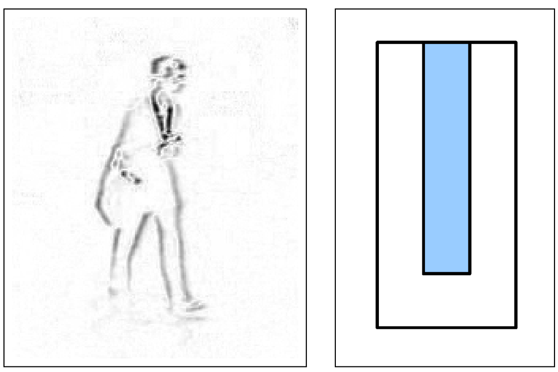


Figure 1. Gait Angular Motion: (a) Hip. (b) Knee.



(a) (b)

Figure 2. Markerless Gait Feature Extration: (a) Motion Image. (b) Haar-based Matching Template.

$$S(x,y,\alpha)=\frac{\sum_{i\in P_{x,y,\alpha}} P_{x,y,\alpha}(i)\times Z(P_{x,y,\alpha}(i))}{\sum_{i\in P_{x,y,\alpha}} P_{x,y,\alpha}(i)\times |1-Z(P_{x,y,\alpha}(i))|} \tag{2}$$

where α is the rotation angle and Z is expressed as :

$$Z(i)=\begin{cases}1 & \text{if } i>\tau\\ 0 & \text{otherwise}\end{cases} \tag{3}$$

As opposed to using a per-frame procedure for pose estimation [18], a frame-to-frame approach is deployed instead for the extraction such that the results from the previous frame are utilised to guide the matching process in the consecutive frames. In order to decrease the search space for a candidate joint trajectory and refine the extraction accuracy, kinematical and anthropometric constraints inferred from the spatial as well as angular data derived from the gait motion model described are enforced during the extraction phase. For instance, during the striking phase, one of the feet will be stabilised at the same position and thus the ankle spatial movement is limited within a smaller area whilst the rotation parameter α will be enclosed within a specific range depending on the phase of the walking cycle. The pose estimation method for the lower legs partially depends on the anatomical proportions of the body segments reported in the medical results of anatomical studies [19] for a subject of height H:

$$\begin{aligned} y'_{hip} &= \min(\mathbf{y}_{sil}) + 0.5\cdot H\\ y'_{knee} &= \min(\mathbf{y}_{sil}) + 0.75\cdot H\\ y'_{ankle} &= \min(\mathbf{y}_{sil}) + 0.90\cdot H \end{aligned} \tag{4}$$

During the double-support stage of the gait cycle where the legs overlap, it is a challenging task to extract the lower limbs accurately partly due to the self-occlusion during the overlap. Thus, the matching procedure is applied for the striking leg using kinematic gait constraints that can assist with the estimation of gait features. The swinging leg is not dealt with during the overlap due to self-occlusion. The overlapping begins when the Euclidean distance between the two ankles is less than a defined threshold which is related to the subject height. The extraction of the swinging leg during the overlap is continued after a certain number of frames which is determined from the average gait cycle model. Experimentally, this number is set to 6 frames for a video recorded with a frame rate of 25 frames per second. To extract the joints trajectories as well the angular measurements when the legs do overlap, a 3^{rd} order polynomial interpolation process is applied.

The orientation of the upper limbs is estimated at each frame $\mathbf{T}=[t_1,t_2,\ldots,t_\varphi,\ldots,t_F]$ with a coarse to fine estimation procedure where at first, the hip position is performed with

$$\begin{cases} x'_{hip\ell} = \frac{1}{P}\cdot\sum_{j=1}^{P}\widetilde{x}_j + (2\ell-3)\cdot H\cdot\ \mu\cdot\ 10^{-3}\\ y'_{hip\ell} = y'_{hip}\cdot(2\ell-3)\cdot\left(\frac{\widetilde{x}_P-\widetilde{x}_1}{2}\right)\cdot\sin(0.3\cdot\mu) \end{cases} \tag{5}$$

where $\widetilde{\mathbf{X}} = [\widetilde{x}_1,\widetilde{x}_2,\ldots,\widetilde{x}_j,\ldots,\widetilde{x}_P]$ is the subset P ($P\le MaxX$) horizontal coordinates from the extracted motion region for the subject S [20].
Equation 5 sets relationship between the horizontal hip position and walking direction μ, estimated with respect

$$P_v(t) = \frac{\begin{bmatrix} x_{h1}(t) - x_{a1}(t) & x_{h2}(t) - x_{a1}(t) & x_{k1}(t) - x_{a1}(t) & x_{k2}(t) - x_{a1}(t) & x_{a2}(t) - x_{a1}(t) \\ y_{h1}(t) - y_{a1}(t) & y_{h2}(t) - y_{a1}(t) & y_{k1}(t) - y_{a1}(t) & y_{k2}(t) - y_{a1}(t) & y_{a2}(t) - y_{a1}(t) \end{bmatrix}}{L} \tag{6}$$

to the horizontal axes of the frame reference. These relationships are deduced with regression analysis applied on the 3D Georgia Tech motion capture dataset. μ is estimated as the angle of inclination of the walking straight line which is inferred from the detected heel strikes on the walking floor.

IV. Gait-Based Identification

The proposed approach for gait-based forensic analysis from video sequences recorded from surveillance CCTV cameras is based on the Instantaneous Posture Matching (IPM) [20]. Medical and psychological research affirmed that the task of natural walking is executed in a different and characteristic way for every subject [7]. Therefore, the limbs position is unique in every instant of the gait motion whilst the kinematic properties of the body can be efficiently employed for identity matching between different videos to confirm a suspect identity. Furthermore, recent investigation by Larsen *et al*. [21], [22] confirmed the usefulness of using anatomical and biomechanical knowledge to identify other individuals for different types of court cases. The Instantaneous Posture Matching approach aims to estimate the mean limbs distance between different video sequences where subjects are walking. The matching procedure is based on the anatomical proportion of the human body within a window of frames. We consider two different video sequences v_1 and v_2 acquired with similar frame rate. To compare the sequences for identity matching and verification, a set of reference frames from the first video are matched progressively against a window of images from the other sequence. Given the joint coordinates (x, y) for the hip x_{h1}, knee x_{k1} and ankle x_{a1} (two of each are extracted for the left and right legs; both sides of the hips are extracted since we consider frontal-view video sequences) for the human body of video v at time t. In order to reconcile the position vector for the extracted joints for direct matching between subjects, we shift the estimated the joints trajectories to a new coordinate system whose origin is set as the left ankle point. To alleviate the effects of different camera resolutions, the new translated positions are normalised by the person height. Therefore, a feature vector $P_v(t)$ of video v at a given frame t is expressed in Equation (6) such that L is the persons height in pixels.

The joints coordinates are referred to the image reference system with the assumption that the matched individuals in the v video sequences have the same walking direction without any loss of generality. The walking direction can be easily obtained as the angle of inclination of the straight line which estimated from the heel-strike points [3], [23]. The extraction of the joints trajectories from the video sequences can be achieved with different methods either manually or using the markerless procedure described in the previous section. After having extracted the normalised joints position vector, the two individuals recorded at different video sequences v_1 and v_2 are considered to have the same identity if the joints distance D expressed in Equation (7) (as the mean distance of the Euclidian distances between the poses of teo people in different videos starting from frames t_1 and t_2, over a subset of W successive frames) is less than a chosen factor:

$$D(v_1, v_2) = \min\{d(v_1, t_1, v_2, t_2) : \\ 0 \le t_1 \le |v_1| - W, 0 \le t_2 \le |v_2| - W\} \le \tau \tag{7}$$

such that $|v_n|$ is the number of frames for video v_n and $d(v_1, t_1, v_2, t_2)$ is given in Equation (8) as:

$$d(v_1, t_1, v_2, t_2) = \left(\frac{\sum_{f=1}^{W} \parallel P_{v1}(t_1 + f) - P_{v2}(t_2 + f) \parallel}{W} \right) \tag{8}$$

The threshold value of τ used in Equation (7) is determined via the analysis of intra- and inter-subject matching differences estimated on larger gait database. In fact, we believe that the use of joints positions is more favorable for forensic analysis because this can be more readily communicated to those without a technical background within a criminal investigation, but there are other methods that might derive a better performance [6]. Moreover, it is well known that the perception of a persons gait varies with change in direction of camera relative to the subjects path. There are now techniques that address viewpoint-invariant gait recognition and which have been used to re-identify subjects across non-intersecting camera views.

V. Experimental Results

The performance of the model-based approach described for estimating the joints' positions of walking people is assessed on videos with smaller resolution. A set of 18 sequences are taken from the CASIA-B gait dataset [24] and used for the evaluation of gait recognition across different viewpoints. The collected data consists of six different viewpoints (36^o, 54^o, 72^o, 90^o, 108^o, 126^o) with 3 sequences for each camera view. Figure (3) shows examples for the automated extraction carried out on the CASIA-B database for different viewpoints. Subsequently, manual labelling of the videos is done to collect ground truth data. Figure 4 depicts the performance error of the algorithm for the recovery of the joints trajectories for various resolutions. The Euclidean distances between the extracted joints and manually labelled points (i.e., ground truth data) are used to estimate the performance error which is computed as the average of the distances normalised to the person' height. The resolution of the videos are reduced gradually from an original size of 320×240

pixels with the aspect ratio being kept constant. The method is still able to derive the joints with an acceptable accuracy level for a smaller resolution of 144×180 with a performance error of 14.3%. However, the algorithm does not cope well when the resolution is further decreased to 75×56 pixels.

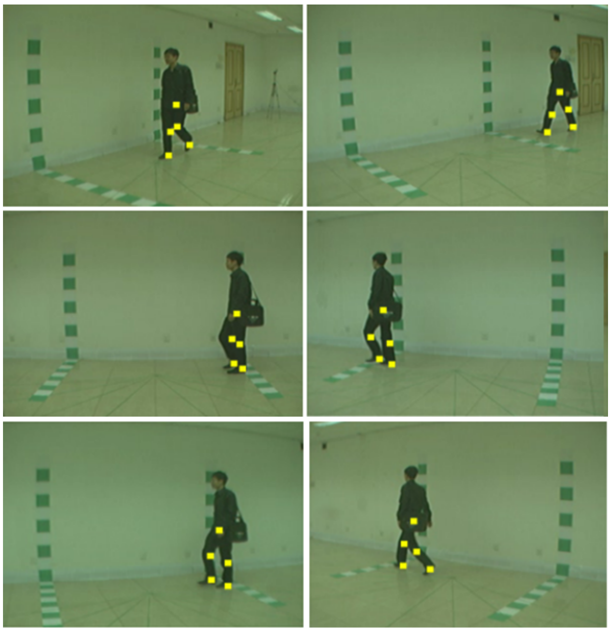


Figure 3. Markerless Extraction of Gait Features on CASIA-B dataset.

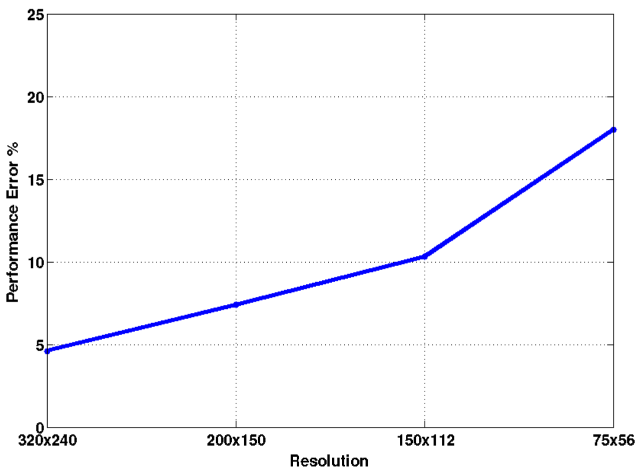


Figure 4. Performance Analysis for The Joint Extraction.

In biometrics, one of the key issues is what are the chances that another individual has the biometric measurements. In other words, evidence can be challenged around the certainty that there exists no other people having the same biometric signature as the perpetrator at any one given time on earth. As we are limited and incapable to screen the entire population, the certainty of finding a possible duplicate is supported using statistical probabilities based on research performed on relatively smaller datasets than the whole population. For gait forensic analysis, a dataset of 101 subjects are taken from the CASIA-B dataset with an average of 35 video sequences for every subject. The automated marker-less extraction method is applied to recover the joints trajectories including the hip, knees and ankles. In the performance experiment, we defined a dataset of $n \in \{2, 3, 4...N = 101\}$ subjects. We calculate the similarity scores S_n^{Intra} and S_n^{Inter} for all the match combinations of sequences of the same subjects and different people respectively. The S_n^{Intra} and S_n^{Inter} are estimated as the mean values for the intra- and inter-match scores computed using the Instantaneous Posture Matching method defined earlier respectively, as:

$$S_n^{Intra} = \frac{\sum_{a=1}^{n} \frac{\sum_{i=1}^{L_a} \sum_{j=i+1}^{L_a} D(v_i^a, v_j^a)}{\frac{L_a(L_a-1)}{2}}}{n} \tag{9}$$

and

$$S_n^{Inter} = \frac{\sum_{a=1}^{n} \sum_{b=a+1}^{n} \frac{\sum_{i=1}^{L_a} \sum_{j=i+1}^{L_a} D(v_i^a, v_j^a)}{L_a \times L_b}}{n(n-1)} \tag{10}$$

such that v_i^a is the i^{th} video sequence of person a. L_a is the number of sequences belonging to candidate a. D is the distance calculated as defined in Equation (7). The general framework for performance analysis is outlined by starting with an initial small dataset of size n=2 and then the database size is progressively increased by adding more (different) subjects in the experimental test. The selection of new people into the dataset is done at random. To avoid bias due to which initial n=2 subjects are selected, the similarity scores S_n^{Intra} and S_n^{Inter} are computed for 100 different initial subsets selected at random. The experimental results are presented in Figure (5) which shows the observed relationship between the dataset size and the similarity match scores for the intra- and inter-classes computed using the proposed Instantaneous Posture Matching method for the different 100 datasets taken at random. The results show that when augmenting the database size, the similarity scores tend to converge to fixed values that are well separated. This might suggest that for larger population, gait analysis can be still deployed and the size of the database should not be a factor affecting the analysis.

VI. Conclusions

In these research studies, we have investigated the scalability issue of gait recognition and how it performs via increasing the number of subjects in the dataset. Gait biometrics is considered as one of the emerging key research areas due to its potential use in a plethora of applications such as forensics and visual surveillance. A model-based markerless approach is described to derive the joints positions of walking subjects from uncalibrated single cameras through the use of a haar-like template matching approach. Matching of subjects is performed through posture comparison through a window of frames. Experimental results carried out on the CASIA-B gait dataset confirmed that regardless of the database size, the intra- and inter-class similarity scores tend to converge to

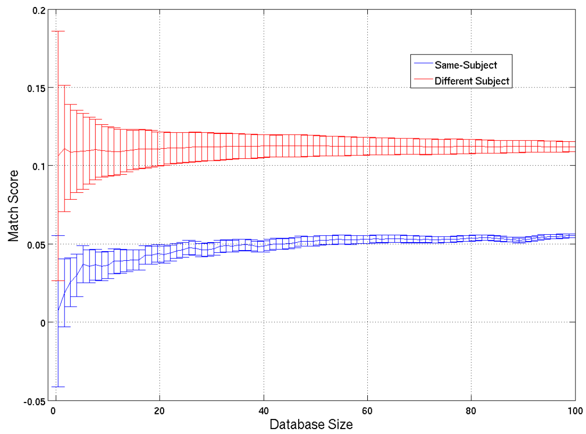


Figure 5. Relationship of instantaneous posture match versus the size of database. Plots of inter-class (nonmatching) and intra-class (matching) results with relation to the database size.

fixed values that are well separated. This suggests that for larger population, gait analysis can be still deployed and the size of the database should not be a factor impacting on the analysis

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