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Human Identification Based Biometric Gait Features using MSRC

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Abstract— **Human identification using gait is a new biometric intended to classify individuals by the way they walk have come to play an increasingly important role in visual surveillance applications. In gait biometric research, various gait classification approaches are available. This paper presents human identification system using the view-invariant approach. The framework of proposed system consists of the subject detection, silhouette extraction, feature extraction, and classification. Firstly, moving subjects are detected from the video sequences. And extractions of human silhouette are done by using background subtraction method. In feature extraction step, motion parameters such as joint angles, angular velocity and gait velocity are calculated using speeded up robust features (SURF) descriptors. This descriptor helps to read the essential points used to generate gait signatures and extracts motion parameters for classification. In the final stage, Meta-sample based sparse representation method (MSRC) is used in classification of the extracted motion parameters and features. Experiments are conducted on the own dataset which obtain overall classification rate of 94.6782%.**

Index Terms—**Biometric, meta-sample based sparse representation classification (MSRC), Silhouette extraction, Speeded Up Robust Feature (SURF).**

I. Introduction

The extraction and analysis of human walking movements, or gait [1], has been an ongoing research area since the beginning of the still camera in 1896. From those research points of view, in gait analysis from visual measurements can be divided into two major categories which are clinical gait analysis used for rehabilitation purposes and biometric gait analysis for automatic person identification.

Biometric systems are becoming increasingly important as they provide more reliable and efficient at the identity verification. Human gait recognition [4] is a new biometric system which contained physical characteristics like face, iris, fingerprint, palm print and DNA and behavioral characteristics such as a way of talk, voice and gait walking. Human gait is an identifying feature of a person that is determined by skeletal structure, body weight, limb length, and habitual posture. Hence, gait can be used as a biometric measure to identify known persons and classify unknown subjects at distance in surveillance system [7]. In such applications, other biometrics such as finger print, face, palm print and iris are failures to match because of insufficient pixels to identify the subject and need user cooperation to get more accurate results. Gait can be detected and measured at low resolution, and therefore it can be used in situations where face or iris information is not available in high enough resolution for recognition. Human gait can vary due to many factors such as change in body weight, skeletal structure, muscular activity, limb lengths and bone structures [13]. However, it still possesses sufficient discriminatory power for personal recognition.

The rest of the paper is as follows. Section 2 describes related work in the computer vision literature. Section 3 introduces the overview of the method and in section 4 describes the methods proposed in this study in detail including feature extraction, human detection and tracking, and motion analysis. Gait recognition based on the MSRC classification techniques is discussed in Section 5. Experimental setup are presented and analyzed in Section 6. Section 7 concludes the paper.

II. Related Works

The analysis of biometric gait recognition has been studied for a longer period of time [**2**]-[**6**] for the use in classification at the surveillance and forensic systems. These are becoming important, since they provide more reliable and efficient means of identity verification or to announce no match. In computer vision, the automated person identification approaches **[7], [8]** for the classification and recognition of human gait have been studied but human gait identification is still a difficult task.

Gait features can also be used for gender classification and some prominent researchers have worked on it. In study [21] describe an automated system that classifies gender by utilizing a set of human gait data an SVM classifier is used to classify gender in the gait patterns which are 96% for 100 subjects, have been achieved on a considerably larger database. In [9] presented a review of research on computer-vision-based human motion analysis. In this area involved giving the special emphasis on three major issues, namely human detection, tracking and activity understanding. There is much evidence from psychophysical experiments [13], [10] and medical and biomechanical analysis [17]-[18] that gait patterns are unique to each individual.

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The background subtraction technique is one of the most common approaches for extracting foreground objects or moving objects from video sequences. Changes in scene lighting can cause problems for many background subtraction methods. In [19] have recently implemented a pixel-wise EM framework for detection of vehicles. Their method attempts to explicitly classify the pixel values into three separate, predetermined distributions corresponding to the road color, the shadow color, and colors corresponding to vehicles. Zoran and Zivkovic [14] presented an improved GMM background subtraction scheme. Recursive equations are used to constantly update the parameters and but also to simultaneously select the appropriate number of components for each pixel .This algorithm can automatically select the needed number of components per pixel and in this way fully adapt to the observed scene. The processing time is reduced but also the segmentation is slightly improved.

The SURF detector focuses its attention on blob-like structures in the image. These structures can be found at corners of objects, but also at locations where the reflection of light on specular surfaces is maximal. Geng Du and Fei Su [17] deals with SURF features in face recognition and gives the detailed comparisons with SIFT features. Experimental results show that the SURF features perform only slightly better in recognition rate than SIFT, but there is an obvious improvement on matching speed. In [18] analyze the usage of Speeded Up Robust Features (SURF) as local descriptors for face recognition. Furthermore, a RANSAC based outlier removal for system combination is proposed. This approach allows matching faces under partial occlusions. Experimental results on the AR-Face and CMU-PIE database using manually aligned faces, unaligned faces, and partially occluded faces show that this approach is robust. In [20] a facial expression recognition method based on SURF descriptor was proposed. Each facial feature vector is normalized and the probability density function descriptor (PDF) is generated. Then weighted majority voting WMV is used for final classification. Experimental results show excellent performance in recognizing facial expressions when applied to the Japanese Female Facial Expression database.

Sparse representation-based classification (SRC) has received many attentions recently in the pattern recognition field [22]-[24]. The sparse representation problem involves finding the most compact representation of a given signal, where the representation is expressed as a linear combination of columns overall of the training samples. Such a sparse representation has been successfully applied to face recognition [22], which suggests that a proper reconstructive model can imply great discriminative power for classification. In [23] propose a new sparse representation-based classification (SRC) scheme for Motor imagery (MI)-based brain-computer interface systems (BCIs) applications. They analyzed the performance of the SRC using experimental datasets. The results showed that the SRC scheme provides highly accurate classification results, which were better than those obtained using the well-known linear discriminant analysis (LDA) classification method. The enhancement of the proposed method in terms of the classification accuracy was verified using cross-validation and a statistical paired t-test ($p < 0.001$).

III. Overview of the Proposed System

In this paper, human identification based on automatic extracted human gait signature is proposed by describing, analyzing and classifying human gait by computer vision techniques without intervention or other subject contacts. Moving object detection is the first step processes for the proposed system. The human body and its silhouette are extracted from the input video by background subtraction method. Background subtraction based on the frame difference method is used to detect the moving object that it easily adapts to the changing background. Frame differencing, also known as temporal difference, uses the video frame at time t-1 as the background model for the frame at time t. It can be reduced computational time and memory storage.

Then, fast interest points detector and descriptor, the speeded up robust feature (SURF) is applied to the foreground of the output of background subtraction. SURF operates in two main stages, namely the detector and the descriptor stages. The detector analyzes the image and returns a list of interest points for prominent features in the foreground image. For each point, the descriptor stage computes a vector characterizing the appearance of the neighborhood of every interest point. Both stages require an integral image to be computed in advance.

Features of the interest points from the detector are used in extraction of motion parameters from the sequence of gait figures to show the human gait patterns. This is represented as joint angles and vertex points, which are together used for gait classification. For the gait feature extraction, width and height of the human silhouette is measured. The dimension of the human silhouette, joint angle, angle velocity and gait velocities from the body segments are calculated as the gait features.

Finally, the extracted gait signals are comparing with gait signals that are stored in a database. Meta-sample based SR classifier (MSRC) [35] is applied to examine the discriminatory ability of the extracted features. Sparse representation (SR) by 1l-norm minimization is robust to noise, outliers and even incomplete measurements, and SR has been successfully used for classification it has been shown in recent years. It classification is coded the query image/signal to be sparse and then classified query image/signal firstly by evaluating which class leads to minimal reconstruction error. Fig:1 summarizes the process flow of the proposed approach. This method involves extracting the body parts, tracking the movement of joints, and recovering the body structure in an image sequence.

IV. Proposed System

4.1 Moving Object Detection

The detection and tracking algorithm is used to extract and track moving silhouettes of a walking figure from the background in each frame, which is based on background subtraction and silhouette correlation. Then foreground objects are segmented from the background in each frame of the video sequence.

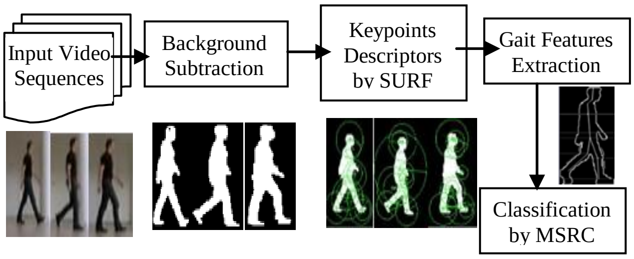
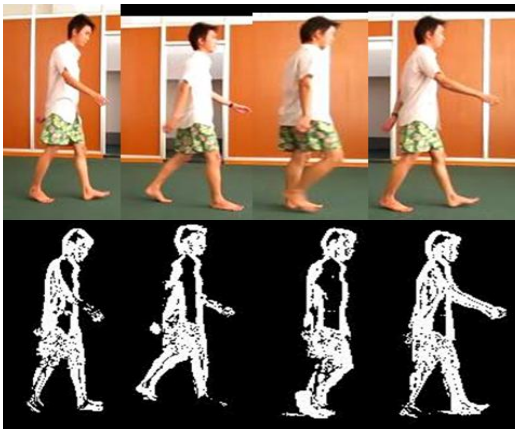


Fig1. Overview of the proposed system

The frame different background subtraction methods are used because of its high performance and low memory requirements. In this method the current frame is subtracted from a reference frame, if the difference between the two is greater than a set threshold value T_h, the pixel is then considered as a part of foreground if not it is taken into the background category. The proposed system will be tested with the different threshold level (T_h=25 and T_h=40).

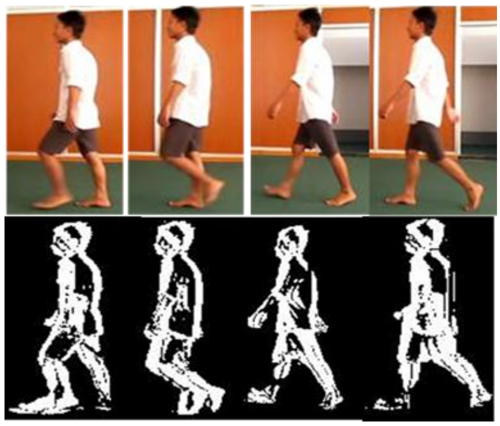
$$|frame_i - frame_{i-1}| > T_h$$

Frame differencing, also known as temporal difference, uses the video frame at time t-1 as the background model for the frame at time t. Fig. show the results of frame different background subtraction method. This technique is sensitive to noise and variations in illumination, and does not consider local consistency properties of the change mask.

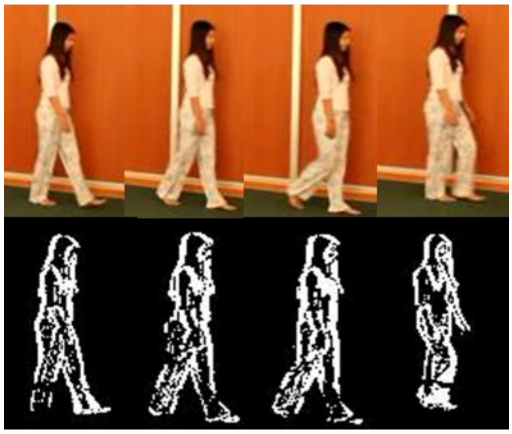


(a) Left to right man walking

(b) Right to left woman walking



(c) Right to left man walking



(d) Left to right woman walking

Fig.2 Results of Background Subtraction method

4.2 Speeded Up Robust Feature

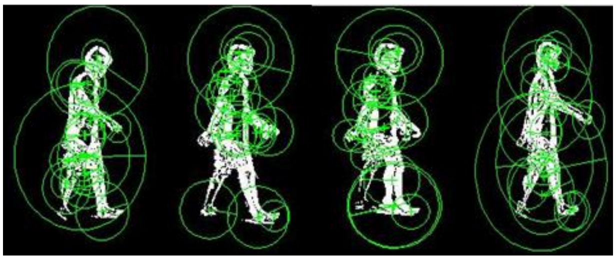
Local features such as Scale Invariant Feature Transform (SIFT) and SURF are usually extracted in a sparse way around interest points. A speed-up robust feature (SURF) is a scale and in-plane rotation invariant feature. It contains interest point detector and descriptor. In SURF [31-33], detectors are first employed to find the interest points in an image, and then the descriptors are used to extract the feature vectors at each interest point.

4.2.1 Interest point detection

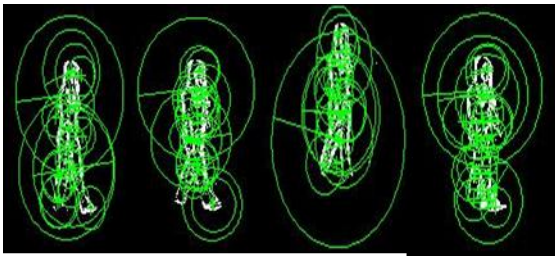
First, the detector select interest points at distinctive locations in the image, such as corners, blobs, and T-junctions [32]. The most valuable property of an interest point detector is its repeatability (i.e. whether it reliably finds the same interest points under different viewing conditions). SURF uses the determinant of the Hessian-matrix approximation operating on the integral image to locate the interest points, which reduces the computation time drastically [29, 33]. To find the interest point, detect blob-like structures at locations where the determinant is at maximum. For scale invariant, the SURF constructs a pyramid scale space, like the SIFT. Different from the SIFT to repeatedly smooth the image with a Gaussian and then sub-sample the image, the SURF directly changes the scale of box filters to implement the scale space due to the use of the box filter and integral image. Given a point x = (x, y) in an image I, the Hessian matrix H(x, σ) in x at scale σ is defined as follows [17]:

$$H(x,\sigma)=\begin{pmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{xy}(x,\sigma) & L_{yy}(x,\sigma) \end{pmatrix}$$

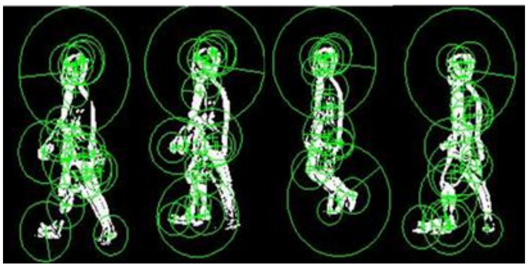
Where $L_{xx}(x, \sigma)$, $L_{xy}(x, \sigma)$ and $L_{yy}(x, \sigma)$ are the convolutions of the Gaussian second order partial derivatives with the image I in point x respectively. These interest points are used in human gait figures.



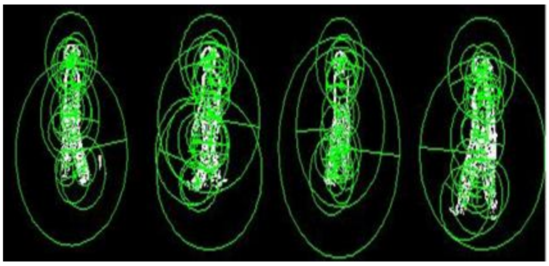
(a) Interest points detector on left to right man walking



(b) Interest points detector on left to right woman walking



(c) Interest points detector on right to left man walking



(d) Interest points detector on right to left woman walking

Fig.3. Result of interest points detector in SURF

4.2.2 Features description

Next, the descriptor stage [31-33] of SURF calculates the neighborhood of every interest point is represented by a feature vector. This descriptor has to be distinctive and at the same time robust to noise, detection displacements and geometric. SURF used the sum of the Haar wavelets response to describe the feature of an interest point by detector. By using Haar wavelets [29] increase the robustness and decrease computation time whose size depends on the features scale σ. To achieve rotation invariance can be rotated according to a feature direction such as horizontal direction and vertical direction.

For the extraction of the feature descriptor [31-33], the first step consists of constructing a square region centered at the interest point and oriented along the orientation decided by the orientation selection method [17]. The region is split up equally into smaller 4×4 square sub-regions. This preserves important spatial information. For each sub-region, compute the Haar wavelet responses at 5×5 equally spaced sample points. The Haar wavelet response in horizontal direction d_x and the vertical direction d_y are first weighted with a Gaussian centered at the interest point. Then d_x and d_y are summed up over each sub-region and form a first set of entries in the feature vector. Hence, each sub-region has a four-dimensional descriptor vector v for its underlying intensity structure [18]

$$v=\left(\sum d_x, \sum d_y, \sum |d_x|, \sum |d_y|\right)$$

Concatenating this for all 4×4 sub-regions, the final result is a 64-dimensional floating point descriptor vector which is commonly used in a subsequent feature matching stage [34].

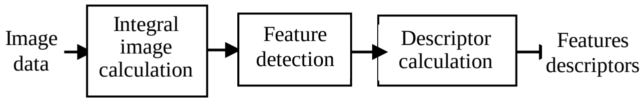


Fig.4. Stages of the SURF algorithm

These features are person-specific, since the number and the positions of points selected by SURF detector and the features around these points computed by SURF descriptor are different in each person's image.

4.3 Extracting Human Gait Figures

Features of the interest points are used in extraction of motion parameters from the sequence of gait figures to show the human gait patterns. This is represented as joint angles and vertex points, which are together used for gait classification. For the gait feature extraction, width and height of the human silhouette is measured. The dimension of the human silhouette, joint angle, angle velocity and gait velocities from the body segments are calculated as the gait features. The horizontal coordinates of each body points are calculated from two border point as

$$x_{center} = x_s + (x_e - x_s)/2 \qquad (1)$$

Where x_s represent first pixel and x_e represent the end pixels on the horizontal line. Human body motion is typically addressed by the movement of the limbs and hands, such as the velocities of the hand or limb segments, and the angular velocity of various body parts. In general, the angle $\theta_{l,k}$ of location (l_x, l_y) at frame k is calculated by

$$\theta_{l,k} = \tan^{-1}((l_x - x_c)/(l_y - y_c)) \qquad (2)$$

The angular velocities $\omega_{l,k}$ at frame k, given an inter-frame time Δt (1/25 sec) is calculated by

$$w_{l,k} = (\theta_{l,k} - \theta_{l,k-1})/\Delta t \qquad (3)$$

Also, the gait velocity v_k at frame k is calculated by

$$v_k = (x_k - x_{k-1})/\Delta t \qquad (4)$$

V. META-SAMPLE BASED SR CLASSIFICATION (MSRC)

The supervised meta-sample based SR classification (MSRC) has been shown to be an effective method for many applications like face recognition, object recognition and object classification. MSRC is extracted a set of meta-samples from the training samples, and then an input testing sample is represented as the linear combination of these meta-samples by l_1-regularized least square method. Classification is achieved by using a discriminating function defined on the representation coefficients [35]. In MSRC it is expected that a testing sample can be well represented by using only the training samples from the same class. It does not contain separate training and testing stages so that the over-fitting problem is much lessened. The classification algorithm can be summarized as following [35]:

Input: matrix of training samples $A=[A_1, A_2,...,A_k]\in R^{m\times n}$ for k classes; testing sample $y\in R^m$

Step1: Normalize the columns of A to have unit L_1 -norm.

Step2: Extract the meta-samples of every class using SVD or NMF.

Step3: Solve the optimization problem defined in

$$J(x,\lambda)=\min_x\{\|W_x-y\|+\lambda\|x\|_1\}$$

Step4: Compute the residuals $r_i(y)=\|y-W\delta_i(x)\|_2$

Output: $identity=\arg\min_i r_i(y)$

VI. EXPERIMENTAL SETUP

In order to test the system properly it is desired to train and test the system using video of actual people walking in front of a camera. The motion was filmed from the side by means of a video camera at 30frames/sec. A database of 1056 videos of 22 people, each of size about 5sec is used to analyze the system performance. MSRC randomly and equally split the data into training and test sets. These videos were taken under different lighting conditions, different speed of walking such as normal walking, fast and slow walking to the viewing plane. Subjects walked from left to right and right to left with difference walking styles. For all types of walking, 176 clips are left to right walking and 176 clips are right to left walking. Using the cross validation method, these classification schemes are implemented for comparison (1) Meta-sample based SR classification (MSRC) [35], (2) Local sparse representation based classification (LSRC) [34] and (3) Sparse representation based classification (SRC) [22-24]. In this system used the Matlab platform as it provides Image Acquisition and Image Processing Toolboxes.

Table I. Person Identification Results (Th=40)

Human	**SRC**	**LSRC**	**MSRC**
Person 1	0.6250	0.7021	0.7225
Person 2	0.6125	0.7225	0.7553
Person 3	0.5341	0.6554	0.8654
Person 4	0.4375	0.6870	0.7850
Person 5	0.3975	0.7350	0.8325
Person 6	0.6875	0.4325	0.8365
Person 7	0.3125	0.6385	0.7301
Person 8	0.4163	0.6263	0.7260
Person 9	0.3750	0.7160	0.7510
Person 10	0.5000	0.5785	0.8670
Person 11	0.5385	0.6570	0.8150
Person 12	0.5263	0.7575	0.8522
Person 13	0.7500	0.7610	0.8321
Person 14	0.6250	0.6550	0.7530
Person 15	0.5000	0.5453	0.5910
Person 16	0.4575	0.5631	0.6570
Person 17	0.5325	0.6675	0.7710
Person 18	0.6000	0.7560	0.7900
Person 19	0.9375	0.9490	0.9500
Person 20	0.5470	0.5970	0.6910
Person 21	0.4531	0.5985	0.7210
Person 22	0.4532	0.5989	0.7550

From table I results, the human identification is tested on the threshold level 40 in background subtraction. From table III results, the human identification results are tested on the threshold level 25. According to the person identification results Table I and Table III, identification rate of threshold level 25 in Table III is better than threshold level 40 in Table I.

Table II. Gait Classification Results (T_h=40)

Gait Types	**SRC**	**LSRC**	**MSRC**
Fast	0.8199	0.8879	0.9065
Normal	0.9000	0.9533	0.9539
Slow	0.8085	0.8585	0.9000

Table II is the gait classification results with threshold level 40 and Table IV is also gait classification results with threshold level 25. According to both table, MSRC classifier is better compare with other two types.

Table III Person Identification Results (T_h=25)

Human	SRC	LSRC	MSRC
Person 1	0.9235	0.9350	0.9550
Person 2	0.9125	0.9375	0.9500
Person 3	0.8250	0.8520	0.9000
Person 4	0.9221	0.9375	0.9750
Person 5	0.9375	0.9389	0.9570
Person 6	0.9375	0.9421	0.9843
Person 7	0.8750	0.8957	0.9050
Person 8	0.8125	0.8750	0.8991
Person 9	0.9375	0.9579	0.9570
Person 10	0.8750	0.8920	0.9852
Person 11	0.9281	0.9494	0.9590
Person 12	0.8790	0.8897	0.8999
Person 13	0.7590	0.8390	0.8550
Person 14	0.9375	0.9530	0.9579
Person 15	0.8750	0.9000	0.9210
Person 16	0.9150	0.9310	0.9399
Person 17	0.8750	0.8950	0.9550
Person 18	0.9221	0.9500	0.9700
Person 19	0.9050	0.9500	0.9590
Person 20	0.8375	0.8770	0.9885
Person 21	0.8746	0.9687	0.9775
Person 22	0.8746	0.9688	0.9789

The proposed system identifies the person on all of three gait types (Normal, Slow and Fast). According to both Table I and Table III, MSRC classifier is better accuracy than other SRC and LSRC.

Table IV. Gait Classification Results

Gait Types	SRC	LSRC	MSRC
Fast	0.8199	0.8879	0.9065
Normal	0.9000	0.9533	0.9539
Slow	0.8085	0.8585	0.9000

From Table II and Table IV, the proposed system can classify the three gait types that are 'Normal Walking', 'Fast Walking' and 'Slow Walking'. From this table, normal walking type is better accuracy than other two types.

VII. Conclusion

Human identification at a distance has gained more interest in visual surveillance systems because it can be classified unauthorized and suspicious persons when they enter a surveillance area which is an important component in surveillance. The system is speed up by using SURF. The threshold level 25 gives the good results for the human identification from the above experimental results. The experimental evaluation of this proposed system confirms the good performance of human identification system except 'slow' type but it is still reasonable results. For further experiments, the proposed system will be tested on the larger value of dataset and will be implemented to classify the gender.

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