Human Gait Recognition Using Image Entropy Vector With Extreme Learning Machines

Muqing Deng*, Jili Li, Jiangmin Tian, Xiaoping Lai, Jiuwen Cao and Zhiping Lin

Abstract—**The compromise between recognition accuracy and computational complexity is among the most difficult tasks in the area of pattern recognition. In order to achieve better performance in terms of both accuracy and speed, we present an efficient method in this paper to exploit the advantages of image entropy features and extreme learning machine (ELM) for human gait recognition. The proposed method consists of two phases: First, an image-entropy-based feature extraction strategy is introduced, in which row-based entropy vectors of binary contour are extracted for each walking sequence. Second, an ELM network is trained by supervised learning. A bagging algorithm is adopted to improve the stability and generalization performance of the ELM network. Repetitive sampling is performed on the training set, on which the ELM network is re-trained. The final recognition result is then determined by a majority vote rule on the multiple ELMs trained through the bagging algorithm. The computational burden can therefore be reduced in this work by using the simplified feature extraction process, effective image entropy features and the fast learning ability of ELM. This paper further constructs a unified multi-view training set containing gait features of each individual observed across different view angles, and discusses the extension of the proposed method for multi-view gait recognition. Extensive experiments on CASIA-A and CASIA-B gait databases demonstrate that the proposed method can achieve encouraging recognition accuracy in both single-view and multi-view situations with outstanding computational efficiency.**

Index Terms—**Gait recognition, Image entropy, Extreme learning machine, Multi-view recognition**

I. INTRODUCTION

Human gait recognition, which concerns recognizing individuals by the way they walk, has attracted considerable attention in recent years. In contrast to traditional biometrics based on face or fingerprint recognition, gait biometrics can be detected without subjects' cooperation at a longer distance and doesn't require high image resolution, making it very suitable for long distance security and surveillance [1].

Pioneering works in [2], [3] have confirmed the feasibility of gait as an identifier of individuals. After that, a vast literature has accumulated in the area of gait recognition [4]. Despite that much progress has been made recently, the compromise between computational complexity and recognition accuracy is still one of the most difficult and inevitable problems in gait recognition. In other words, it is highly challenging to design a gait recognition algorithm that could achieve the best performance in terms of both speed and accuracy. Most of the existing works focus on the correct recognition rates by using various complicated algorithms, but suffer from very high computational complexity, which limits their applicability in real-world scenarios [5], [6]. Attempts to resolve this dilemma have leaded to the emergence of hybrid systems [6], which combine various techniques and unify the advantages of these different methods in a more efficient manner.

In view of the above considerations, we aim to develop a hybrid and efficient gait recognition scheme in this paper, which is a cascade of gait image entropy and ELM for gait recognition. Gait cycles of walking sequences are firstly determined and an image entropy based feature extraction strategy is introduced. Image entropy of each row in the gait contour images is calculated and form a multi-dimensional entropy vector for each frame. The mean value of the obtained image entropy vectors for all frames of the walking sequences is selected as the gait features for subsequent recognition task. A single-layer neural network based on ELM is constructed and repetitive sampling is performed on the training set, on which the ELM network is re-trained. The final recognition result is then determined by a majority vote rule on the multiple ELMs trained through the bagging algorithm. Finally, we discuss the multi-view recognition problem for the proposed method. The overall flowchart of the proposed method is shown in Fig.1.

Compared with other methods on gait recognition, the contributions of this paper lie in the following aspects: (1) A new image entropy based feature extraction strategy for individual identification is proposed. The gait entropy vectors are used, for the first time, to capture the temporal and spatial characteristics underlying the shallow gait silhouette. The computational complexity can be reduced considerably by using the the simplified feature extraction process in the extraction of the entropy features. (2) We combine the image entropy features and ELM algorithm to further improve the recognition rate. The Bag-ELM algorithm is adopted to enhance the performance of ELM on stability and generalization. The computational burden can be reduced in this work by using the fast learning ability of ELM. Encouraging recognition accuracy can be achieved with outstanding computational efficiency. (3) The proposed method constitutes a unified framework for both single-view and multi-view situations. It is easy to extend the proposed gait recognition technique, for multi-view gait recognition using the image entropy and ELM algorithm.

This work was supported by the NNSF of China under Grant 61803133, U1909209, the National Program for Major Research Instruments under Grant 61527811.

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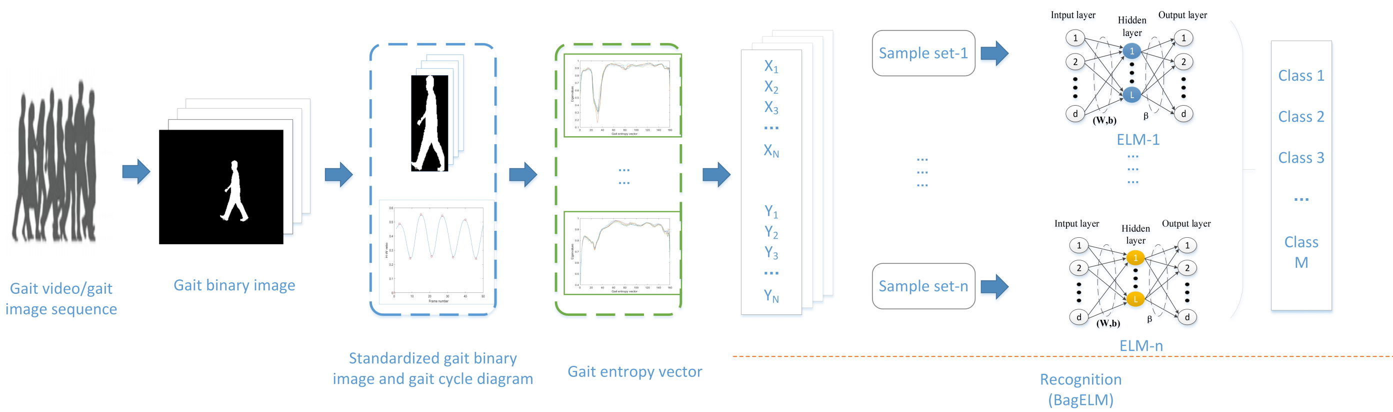

Fig. 1. Overview of our gait recognition method.

II. Related work

Existing gait recognition methods can be roughly divided into two different categories: model-based methods and silhouette-based methods.

Among these existing works, one of the crucial factors for an efficient gait recognition system is the extraction of salient features. The extracted gait features should effectively capture the gait dynamics characteristics and yield good discriminability across individuals. Lee et al. [7] divided the human silhouette image into seven parts, each of which was represented by an ellipse. A total of 29 parameters were extracted from the human silhouette image for gait recognition. Han et al. [8] averaged the walking silhouettes in one walking period and formed the Gait Energy Image (GEI) for the identification task. Lam et al. [9] proposed a gait flow image (GFI) algorithm by calculating the optical watershed. Since the time-varying dynamics characteristics is the essential attribute of the gait motion [10], special emphasis is given in this paper on image entropy, one of gait dynamics descriptors, to improve the recognition rate with reduced computational complexity using simplified feature extraction process. To the best knowledge of the authors, there has been very little work on extracting image entropy directly for gait recognition, though the utility of entropy has been well recognized by the pattern recognition community.

Another crucial factor for a successful gait recognition algorithm is the classifier. In the past few years, artificial neural networks techniques have already had tremendous influence in the area of gait recognition. For instance, radial basis function (RBF) networks were adopted in [11] for gait dynamics extraction and the recognition task. Convolutional neural network (CNN) was constructed in [12] for view-invariant gait recognition. Wu et al. [13] designed a globally trainable deep model by using deep features and hand-crafted representations. Among these artificial neural networks methods, ELM is of particular interest to the research community for its fast learning speed as well as its real-time processing capability [14]. It was first motivated by the single hidden layer feed-forward neural networks and then found capabilities in face recognition, image retrieval, image processing and computer vision. It is shown that ELM can perform extremely quickly due to its random selection of the hidden node parameters.

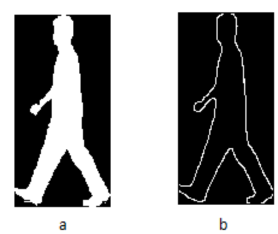

Fig. 2. Silhouette contour extraction: (a) Standardized binary silhouette image; (b) Silhouette contour.

III. Proposed gait recognition method

A. Image entropy feature extraction

Human walking is a form of continuous and dynamical motion and the dynamics nature is its essential attribute. Apparently, it is difficult to reflect the essential dynamic characteristics for human walking by using conventional time/frequency domain features. Therefore, we aim to address this issue in the following.

1) Silhouette extraction: The first step of the proposed algorithm is silhouette extraction and segmentation. Walking silhouettes can be extracted using the method in [15] and a preprocessing procedure is applied to the extracted silhouettes, including filling in holes, removing noises, edge images extraction, dilation and erosion procedure. The gait binary image is further normalized into the same size of 160×80. Edge images can then be obtained by applying a Canny operator with hysteresis thresholding, as shown in Fig. 2.

Two important cues in gait sequence are the width and height of the walking silhouette. By observing, the height and width of the silhouette is changing periodically with the time-lapse. The height of the silhouette reaches a maximum when the legs overlap and drops to a minimum when the legs are

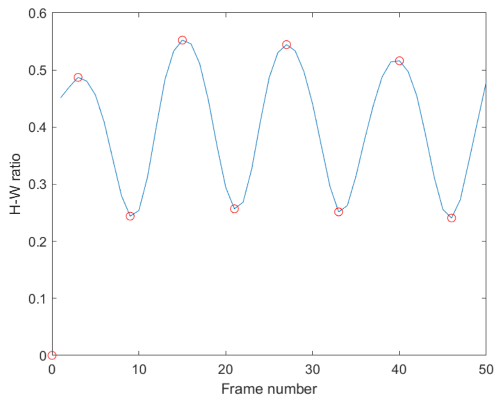

Fig. 3. The H-W ratio curve of a gait sequence.

farthest apart. At the same time, the width reaches a maximum when the two legs are full stride stance and drop to a minimum when the legs are heels together stance. Consequently, this paper employs the aspect ratio of the walking silhouette (height/width, H-W ratio) to get the estimation of the gait cycle, as shown in Fig. 3.

2) Image entropy vector: The concept of entropy was originated in 1803 revealing the energy exhaustion in thermodynamics [16]. This thermodynamic concept was later brought into the field of information theory with the name information entropy introduced in 1948 by Shannon [17]. In this work, we consider the improved image entropy vector based on information entropy as features.

Gait image is composed of a number of pixels and the probability distribution of the pixel gray values for each image is unique. Let the set of gray values be f, the grayscale value level be i, the probability of the occurrence of each grayscale level p_i can be defined by

$$p_i = \frac{f(i)}{\sum_{i=1}^{k} f(i)} \tag{1}$$

where k represents the number of grayscale levels in the whole image. All the probability values satisfy the condition: $\sum_{i=1}^{k} p_i = 1$.

Then the image entropy $H(f)$ of the gait image can be defined as

$$H(f) = \sum_{i=1}^{k} p_i \log \frac{1}{p_i} \tag{2}$$

For each gait binary image, although its number of grayscale level is much less than the ordinary gray image, it is considered as a kind of special grayscale image in this work. The grayscale values of each pixel appear random, and the probability of each pixel appearing is independent. We divide the gait silhouette into 160 equal row subimage from top to bottom, and calculate the image entropy for each row subimage, as shown in Fig. 4. Image entropies for all 160 rows are integrated as the feature vector for each frame. Gait entropy vector can be obtained by averaging the entropy values of corresponding row subimages respectively for all frame in one walking cycle. Fig. 5 shows some examples of gait entropy vectors. The pseudo-code of the proposed gait entropy vector extraction algorithm is shown in Algorithm 1. Fig. 6 shows the entropy feature curves of one person under different walking views.

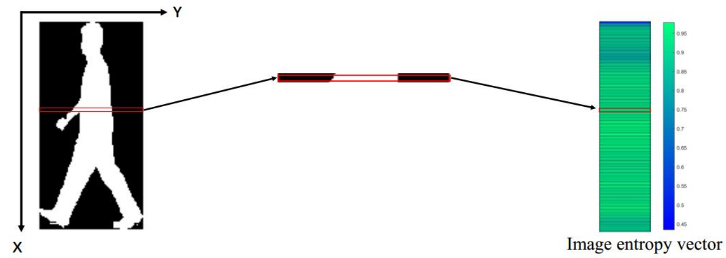

Fig. 4. Image entropy calculation for each row subimage.

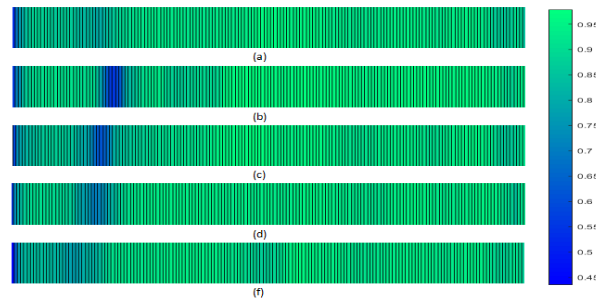

Fig. 5. The gait entropy vector. (a)-(f) represents the gait entropy vector of different persons.

Algorithm 1 Extraction process of gait entropy vector

Require: A standardized gait binary sequence $A(x,y)|(x \leq 160, y \leq 80)$ of period T,
Independent training number $K = x = 160$
Zero valued vector B_t

Ensure: The gait entropy vector, B^*;

Set $k = 1$ $t = 1$
while $t < T$ **do**
  while $k < K$ **do**
    Obtain all pixels of the kth line of the normalized gait binary image
    Calculate the image entropy$B_t(1,k)$ of the kth row vector
    $k = k + 1$
  end while
end while
The gait entropy vector is $B^* = \frac{\sum_{t=1}^{T} B_t}{T}$;

B. ELM-based gait recognition scheme

ELM was originally proposed for the learning problem of single hidden layer feedforward neural networks (SLFNs) and then extended to generalized feedforward networks. ELM takes the advantages of its fast learning speed and real time

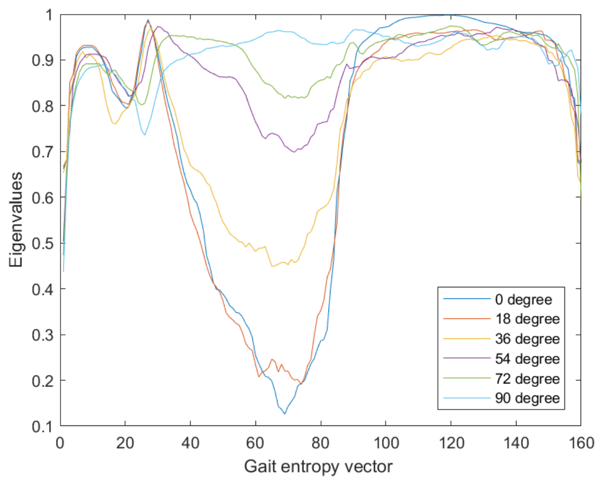

Fig. 6. Gait entropy vectors for one person under different walking views.

processing capability, and these notable merits are attributed to the random selection of the hidden node parameters (input weights and bias) [18], [19].

A single hidden layer neural network through ELM mechanism with L hidden layer nodes is constructed in this paper. Denote $X_j = [X_{j1}, X_{j2}, \ldots, X_{jn}]^T$ as the input vector, $o_j = [o_{j1}, o_{j2}, \ldots, o_{jm}]^T$ the network output vector, and $t_j = [t_{j1}, t_{j2}, \ldots, t_{jm}]^T$ as the target output vector, the network model can be written in the following form:

$$\sum_{i=1}^{L} \beta_i g(W_i \cdot X_j + b_i) = o_j, j = 1, \cdots, n \tag{3}$$

where $g(\cdot)$ is the activation function, $W_i = [w_{i1}, w_{i2}, \cdots, w_{in}]^T$ is the input weight, β_i is the output weight, b_i is the offset of the ith single hidden layer unit. The goal of ELM is to minimize the error between t_j and o_j:

$$\sum_{j=1}^{n} \|o_j - t_j\| = 0 \tag{4}$$

That is, we should find appropriate β_i, W_i and b_i such that:

$$\sum_{i=1}^{L} \beta_i g(W_i \cdot X_j + b_i) = t_j, j = 1, \cdots, n \tag{5}$$

It can be represented by the following form:

$$H\beta = T \tag{6}$$

Where

$$H(W_1, \cdots, W_L, b_1, \cdots, b_L, X_1, \cdots, X_L) =$$
$$\begin{bmatrix} g(W_1, \cdot, X_1 + b_1) & \cdots & g(W_L, \cdot, X_1 + b_L) \\ \vdots & \ldots & \vdots \\ g(W_1, \cdot, X_n + b_1) & \cdots & g(W_L, \cdot, X_n + b_L) \end{bmatrix} \tag{7}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}, T = \begin{bmatrix} T_1^T \\ \vdots \\ T_n^T \end{bmatrix}$$

H is called the output matrix of the hidden layer, β is the output weight, and T is the desired output. Once the input weight W_i and the offset b_i of the hidden layer are randomly determined in the ELM, the output matrix H of the hidden layer can be determined. Then, the training single hidden layer neural network can be transformed into solving a linear system $H\beta = T$. And the output weight β can be determined by:

$$\widehat{\beta} = H^{+}T \tag{8}$$

where H^{+} is the Moore-Penrose generalized inverse of the matrix.

ELM adopts a One-Against-All (OAA) method to transform the multi-classification problem into a multi-output function regression problem. The class label of the gait sample with the largest output value is used to represent the class label of the given sample. For a C-labels classification problem, the output label t_i of a sample x_i is usually encoded to a C-dimensional vector $(t_{i1}, t_{i2}, \cdots, t_{ic})^T$ with $t_{ic} \in -1, 1, (c = 1, 2, \cdots, C)$. In the OAA approach, if the class label t_i of the sample x_i is c, then t_{ic} will be set to be 1 and the others are set as -1 in the new formed C-dimensional output vector. Therefore, the class label c^{test} of a testing sample x^{test} predicted by the ELM algorithm is the index of the largest entry in the corresponding output vector [18].

In order to improve the classification performance of ELM, we further introduce an improved ELM algorithm that combines the bagging algorithm with ELM, namely Bagging-based ELM (BagELM) [20] and makes decisions by a majority voting method. Specifically, we firstly construct an ELM classifier and a training set. The Bagging algorithm performs repetitive sampling on the training set in the training phase. That is, the training set is re-sampled and a new training sample set is obtained each time. The ELM uses the new training sample set for training each time separately. The learning parameters of the ELM are randomly and independently initialized for each time. The final category label is then determined by a majority vote on all results obtained for multiple ELMs.

Compared with the conventional ELM algorithm, the BagELM algorithm takes the advantages of the bagging method to select the majority of the prediction results as the final integration decision, which can effectively reduce the influence of the random interference of the single hypothesis on the prediction result and improve the classification performance as well as the generalization ability of ELM.

IV. Experiments

In this section, the proposed algorithm is implemented on the MATLAB platform and evaluated on two benchmark gait databases: (a) CASIA-A database; (b) CASIA-B database. These two databases directly support the study of gait recognition. CASIA-B database contains a large number of subjects and CASIA-A database has been widely used in the literature.

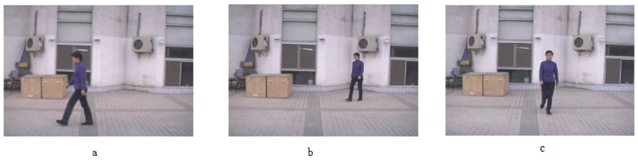

Fig. 7. Sample frames from 3 different views of one subject in CASIA-A gait database.

A. Experiments on CASIA-A gait database

This paper first evaluates the proposed method on CASIA-A database [21], which includes sequences from 20 different subjects under 3 different views: $0°$, $45°$ and $90°$. Each subject walks along the straight line 4 times for each view angle. Fig.7 shows some sample images in CASIA-A database.

1) Recognition accuracy on CASIA-A gait database with no view variations: Two types of experiments are conducted in this database. The first type is the gait recognition with no view variations. That is, both of the training and test patterns used in the evaluation are walking sequences in the lateral view ($0°$). We assign two sequences to the training set and the remaining sequences to the test set. The recognition results are shown in Table I.

The proposed gait entropy features can make full use of dynamics characteristics to dispel influence caused by insufficient image information. By combining the gait entropy features and Bag-ELM algorithm, we can achieve the recognition rate of 95.0%, which outperforms other existing works.

TABLE I
RECOGNITION ACCURACY (%) ON CASIA-A GAIT DATABASE WITH NO VIEW VARIATIONS. HERE, CCR=CORRECT CLASSIFICATION RATE.

Algorithms	CCR (%)
Lee and Grimson [7]	87.5
Lu and Zhang [22]	92.5
Lee et al. [23]	91.3
Gait entropy vector+NN	**83.3**
Gait entropy vector+SVM (lin)	**77.5**
Gait entropy vector+ELM (radbas)	**92.5**
Gait entropy vector+BagELM (radbas)	**95.0**

2) Recognition accuracy on CASIA-A gait database with view variations: The second type of experiment is the gait recognition with view variations. We evaluate the proposed method in the muliti-view environment. Detailed experimental design is listed in Table II. The process of training and recognition is shown in Section II and is omitted here for clarity and conciseness.

TABLE II
THREE EXPERIMENTS ON CASIA-A GAIT DATABASE UNDER THE CHANGES OF VIEW CONDITIONS.

Experiment	Gallery set	Probe set	Gallery size	Probe size
A1	0°	0°	20×2	20×2
B1	45°	45°	20×2	20×2
C1	90°	90°	20×2	20×2

The proposed gait entropy features can still work well in different view conditions. Table III compares the best and average results of proposed method between ELM and BagELM algorithm. Three different activation function, namely sin, tribas and radbas are used in the ELM and BagELM algorithms. We can see that the recognition performance with BagELM is better than the one with ELM. The recognition rates with radbas are the best among the proposed three activation function.

Table IV further compares the classification performance of BagELM algorithm with the ones of conventional classification algorithms, such as nearest neighbor algorithm (NN) and support vector machine (SVM). From the experimental results shown in Table IV, we can find that the BagELM algorithm is superior to the mentioned NN and SVM algorithms in the classification performance evaluation on the database.

TABLE III
RECOGNITION ACCURACY (%) ON CASIA-A GAIT DATABASE UNDER CHANGES OF VIEW CONDITIONS. HERE, SIN (TRIBAS, RADBAS) REPRESENTS THE ACTIVATION FUNCTION USED IN THE ELM ALGORITHM.

Experiment	ELM			BagELM		
	sin	tribas	radbas	sin	tribas	radbas
A1	90.0	92.5	92.5	90.0	95.0	95.0
B1	70.0	67.5	67.5	70.0	67.5	70.0
C1	65.0	70.0	70.0	67.5	70.0	70.0
Average	75.0	76.7	76.7	**75.8**	**77.5**	**78.3**

TABLE IV
COMPARISONS WITH OTHER EXISTING CLASSIFICATION ALGORITHMS (%) ON THE CASIA-A GAIT DATABASE.

Experiment	NN	SVM (lin)	BagELM (radbas)
A1	83.3	77.5	95.0
B1	67.5	52.5	70.0
C1	70.0	58.8	70.0
Average	73.6	62.9	**78.3**

Secondly, we construct a unified training set consisting of gait sequences from different view angles and investigate the view-invariant problem in the proposed method. Three experiments designed on this database are listed in Table V. We assign sequences to training set for all the 3 view conditions to construct a unified training set. Each view conditions contains two sequences for all 20 subjects. That is, there are 20×2×3=120 sequences in the training set. The remaining two sequences of all 20 subjects from single view angle were used as test sets. That is, there are 20×2×1=20 sequences in each test set. The recognition performance of the proposed methods is reported in Table VI. When a test sequence with unknown view angle appears, it can be rapidly recognized, making it more applicable in the real-world environment.

TABLE V
THREE EXPERIMENTS ON CASIA-A GAIT DATABASE FOR VIEW-INVARIANT GAIT RECOGNITION.

Experiment	Gallery set	Probe set	Gallery size	Probe size
A2	0°,45°,90°	0°	20×2×3	20×2×1
B2	0°,45°,90°	45°	20×2×3	20×2×1
C2	0°,45°,90°	90°	20×2×3	20×2×1

TABLE VI
VIEW-INVARIANT GAIT RECOGNITION PERFORMANCE ON CASIA-A GAIT DATABASE. HERE, SIN (TRIBAS, RADBAS) REPRESENTS THE ACTIVATION FUNCTION USED IN THE BAGELM ALGORITHM.

Experiment	BagELM(%)		
	sin	tribas	radbas
A2	90.0	95.0	95.0
B2	72.5	67.5	72.5
C2	70.0	67.5	70.0
Average	77.5	76.7	**79.2**

3) Computational complexity analysis on CASIA-A gait Database: As we know, the main computation in the whole processing procedure is the computational load of feature extraction and ELM training. In the entropy feature extraction phase, the average time is about 1.4937 s for one walking sequence (as shown in Table VII).

TABLE VII
FEATURE EXTRACTION TIME (/S) OF A SINGLE SEQUENCE ON CASIA-A GAIT DATABASE

Experiments	nm-01	nm-02	nm-03	nm-04
A1	1.3028	1.4229	1.3941	1.3760
B1	1.5951	1.6134	1.7064	1.6004
C1	1.4399	1.4562	1.5424	1.4746
Average	1.4459	1.4975	1.5476	1.4837

TABLE VIII
TRAINING TIME CONSUMPTION IN THE EXPERIMENTS ON CASIA-A GAIT DATABASE

Experiments	ELM (/s)			BagELM (/s)		
	sin	tribas	radbas	sin	tribas	radbas
A1	0.00030	0.00049	0.00026	0.00062	0.00057	0.00063
B1	0.00045	0.00059	0.00030	0.00061	0.00061	0.00059
C1	0.00068	0.00045	0.00038	0.00059	0.00061	0.00059
Average	**0.00048**	**0.00051**	**0.00031**	0.00060	0.00060	0.00060

TABLE IX
TESTING TIME CONSUMPTION IN THE EXPERIMENTS ON CASIA-A GAIT DATABASE

Experiments	ELM (/s)			BagELM (/s)		
	sin	tribas	radbas	sin	tribas	radbas
A1	0.00029	0.00031	0.00009	0.00053	0.00073	0.00059
B1	0.00029	0.00035	0.00035	0.00047	0.00072	0.00051
C1	0.00029	0.00029	0.00030	0.00058	0.00064	0.00057
Average	**0.00029**	**0.00031**	**0.00025**	0.00053	0.00070	0.00056

In the off-line training phase, it takes on average 0.0.00046s for training one gait pattern (as shown in Table VIII). In the on-line test phase, for recognizing one target gait pattern, it takes on average 0.00028s in ELM method and it takes on average 0.0.00060s in BagELM method (as shown in Table IX).

B. Experiments on CASIA-B gait database

This paper further reports experimental results of proposed method on CASIA-B database [24], which contains gait sequences of 124 subjects captured from 11 different view angles (namely $0°$, $18°$, $36°$, $54°$, $72°$, $90°$, $108°$, $126°$, $144°$, $162°$ and $180°$). At each view angle, each subject is required to walk along a straight line in the common speed for 6 times, namely nm-01, nm-02, ..., nm-06, respectively. Fig. 8 shows sample images of 11 different view angles in this gait database.

Fig. 8. Sample frames from 11 different views of one subject in CASIA-B gait database.

1) Recognition accuracy on CASIA-B gait database with no view variations: In our experiments, as mentioned, human silhouettes are extracted from the walking sequences and image entropies are calculated. Similar to Section 3.1, two types of experiments are carried out in this database. The first type is the gait recognition with no view variations. We assign four lateral-view sequences for each of 124 subjects to the training set (124×4=496), and the remaining two lateral-view sequences to the test set (124×2=248). Detailed recognition results are shown in Table X.

TABLE X
RECOGNITION ACCURACY ON CASIA-B GAIT DATABASE WITH NO VIEW VARIATIONS

Algorithms	CCR (%)
L. Wang et al [21]	77.4
M. Goffredo et al [25]	86.5
W. Bian et al [26]	85.0
Gait entropy vector+NN	90.7
Gait entropy vector+SVM (lin)	90.9
Gait entropy vector+ELM (radbas)	90.9
Gait entropy vector+BagELM (radbas)	94.2

2) Recognition accuracy on CASIA-B gait database under changes of view conditions: The second type of experiment is the gait recognition with view variations. We construct a unified training set consisting of gait sequences from different view angles and investigate the view-invariant problem in the proposed method. Eleven experiments designed for this database are listed in Table XI. We assign three sequences to training set for the 124 subjects in all eleven views to construct a unified training database. That is, $124 \times 3 \times 11 = 4092$ patterns in the training dataset. The recognition performance of our method is presented in Table XII.

Since the recognition rates of a poor algorithm can still be high if the amount of subjects is small, therefore, we evaluate the proposed method by using different amounts of subjects: 31 subjects, 62 subjects, 93 subjects, and 124 subjects. It is shown from Fig. 9 that the proposed method is insensitive to the numbers of subjects. Fig. 10 further reports the experimental results of the proposed method under different gallery sizes. We select 124×2 sequences as the test set, while the remaining sequences are divided into four subsets randomly as the training sets, in which each subset

TABLE XI
11 EXPERIMENTS ON CASIA-B GAIT DATABASE FOR ROBUSTNESS TEST

Experiment	Gallery view	Probe view	Gallery size	Probe size
D2	$0° \cdots 180°$	$0°$	$124\times3\times11$	$124\times3\times1$
E2	$0° \cdots 180°$	$18°$	$124\times3\times11$	$124\times3\times1$
F2	$0° \cdots 180°$	$36°$	$124\times3\times11$	$124\times3\times1$
G2	$0° \cdots 180°$	$54°$	$124\times3\times11$	$124\times3\times1$
H2	$0° \cdots 180°$	$72°$	$124\times3\times11$	$124\times3\times1$
I2	$0° \cdots 180°$	$90°$	$124\times3\times11$	$124\times3\times1$
J2	$0° \cdots 180°$	$108°$	$124\times3\times11$	$124\times3\times1$
K2	$0° \cdots 180°$	$126°$	$124\times3\times11$	$124\times3\times1$
L2	$0° \cdots 180°$	$144°$	$124\times3\times11$	$124\times3\times1$
M2	$0° \cdots 180°$	$162°$	$124\times3\times11$	$124\times3\times1$
N2	$0° \cdots 180°$	$180°$	$124\times3\times11$	$124\times3\times1$

TABLE XII
GAIT RECOGNITION PERFORMANCE ON CASIA-B GAIT DATABASE

Experiment	BagELM(%)			Refs. [27]
	sin	tribas	radbas	
D2	73.4	70.6	65.9	55.4
E2	71.6	70.2	66.7	44.2
F2	51.6	50.3	49.8	66.7
G2	63.5	61.0	60.2	77.8
H2	83.4	73.0	85.2	77.8
I2	87.8	94.3	90.4	87.9
J2	88.6	95.0	91.1	66.7
K2	88.5	89.2	87.3	77
L2	91.6	93.6	90.5	75.8
M2	90.1	88.8	90.6	76.7
N2	91.0	91.1	91.7	57.9
Average	80.1	79.7	79.0	69.4

contains 124×1, 124×2, 124×3, and 124×4 sequences, respectively. Experimental results reveal that the proposed method is not sensitive to the change of gallery sizes.

3) Computational complexity analysis on CASIA-B Gait Database: The lower complexity is the main advantage of the proposed method in this paper. The average time of one sequence feature extraction is 2.6135s. The average training time of ELM and BagELM are 0.00395s and 0.00520s in the off-line training phase. In the on-line test phase, for recognizing one target gait pattern, it takes on average 0.00049s in ELM method and it takes on average 0.00415s in BagELM method.

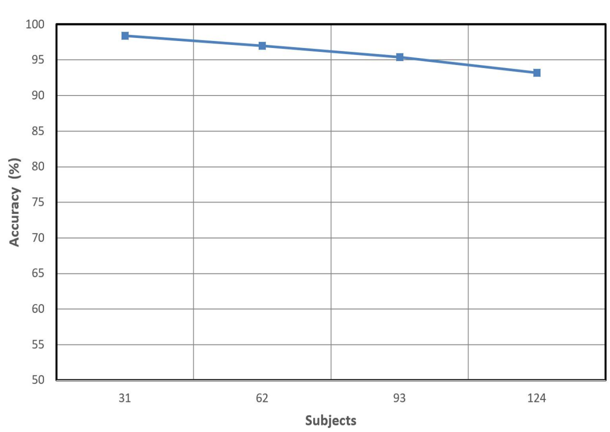

Fig. 9. Recognition accuracy under different numbers of subjects.

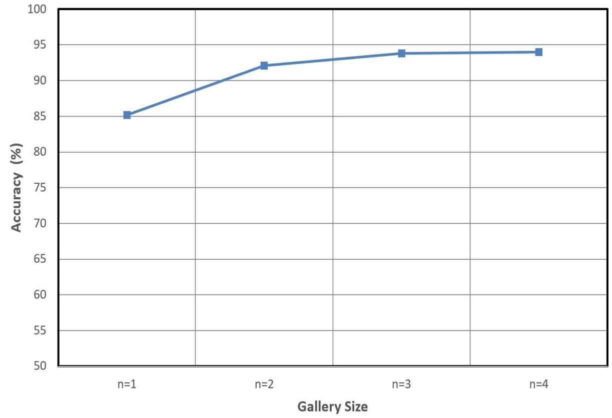

Fig. 10. Recognition accuracy under different gallery sizes.

V. CONCLUSION

In this paper, a new gait recognition method based on image entropy feature and ELM is proposed. For the first time, the image entropy features are introduced in the field of gait recognition. We extract the row vector image entropy of the gait contour and obtain the gait entropy vector based on the whole period, in which the data normalization and data dimension reduction steps are avoided to reduce the computational complexity. We further use the improved ELM network to enhance the performance of ELM in terms of stability and generalization. From the experimental results in this paper, encouraging recognition accuracy in single-view and multi-view situations can be achieved with excellent computational efficiency. Future work will focus on low-resolution gait recognition in the real-world environment.

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