Human Gait Gender Classification using 2D Discrete Wavelet Transforms Energy

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Summary
Human Gait as the recognition object is the famous biometrics system recently. Many researchers had focused this issue to consider for a new recognition system. One of the important advantage in this recognition compare to other is it does not require observed subject's attention and assistance. There are many human gait datasets created within the last 10 years. Some databases that widely used are University Of South Florida (USF) Gait Dataset, Chinese Academy of Sciences (CASIA) Gait Dataset, and Southampton University (SOTON) Gait Dataset. This paper classifies human gender using the energy of 2D-Discrete Wavelet Transform in CASIA Gait Database. By using Backpropagation, the classification result is 92,9% accuracy.

Key words:
Gait Recognition, 2D Discrete Wavelet Transform (2D DWT), 2D Lifting Wavelet Transform (LWT), Haar Wavelet, CASIA Gait Dataset

1. Introduction

In recent years, there has been an increased attention on effectively identifying individuals for prevention of terrorist attacks. Many biometric technologies have emerged for identifying and verifying individuals by analyzing face, fingerprint, palm print, iris, gait or a combination of these traits [1][10][21].

Human Gait as the recognition object is the famous biometrics system recently. Many researchers had focused this issue to consider for a new recognition system [2][3][4][5][11][14][17][18][19][20][20][24]. Human Gait recognition giving some advantage compared to other recognition system. Gait recognition system does not require observed subject's attention and assistance. It can also capture gait at a far distance without requiring physical information from subjects [3][4][5].

Human Gait Recognition as a recognition system divided in three main subject; preprocessing, feature reduction and extraction system, and classification.

There are 2 pre-processing subsystems to be used: model based and model free approach. Model-based approaches obtain a set of static or dynamic skeleton parameters via modeling or tracking body components such as limbs, legs, arms and thighs. Gait signatures derived from these model parameters employed for identification and recognition of an individual. It is obvious that model-based approaches are view-invariant and scale-independent. These advantages are significant for practical applications, because it is unlikely that reference sequences and test sequences taken from the same viewpoint. Model-free approaches focus on shapes of silhouettes or the entire movement of physical bodies. Model-free approaches are insensitive to the quality of silhouettes. Its advantage is a low computational costs comparing to model-based approaches. However, they are usually not robust to viewpoints and scale [3].

There are some Human Gait Datasets widely used by researchers today. Many human gait datasets created within the last 10 years. Some of widely used datasets are University of South Florida (USF) Gait Dataset, Chinese Academy of Sciences (CASIA) Gait Dataset, and Southampton University (SOTON) Gait Dataset.

2D DWT is a widely used as one methods to transforms data to another yet simpler data to be analyzed. Many researchers had used this method to be implemented to such wide application [10][12][13][15][16][22]. For image and pattern recognition, 2D DWT is commonly used as edge or texture detection. Some of them also used the energy as the feature [10][24].

This paper will presents the classification of Human gait gender classification using the energy 2D Discrete Wavelet Transform (2D-DWT).

2. Proposed Methods

The classification of human gait in this paper consists of three part, preprocessing, feature extraction, and classification. Figure 1 shows the complete overview of proposed human gait gender classification.

2.1 Preprocessing

Some of the references use model-based gait as the preprocessing system. Model-based approaches are sensitive to the quality of gait sequences. Thus, to archive a high accuracy require high quality gait image sequences. Another disadvantage of the model-base approach is its

Manuscript received December 5, 2011
Manuscript revised December 20, 2011

large computation and relatively high time costs due to parameters calculations [2].

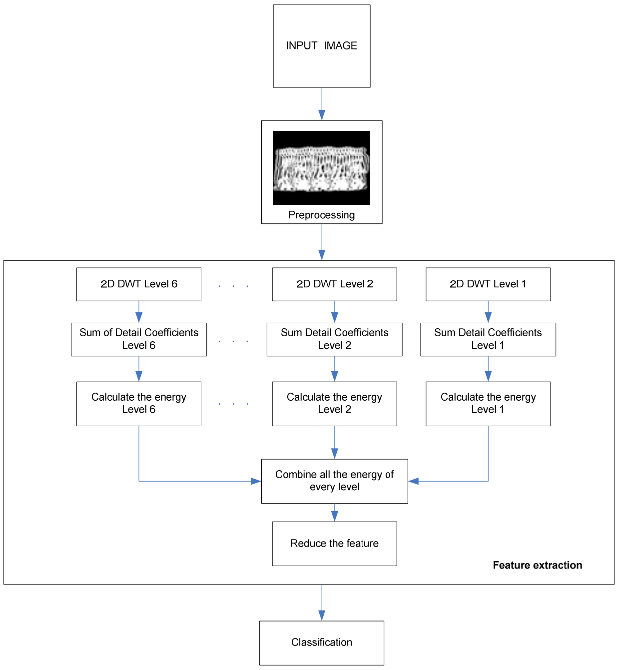


Figure 1. Complete overview of Proposed Human Gait Gender Classification

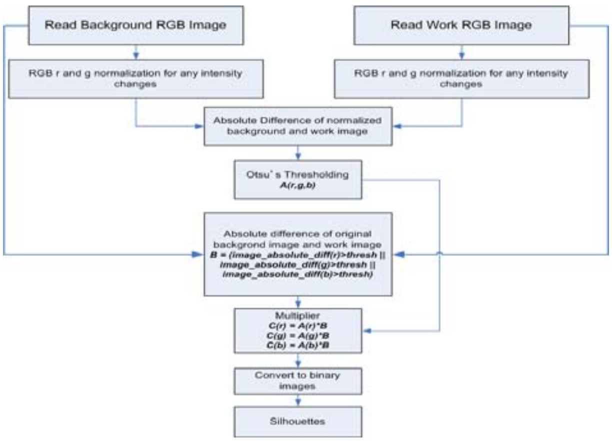


Figure 2. Schematic diagram of Preprocessing to create silhouettes

The model free preprocessing used in this paper by using the motion parameter per frame [22]. First, we have to get the silhouettes image. There are plenty methods that can be used to create the silhouettes image [23]. Figure 2 shows the schematic diagram to create silhouettes. After we get the silhouettes, the motion of the human body can be achieved by using background subtraction. The motion we get also per frame and per video sequence. Figure 3a is the results of the silhouettes image. Figure 3b is the example of the human motion per frame. Figure 3c is the example of human motion per video sequence.

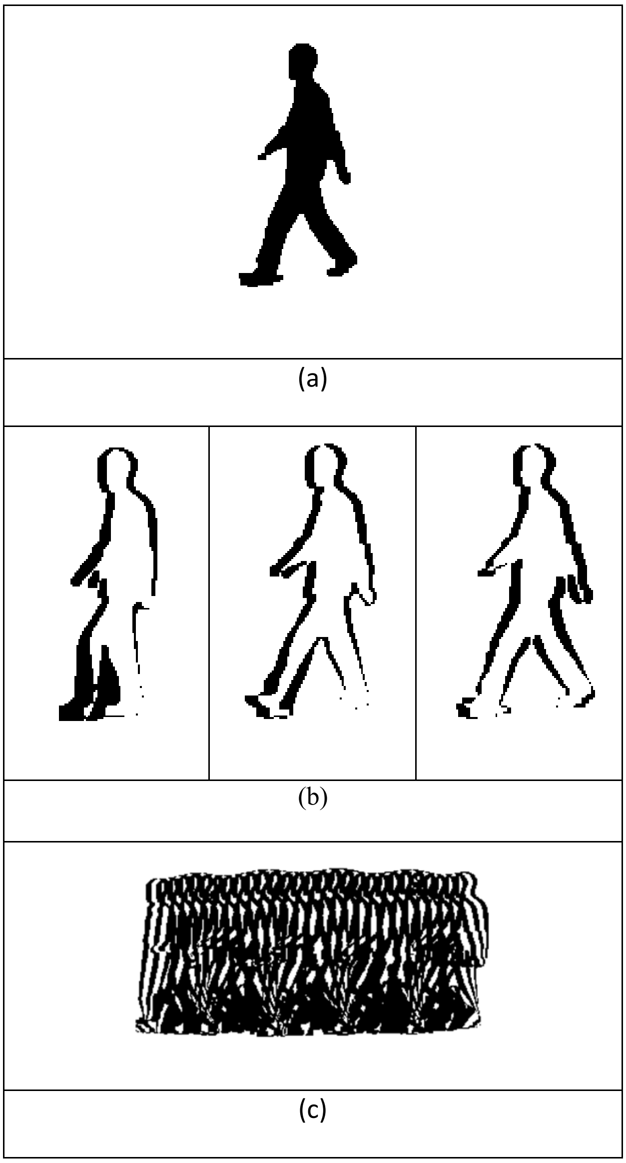


Figure 3. (a) Silhouettes image, (b) Motion image per frame, (c) Motion image per video sequence.

2.2 Feature Extraction

2.2.1 2-D Discrete Wavelet Transforms

Discrete wavelet transform (DWT) represents an image as a subset of wavelet functions using different locations and scales [8]. It makes some decomposition images. Any decomposition of an image into wavelet involves a pair of waveforms: the high frequencies corresponding to the detailed parts of an image and the low frequencies corresponding to the smooth parts of an image. DWT for an image as a 2-D signal can be derived from a 1-D DWT. According to the characteristic of the DW decomposition, an image can be decomposed to four sub-band images through a 1-level 2-D DWT, as shown in Figure 4. These four sub-band images in Figure 4 can be mapped to four sub-band elements representing LL (Approximation), HL (Vertical), LH (Horizontal), and HH (Diagonal) respectively.

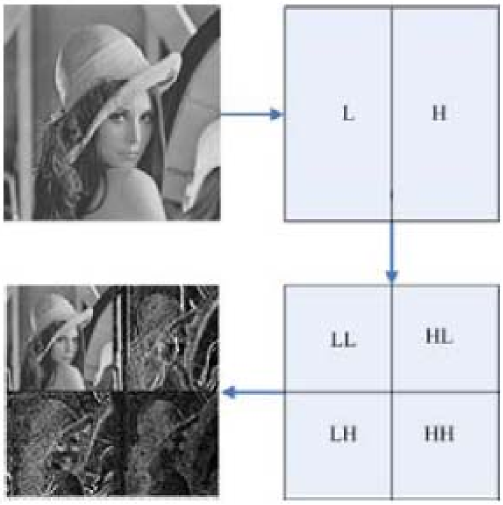


Figure 4. 1-Level Decomposition 2D DWT

The discrete Wavelet Transform will decompose a given signal into other signal known as the approximation and detail coefficients. A given function f(t) can be expressed through the following representation:

$$f(t) = \sum_{j=1}^{L}\sum_{K=-\infty}^{\infty} d(j,K)\varphi(2^{-j}t-K) + \sum_{K=-\infty}^{\infty} a(L,K)\theta(2^{-L}t-K) \quad (1)$$

where: $\varphi(t)$ is the mother wavelet and $\theta(t)$ is the scaling function. $a(L,K)$ is called the approximation coefficient at scale L and d(j,K) is called the detail coefficients at scale j. The approximation and detail coefficients can be expressed as

$$a(L,K) = \frac{1}{\sqrt{2^L}}\int_{-\infty}^{\infty} f(t)\theta(2^{-L}t-K)dt \quad (2)$$

$$d(j,K) = \frac{1}{\sqrt{2^j}}\int_{-\infty}^{\infty} f(t)\varphi(2^{-j}t-K)dt \quad (3)$$

Based on the choice of the mother wavelet φ(t) and scaling function θ(t), different families of wavelets can be constructed [7]. We will use the Haar (DB1) Wavelet and in level-6 decomposition.

2.2.2 Wavelet Energy as a Feature

To draw easier the characteristics of the Wavelet coefficients, we use the energy of each coefficient, then creates the 2D scatter graph for every combination of the coefficients.

These are the formula of the energy for every coefficients in a frame sequence (video) :

$$E_{a(L,K)} = \sum_{l=1}^{video} \sqrt[2]{\sum_{l=1}^{frame} |a(L,K)|^2} \quad (4)$$

$$E_{d(j,K)} = \sum_{j=1}^{video} \sqrt[2]{\sum_{j=1}^{frame} |d(j,K)|^2} \quad (5)$$

Then we do an energy normalization using the formula below,

$$E_{Total} = E_{a(L,K)} + E_{d(j,K)} \quad (6)$$

$$\%E_{a(L,K)} = \frac{100 \times E_{a(L,K)}}{E_{Total}} \quad (7)$$

$$\%E_{d(j,K)} = \frac{100 \times E_{d(j,K)}}{E_{Total}}\% \quad (8)$$

Which percentage of total energy is:

$$100\%\ Energy = \left(\%E_{a(L,K)} + \%E_{d(j,K)}\right) \quad (9)$$

Then we normalize the energy data using simple normalization,

By using all those formula, we apply the wavelet transform to the motion frame sequence, averaging all the energy from one video (using the figure 3.c. preprocessing data).

We will use all the energy of 6 level decomposition. First we combine all the detail coefficients to get one row of a new data. Second, we will use a combination of Horizontal and Vertical coefficients. Figure 5 show the illustration to combine the detail coefficients data in level 1 until level 6. Figure 6 show the illustration to combine the horizontal and vertical coefficients data in level 1 until level 6.

If we draw all the combination level, the result chart will look like in the figure 7.a and 7.b. Since the image resolution is 320 by 240 pixels, the length of the combination data is 315. As shown in Figure 7.a data 1 until data 160 is the summation of detail coefficient in level 1. Data 161 until data 240 is the summation of detail coefficient in level 2, and so on.

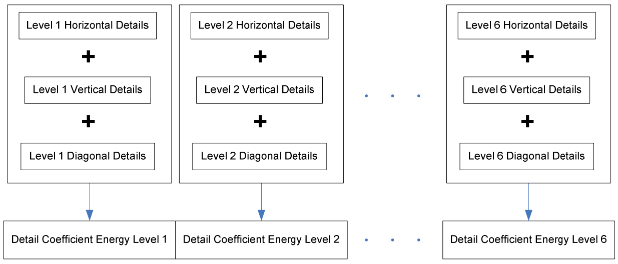


Figure 5. Energy Combination of Detail Coefficients

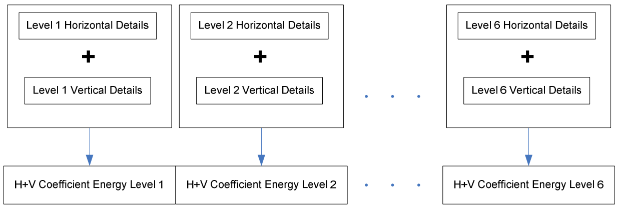
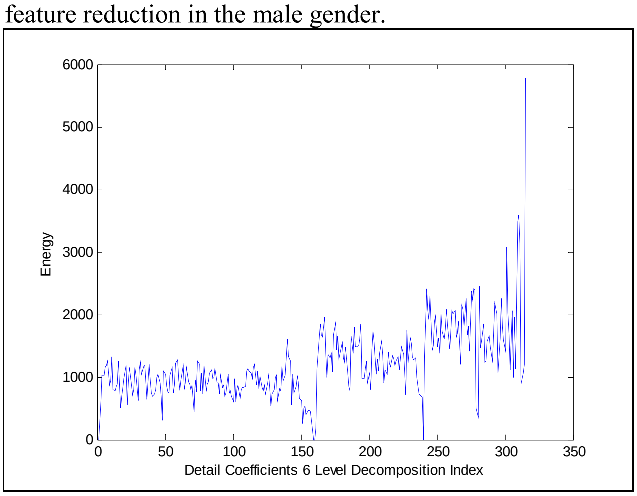


Figure 6. Energy Combination of H & V Coefficients

2.2.3. Feature Data Reduction

The dimensionality of features extracted from gait sequences is usually higher than training data, which gives rise to the failure of conventional classification algorithms. Most of the pattern recognition usually reduces the feature data before make such a classification [11]. This is well known as the under-sample problem. Thus, a feature reduction algorithm is required to obtain useful and informative features for classification. Principal component analysis (PCA) and linear discriminate analysis (LDA) are traditional but widely used feature reduction methods. The proposed method will use Wavelet based multi-scale PCA [25] to reduce the feature data.

Figure 7.a shows the feature data for the female gender using the proposed methods. Figure 7.b is the feature data chart for the male gender. Figure 7.c is the chart data after made such feature reduction in the female gender. Figure 7.d is the chart data after made such feature reduction in the male gender.



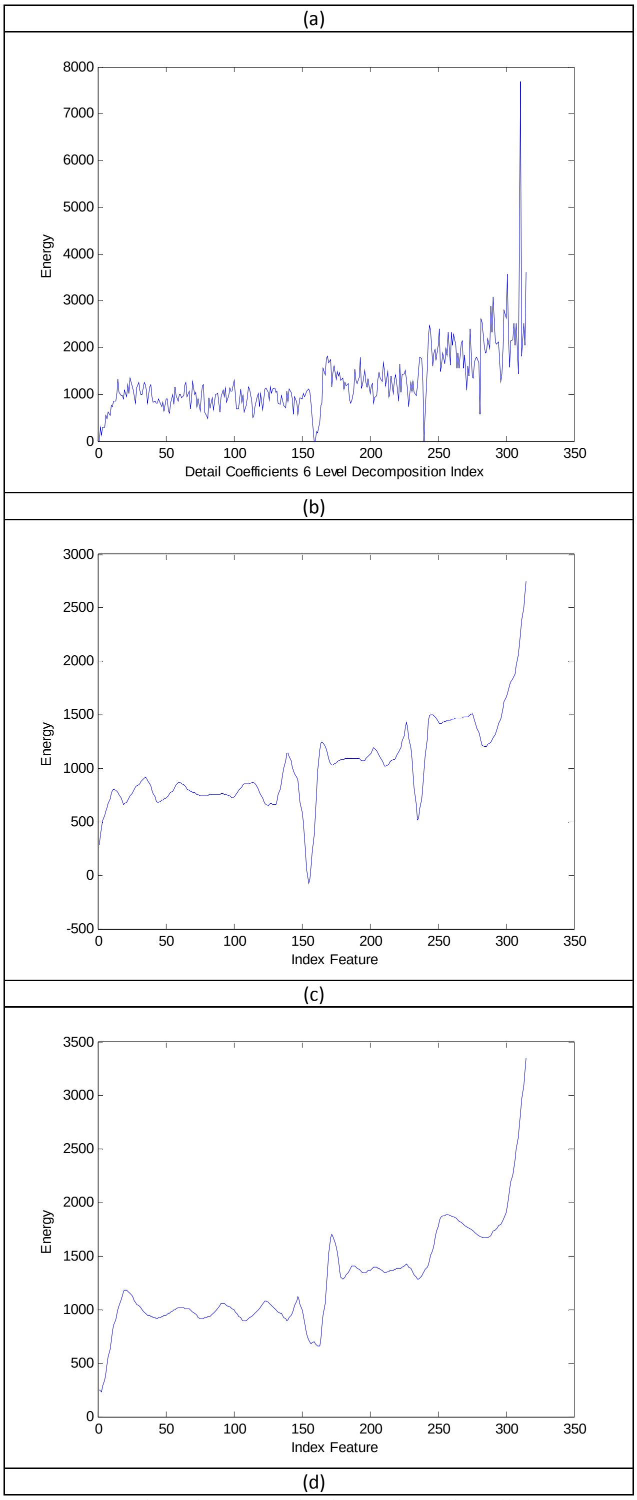


Figure 7. Chart of (a). Example of 6 Level Detail Coefficients Decomposition Index in Male data (b). Example of 6 Level Detail Coefficients Decomposition Index in Female data (c). image (a) after doing the feature reduction (d). image (b) after doing the feature reduction

3. Implementation and Results

We will implement the proposed methods to the CASIA (Chinese Academy of Sciences) Gait Database. CASIA Gait dataset has four class datasets: Dataset A, Dataset B (multi-view dataset), Dataset C (infrared dataset), and Dataset D (foot pressure measurement dataset). We will use the B class dataset in 90 degrees point of view. Figure 8 shows the CASIA Gait image database example of male and female gender [9].

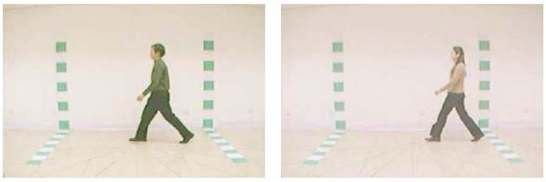


Figure 8. CASIA Gait image example of male and female

Table 1: Training Specification

Gender	***Training (Video)***			***Testing (Video)***
	Train	***Validation***	***Test***	
Male	162	9	9	42
Female	162	9	9	42

By using the combination of Detail coefficients, the result for the classification task is shown in Table 2:

Table 2 Classification Results of the Method for Combination of Delta Coefficients

	Actual classification	
Predicted classification	True Positive = 50.0 %	False Positive = 9.5 %
	False Negative = 0.0 %	True Negative = 40.5 %

The precision, recall, and accuracy results are:

Precision = 50 / (50+9.5) % = 84.033 %

Recall = 50 / (50+0) = 100 %

Accuracy = (50+40.5) / (50+9.5+0+40.5) = 90.5 %

The accurate of classification reached 90.5% using back-propagation neural network.

By using the combination of Horizontal and Vertical coefficients, the result for the classification task shown in the table below:

	Actual classification	
Predicted classification	True Positive = 50.0 %	False Positive = 7.1 %
	False Negative = 0.0 %	True Negative = 42.9 %

The precision, recall, and accuracy results are:

Precision = 50 / (50+7.1) % = 87.565 %

Recall = 50 / (50+0) = 100 %

Accuracy = (50+42.9) / (50+7.1+0+42.9) = 92.9 %

The accurate of classification reached 92.9% using back-propagation neural network.

4. Conclusion

The entire system is using model free motion based spatial information as the preprocessing image. 2D DWT, Haar Wavelet and 6 level decomposition energy as a feature extraction, and classify the data using back-propagation. Implemented in the CASIA Gait Database, we conclude as following:

(1) The classification accuracy is 90.5 % if Detail coefficient combination used.
(2) The classification accuracy is 92.9% if Horizontal and Vertical coefficient used,

This research shows that by using 2D discrete wavelet transform energy is enough to use as a feature for human gait gender classification.
The preprocessing used in this proposed method is a model free based. There are some advantages by using this method. First, the development of the program is not complex. Because it is not too complex, another advantage of this method is low cost computation system. However, this research only uses the spatial information of the video. This has not yet included the temporal information for the analysis. It can also possible to increase the classification accuracy By using the temporal information. On the other hand, we can add some more spatial information by using model based preprocessing image generation. There is some spatial information such as stride dan cadence parameter, distance between head and foot, the distance between foot and pelvis. Some other classification might give a better result to the recognition of human gait gender such as a k-nearest neighbor [14].

Acknowledgments

Portions of the research in this paper use the CASIA Gait Database collected by Institute of Automation, Chinese Academy of Sciences. In his connection, authors would like to thank to Chinese Academy of Sciences for their providing of the Gait database.

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