ISSN: 0974-2115
www.jchps.com Journal of Chemical and Pharmaceutical Sciences

Gait Recognition as non – intrusive biometric using view in variant methods

J.B. Anushka Mercy[1*], Beulah David.D[1,] Jacob Asirvatham.A[2]
[1]Department of Computer Science, Jeppiaar Engineering College, Chennai - 119
[2]Senior Software Consultant, Sys Universe Technologies Pvt. Ltd., Chennai
***Corresponding author: E-Mail: mercy.anushka@gmail.com**

ABSTRACT

Gait patterns have been used widely in recent years to authenticate users. Because it doesn't require user intrusion, it is often used as a biometric to make authentication processes easier and hassle free. But there are various issues with this process. To start with, the viewing angle has to be constant which is quite difficult to achieve with limited number of cameras. Speed too can alter the way a person walks and cause inconsistencies in identification. Furthermore, complications might arise if the subject is carrying something. The weight can affect his walking pattern. Besides, a recent accident could also transform a person's walking pattern and lead to wrong identification. Other biometrics such as face detection can be combined with this technique to reduce the issues leading to erroneous identification. In this paper, we propose a system to overcome the viewing angle discrepancies. The system takes in walking sequences as input and processes them to create images. This is converted into 3D images by means of stereovision algorithms. Using which, we can effectively match the real-time image with various image sequences in the database. Side face detection can enhance the accuracy further.

KEYWORDS: Gait Energy Image (GEI), random subspace method (RSM) and majority voting (MV).

INTRODUCTION

Gait techniques have often been used to identify people based on their walking pattern. But they are not yet employed commercially because of the various issues that arise starting from the person's clothing to his walking speed. However, there are some instances where the gait technique has been successfully used. In one such case, a burglar was caught using Gait. The footage available from the scene wasn't clear enough for a facial identification but his walking pattern was adequate. This was further fed into the system and the man was identified and arrested. But since it highly important to identify the right suspect, we cannot allow even the smallest miscalculations. Hence we need robust software which would reduce the transformation errors to the maximum. Also facial recognition and foot pressure identification is used in addition with gait to slim identification faults.

Gait recognition is a biometric method for recognizing people's walking pattern without intrusion. Patterns can be recognised from a distance from even low quality videos, making them much more efficient than other biometric mechanisms. But there are limitations to employing them in real life. The most important being the distortions in views that generally occur in real situations. The most challenging task here is to match the pattern across diverse views.

We come across two different approaches proposed which will overcome this issue. An appearance-based approach, and a model-based approach. Appearance-based mechanisms extract gait attributes directly from image sequences captured.

On the other hand, model-based mechanisms derive model attributes from images. 3D model-based mechanisms are preferred because of their view-unvarying nature. But it is often challenging to generate 3D models of high certainty from images taken using just surveillance cameras. Therefore, we concentrate on appearance-based mechanisms in this paper. Many methods have been suggested to overcome the view issue in appearance-based approaches. Broadly, they fall into three groups: view-invariant, visual hull-based, and view transformation-based methods.

View-invariant approaches can be categorised as subspace-based, geometry-based, and metric learning based methods. Except for the view invariant approach, the remaining approaches use discrete views which are contained in the training set alone and can affect the accuracy if target views aren't from the training sets. View transformation methods extended to arbitrary views solve the discretion issues. 3D gait sequences of multiple training views are taken and the features of the target subjects are created by projecting the sequences into 2D spaces related to the target views.

The difference is employing multiple non target cases instead of target images. Also, we employ part dependant view selection which separates the gait characteristics along several body parts to fix destination views for each body part.

Existing Systems: The proposed system overcomes the complexities that arise using the following methods. The methods use various approaches to solve various issues that trouble gait recognition.

Shuai Zheng (2011), offered a solution for viewing angle variation issues. The gait energy image was used to create a robust view transformation model. The features were extracted from the energy image using the partial least square method. It eventually performed better by remaining robust to clothing, viewing angle variations and carrying condition changes. Xiaoli Zhou (2007), utilised the side face of a person and his walking pattern. The side angle of face isn't usually of high resolution and hence an image was constructed out of consecutive video frames called enhanced side face Image. The gait energy image was created by exploiting the spatio-temporal compact representation. The data was then fused to create parameters for recognition.

Konstantios Moustakas (2010), explained how Soft biometrics include systems that are used to acquire the biometric aspects which are usually easy to acquire but lack the discriminative powers of common biometric techniques. The analysis was dependent on radon transforms on gait energy images. The main features acquired here are a person's stride length and height. These methods are often clubbed with other efficient biometrics to enhance performance. Worapan Kusakunniran (2013), proposed a framework to construct new invariant feature for gait recognition. View normalization was done on the input layer to normalize gaits from arbitrary views. In variant low-rank textures transforms a certain view into canonical view. Later, an improved scheme on Procrustes analysis was applied on the silhouettes.

Liang Wang (2003), proposed to build an algorithm for gait recognition using statistical shape analysis. Firstly, a background subtraction algorithm was used to reduce the working area. The silhouettes thus extracted are represented as sequences of vector configurations. These were done on a common coordinate frame which in turn is analyzed using procrustes shape analysis technique. The dynamics of gait wasn't efficiently explained but the structural characteristics were clearly interpreted.

Shiqi Yu (2009), explained in detail the methods to identify the gender of various humans. Prior knowledge was combined with automatic procedures which would improve classification accuracy. Also, a numerical analysis which takes into account various human components like head, hair, back and thigh helped greatly in differentiating the features. Imed Bouchrika (2014), stated that Haar-like templates can be used to extract gait features from various viewpoints. Angular model templates which define the human motion were employed to guide marker less model. The features extracted include angular measurements for the lower legs with the displacement of the body. To enhance efficiency, a feature selection algorithm is used which relies on the proximity of the neighbours in the same class. The rate of classification was found to be 73.6% after a rectification process.

Nitchan Jianwattanapaisarn (2014), proposed a method to get gait features from Microsoft Kinect. A distance function between two walking sequences was constructed using combinations of skeletal static features. Skeletal kinematic features were obtained from movements and silhouette features. Later, a function was used for classification.

Soharab Hossain Shaikh (2014), said feature vector generation and subsequent classification depend on the whole silhouette and this involves a huge amount of data. They proposed a system where, the partial silhouette has enough discriminating information for gait recognition. Swinging hands of a human body was found to contain maximum discriminating features.

Yu Guan (2015), found the effect of covariates as an unknown partial feature corruption problem. Since the locations of corruptions may differ for different query gaits, relevant features may become irrelevant when walking condition changes making it difficult to train one fixed classifier that is robust. To overcome, he proposed a classifier ensemble method based on the random subspace method (RSM) and majority voting (MV).

Ashok Veeraraghavan (2005), stated Kendall's definition of shape for feature extraction. Since the shape feature rests on a non-Euclidean manifold, they propose parametric models like the autoregressive model and autoregressive moving average model on the tangent space and demonstrated the ability of these models to capture the nature of shape deformations using experiments on gait based human recognition. The shape deformations of a person's silhouette was exploited as a discriminating feature and provided recognition results using the nonparametric model.

Daigo Muramatsu (2015), proposed methods to reduce the faults that occur due to viewing angles. A system called Arbitrary View Transformation angle incorporated 3D images as training views and 2D images as target views. Doing so, the recognition degradation from falsely identified angles is managed. Also, Part-Dependant view selection schemes split the gait features into several parts to curtail transformation errors.

Worapan Kusakunniran (2012), proposed a method which aims to reduce the errors that might arise due to the variations in viewing angles. Normalization techniques were used to convert various views of the subject into a common view. Regression functions which employ sparse regression are elastic net for VTM construction.

2. PROPOSED METHOD

The existing system proposed a method where the 3D images of the training set was alone necessary and these can be used to map the target images to their corresponding angle deviations. We propose a system where the target images are converted into 3D images with stereovision algorithms.

Video Sequence to Frame Conversion: The video is converted to individual frames using various procedures. These would in turn be used as a sequence to differentiate one frame from the next. This difference can be exploited to make the accuracy levels higher.

Fig.1 Frame Conversion

Background Subtraction and Random View Method: Low Rank Subtraction or foreground subtraction is applied to get the particular person into focus. There are two phases explained here. The enlistment phase and the actual recognition phase. The gait sequences are fed in with an identification number. These usually carry the projection matrices. The matrices are used to generate the training data with target views. The background separation algorithms are used to segment the person alone. After which, the gait features are extracted from the silhouette sequences. These features are then enlisted with their identification number in the gallery and probe respectively. In the recognition phase, training features of the target views are generated from the multiple 3D volumes available in training sets. Here, we take the gallery and probe view as the source views. The intermediate between these views are considered destination views. The training view features are trained by the Random View Method. Also, the Part Dependant Views are used here so that the destination views selected so that the gait features are matched for each part accurately. These scores are added up for recognition.

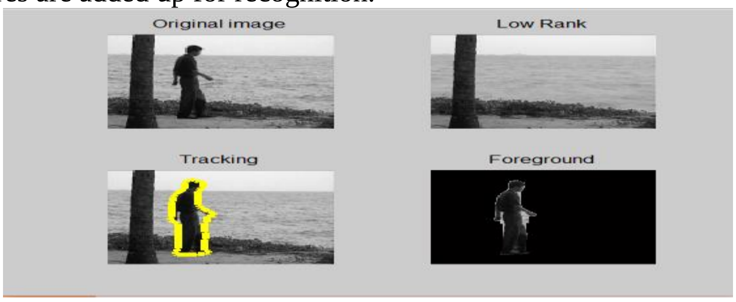


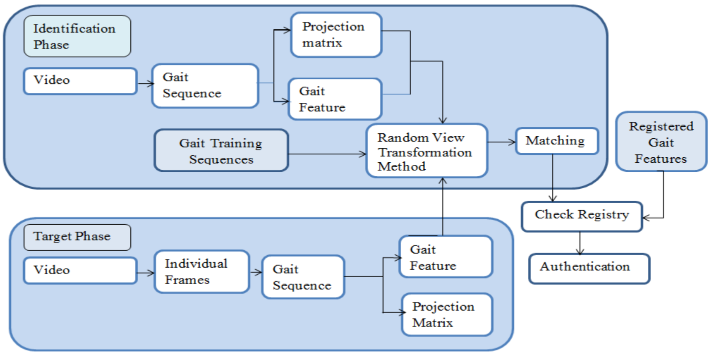
Fig.2. Background Subtraction

Random View Framework: This approach is distinct because of its discreteness in the training views. Usually, the training dataset is made of 2D image series from various distinct views. However, it is impractical to generate 2D image sequences from random views from these 2D training datasets. Hence, we use 3D volume sequences during training itself. Using these 3D sequences, we can create 2D images in random by re-projecting the matrices. This is very essential in creating the data associated with target views. Be it any view for the target subject, we can create a random view leading to the training views making the identification a lot simpler.

View Transformation: The method includes an enrolment phase and a recognition phase. In both phases, gait image sequences are input together with an ID number. We assume that projection matrices associated with the data are available; these projection matrices are used to generate training data with the target views. Silhouette image sequences are extracted from the gait image sequences using background subtraction-based graph cut segmentation, and then gait features are extracted from the silhouette image sequences. Computer stereo vision is the extraction of 3D information from digital images, such as obtained by a CCTV camera. By comparing information about a scene from two vantage points, 3D information can be extracted by examination of the relative positions of objects in the two panels. This is similar to the biological process Stereopsis.

Random View Generation: This can be determined by two main phases called image re-projection and matrix transformation. A cycle is created of the 3D gait volume sequence related to a training subject. Note down the number of training subjects and the number of volumes included in one gait cycle of that particular subject. To re-project, a silhouette image sequence of a subject is first taken from a particular view. Using a function that projects a 3D volume onto a 2D image plane using projection matrix, we extract gait feature from a gait silhouette image sequence. As the gait feature, any feature with a fixed dimension or frequency domain feature is acceptable. In Transformation Matrix Generation, we generate a training matrix for VTM generation using extracted features on training data. Using the training gait features and destination view, we generate training matrix. Note that the training matrix is dependent on the three views.

Segment View Selection: The recognition accuracy of the approach is influenced by the destination view, an appropriate destination view for recognition must first be identified. The appropriate destination view differs for each body part, hence we propose a scheme where an appropriate destination view for each body part is selected independently. We consider four body parts based on known anatomical properties and separate a gait feature into multiple subjects using the synchronised camera system. Scores plays an important role in this study, however method that combines the part-based, we simply add the part-based scores.



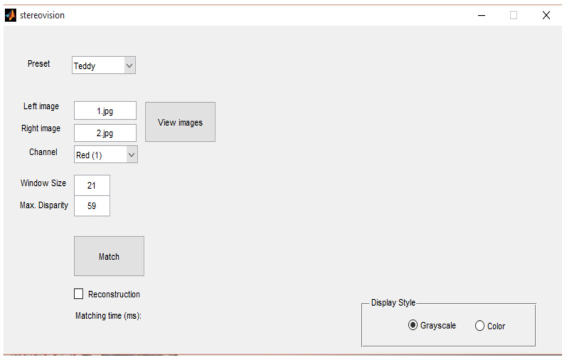


Fig.3. Architecture Diagram **Fig.4. Stereovision**

3. EXPRIMENTAL RESULTS

Image Extraction: While training the dataset, we collected gait image sequences from the four segments using a mask matrix a single region, namely, the legs, chest, head, and waist, respectively. For each of these parts, we first divide the training data into two non-imbricating data subsets: model training data and approved data.

In part-based gait recognition, the fusion is performed where they were made to walk on a treadmill and their pattern is captured. Projection matrices are created from silhouette images, where the sequences are modified manually. We constructed a 3D volume from the silhouette images for multiple views using a visual cone intersection technique. From a gait image sequence we extracted the gait feature, because this achieves comparable recognition to Gait Energy Image. A higher dimensional feature is preferable for the VTM.

Gait Feature Extraction: From a gait image sequence we extracted the FDF as the gait feature, because this achieves comparable recognition accuracy to the GEI for a large-population dataset, and the dimension of the FDF is higher than that of the GEI. Classification Based on Side Face and Gait Features using detection of moving objects uses a background subtraction algorithm based on Gaussian mixture models. Morphological operations are applied to the resulting foreground mask to eliminate noise. Blob analysis detects groups of connected pixels, which are likely to correspond to moving objects.

Authentication: Projecting the 3D volume sequences onto a 2D image plane using associated projection matrices, and then generated gait features for these views. The generated gait features were divided into two subsets. The subset for model training was used for VTM generation, while that for validation was used to calculate the transformation error. This can be matched with the available dataset and a match can be found.

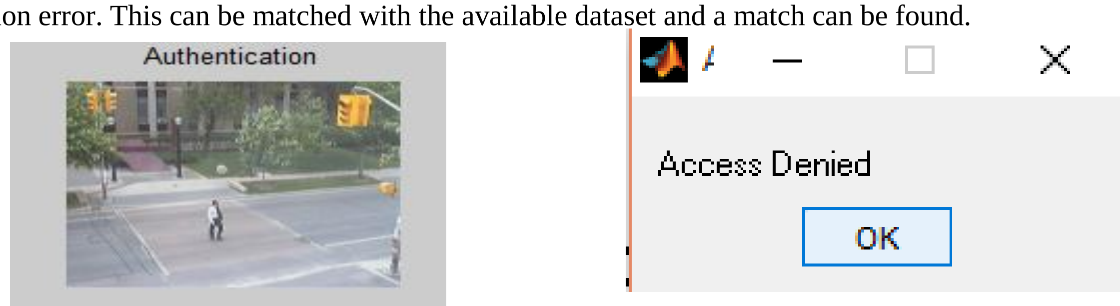


Fig.5.Unauthorized access

4. CONCLUSION

In this paper, we proposed a method for cross-view random gait recognition. There are two main advantages to this technique. Usage of Arbitrary Views while matching when Conventional VTM's propose a discrete method which can be overcome using arbitrary techniques. Gait volumes of target individuals need not be extracted, proving the current method to be easier during matching. Part Dependant Conversion error which usually indicates the conversion error for each body part is dependent on the destination view. This paper clearly identifies the impact of view variations in the destination view. Also, the proposed random view framework improves the accuracy of other approaches. Adding features like side face recognition can improve accuracy rates further. The side face detection approach is also a long distance nonintrusive approach which can be incorporated here. Provided, there are procedures to register faces separately.

REFERENCES

Ariyanto G, and Nixon M.S, Marionette mass-spring model for 3D gait biometrics, in Proc. 5th IAPR Int. Conf. Biometrics, 2012, 354–359.

Ashok Veeraraghavan, Matching Shape Sequences in video with applications in human Movement analysis, IEEE Transactions on Pattern Analysis, 2005.

Bobick A.F, and Johnson A.Y, Gait recognition using static, activityspecific parameters, in Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit., 1, 2001, I423–I430.

Daigo Muramatsu, Gait-Based Person Recognition Using Arbitrary View Transformation Model, IEEE Transactions On Image Processing, 2015.

Goffredo M, Bouchrika I, Carter J.N, and Nixon M.S, Self-calibrating view-invariant gait biometrics, IEEE Trans. Syst., Man, Cybern. B, Cybern., 40 (4), 2010, 997–1008.

Imed Bouchrika, Markerless Extraction of Gait Features using Haar-like Template for View-Invariant Biometrics, 15th International Conference on science and techniques of automatic control, 2014.

Kale A, Roy-Chowdhury A.K, and Chellappa R, Towards a view invariant gait recognition algorithm, in Proc. IEEE Conf. Adv. Video Signal Based Surveill., 2003, 143–150.

Konstantios Moustakas, Gait recognition using geometric features and soft biometrics, IEEE Signal Processing, 2010.

Kusakunniran W, Wu Q, Zhang J, and Li H, Gait recognition under various viewing angles based on correlated motion regression, IEEE Trans. Circuits Syst. Video Technol., 22 (6), 2012, 966–980.

Liang Wang, Automatic gait recognition based on statistical shape analysis, IEEE Transactions on Image Processing, 2003.

Makihara Y, Sagawa R, Mukaigawa Y, Echigo T, and Yagi Y, Gait recognition using a view transformation model in the frequency domain, in Proc. 9th Eur. Conf. Comput. Vis., Graz, Austria, 2006.

Makihara Y, Sagawa R, Mukaigawa Y, Echigo T, and Yagi Y, Gait recognition using a view transformation model in the frequency domain, in Proc. 9th Eur. Conf. Comput. Vis., Graz, Austria, 2006, 151–163.

Nitchan Jianwattanapaisarn, Human Identification using Skeletal Gait and silhouette data extracted by Microsoft Kinect, SCIS &ISIS, 2014.

Shiqi Yu, A study based on gender classification, IEEE Transactions on Image Processing, 2009.

Shuai Zheng, Robust view transformation model for gait recognition, 18th International IEEE Conference on Image processing, 2011.

Soharab Hossain Shaikh, Gait Recognition using Partial Silhouette-based approach, International Conference on Signal processing and integrated networks, 2014.

Urtasun R, and Fua P, 3D tracking for gait characterization and recognition, in Proc. 6th IEEE Int. Conf. Autom. Face Gesture Recognit., 2004, 17–22.

Worapan Kusakunniran, A New View-Invariant Feature for Cross-View Gait Recognition, IEEE Transactions on Information Forensics and Security, 2013.

Worapan Kusakunniran, Gait Recognition Under Various Viewing Angles Based on Correlated Motion Regression, IEEE Transactions On Circuits And Systems For Video Technology, 2012.

Xiaoli Zhou, Integrating face and gait for human recognition at a distance in video, IEEE Transaction on system, MAN and Cybernetics, 2007.

Yam C, Nixon M, and Carter J, Automated person recognition by walking and running via model-based approaches, Pattern Recognit., 37 (5), 2004, 1057–1072.

Yang H.D, and Lee S.W, Reconstruction of 3D human body pose for gait recognition, in Proc. IAPR Int. Conf. Biometrics, 2006, 619–625.

Yu Guan, On reducing the effect of covariate factors in gait recognition: A classifier ensemble method, IEEE Transactions on Pattern Analysis, 2015.