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Human Identification System Based on Gait using Active Horizontal Levels (AHLs) Feature and Chi-Square Attributes Selection (CSAS)

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Abstract

Nowadays, gait is a crucial field for many pattern recognition researchers. It is considered as a good way for biometric authentication in many surveillance systems. In this paper, a new method has been introduced to identify night walker images captured by infrared cameras. This method depends on the silhouette’s presence on different horizontal levels. A new proposed algorithm to select the Active Horizontal Levels (AHLs) feature has been presented. Chi-Square attributes (feature) selection and K-Nearest Neighbor classifier have been used to choose the AHLs that lead to the highest identification rate. The proposed method was evaluated against CASIA-C gait database, to recognize person from one image. The experimental results reveal the effectiveness of our proposed algorithm against other gait identification algorithms.

Keywords: *Gait Identification, Feature Extraction, Attribute Selection and Biometric Authentication*

1. Introduction

Biometric-based technologies include identification based on physiological characteristics (such as face, fingerprints, hand geometry, hand veins, iris, retina, ear, voice, etc ...) and behavioral traits (such as gait, signature, keystroke dynamics, etc...) [1]. Gait is a behavioral barometric that is superior in person’s authentication. Thus, utilizing gait as identification criteria identifies certain distinct phases or stances. Study of human gait and its mathematical modeling has implications for different areas like surveillance, medical diagnosis, entertainment industry, video communications, etc. The attractiveness of gait as a biometric arises from the fact that it is nonintrusive and can be detected and measured even in low resolution video. Gait as a biometric method has some advantages such as being difficult to hide, steal, or fake. Furthermore, gait can be recognizable from distance. However, most other biometrics can be captured only by physical contact or at a close distance from the recording probe. Moreover, users do not need to unveil additional information about them other than already available. Despite the advantages enjoyed by gait, it faces many challenges that the existing gait identification methods are sensitive to such as. Type of clothes, speed of the person, illumination changes and person’s directions [1-4].

A general statement of the problem can be formulated as follows. “Given a video/still image of a walking person, and it is required to identify her / him using a predefined database of person's gait, in case variation of clothes type and walking speed”. A possible solution of the general problem may be subdivided into three different stages [5]. Pre-processing, feature extraction and decision. The preprocessing stage is to simplify pattern identification problem with throwing away any unimportant information. The stage of extraction of the features is the most critical one. At the third stage, a decision is to be taken from the data collected from the previous stage.

In this paper, we implement a person's identification approach. Based on gait, a new feature extraction algorithm has been introduced. The extracted feature represents person's presence at different horizontal levels. Active Horizontal Levels (AHLs) are selected to create a set of horizontal levels that achieves the best identification results. The proposed algorithm is implemented and evaluated against CASIA (Chinese Academy of Sciences the Institute of Automation) database [6]. Finally, a comparative study is introduced, where AHLs feature is compared with other methods published in literature and provides significant improvement.

The remaining of the paper is organized as follows. Section 2 presents a general survey for some new researches, which were performed related to gait identification. Section 3 explains the new feature extraction algorithm depending on gait. Section 4 discusses the performance of the proposed algorithm (AHLs) against other feature extraction algorithms that used CASIA database. Section 5 contains conclusions drawn from the study performed on this paper.

2. Related Works

Gait has played an important role in biometric authentication due to its unique characteristics compared with other biometrics. In recent years, there has been an increase in research works related to gait-based human identification. The techniques used for gait identification can be divided into two categories. Model-based methods and motion-based methods [7]. Model-based methods aim to explicitly model human body or motion. They usually perform model matching in each frame of a walking sequence so that the parameters such as trajectories are measured on the model. Zhang et al. [8] developed a 2-step, model-based approach, in which reliable gait features were extracted by fitting a five-link biped human locomotion model for each image to avoid shape information. Sundaresan et al. [9] proposed a Hidden-Markov model-based framework for individual identification by gait. The effectiveness of model-based methods, especially in body structure / motion modeling and parameter recovery from a walking video, is still limited. They allow for current imperfect vision techniques (e.g., tracking and localizing human body accurately in 2D or 3D space has been a long-term challenging and unsolved problem). Further, the computational cost of model-based methods is relatively high.

However, motion-based approaches can be further divided into two main classes [7]. The first class called the state space methods. These methods considered gait motion to be composed of a sequence of static body poses and recognized it by considering temporal variations of observations with respect to these static poses. Tan et al. [10] used orthogonal diagonal projection for gait identification. Furthermore, Tan et al. [11] recognized night walkers based on one pseudo shape representation of gait, using Principle Component Analysis (PCA), PCA+ Linear Discriminate Analysis (LDA) and PCA+LDA+ Relevant Component Analysis (RCA) feature extraction methods. Tao et al. [12] introduced a set of Gabor-based human-gait appearance model and proposed a General Tensor Discriminate

Analysis (GTDA) to solve the carrying status in gait identification. Wang et al. [13] performed eigenspace transformation to time-varying silhouette shapes in features extraction. Kale et al. [14] used Hidden-Markov motion-based models in gait identification. However, Collins et al. [15] established a method based on template matching of body silhouettes in key frames for human identification. Cuntoor et al. [16] investigated different techniques to combine classification results of multiple measurements extracted from the gait sequences and demonstrated the improvement in identification performance. Three aspects of gait were discussed. Motion of the hands and legs, dynamics of the legs and frontal gait. Sum, Product and Minimum rules were used to combine the decisions made using the separate features.

The second class called the spatiotemporal methods. These methods generally characterized the spatiotemporal distribution generated by gait motion in its continuum. BenAbdelkader et al. [17] used image self-similarity plots of a moving person to recognize gait. More recently, Acquah et al. [18] described an automatic gait identification method using the spatiotemporal symmetry. Guha and Ward [19] proposed a novel silhouette-based feature extraction algorithm called Differential Radon Transform (DiffRT). It is a variant of Radon Transform (RT), in the sense that it relies on the idea of tracing an image with a set of straight lines along different directions. Liu et al. [20] mapped a video sequence of silhouettes into a pair of two-dimensional spatio-temporal patterns that are periodic along the time axis. Mathematically, such patterns are called “frieze” patterns. Moment-based frieze alignment was used in human identification. Lee et al. [21] introduced a shape variation-based frieze pattern (SVB frieze pattern) representation for gait. This means that the original frieze pattern can be decomposed into a key frame representing the shape component and an SVB frieze pattern representing the motion component after subtracting the key frame. A temporal symmetry map of gait patterns was also constructed and combined with vertical / horizontal SVB frieze patterns for measuring the dissimilarity between gait sequences.

It is worth pointing out the differences between our work and some of the aforementioned references for gait identification. Cuntoor et al. in [16] proposed the width vector, which calculated the width of the horizontal levels of the frontal view, as a feature extracted from the sequence of the walking person. However, our method explores the side view and depends on the silhouette’s presence on different horizontal levels. Furthermore, the maximum horizontal level occurrence is used in the normalization step of each image in the preprocessing phase and will be explained later. Moreover, we focus on the cues in the presence in the horizontal levels with a step of five levels and selectively employ a subset of these horizontal levels that leads to best results. On the other hand, frieze pattern exploited in [20] [21] used the horizontal and vertical projections on each level rather than selected horizontal level.

3. Architecture of the Proposed Model

The architecture of the proposed model for human identification system based on gait identification passes through two processes. The Learning process (Enrolment) and the Identification process (Testing) as shown in Figure (1). The major functional units for each process will be introduced in the subsequent sections. The proposed model has been implemented using Matlab R2010b as a programming language.

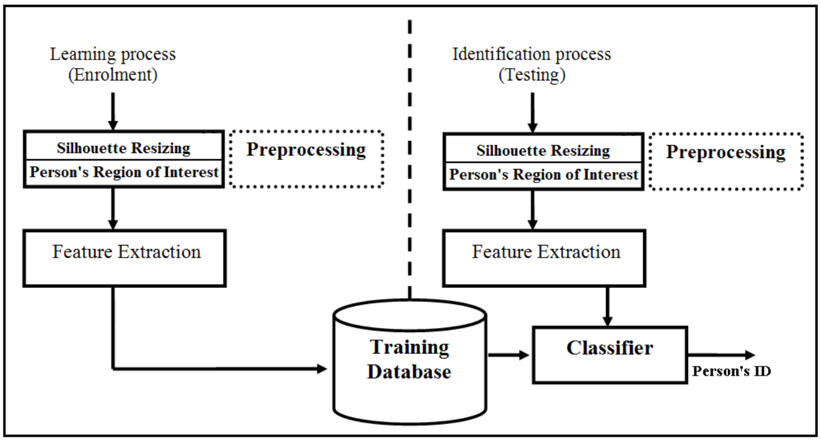

Figure (1): The architecture of the proposed model

3.1 Pre-processing Phase

The CASIA gait database is one of the largest databases that are used in human identification using gait. The CASIA gait database has three datasets (A, B and C), the CASIA-C dataset will be used in our experiments. It was captured by an infrared (thermal) camera at night. It contains a total of 153 different walking persons. Each person's sequence has 55 images. Moreover, CASIA-C, a speed-invariant gait dataset, takes into account four walking styles. Normal walking, slow walking, fast walking and normal walking carrying a bag. The walking person in the gait silhouette is detected by scanning the image firstly from top, left to right until the first pixel belongs to the person is reached. Then, from bottom, left to right until the first pixel belongs to the person is reached. The CASIA database provides images that are 300×240 pixels. If all rows of the image are concatenated into only one vector, the dimension of the problem would be to classify a vector with 72,000 elements. This dimension is too huge for computing, and even though having such capacity, satisfactory results are not guaranteed.

The pre-processing phase includes resizing the silhouette images in CASIA gait database to 100×80 pixels each. Then, the resized silhouette is followed by defining the person's region of interest in CASIA-C dataset as shown in Figure (2). The main reason for the preprocessing is two folded. The first one is the attempt to reduce the size of pattern vector. The second one is to isolate only information that distinguishes individuals for images.

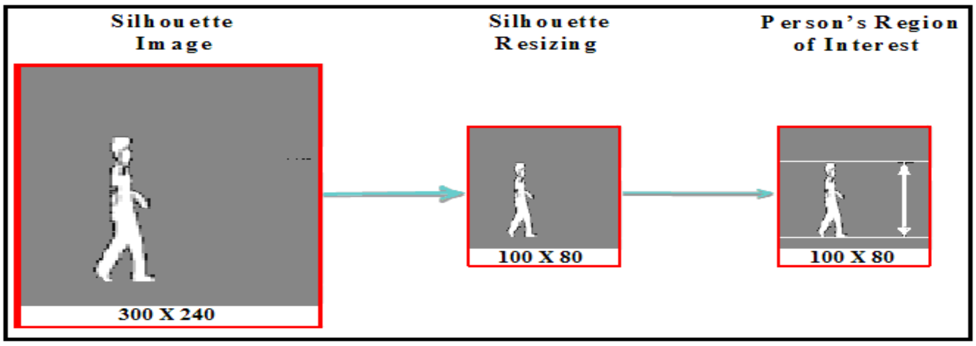

Figure (2): Pre-processing phase

List 1: Feature Extraction Algorithm

Initialization:

d = 1, d = 1… N (where d is the horizontal level and N is the maximum number of levels)

Step-1: Calculate X[d], where X[d] is the number of pixels for a person's appearance on horizontal level d

Step-2: Increment d.

Step-3: Repeat Step-1 and 2 until d = N.

Step-4: Find maximum value X_{Max} for X[d] elements.

Step-5: Divide each element in X[d] by X_{Max} to generate Normalized Image Feature Vectors (NIFV). And thus overcoming the scaling problem.

3.2 Feature Extraction Phase

In this phase, two algorithms are presented. These are feature extraction algorithm and AHL algorithm.

a) ***Feature Extraction Algorithm***: The key to the success of any gait identification system is the gait features extraction. Consequently, this paper resorts to the use of appearance features to characterize human gait. More precisely, each pre-processed silhouette is projected on many horizontal levels (for example 1%, 2%…99%, 100% of the silhouette's height). At each horizontal level, the valid number of human pixels is recorded. Thus, for each silhouette a vector of the valid number of human pixels in these horizontal levels is recorded so as to obtain a vector of human pixels counter along all horizontal levels. We denote the presence counter for the d projection level by X[d], where d varies from 1 to N and N is the maximum number of levels and thus X={X[1], X[2], …, X[100]}. These levels fulfill the description of the gait pattern. Then for normalization, the extracted feature vector X is divided by the maximum number of pixels in the projection level value to generate the Normalized Image Feature Vector (NIFV). Figure (3) shows the horizontal levels for a normal walking person's silhouette. Moreover, the NIFVs of the sequence of images belonging to the same person are combined to build a two-dimensional NIFV. List 1 introduces feature extraction algorithm.

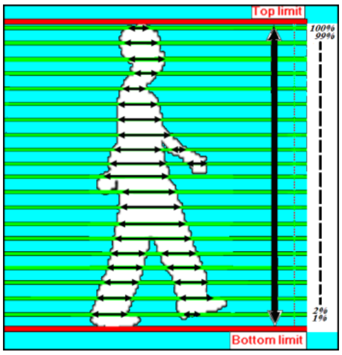

Figure (3): Horizontal levels for a normal walking person's silhouette

b) ***Active Horizontal Level Algorithm:*** The second algorithm towards feature extraction phase is finding the AHLs that can be used for person's authentication. Feature selection is the process of removing features from the data set that are irrelevant with respect to the task that is to be performed. Feature selection can be extremely useful in reducing the dimensionality of the data to be processed by the classifier, reducing execution time and improving predictive accuracy (inclusion of irrelevant features can introduce noise into the data, thus obscuring relevant features). It is worth noting that even though some machine learning algorithms perform some degree of feature selection themselves (such as classification trees). Feature space reduction can be useful even for these machine learning algorithms. Reducing the dimensionality of the data decreases the size of the hypothesis space and thus results in faster execution time. In general, feature selection techniques can be divided into two categories [22]. *Filter methods* and *wrapper methods*. Wrapper methods generally result in better performance than filter methods. Different feature ranking and feature selection techniques have been proposed in machine learning literature, such as: Correlation-based Feature Selection (CFS), Principal Component Analysis (PCA), Gain Ratio Attributes Selection (GRAS), Information Gain Ratio Attributes Selection (IGRAS), Chi-Square Attributes Selection (CSAS) and Support Vector Machine Feature Elimination (SVMFE). Moreover, forward selection, backward elimination, bi-directional search, best-first search, Genetic search and other methods [22] are often used in this task.

In this paper the performance of the feature selection algorithms (GRAS, IGRAS and CSAS) are evaluated, and the classifiers chosen including a wide range of paradigms (Neural Network with multilayer perceptron, IBK, Kstar, NNge, J48, and FT) are compared. Moreover, the mentioned classifiers techniques are used to evaluate the proposed AHL method.

The used Neural Network (***NN***) classifier is a predictive model loosely based on the action of biological neurons placed in several layers. The input layer takes the input feature (AHLs) and distributes it to the hidden layers which do all the necessary computations and outputs. The implemented ***IBK*** classifier is a K-Nearest Neighbor (K-NN) classifier and constructs decision boundaries by just storing the complete training data. The ***Kstar*** classifier is an instance-based classifier [23]. The ***NNge*** classifier is a Nearest-Neighbor-like algorithm, using non-nested generalized exemplars, which are hyper rectangles that can be viewed as if-then rules [24]. The ***J48*** classifier is the WEKA implementation of the C4.5 algorithm [25]. The Functional Trees (***FT)*** classifier combines a standard univariate Decision Tree (DT), such as C4.5, with linear functions of the attributes by means of linear regressions [25]. The written code was based on the WEKA data mining package and the default parameters used for each algorithm. All experiments were carried out using a 10-fold Cross Validation (CV) approach to control the validity of experiments. AHL algorithm is presented in List 2. First, select a sequence NIFV's and consider them as a Reference NIFV's (RNIFV's). Second, calculate Gain Ratio value for every attribute (distance value). Select the attribute that has the highest Gain Ratio value. Then calculate the accuracy, using K-Nearest Neighbor (***IBK***) classifier, which achieved the best accuracy among all other classifiers. Finally, repeat the previous steps as long as the accuracy is not decreased to get all possible AHL. Classification accuracy is calculated by dividing the number of correct classified instances by the total number of instances [22].

List 2: AHL Algorithm

```
main()
{       Reset L= []; // AHL's vector.
d =1
Do {
      AC[d]= Chi-Square Value[d] // Chi-Square value for  d th attribute (level)
   }While (d ≤ N)// ( where N is the maximum number of levels)
    //The AC[d] stored in a decreasing Order.
Do {
     Get index d of maximum value for AC[d] and place it in AHL's vector L
     Calculate the accuracy by using IBK as classifier and  place the attribute (d) to L attributes vector.
   } While (value of accuracy increases)
}
```

4. Discussion and Experimental Results

To evaluate the proposed model, three experiments were performed.

Experiment 1: In this experiment, the best feature selection technique and classifier are both selected to use them in the AHL algorithm. The following steps are applied using a number of feature selection techniques including CSAS, GRAS and IGRAS. The Feature Extraction algorithm is applied on 10% from CASIA-C database. In the classification, all attributes of the dataset have been first selected. Then cross validation of 10 folds have been chosen as test method using Weka implementation. Table 1 shows the accuracies using Neural Network, IBK, Kstar, NNge, J48, and FT classifiers, among different feature selection techniques including CSAS, GRAS and IGRAS algorithms.

Table 1: The resultant accuracies using six classifiers with three attribute selection techniques

Attribute Selection / Classifier	CSAS Reduction Rate 59%	GRAS Reduction Rate 59%	IGRAS Reduction Rate 59%	All Attribute Reduction Rate 0%
NN	78.1%	78.1%	78.1%	78.1%
IBK	79.2%	79.2%	79.2%	79.2%
Kstar	74%	74%	74%	74%
NNge	70.8%	70.8%	70.8%	70.8%
J48	43.2%	42.4%	42.8%	42.4%
FT	76%	76%	76%	76%
Average Accuracy	**70.22%**	**70.05%**	**70.12%**	**70.12%**

Figure (4) shows the comparison of accuracies for the three attribute selection techniques and using six classifiers. The average accuracy for CSAS (**70.22%**) as good as IGRAS(**70.12%**), better than GRAS (**70.05%**), and as good as using all attributes (**70.12%**) without selection. Furthermore, the reduction ratios for all attribute selection techniques are equal (59%).

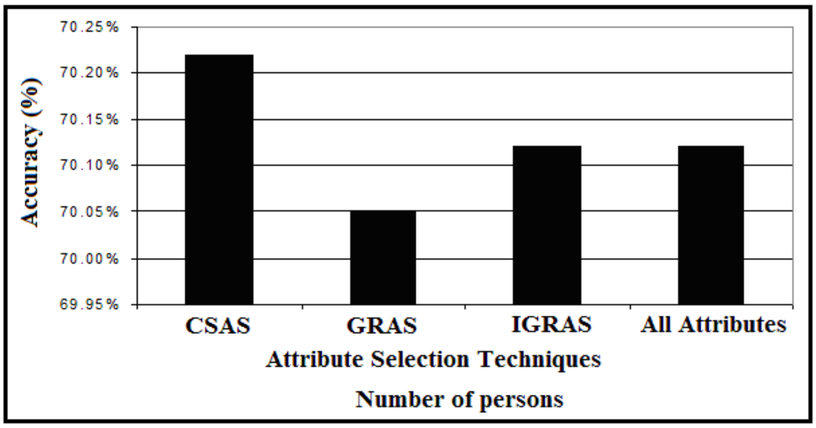

Figure (4): Average accuracies for using different classifiers with CSAS, GRAS and IGRAS

Experiment 2: In this experiment, the AHL algorithm is applied to determine the best attributes (levels) with best accuracy. From experiment 1, the average accuracy of CSAS technique was better than GRAS, IGRAS techniques, and better than using all attributes. Furthermore the accuracy of IBK classifier was better than NN, Kstar, NNge, and FT classifiers and superior than J48 classifier. Therefore, the CSAS technique and IBK classifier were selected to perform the proposed AHL algorithm. Figure (5) shows the accuracy results for different number of AHLs based on cross validation of 10 folds as a test method using the IBK classifier on 10% from CASIA-C gait database. It could be noticed that the minimum number of AHLs is 40 levels that achieve the best accuracy (80.4 %). Table 2 represents the AHL vector.

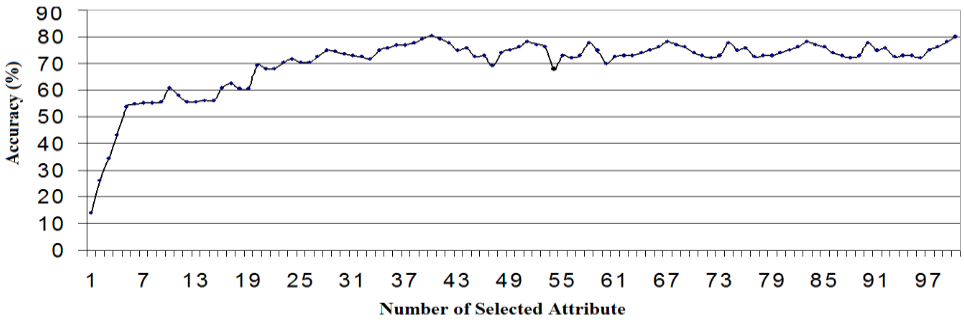

Figure (5): Accuracy results for different number of AHLs

Table 2: AHLs sets versus their accuracies % based on cross validation of 10 folds as a test method using Weka implementation

Line No.	AHL's	Accuracy (%)
1	X[14]	14
2	X[14,25]	26
3	X[14,25,22]	34.4
4	X[14,25,22,13]	43.2
5	X[14,25,22,13,79]	53.6
6	X[14,25,22,13,79,23]	54.8
7	X[14,25,22,13,79,23,24]	55.2
8	X[14,25,22,13,79,23,24,34]	55.2
9	X[14,25,22,13,79,23,24,34,31]	55.6
10	X[14,25,22,13,79,23,24,34,31,83]	60.8
11	X[14,25,22,13,79,23,24,34,31,83,84]	58
12	X[14,25,22,13,79,23,24,34,31,83,84,82]	55.6
13	X[14,25,22,13,79,23,24,34,31,83,84,82,80]	55.6
14	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33]	56
15	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29]	56
16	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15]	60.8
17	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37]	62.4
18	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85]	60.4
19	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87]	60.4
20	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43]	69.2
21	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30]	68
22	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81]	68
23	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20]	70.4
24	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88]	71.6
25	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90]	70.4
26	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89]	70.4
27	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11]	72.4
28	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12]	74.8
29	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28]	74.4
30	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26]	73.6
31	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27]	72.8
32	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86]	72.4
33	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32]	71.6
34	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16]	74.8
35	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16,19]	75.6
36	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16,19,18]	76.8
37	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16,19,18,45]	76.8
38	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16,19,18,45,77]	77.6
39	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16,19,18,45,77,9]	79.2
40	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16,19,18,45,77,9,38]	80.4
41	X[14,25,22,13,79,23,24,34,31,83,84,82,80,33,29,15,37,85,87,43,30,81,20,88,90,89,11,12,28,26,27,86,32,16,19,18,45,77,9,38,17]	79.2

Experiment 3: This experiment was implemented to study the effect of the training dataset's size on the accuracy. Different portion of CASIA-C database (10%, 20%… and 90%) are used as training dataset size. Six Classifier techniques (NN, IBK, Kstar, NNge, J48 and FT) are used to choose the best classifier achieving the best accuracy with the best training portion of CASIA-C database. Since the size of training dataset is very important in module building time. Table 3 shows the accuracies for the used six classifiers and AHL selection method. All classifiers are implemented at portions of CASIA-C database as training dataset.

Table3: Accuracies of six classifiers for different portions of CASIA-C gait database as training dataset

% Trained / Classifier	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%	10-Folds CV
NN	20.4%	35.5%	42.3%	52.7%	60.3%	63.7%	71.6%	72.7%	77%	97%	**78.3%**
IBK	21.6%	37%	44.7%	56%	61.1%	67%	70.7%	72.7%	74.7%	100%	**79.3%**
Kstar	18.8%	32.8%	40.2%	50%	56.5%	63%	64.4%	64.7%	65.3%	100%	**76.4%**
NNge	16%	24.3%	25.7%	31.8%	34.4%	40.3%	50.2%	53.3%	56%	100%	**64%**
J48	4.7%	8.8%	8.6%	12.2%	18.9%	16.3%	26.7%	24.7%	25.3%	88%	**31.6%**
FT	17.3%	31.7%	36.8%	46.2%	49.6%	58%	63.1%	68.7%	69.3%	100%	**72.8%**

Figure (6) shows the accuracy results based on Cross Validation (CV) of 10 folds as a test method and Average Accuracies (AA) for the six classifiers used. NN, IBK, Kstar, NNge, J48 and FT. The experimental results indicate that the obtained accuracy using NN is the best and the accuracy obtained by IBK and FT are better than that produced by Kstar, NNge, and J48.

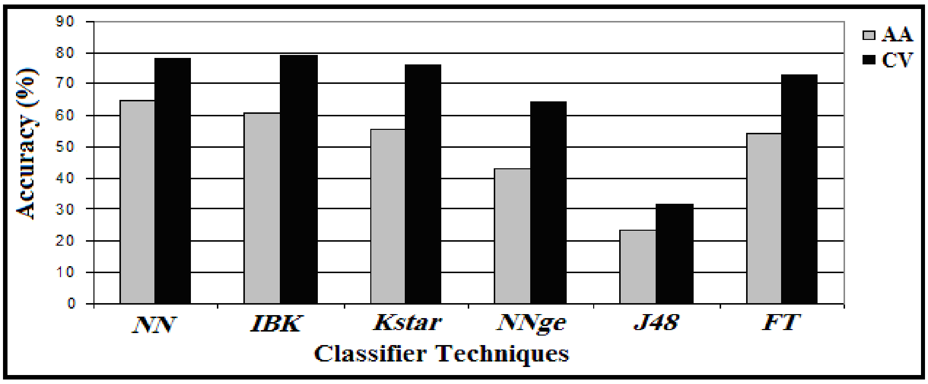

Figure (6): Accuracy results for different classifiers

5. Comparative Study

Since there is not a general gait database for evaluating gait identification performance, and the total number of persons of each database vary huge from 4 to 124 persons. So it is difficult to compare the performance of different algorithms. In this experiment, we use the collection of two normal walking sequences of each person as the Enrolment data. However for Testing data two normal carrying a bag walking sequences for each person are used. Thus, we build our Enrolment data set by a total of 153 (persons) × 2(two normal walking sequences) = 306 sequences and each sequence is composed of 55 images having a total of 16830 images. On the other hand, the Testing data set consists of 153(persons) × 2(walking sequences. Two normal carrying a bag) = 306 sequences composing a total of 16830 images.

Figure (7) shows the comparison of gait identification performance of our proposed method with the orthogonal diagonal projections method in [10]. Both methods are evaluated by using one image at different number of persons in test database of CASIA-C dataset, using the IBK (K-NN) classifier for one image. It is seen that the accuracy of our proposed method is superior to that method proposed in [10] in case using normal walking carrying a bag as testing data.

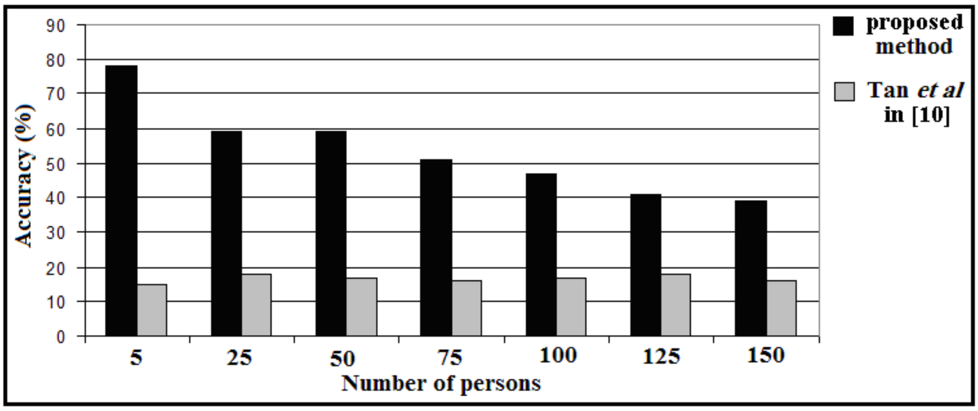

Figure (7): Accuracy results comparing our proposed method with the orthogonal diagonal projections in [10]

Table 4 and Figure (8) show the comparison of speed-invariant gait identification accuracy of our proposed method with the Uniprojective Feature method in [26], Weighted Binary Pattern method in [27] and Procrustes Shape Analysis (PSA) in [28]. All methods are evaluated by using sequence of images in CASIA-C dataset, using the IBK (K-NN) classifier. A total of 50 persons walking with different speed are used in this experiment. It is seen that the accuracy of our proposed method is better than that methods proposed in [26-28].

Table 4: Comparison of speed-invariant gait identification accuracy based on CASIA-C gait dataset

Enrollment	Testing	Uniprojective Feature [26]	Weighted Binary Pattern [27]	Procrustes Shape Analysis (PSA) [28]	**Proposed**
Normal	Normal	98%	99%	98%	**99**%
Normal	Slow	84%	86%	92%	**94**%
Normal	Quick	88%	90%	92%	**93**%
Slow	Quick	---	60%	93%	**94**%

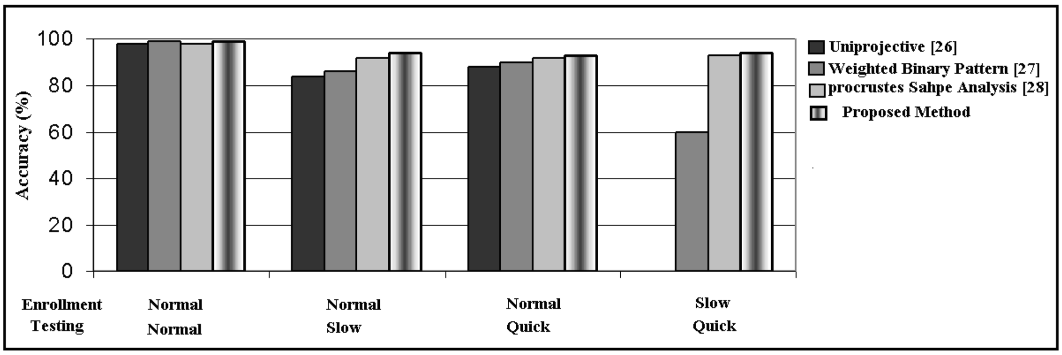

Figure (8): Accuracy results comparing our proposed method another methods [26-28]

6. Conclusions

This paper has addressed the problem of gait identification based on appearance features in human gait, with considering the issues of distance metrics and scales. Our major contribution lies on offering a promising method to extract gait feature (AHL). These features are invariant under scale, transform, and illumination. Experimental results on CASIA-C gait database [6] indicate that the proposed algorithm is better than that algorithm proposed in [10] in case of using normal walking sequence as training dataset, and normal walking sequence carrying a bag as testing dataset. Moreover, the proposed method achieves high performance for speed-invariant gait identification and also significantly outperforms other existing methods [26-28].

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