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IDENTIFY HUMAN GENDER BY ARBITRARY WALKING DIRECTION USING TEMPORAL SEQUENCE PATTERNS

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Abstract— **A biometric system identifies an individual based on characteristics and unique features shoThis systemd by individuals. This system developing automates investigate the problem of human identity and gender recognition from gait sequences with arbitrary walking directions, so that a more practical human gait analysis system can be developed. This system conducted a number of human identity and gender recognition experiments from gait sequences with arbitrary walking directions. Most current approaches make the unrealistic assumption that persons walk along a fixed direction or a pre-defined path. Given a gait sequence collected from arbitrary walking directions, This system first obtain human silhouettes by background subtraction and cluster them into several clusters. For each cluster, This system compute the cluster-based averaged gait image as features.**

Index Terms—**Human gait analysis, identity recognition, gender recognition, metric learning, sparse reconstruction.**

I. INTRODUCTION

There has been much work on human gait analysis over the past decades for human identification, gender classification and age estimation. Hothis systemver, most datasets and gait recognition approaches assume that people walk along a fixed direction or a pre-defined path. This is generally unrealistic because people usually walk freely in the scene and the walking directions may be time-varying. In this system, this system investigate the problem of human identity and gender recognition from gait sequences with arbitrary walking directions, so that a more practical human gait analysis system can be developed. Since human gait analysis is known to be sensitive to the varying views human identification and gender recognition from gait sequences with arbitrary walking directions are difficult. To study this new problem, this system first collect a new gait dataset, where people walk freely in the scene, and the walking directions are arbitrary and time-varying throughout the sequence.

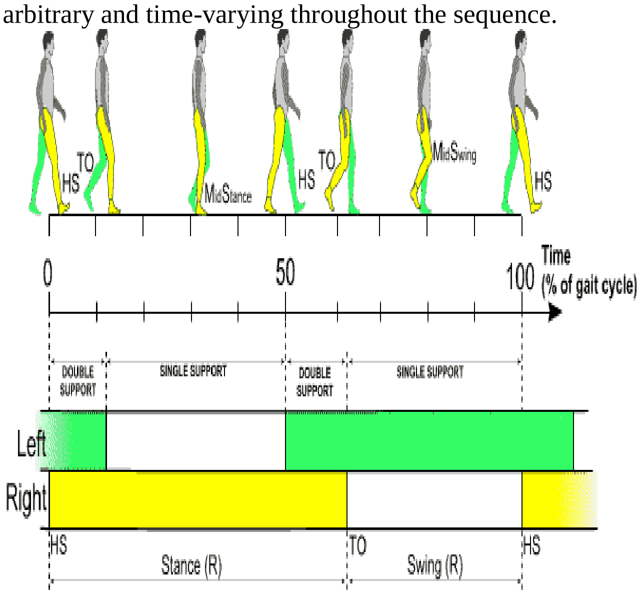

Fig. 1. The Human Gait

In this system obtain human silhouettes by background subtraction in each gait sequence and cluster them into several clusters. For each cluster, this system compute the cluster-based averaged gait image (C-AGI) as the feature. Subsequently, this system propose a metric learning approach to learn a distance metric to extract more discriminative information for recognition.

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II. PROPOSED ALOGORITHM

In proposed system we used Affinity propagation clustering for feature extraction and SVM method for classification. We have to process the video into frame conversion after the frame conversion we have find the object in this video.by using the object have to apply the AP clustering for feature extraction .By using SVMclassifier to classify the videos and finding the gender. Compare to existing system our method is giving better output.

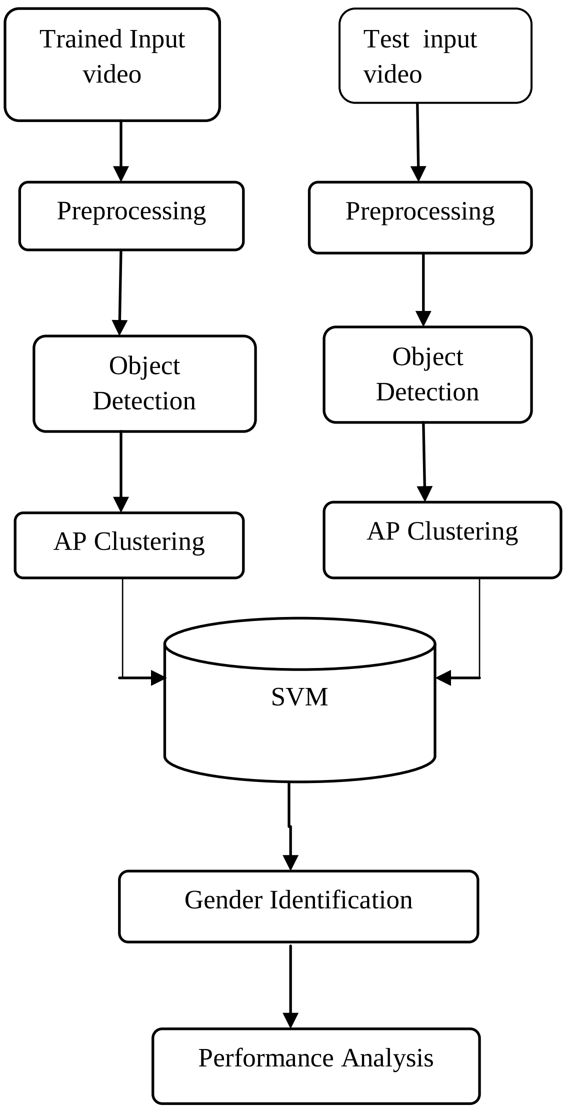

Fig. 2. Flow chart

III. PREPROCESING

The median filter is a nonlinear digital filtering technique, often used to remove noise. Such noise reduction is a typical preprocessing step to improve the results .The Video is converted into number of frames.Each Frames are calculated and removing the unwanted noise.Image pre-processing can significantly increase the reliability of an optical inspection. Several filter operations which intensify or reduce certain image details enable an easier or faster evaluation. Users are able to optimize a camera image with just a few clicks. Preprocessing images commonly involves removing low-frequency background noise, normalizing the intensity of the individual particles images, removing reflections, and masking portions of images.Image preprocessing is the technique of enhancing data images prior to computational processing.

Background subtraction removes a low-frequency 2D background from each slab of an image using the rolling-ball method. The method involves considering the 2-D grayscale image as a 3-D surface, where height is given by pixel intensity. The surface mapped by the center of a ball as it rolls over the 3-D surface identifies a smoother background surface (after adjusting its height by the ball radius) which ignores features which are narrower than the ball's radius. These narrow features are left after subtraction of the background. Background subtraction is a method for identifying moving objects against a static background. Background subtraction provides a set of pixels within the region of a moving object. Alternatively, one may only be interested in the outline of that region. A motion field, is a projection of motion in a scene onto the image plane.

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Fig. 3. Input video for gender identity using gait

Fig. 4. Preprocessing

IV. OBJECT DETECTION

Object detection is the process of finding instances of real-world objects such as faces, bicycles, and buildings in images or videos. Object detection algorithms typically use extracted features and learning algorithms to recognize instances of an object category. It is commonly used in applications such as image retrieval, security, surveillance, and automated vehicle parking systems.

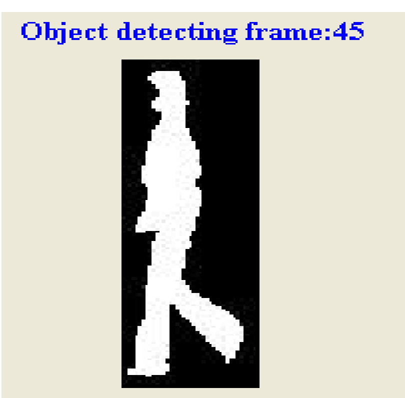

Fig. 5. Object Detection

The main objective of the process is to track a moving person in a video. To get the motion vectors of the object in the video. Tracking an object in a video is a challenging process. Tracking objects in a video has applications in video surveillance and other some applications. The objects can be tracked based on the compression domain and pixel domain. This paper presents a compressed-domain object tracking method. This uses only MVs and block coding mode information to perform fast and fairly accurate tracking.

V. AFFINITY PROPAGATION CLUSTERING

An algorithm that identifies exemplars among data points and forms clusters of data points around these exemplars. It operates by simultaneously considering all data point as potential exemplars and exchanging messages between data points until a good set of exemplars and clusters emerges. An exemplar learning algorithm that takes as input an initial set of exemplars (often randomly-selected) and then iteratively refines that set while changing the clusters to match the set of exemplars. It is similar to k-means clustering or the EM algorithm, except that the centers must lie on data points.The gait energy image (GEI) feature is powerful in representing human gaits owing to its robustness against preprocessing noises. Since persons walk freely, it is very challenging to estimate the gait period in the gait sequence. Moreover, previous studies have shown that the GEI feature is sensitive to the varying views. Hence we cannot compute the GEI feature for the whole gait sequence directly.

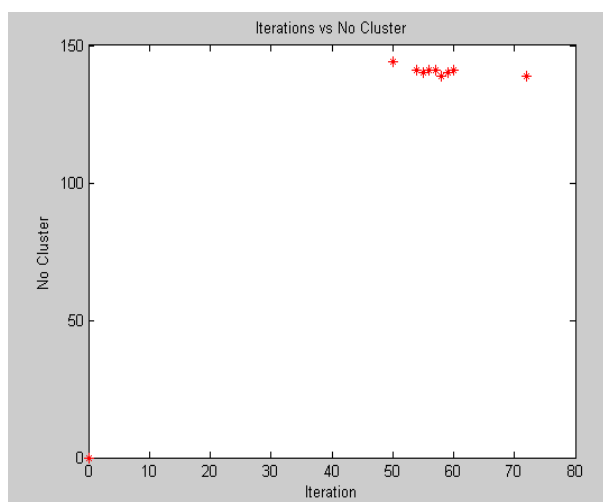

Fig. 6. Number of clusters

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Updtated values of Iteration 50

Number of identified clusters:136

Fitness (net similarity):29906.00

Similarities of data points to exemplars:29634.00

Preferences of selected exemplars:272.00

VI. SVM CLASSIFIER

Support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output. After training the SVM model is created. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. Support vector machines are supervised learning models with associated learning algorithms that analyze data and recognize patterns used for classification and regression analysis.

The basic SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Classification accuracy is computed. SVM maps input vectors to a higher dimensional vector space where an optimal hyper plane is constructed. Among the many hyper planes available, there is only one hyper plane that maximizes the distance between itself and the nearest data vectors of each category.This hyper plane which maximizes the margin is called the optimal separating hyper plane and the margin is defined as the sum of distances of the hyper plane to the closest training vectors of each category.

VII. GENDER IDENTIFICATION

Besides gait recognition, we also investigate gait-based gender recognition from arbitrary walking directions. We adopt the leave-one-person-out strategy to conduct gender recognition experiments. Specifically, we take four gait videos for each person as the testing set and the remaining as the training set. We repeat this 20 times and record the average classification rate as the final classification accuracy. In out gait-based human identity recognition experiments, we randomly selected *n* gait sequences per subject from our dataset to construct the training set and use the remaining to form the testing set. We run the experiment 10 times by randomly splitting the training and test sets.

VIII. PERFORMANCE MEASURES

The performance of the system is measured by calculating the accuracy, Sensitivity and specificity of the classifier. The accuracy of the classifier represents to which extend the classifier classifies the images based on the given label. The sensitivity of the classifier represents how exactly the classifier correctly classifies the data to each category. The specificity of the classifier represents how exactly the classifier correctly rejects the data to each category.

IX. EXPERIMENTAL RESULTS

we perform gait-based human identity and gender recognition experiments to verify the efficacy of our proposed approach.

Fig. 7. Gender detection

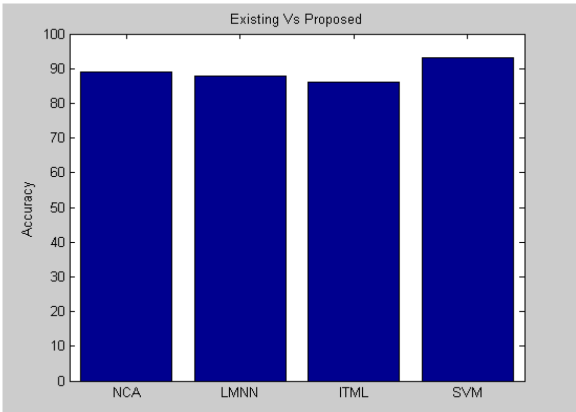

Fig. 8. Performance analysis

X. CONCLUSION

We have successfully proposed a sparse reconstruction based metric learning approach for gait-based human identity and gender recognition from arbitrary walking directions. We have applied our proposed SVM method on the existing and achieved comparable recognition rate with most existing state-of-the-art gait-based human identity and gender recognition methods. That is because our method applies the point-to-set distance to learn the distance metric while others use the point-to-point distance metric which may not effectively model the large variations in intra-class pose and view, especially when the number of training samples is limited. We have applied our proposed SRML method on the existing gait datasets and achieved comparable recognition rate with most existing state-of-the-art gait-based human identity and gender recognition methods.

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