Gait Cycle analysis using Pattern Recognition

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***Abstract*— One of the most significant human characteristics is motion ability, which includes gait as the foundation of human transitional movement. Many academics had concentrated on this topic in order to consider a novel recognition system. Many human gait datasets have been developed in the previous ten years. The Gait Dataset of the University of South Florida (USF), the Gait Dataset of the Chinese Academy of Sciences (CASIA), and the Gait Dataset of Southampton University (SOTON) are some of the most extensively utilised datasets. The CASIA Gait Dataset will be examined in this research to determine its properties.Gait patterns were gathered in this investigation utilising a wireless platform with two sensors attached to the individuals' chest and right ankle. The raw data was then subjected to certain preprocessing techniques.The performance of many temporal and frequency domain features is evaluated using five different classifiers, and a full comparison is made in this work.**

***Keywords* : Python, KNN, SVM, Decision Tree, Naive Bayes**

I. Introduction

In recent years, there has been a greater focus on identifying persons effectively in order to avoid terrorist acts. Many bio-metric technologies have arisen that analyse the face, fingerprint, palm print, iris, gait, or a combination of these attributes to identify and authenticate persons.[3]

When compared to other recognition systems, human gait recognition has several advantages. The attention and participation of the observed individual are not required by the gait recognition system. It may also collect gait from a distance without asking people to provide any physical information.

Preprocessing, feature reduction and extraction system, and classification are the three primary subjects of Human Gait Recognition as a recognition system.[2]

Each participant was instructed to walk normally from the lab to a designated location outside the building. As a result, the route was about equal for all of the subjects. During their trek, the subjects should pass through two doors and make one left turn. The kind of floor was a crucial issue in this experiment since it has a considerable impact on human walking patterns.[2]

II. Overview of Dataset

It is hard to categorise people using the raw data generated by two sensor nodes due to their nature. The raw accelerometer data for the ankle node is shown in 3-dimensional form in the diagram. As a result, a number of characteristics were retrieved from these raw signals and sent into the classifiers as input. The characteristics were chosen in accordance with the application and experiment platform (sensor network placements on the subject's body). The raw data's complexity is reduced in this way, and some useful information is recovered. When

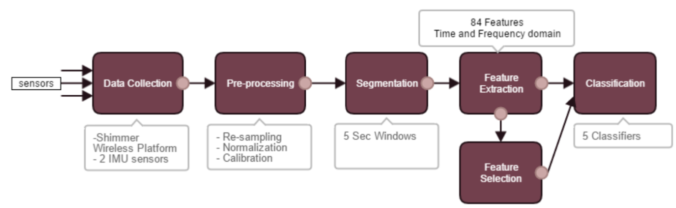

Fig. 1. Architecture of model

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III. Literature Review

Gait patterns were classified using five different classification methods:

In pattern recognition, nearest neighbour classifiers [6] are a type of non-parametric approach. The approach identifies objects based on the feature space's nearest training sample point. Based on a majority vote among the classes of the k closest training points, the kNN classifier allocates a point to a certain class.

The decision tree classifier [4] is a machine learning and data mining approach that use a decision tree as a prediction model, mapping observations about an item to inferences about the item's target value. A decision tree is a flowchart-like structure in which each internal (non-leaf) node represents an attribute test, each branch represents a test result, and each leaf (or terminal) node stores a class label. The root node is the topmost node in a tree.

Linear discriminant analysis (LDA) [5] is a method for finding a linear combination of characteristics that describes or separates two or more classes of objects or events that is used in statistics, pattern recognition, and machine learning.

A Support Vector Machine (SVM) [7] is a supervised learning model that classifies data by determining the optimum hyperplane that divides all data points belonging to one class from those belonging to the other. The support vectors are the data points nearest to the separating hyperplane, which are located on the slab's edge.

IV. Methodology and Justification

GEI was chosen as the best compromise between computational cost and recognition performance in this article among all accessible feature representations. It is a straightforward and simple representation to calculate, making it an effective compromise between computational cost and recognition performance. Our system is depicted in Figure 2 and is separated into two primary modules: the first consists of picking characteristics from the GEI that are robust to confounders. Because the selection technique should not be overspecialized for a specific training set [8], we run it on a feature selection set separate from the training and testing sets (all feature selection sequences were deleted from the training and testing sets).The second module uses the GEI characteristics specified in the previous module to estimate the performance of our strategy (Correct Classification Rate).

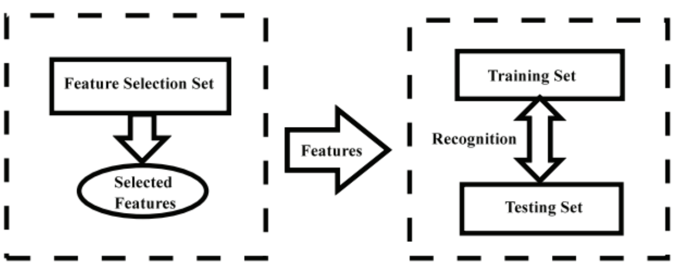

Fig. 2. Architecture of model

Because horizontal motion is much more characterised by an individual's gait than vertical motion [9], rather than estimating the motion of each pixel by calculating its entropy [10] we estimate the horizontal motion by taking the entropy of each row from the GEI(see sec A) considered as a new feature unit, and the resulting vector e RN represents the motion based vector (see Sec B). The aim is to determine the common dynamic human body part that is robust to covariates across multiple gait sequences (i.e. the shared human body part that has the greatest motion/entropy value across different gait sequences).. The human body parts-based motion is estimated using Vert and Bleakley's group fused Lasso method [11], which seeks to estimate where the majority or all of the motion-based vectors ekP k=1 jointly change (i.e. segment the motion vectors into shared blocks with the same motion value). The performance of the specified human body part (GEI features) is calculated in the second module using Canonical Discriminant Analysis (CDA) [12]. (see Sec C).

A. Gait Energy Image

The gait patterns are represented spatially and temporally by the GEI. It entails depicting the gait cycle with a single grayscale picture created by averaging the silhouettes retrieved throughout the course of a whole gait cycle [13]. The following equation is used to calculate GEI.

$$\mathbf{G}(x,y) = \frac{1}{F}\sum_{t=1}^{F}\mathbf{B}(x,y,t)$$

In the above equation F is the total number of frames in a gait cycle, B is a silhouette picture, x and y are the image's coordinates, and t is the cycle's frame number.

B. Motion Based Vector

$$\begin{cases} \mathbf{e}(i) = -\sum_{k=0}^{K} p_k^i \log_2 p_k^i \\ i \in [1, N] \end{cases}$$

A motion-based vector e belongs to R raise to N is calculated by computing the Shannon entropy of every row from the GEI viewed as a new feature unit (see Fig. 3).

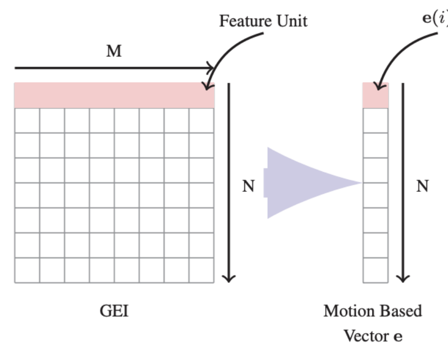

Fig. 3. Illustration of the motion based vector

C. Canonical Discriminant Analysis

Principal Component Analysis (PCA) is equivalent to Canonical Discriminant Analysis (CDA). We keep 2c eigenvectors after PCA, as suggested in, where c is the number of classes (the entire explantation may be found in [12]). The goal of the PCA is to be able to capture the majority of the changes in the original data with only a few orthogonal principle components. Multiple Discriminant Analysis aims to maximise distance across classes while maintaining distance within them.The correct classification rate (CCR), which is the ratio of the number of well categorised samples to the total number of samples, is used to measure the performance of our technique. [14]

V. References

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