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AI BASED GAIT RECOGNITION FOR BIOMETRIC SURVELLIANCE

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Abstract — *Human gait recognition is distance-based second generation biometrics, which is unobtrusive. Human gait recognition is nothing but identifying a person from its walking style. Human Cooperation is not required in this biometric system. There are two approaches to gait recognition, which are model-based and model-free approaches. The proposed system is developed on the model-free gait recognition approach. The system focused on motion free gait image representation, dimensionality reduction of extracted features and classification.*

Keywords—Gait, Biometrics, Unobtrusive

I. INTRODUCTION

One of the several physical and behavioral characteristics of an individual that can be used to identify them is their gait [1]. A person's gait is the way they walk. Numerous studies have demonstrated that gait information can be used to differentiate between people. In criminal cases, gait has even been used to identify offenders based on how they walk. In addition to being used to identify and evaluate individuals, gait patterns like the Parkinson shuffle can also be used to diagnose and evaluate clinical disorders. In comparison with other first-generation biometric modalities that include fingerprint and iris recognition, gait has the advantage of being unobtrusive, in that it requires no subject contact. Gait recognition is based on the notion that each person has a distinctive and idiosyncratic way of walking, which can easily be discerned from a biomechanics viewpoint. Most people agree that the human gait is a distinctive feature that makes us difficult to duplicate or conceal. As such, it serves as a vital biometric characteristic for identifying humans. As a result, gait identification has been acknowledged as a crucial identifying technology for a variety of applications in criminal prevention and detection systems in high-security public spaces, including stations, banks, airports, and military installations. Gait recognition has also seen a lot of use recently in cyber-physical healthcare systems enabled by wearable devices that are networked, as well as in systems that predict gender, age, and ethnicity.

Model-free approach:

In a model-free approach, different types of features are extracted like the whole motion of human bodies, silhouette width vector of Fourier descriptors. It also focuses on silhouette shape and the dynamic information, which is used for pattern matching. Dynamic information is collected by using temporal alignment techniques.
Without fitting a model, it generates gait signatures directly from the silhouettes that are taken from the video sequences. The most widely used gait representation is the gait energy image (GEI), which uses a grey image to capture the spatial and temporal gait information. In order to portray a human motion sequence in a single image while maintaining temporal information, GEI is created by averaging silhouettes over the course of a gait cycle [1]. Model-free approaches have the advantages of simplicity and computing economy, but they

still need to be improved in terms of resilience against changes in lighting, clothing, scaling, and viewpoints.

II. LITERATURE SURVEY

Image acquisition, pre-processing to separate the binarized silhouettes from the background, training and/or feature extraction from silhouettes, and, finally, classification or recognition of gait sequences by matching the testing and training feature spaces are the four main steps in the gait recognition process. Assuming that the silhouettes originate from stationary cameras capturing motionless scenes, basic and less computationally intensive methods such as background segmentation can be employed to pre-process the silhouettes.

Despite demonstrating the capacity to achieve accurate gait identification, the model-based approach has encountered certain difficulties. For example, it is challenging to identify the body segments from the silhouettes of the binarized photos due to the numerous occlusions and shadows in the images. The modelling of the human body frequently requires the complex and computationally demanding operation of converting high-quality 2D photographs into 3D computer models in order to boost recognition accuracy [2].

Consecutive motion-based and spatiotemporal motion-based techniques are the two categories into which model-free, also known as motion-based approaches, can be divided. While the spatiotemporal technique portrays gait by visualising the distribution of motion through space and time, sequential motion approaches represent gait as a time series of human poses [3]. The suggested sequential motion-based method entails documenting the motion's history as well as depicting the motion using temporal templates that show where the motion has happened. The main areas of variation amongst the spatiotemporal approaches suggested in the literature are the methods for pre-processing, feature extraction, and categorization applied to the silhouette-based gait.

Instead of keeping an inventory of gait patterns as a series of templates, the authors presented a feature selection process termed gait energy image (GEI), which records the past of gait patterns in a single 2D template. The averaging of the silhouette's pixels across several gait cycle frames yields the spatiotemporal GEI characteristic. Real and artificial (distorted) gait templates were fused statistically to create the recognition feature. In addition to saving space, this method reports excellent recognition [4]. .

III. METHODOLOGY

A biometric produced by a model-based approach has high dependability on the original data. Using video feeds from conventional cameras and without using a special hardware, implicates the development of a body motion capture system. For gait recognition, the proposed approach includes uses components such as gait capture, image segmentation, feature extraction, and gait recognition interface.

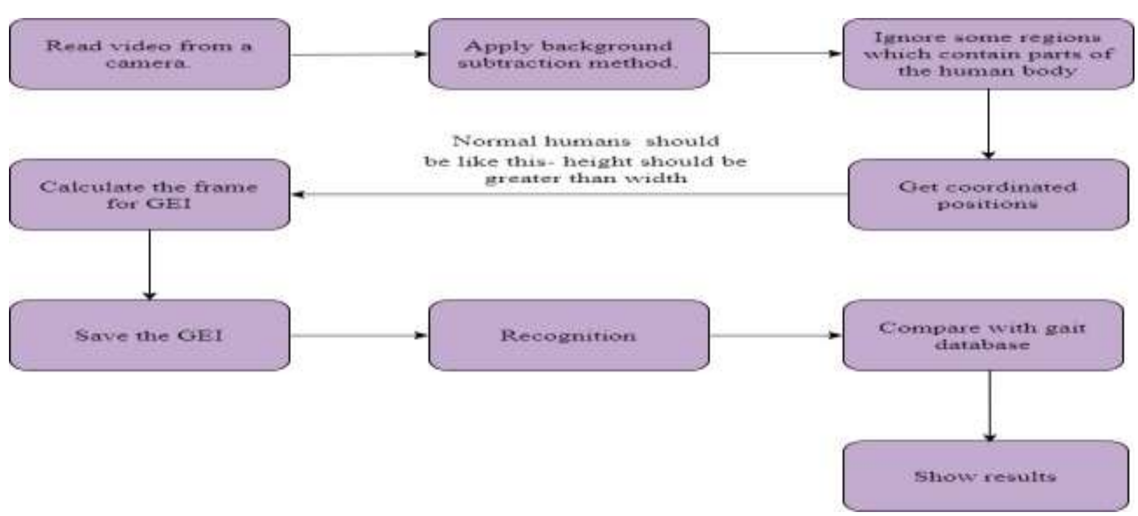

Fig 1 – Proposed System

1. **Reading video from camera** - In OpenCV, a video can be read either by using the feed from a camera connected to a computer or by reading a video file. The first step towards reading a video file is to create a VideoCapture object. Its argument can be either the device index or the name of the video file to be read.
In most cases, only one camera is connected to the system. So, all we do is pass '0' and OpenCV uses the only camera attached to the computer. When more than one camera is connected to the computer, we can select the second camera by passing '1', the third camera by passing '2' and so on.

2. **Apply background subtraction method** - Once the walking subject is captured from a distance, then background subtraction is performed on the image by using background subtraction techniques (RunningGaussian Average, Temporal Median Filter, Mixture of Gaussians, Kernel density estimation (KDE), Sequential KD approximation, Concurrence of image variations, Eigen backgrounds).
As the videos are captured indoor, it is hard for the newly built Outdoor-Gait to extract human profiles due to the varying light and complex backgrounds. We test several popular segmentation methods on this database. As shown in Fig, the segmentation results from Background Subtraction (BGS) and Gaussian Mixture Model (GMM) contain much noise, e.g., the shadow and the missing parts of a human body, whereas FCN can obtain good silhouettes even in challenging backgrounds[4]. Therefore, we use FCN to generate all silhouettes of Outdoor-Gait. We first resize each input image into a size of 64 × 64, then normalize them by subtracting the mean values and scaling them with a factor of 1/255. There are no extra data augmentation in our experiments.

3. Calculating the frame for GEI - : Different types of gait detection methods employ distinct gait features, which have an impact on the recognition's accuracy [5]. There are two types of gait features: machine-learned and hand-crafted. While machine-learned ones are typically superior for the particular dataset, hand-crafted ones are easily generalised to different datasets..

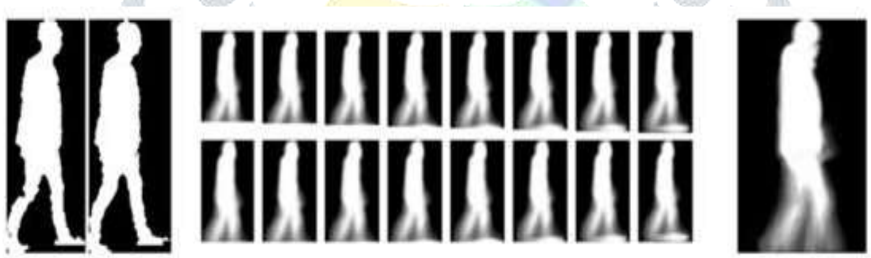

Fig 2 – GEI Frame

$$\mathbf{B}(\alpha)_{x,y} = \begin{vmatrix} 1 & \text{if } P_{x,y} = \alpha \\ 0 & \text{otherwise} \end{vmatrix} \quad \forall \alpha \in 1, NB$$

------------>(1)

Then, the points in each binary region are connected into regions of 1s and 0s. Four geometrical measures are made on these data. First, in each binary plane, the number of regions of 1s and 0s (the number of connected sets of 1s and 0s) is counted to give NOC1 and NOC0[5]. Then, in each plane, each of the connected regions is described by its irregularity which is a local shape measure of a region R of connected 1s giving irregularity I1 defined by:-

$$I1(\mathbf{R}) = \frac{1 + \sqrt{\pi}\max_{i \in \mathbf{R}} \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}}{\sqrt{N(\mathbf{R})}} - 1$$

------->(2)

The irregularity of the connected 0s, I0(R), is similarly defined. When this is applied to the regions of 1s and 0s it gives two further geometric measures, IRGL1(i) and IRGL0(i), respectively. To balance the contributions from different regions, the irregularity of the regions of 1s in a particular plane is formed as a weighted sum WI1(α) as

$$WI1(\alpha) = \frac{\sum_{\mathbf{R} \in \mathbf{B}(\alpha)} N(\mathbf{R}) I(\mathbf{R})}{\sum_{\mathbf{R} \in \mathbf{P}} N(\mathbf{R})}$$

-------->(3)

and the final statistic is the sample standard deviation ssd as

$$ssd = \sqrt{\frac{1}{\sum_{\alpha=1}^{NB} m(\alpha)} \sum_{\alpha=1}^{NB} (\alpha - \bar{s})^2 \, m(\alpha)}$$

------->(4)

4 Classification:- The k-nearest neighbour rule. In application, usually has a description of a texture sample and we want to find which element of a database best matches that sample [6]. Thus is classification: to associate the appropriate class label (type of texture) with the test sample by using the measurements that describe it[7]. One way to make the association is by finding the member of the class (the sample of a known texture) with measurements which differ by the least amount from the test sample's measurements. In terms of Euclidean distance, the difference d between the M descriptions of a sample, s, and the description of a known texture, k, is

$$I1(\mathbf{R}) = \frac{1 + \sqrt{\pi}\max_{i \in \mathbf{R}} \sqrt{(x_i - \bar{x})^2 + (y_i - \bar{y})^2}}{\sqrt{N(\mathbf{R})}} - 1$$

------->(5)

The irregularity of the connected 0s, I0(R), is similarly defined. When this is applied to the regions of 1s and 0s it gives two further geometric measures, IRGL1(i) and IRGL0(i), respectively[8]. To balance the contributions from different regions, the irregularity of the regions of 1s in a particular plane is formed as a weighted sum WI1(α) as The distance between n and m patterns has been calculated according to following formula[9]:

$$D(n, m) = \sum_{c=1}^{6} D_c$$

-------->(6)

5. *Recognition*:- After the classification recognition part comes, in which again the video input is being taken continuously and also the image frames are being extracted[10]. Again feature extraction is being done and the output is compared with the gei dataset. If found a match a contour over the body of subject displays the name of the identified person. The result is shown on the gait recognition UI.

Fig-3 Gait Recognition

I V . CONCLUSION

The proposed system is human gait analysis for the biometric surveillance. The literature review is carried out to understand the drawbacks of the existing human gait analysis models and to identify the gaps. The proposed methodology focused on motion free gait image representation, dimensionality reduction of extracted features and classification. This gait recognition system needs a clean background, an example a white wall. This demo only takes GEI as its feature, so it can only recognize persons with the same views,for example people walk with the same angle for both registration and recognition

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