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Human Gait Identification using Depth Gradient Histogram Energy Image

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Abstract: ***Earlier work where we evaluated how traditional Gait Energy Image (GEI) can be used to identify human gait and eventually human ID. However, we also witnessed how inaccurate segmentation (due to unclear foreground-background boundary, human walking direction w.r.t camera axis etc.) may disturb the overall identification performance. To overcome this limitation, present work focuses on using edge and depth gradients extracted from 3D depth data of human gaits. In this paper, first, brief survey of various approaches is outlined. Then promising feature called Depth Gradient Histogram Energy Image (DGHEI) obtained by Histogram of Oriented Gradients (HOG) is presented. Paper also covers performance comparison between 2D GEI and 3D DGHEI based clue to identify human gait.***

Keywords: Gait identification, PCA, DGHEI, HOG, oriented gradient, 3D data

1. Introduction

Biometrics is automated of recognizing person based on physiological or behavioural characteristics. The need for biometrics can be found in many areas such as federal, state and local governments, in the military and commercial applications. Biometric technologies are becoming the foundation of an extensive array of highly secured identification and personal verification solutions.

Biological or behavioural characteristics as fingerprint, face or iris generally require physical contact views from certain aspects a cooperative subject. These methods cannot reliably recognize non cooperating individuals at a distance in the real world under changing environmental conditions. Gait is a relatively new biometric without these disadvantages. Gait recognition an attractive method of identification due to Unobtrusive, Distance recognition, reduced detail (It does not require high quality captured image i.e. unlike face recognition) and Difficult to conceal (i.e. unlike Face or Fingerprint scans)

However, gait also has some limitations: it can be affected by clothing, shoes or environmental context. Moreover, special physical Conditions such as injury can also change a person's walking style. It reduces the discriminating power of gait as a biometric but the inherent gait characteristic of an individual still makes it irreplaceable and useful in visual surveillance.

In this paper, we present economical and non-intrusive way to evaluate human gait for biometric authentication for 3D Depth data which overcome limitations of 2D color data. Recent research for depth based gait recognition is growing. Gait recognition by entropy estimation and generated DGHEI *(Depth Gradient Histogram Energy Image)* to use depth & edge gradients *of* human silhouette *by* HOG *(Histogram of*

Oriented Gradients), which save computation time and storage space as well as increase recognition accuracy.

In section 2, we will review some of the state of the art related to gait recognition. Section 3 we discuss about the pre-processing part and section 4 include feature extraction techniques used for proposed approach. Section 5 describes the proposed algorithm. Section 6 discusses the experimental results & conclusions are drawn last.

2. State of the art

Gait recognition system classified depending on the sensor used into three groups. FS based, WS based, MV based.

In Floor Sensor (FS) based approach, a set of sensors or force plates are installed on the floor such sensors enable to measure gait related features, when walks on them. Middleton et al. [2] used three features, stride length, stride cadence and time on toe to time on heel ratio for recognition. 80% recognition rate based on data set from 15 individuals. In Wearable sensor (WS) based gait recognition, gait is collected using body worn motion recording (MR) sensors.

The MR sensors can be worn at different locations on the human body. MR sensor was carried in the trousers pocket. 86.3 % recognition rate were achieved. Most of the current gait recognition methods are MV (Motion Vision) based. In this category, gait is captured using a video-camera from distance. Video and image processing techniques are employed to extract gait features for recognition purposes. Mainly divided into two groups, appearance based methods and model based methods. Appearance based method can be subdivide into two types, state space methods and spatio-temporal methods. Most of the MV-based gait recognition algorithms are based on the human silhouette.

Sarkar et al.[2] with a data set consisting of 1870 gait sequences from 122 subjects obtained 78% recognition rate Application areas for MV-based gait recognition are usually surveillance and forensics. The primary advantage of MV-based gait biometric compared to other modalities is in being captured from the distance when other biometrics is not accessible.

C. Nandini and CN Ravi Kumar [5] have proposed a silhouette extracted using Shannon entropy and extract the height of the subject and periodicity of the gait. Classification using nearest neighbour, Tested on UMD and own dataset. Ju and Bir [6] proposed Gait energy image, selected USF Human ID gait database for gait recognition purpose compare with other dataset. Bobick and Davis [8] propose motion-energy image (MEI) and motion-history image (MHI) for human movement type representation and recognition. Both MEI and MHI are vector-images where the vector value at each pixel is a function of the motion properties at this location in an image sequence.

Moshe Gabel, Ran Gliand Bachrach, Erin Renshaw and Assaf Schuster [13] Microsoft researcher presented approach for full body gait analysis include arm kinematics, stride information, measure stride interval consider virtual skeleton as input using Kinect sensor.Martin Hofmann, Sebastian Bachmann, Gerhard Rigoll[12] proposed people can be identified by the way they walk using efficient methods based on Gait energy image and depth data using depth Gradient Histogram Energy Image to improve performance.

Johannes Preis, Mortiz Kessel, Martin Werner, Claudia Linnhoff-Popien [14] propose approach for gait skeleton tracking & detection in real time using Kinect. It covers number of body features together with step length and speed, recognition rate more than 90% with nine test persons.Tanvi Banerjee, M.Keller, Majorie Skubic [15] developed algorithm to identify older residents using their gait sequences collected data using kinect. The feature clustered using Possibilistic C Means for resident identification. Adrain Ball, David Rye, Fabio Ramos, Mari Velonki [16] investigate recognize individual persons from their gait using 3-D ‘skeleton’ data.

Sonal N. Kharecha, C.Nandini, C.N. Ravi Kumar [17] proposed approach to identify by the way they walk using efficient methods based on Gait energy image for 2D data Depth Gait energy image for 3D data, both cases achieve more than 90% recognition accuracy.

3. Pre processing

To be able to track any moving objects in a video, it can be possible either using background subtraction or foreground separation. The objects subtracted from the background and returns an object as the foreground. For the 2D Color data object in this case human detection using background subtraction while for 3D depth data object detection using foreground separation gives better result. The video of object walking is captured and convert into consecutive sequences of frames. Each frame aim to extract object for gait recognition. A simple approach is used for the background subtraction. The idea of background subtraction is to subtract or difference the current image from a reference background model. If the difference of pixel is larger than threshold T then classify as foreground, else it is background.

The subtraction identifies non-stationary or new objects that human detection & tracking. However, it works only if static background estimate or known while foreground constantly moving.

Figure 1: Background Subtraction and Object Detection

4. Feature Extraction

4.1 Entropy

Entropy is useful for selecting unique feature. It is useful when you have obtained data on a number of poses (possibly a large number of poses – Human silhouettes), and believe that there is some redundancy in those poses (Human silhouettes). In this case, possibly because they are measuring the same construct. Because of this redundancy, you believe that it should be possible to reduce the observed poses (Human silhouettes) into a smaller number of poses (Human silhouettes) contain single full gait cycle.

4.2 DGHEI

Given a human walking sequence, a human silhouette is extracted from each frame using the method in after applying size normalization and horizontal alignment to each extracted silhouette image, single full gait cycles are segmented by estimating gait frequency using an entropy estimation technique after this compute DGHEI. DGHEI is new representation extends the DGEI. DGEI simple averaging depth information which has resulted in inaccurate segmentation (due to unclear foreground-background boundary) this limitations overcome by DGHEI, which works as depth information first aggregated in gradient direction histograms of non-overlapping regions. There for DGHEI first step is to compute magnitude r(x,y) and orientation θ(x,y) of human silhouettes, where x and y are image coordinates of human silhouettes.

$$r(x,y) = \sqrt{u((x,y)*(x,y)) + v((x,y)*(x,y))} \qquad (1)$$

$$\theta(x,y) = a\tan 2(u(x,y), v(x,y)) + \Pi \qquad (2)$$

Where $u(x,y) = I(x-1,y) - I(x+1,y)$ *and* $v(x,y) = I(x,y-1) - I(x,y+1)$

It consists of calculating histograms of oriented gradients at each frame t. Calculated gradient orientations at each pixel are discretized into 9 orientations:

$$\hat{\theta}(x,y) = \left(\frac{9*\theta(x,y)}{2*\Pi}\right) \qquad (3)$$

Then, these discretized gradient orientations are then aggregated into a dense grid of non-overlapping square image regions, the so called “cells” (each containing typically 8×8 pixels). Each of these cells is thus represented by a 9-bin histogram of oriented gradients. Finally, each cell is normalized four times (by blocks of four surrounding cells each) leading to 9 · 4 = 36 values for each cell. (Details to be found in [2]).

Next, following the averaging concept of GEI, the Calculated gradient histograms are finally averaged over a full gait cycle consisting of T frames and result in the DGHEI

$$H(i,j,f) = \frac{1}{T}\sum_{t=1}^{T} h_t(i,j,f) \qquad (4)$$

Here, i and j are pointing to the histogram cell at position (i,j) and f = {1...36} is the index to the histogram bin. Each gait cycle is finally represented by a multidimensional feature vector H(i,j,f).

5. Proposed Algorithm

5.1 Training Phase

The proposed approach for the Training phase

1. Read HOG (Feature Extracted) Frame of a person.
2. For each image perform the Feature data analysis using PCA
3. Finally get the new projected Eigen feature Vectors of individual person.
4. New projected training features, as Eigen image of individual person.

The above steps 1 to 4 are performed for all the frames of the person's video and store the respective result.

5.2 Testing Phase

The proposed approach for the Testing phase

1 Step 1 to 4 in the training phase is repeated for the different input test sample (which does not include in training data set) of a subject.

2 The generate Eigen image (biometric pattern) of test sample and stored Eigen images (biometric templates) of training phase compared by Euclidean distance.

For classification we have used the Euclidean Distance method of matching. The Final decision of the recognition technique is based on the minimum Euclidean distance between training dataset and test sample.

6. Experiment Results

For Experiments of 3D Depth data, we use a newly recorded large database the TUM Gait from Audio, Image and Depth (GAID) database. This database was recorded with the Kinect sensor and therefore features both a video stream, a depth stream as well as a four channel audio stream. Even though audio was recorded for potentially allow audio based gait recognition, but for this work only depth data is used. Both video and depth have a resolution of 640 X 480 at a frame rate of 30 fps. A total of 305 people were recorded, different genders. Each person is captured in 10 sequences, 6 are recorded in normal walking, 2 are carrying a backpack, and the remaining 2 are captured with disposable coating shoes. Out of this 32 people consider for second recording session, they have 10 additional sequences. The people walk perpendicular to the camera at a distance of approximately 4 meters. The gait of a person is best reflected when he/she presents an orthogonal (perpendicular) to the camera. Hence, most gait recognition algorithms rely on the availability of the side view of the subject. We consider the only side view of 2D and 3D subject data.

First Feature, Entropy apply to all frame sequence, of different dataset and select the no. of gait frames which cover single full gait cycle for individual. i.e. Consider 12 People 4 sequence parallel to image plane) total 48(12 x 4) image folders, frame range 49-86 for 12 people total no. of frames in given dataset 3407 after apply entropy feature to dataset total no. frames consider only 1468 with frame range 21-43. So, that it proves by reduce total 1939 image frame for processing with lower no of frame range for 12 people. (from 3407(49-86 frame range) to 1468(21-43 frame range).its affect to System performance, computation time reduce by processing less no. of frames. Proposed approach apply on how many image sequence, size of training and testing dataset with number of sequences all details given in Table 1. Figure 2 represent 2D color image of different person from TUM-GAID Dataset. Figure 3 represent 3D-Depth Row image, respective Silhouette for Raw image, HOG, average HOG of one full sequence from left to right w.r.t. one person from TUM- GAID Dataset. Figure 4 gives detail about how algorithm works.

Table 1: Proposed Approach on 3D Dataset

TUM-GAID (3D)			
	People	Sequence	Total
Selected Image folders from the given DB	20	6 (parallel to image plane)	120
DGHEI generate on Entropy range	20	3	60
Eigen image	20	3	60
Train Dataset	20	3	60
Test Dataset	20	1 (not use in train dataset)	20

Figure 2: Training Data (Different Person -2D from TUM –GAID Dataset)

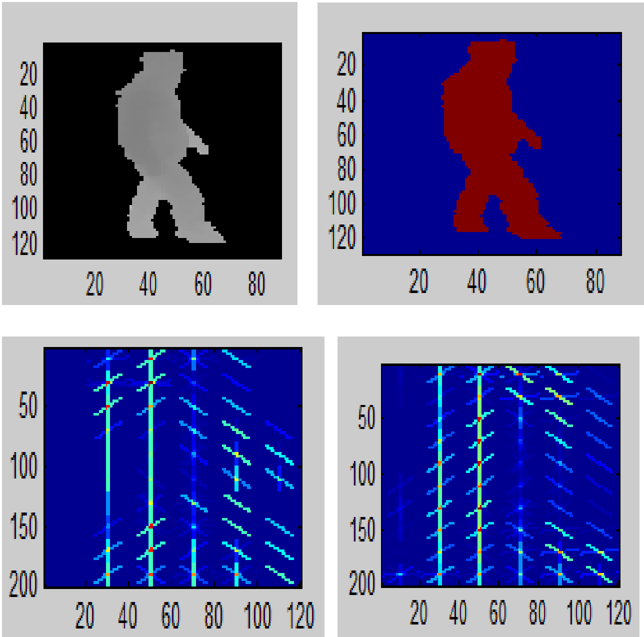

Figure 3: 3D-Depth-Raw image, respective Silhouette for Raw image, HOG, average HOG of one full sequence (From Left to right w.r.t. one person from TUM GAID Dataset)

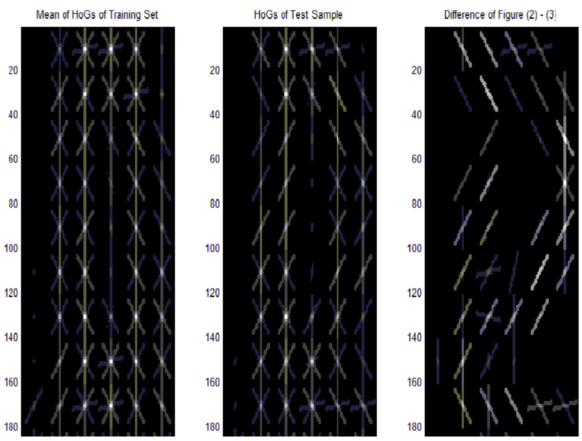

Figure 4: Compare Test image with train images

7. Conclusion & discussion

The proposed approach, depth based gait recognition which is relatively different approach for gait recognition. Its appearance based spatio-temporal gait representation, called the Depth Gradient Histogram Energy image (DGHEI), for individual recognition using depth information of 3D data for gait recognition so the inherent representational power of DGHEI and possibility of good segmentation in 3D depth data compare to 2D color data demonstrates that matching features learned from real gait templates achieve better recognition performance than direct matching between individual silhouette frame pairs algorithm.

DGHEI robust representation of human motion sequence in a single image while preserving temporal information. However, we also witnessed how inaccurate segmentation in 2D Data (due to unclear foreground-background boundary, human walking direction w.r.t camera axis etc.) may disturb the overall identification performance. To overcome this limitation, present work focuses on using edge and depth gradients extracted from 3D depth data of human gaits. Then promising feature called Depth Gradient Histogram Energy Image (DGHEI) obtained by Histogram of Oriented Gradients (HOG) is presented. Moreover, entropy estimate gait cycle for DGHEI and selection of most discriminate features by PCA, features lead to increase accuracy of overall system. We used minimum Euclidean distance for classification.

Our aim to propose this approach for good segmentation with higher recognition rate. Compare proposed approach with our earlier work on 2D data with different datasets (CASIA and own created Dataset) and 3D data, achieved **90%** and **91.66%** recognition rate respectively. To get higher rate apply HOG based DGHEI Feature extraction on newly created TUM GAID Database for 3D Depth data and same collection data possible using Kinect sensor with imagery setup as defined in TUM GAID. For 3D Dataset & DGHEI Feature **95%** recognition rate is possible which more than earlier work.

Our aim to test different feature extraction technique on collection of data from the various sensors. Previous work we covered 2D & 3D data with feature Gait energy image, Depth Gait energy image. This work on 3D data using Depth Gradient histogram Energy image (DGHEI) on one of the newly and largest recorded TUM-GAID Database. Same collection of data possible using Kinect sensor with imagery setup as defined in TUM GAID.

Our contribution to evaluate that this model free method work well with 3D Depth Features has led to the increased in recognition accuracy of the entire system. Experimental results and performance comparison show that the proposed recognition approach achieves highly competitive performance with respect to other comparison gait recognition approaches.

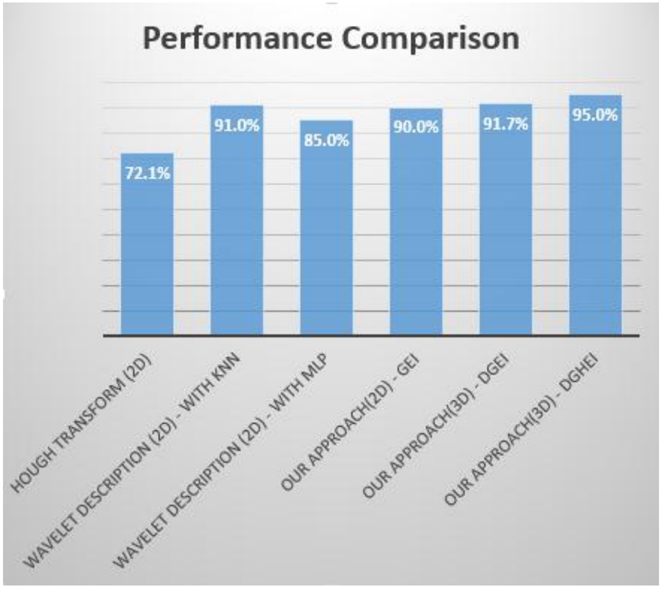

Figure 5: Performance comparison

However, we found that the recognition rate decreased when slight angle profile stances with drastic changes in clothing were given to test. The research continues in depth based gait recognition coming out with novel robust technique where in the real time datasets will be tested for time and cloth variations with input frames for cluttered background.

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