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Fast Face Gender Recognition by Using Local Ternary Pattern and Extreme Learning Machine

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Abstract

Human face gender recognition requires fast image processing with high accuracy. Existing face gender recognition methods used traditional local features and machine learning methods have shortcomings of low accuracy or slow speed. In this paper, a new framework for face gender recognition to reach fast face gender recognition is proposed, which is based on Local Ternary Pattern (LTP) and Extreme Learning Machine (ELM). LTP is a generalization of Local Binary Pattern (LBP) that is in the presence of monotonic illumination variations on a face image, and has high discriminative power for texture classification. It is also more discriminate and less sensitive to noise in uniform regions. On the other hand, ELM is a new learning algorithm for generalizing single hidden layer feed forward networks without tuning parameters. The main advantages of ELM are the less stringent optimization constraints, faster operations, easy implementation, and usually improved generalization performance. The experimental results on public databases show that, in comparisons with existing algorithms, the proposed method has higher precision and better generalization performance at extremely fast learning speed.

Keywords: *Extreme Learning Machine; Gender Recognition; Local Ternary Pattern.*

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1. Introduction

Human face gender identification is a two-class classification problem that automatically identifies and analyzes human face gender attributes using face image information [1]. Gender identification shows wide application prospects. Human face gender identification strengths the capacity of human-computer interaction especially in some intelligence environments that require gender for gender specific restriction sites. For example, in an intelligent robot, intelligent computers and other electronic products need to automatically recognize a user's gender to provide appropriate user interfaces and services to allow a variety of electronic products to be more personalized and user-friendly through face gender identification.

Human beings can easily identify the human gender, but computers or machines find it challenging. Recently several attempts have been made on automatic human face gender identification with a machine learning algorithm or other approaches [2]. Similar to other pattern classification problems [3], two key steps for face gender classification are feature extraction and pattern classification. For feature extraction the simplest method is to use gray-scale or color pixel vectors as features. However, the accuracy of this method is not high. Other methods come from the theory of subspace transformation, such as Principal Component Analysis (PCA), Independent Component Analysis (ICA), and Linear Discriminant Analysis (LDA), which project face features into a low-dimensional space and then perform recognition [4] [5] [6]. These methods have been shown to be efficient but are not robust enough to illumination changes and facial expression [7]. Recently, a more generic local-appearance-based approach was proposed that considers the entire face as a whole by dividing the input face image into blocks without considering any salient region, for facial feature extraction. These methods are the right choice for overcoming the problems described above. Among them, the Local Binary Pattern (LBP) is widely applied in face image processing [8] [9] in different applications including gender recognition [10] [11] [12]. LBP provides an invariant description in the presence of monotonic illumination variations on a face image, and has high discriminative power for texture classification. However, its performance degrades with non-monotonic illumination variation, random noise, and change in pose, age, and expression. Jabid, Kabir and Chae [5] proposed using Local Directional Pattern (LDP) to represent the gender characteristic. LDP has demonstrated better performance in gender classification that considers the edge response values in different directions instead of pixel intensities, hence providing more consistency in the presence of noise. However, because they threshold at exactly the value of the central pixel, they tend to be sensitive to noise, particularly in near-uniform image regions and smooth, weak illumination gradients. To solve this problem, Tang and Triggs [13]introduced a generalization of LBP called Local Ternary Patterns (LTP) for feature extraction, which are more discriminant and less sensitive to noise in uniform regions.

Face gender classification plays a significant role in the accuracy of identifying face gender. Traditional classifiers such as K-nearest-neighbor (KNN), Fisher linear

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discriminant (FLD), back propagation (BP) neural network and Support Vector Machine (SVM) [15] are not satisfactory. The BP neural network algorithm based on feed-forward neural network needs to set a large number of neural network training parameters and choosing the right parameters is difficult. BP also has demerits such as a very easy local optimal solution, non-convergence and long training time. The SVM needs to set the kernel function, error control parameters, penalty factor, and other parameters and requires much time to learn. Recently, based on a single-hidden layer feed-forward neural network (SLFN), Huang proposed a new learning algorithm, named ELM [14][15][16] to solve the classification and regression problems with a simple process. Compared with a BP neural network, SVM, and other traditional learning algorithms [17], the processing speed with ELM reduced significantly. Zong, Zhou and Huang [18] applied ELM to face recognition and compared it with SVM, and found that ELM and SVM have similar prediction accuracy but ELM has obvious advantages in terms of preferences and learning speed. ELM for classification usually achieves better generalization performance without intensive human intervention.

This paper describes a new framework for building robust face gender classification systems using LTP to represent the gender feature and the ELM for classifications. LTP [13] is a generalization of LBP that is more discriminant and less sensitive to noise in uniform regions. It also maintains the ability to faithfully describe the object of interest in noisy environment. On the other hand, ELM is a three-layer feed forward network with single-hidden layer. Because its hidden node parameters are independent from the target functions or the training datasets, these parameters can be analytically determined instead of being tuned. ELM algorithm tends to provide the good generalization performance at extremely fast learning speed. Therefore we propose to combine LTP and ELM together to improve the performance of face gender recognition which renders face gender classification possible in real-time with fast speed and high accuracy. The proposed method has three steps. First, the image is divided into several blocks, followed by encoding with a LTP operator that enhances local image information. Then, histograms are extracted from each block and concatenated to a vector. Finally, the face gender is classified by ELM. Experimental results on public databases show: (i) For feature extraction, the accuracy of the proposed method is obviously enhanced compared with PCA and LBP; and (ii) For classification, the learning speed of ELM is obviously reduced, and ELM has higher precision and better generalization ability compared with BP and SVM. The proposed method is suitable for face gender classification that needs fast speed, and high accuracy for real time detection.

The rest of this paper is organized as following: Section 2 introduces some background theories on LTP and ELM. Section 3 explains the proposed method in detail. Section 4 analyzes the experimental results. Finally, the related conclusion and future works are proposed in Section 5.

2. Related Works

2.1 Local Ternary Pattern

LBP provides an invariant description in the presence of monotonic illumination variations on a face image, and has high discriminative power for texture classification. The critical issue regarding LBP is its sensitivity to noise. For instance, in **Fig. 1**, the corresponding LBP is 10011011, or 155.

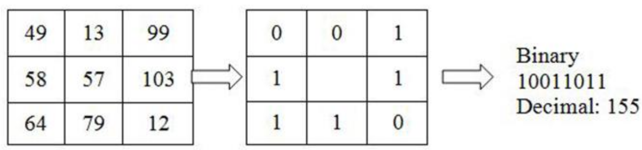

Fig. 1. Calculation of the LBP.

If we change the intensity value of the center-left pixel from 58 to 56, there will be a different LBP: 00011011, or 27 in **Fig. 2**. We can clear observe that it is still quite similar between the two bit patterns and the Hamming distance is equal to 1. But the last decimal results are very different.

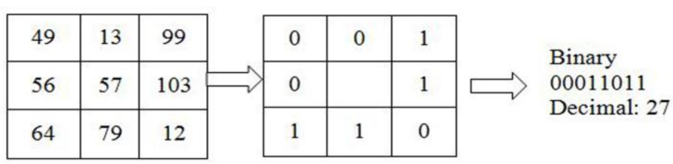

Fig. 2. Calculation of the LBP by modifying the value of the center-left pixel from 58 to 56.

Local Ternary Pattern is proposed as a natural extension of the original LBP to deal with this problem. It extends LBP into three-valued codes for texture classification, namely, Local Ternary Patterns (LTP). In LTP gray levels in a zone of width $\pm t$ around i_c are quantized to zero; the ones above it are quantized to $+1$; the ones below it are set to -1; and the indicator $s(u)$ is replaced with a three-valued function:

$$s'(u,i_c,t)=\begin{cases}1, & u \geq i_c+t\\ 0, & |u-i_c|<t\\ -1, & u \leq i_c-t\end{cases}, \tag{1}$$

where the binary LBP code is replaced by a ternary LTP code. Here, t is a user-specified threshold, making LTP codes more resistant to noise but no longer strictly invariant to gray-level transformations. The LTP encoding procedure is illustrated in **Fig. 3**, and shows

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that the threshold t was set to 7 and the tolerance interval is [50, 64].

When using LTP we could use 3n valued codes, and the uniform pattern argument will

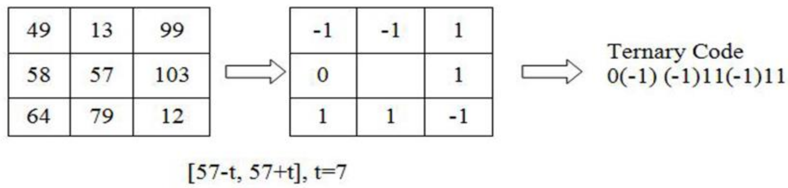

Fig. 3. The basic LTP operators.

apply in the ternary case which splits ternary pattern into its positive and negative as shown in **Fig. 4**.

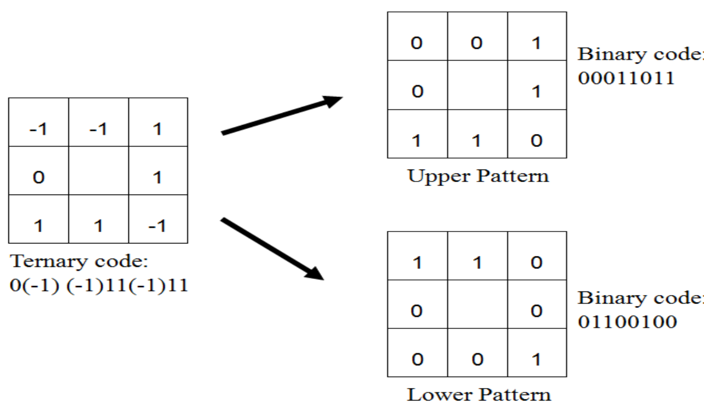

Fig. 4. LTP code into positive and negative LBP codes.

2.2 Extreme Learning Machine

Huang, Zhu, and Siew [16] proposed the ELM algorithm based on the SLFN algorithm. For N samples $\{X_i, T_i\}$, $X_i = [x_{i1}, x_{i2}, ..., x_{in}]^T \in R^m$, $T_i = [t_{i1}, t_{i2}, ..., t_{im}]^T \in R^m$, a hidden layer has $\tilde{N}$ units and excitation function $f(x)$ in the ELM:

$$\sum_{i=1}^{\tilde{N}} \beta_i f_i(X_j) = \sum_{i=1}^{\tilde{N}} \beta_i f(a_i \bullet X_j + b_i) = t_j,\ j = 1, 2, ..., N \tag{2}$$

where $a_i = [a_{i1}, a_{i2}, ..., a_{in}]^T$ is the input weight with the ith unit of the hidden layer and b_i is the deviation. The weight between the ith unit of the hidden layer and the output layer is $\beta_i = [\beta_{i1}, \beta_{i2}, ..., \beta_{im}]^T$. f is the excitation function that can be expressed as "sigmoidal","sine","radial basis" and "bribas". The above equation can be defined as follows:

$$H\beta = T \tag{3}$$

$$H(a_1,...,a_{\tilde{N}},b_1,...,b_{\tilde{N}},X_1,...,X_N) = \begin{bmatrix} f(a_1 \bullet X_1 + b_1) & \dots & f(a_{\tilde{N}} \bullet X_1 + b_{\tilde{N}}) \\ & \dots & \\ f(a_1 \bullet X_N + b_1) & \dots & f(a_{\tilde{N}} \bullet X_N + b_{\tilde{N}}) \end{bmatrix}_{N\times\tilde{N}} \tag{4}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \\ \beta_N^T \end{bmatrix}_{\tilde{N}\times m} \quad T = \begin{bmatrix} t_1^T \\ \\ t_N^T \end{bmatrix}_{N\times m} \tag{5}$$

ε_j is defined to express the error between expectation value and practical value:

$$\sum_{i=1}^{\tilde{N}} \beta_i f(a_i \bullet X_j + b_i) - Y_j = \varepsilon_j,\ j = 1,2,...,N \tag{6}$$

$E(W)$ is defined to express the error square between expectation value and practical value. The problem is to search for the optimal weight $W = (a,b,\beta)$ that makes $E(W)$ the smallest:

$$\arg\min_{W=(a,b,\beta)} E(W) = \arg\min_{W=(a,b,\beta)} \|\varepsilon\|^2 \tag{7}$$

The problem can also be finding following optimal solutions:

$$H\beta = Y \tag{8}$$

Huang and Chen [14] has confirmed that when the excitation function is infinite differentiable, there is no need to adjust all of the network parameters. Input connection weights a_i and hidden node deviations b_i can be chosen randomly before the training begins and are fixed in the training process. Therefore, the main job is to search for the output weight between hidden layer and output layer, and it can be achieved by solving the linear equations using the least squares method:

$$\begin{aligned} &\left\| H(a_1,...,a_{\tilde{N}},b_1,...,b_{\tilde{N}},X_1,...,X)\beta - Y \right\| = \\ &\min_{\beta} \| H(a_1,...,a_{\tilde{N}},b_1,...,b_{\tilde{N}},X_1,...,X)\beta - Y \| \end{aligned} \tag{9}$$

Where $\beta = H^{+}Y$ and H^{+} is the Moore-Penrosefo generalized inverse of the output layer matrix **H**. The optimal solution has some important characteristics. Through this solution, we can obtain the minimun training error, the minimum paradigm of the weight vector, and the best generalization performance.Therefore, the solution to the final question

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is changed to searching for the optimal output connection weight. If the optimal solution of the output connection weight has been found out, we can obtain the minimum error between actual output values and the ideal target value, and obtain the classification of the training sets. So, compared with the conditional SLFNS, ELM has no need to adjust the value of a_i and b_i in the training process. It only needs to adjust the β value according to the corresponding algorithms.

3. Proposed Face Gender Recognition Using LTP and ELM

This section presents an approach for face gender recognition by using LTP feature and ELM classifier. In the proposed method, the LTP operator is used to represent the face gender image, and ELM is used to classify the face gender image. **Fig. 5** shows the diagram of the ELM-based human face gender identification system.

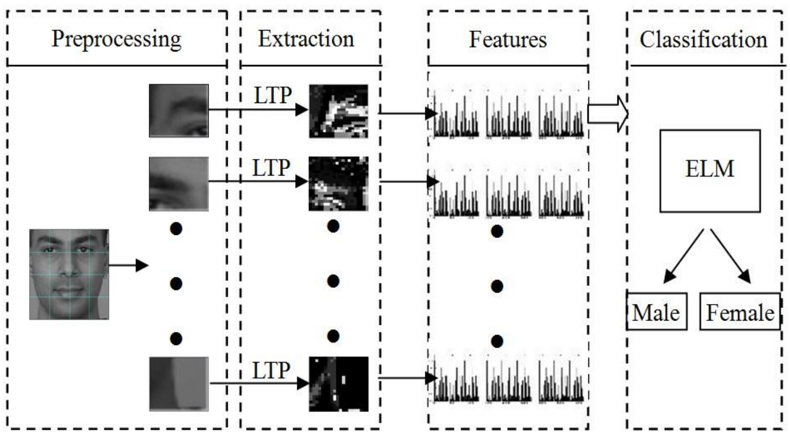

Fig. 5. Block diagram of the ELM-based human face gender identification system.

3.1 Face Gender Representation with LTP

Four steps are used to represent face gender using the LTP feature from the original face image. First, the original image is divided into m*n sub-images for local representation of the face gender. Secondly, the LTP operator is applied to every sub-image to obtain the LTP image using the LTP_upper pattern. Thirdly, a histogram is extracted from each sub-LTP image to build the local representation of the face gender. Finally, all of the histograms are concatenated into one feature vector to build the global representation. **Fig. 6** shows an example of an LTP_Upper pattern image generated from a sub-image. The proposed algorithm is summarized as fellows:

Algorithm: Face Gender Recognition with LTP
Step1: Set parameter P, R, Threshold
Step2: Face image divided into m*n sub-block { $M_0, M_1, ..., M_{m*n}$ }
Step3: LTP $s'(u,i_c,t)=\begin{cases}1, & u \ge i_c+t \\ 0, & \lvert u-i_c\rvert < t \\ -1, & u \le i_c - t\end{cases}$, where $u, i_c \in M_i$
Step4: LTP_Upper Pattern $s'(u,i_c,t)=\begin{cases}1, & u \ge i_c+t \\ 0, & \lvert u-i_c\rvert < t\end{cases}$, and $M_i \rightarrow I_i$
Step5: Histogram of LTP_Upper, Choose a 59 bin histogram with a uniform pattern $I_i \rightarrow H_i$
Step6: Face Features $M_{face} = [H_1, H_2, ...H_i, ...H_{m*n}]$

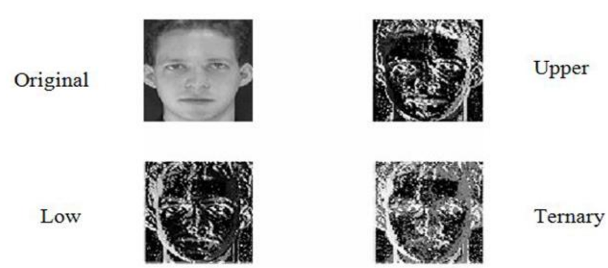

Fig. 6. The LTP images with upper, low and ternary images.

3.2 Classification by ELM

Face features generated using the LTP descriptors is fed into the ELM classifier to recognize the face either as a male or a female. The overall procedure includes two phases: the ELM training phase and testing phase. The ELM training phase is summarized as follows.

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Algorithm: ELM training phase
Step1: Training Sets. Data_Train = [$M_{face_1}, M_{face_2}, ..., M_{face_N}$], where N is the total training samples.
Step2: Set Parameters input weights $A = \{a_1, a_2, ..., a_n\}$, bias $B = \{b_1, b_2, ..., b_m\}$.
Step3: $t_j = \sum_{i=1}^{L} \beta_i f(a_i \bullet M_j + b_i) \rightarrow T = \{t_1, t_2, ..., t_k\}$.
Step4: $H\beta = T, \beta = [\beta_1, \beta_2, ..., \beta_L]$.
Step5: Calculate $\beta = H^{+}Y, Y = [y_1, y_2, ..., y_n]$ Y is class label of face.
Step6: Calculate T and compare T and Y.
Step7: Training Accuracy.

In a process similar to the three steps outlined in the training phase, we test the model parameters obtained from the training model, and then we can obtain the actual output through the test image .The ELM testing phase is summarized as follows.

Algorithm: ELM testing phase
Step1: Obtain optimum parameters A', B', β'(results of Training phase) and N. Where N is the number of hidden nodes.
Step2: Testing Sets. Data_Test=$[M_1', M_2', ..., M'_m]$ Where m is the total testing samples.
Step3: $t_j' = \sum_{i=1}^{L} \beta_i' f(a_i' \bullet M'_j + b_i') \rightarrow T' = \{t_1', t_2', ...t_k'\}$.
Step4: Compare *T'* and Y'.
Step5: Testing Accuracy.

4. Experiments and Analysis

4.1 Gender Public Database

To test the performance of the proposed method in human face gender recognition, we conduct experiments using two public face databases: the Stanford University database [19] and the FERET database [20]. The Stanford University database consists of 200 male and 200 female images collected from the school's hospital. All images are 200*200 pixels and black and white photos with frontal acquisition. Some of the face images show in **Fig. 7**. In contrast, the FERET database consists of 14,051 gray-scale images representing 1,199 individuals. The images contain several variations, such as lighting, facial expressions; pose angle, and aging effects. In our experiments, we collected 2,000 face images that were 80*80 pixels. Half of those images were of females and half were of males.

Fig. 7. Examples of some of the images in Stanford University database.

4.2 Experimental Results

We first conducted several experiments using the proposed algorithms on Stanford University database. We randomly selected images of 160 males and 160 females as a training set; the remaining images were used as a test set. PCA coefficients with 95% energy were used for dimension reduction. Because of the large variation range of features, all samples are normalized between –1 and 1 before using them in the learning algorithms as input.

4.2.1 Discussion on Block Partition

When we use the method of LBP for face recognition, we will divide the image into several regions. Those regions can well partition some feature information and keep unique local feature. How to conduct the block partition is an important factor in retaining the degree of recognition power. Because the pixel size of face image is 200*200, we investigated the effect to the final recognition accuracy by using following five different block partitions 4*4, 5*5, 8*8, 10*10 and 20*20. **Fig. 8** show the recognition results against these 5 different block partitions. It clearly shows that the recognition accuracy is

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achieving the best performance accuracy rate of 95.625% when the size is 4*4, and the lowest rate of 90.875% when in 20*20. From **Fig. 9** we can see that the consumption time for training and testing is increasing when the block size is increasing. In balancing the recognition accuracy and the consumption time, we choose the 4*4 block.

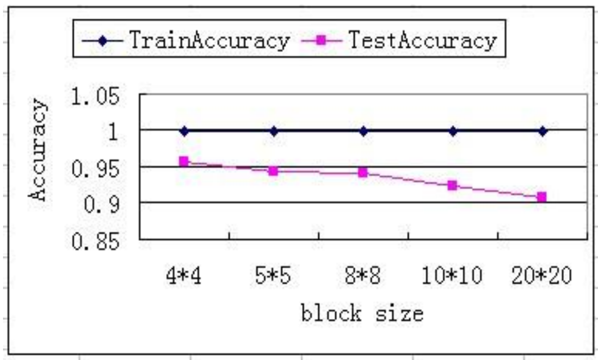

Fig. 8. Accuracy of different block.

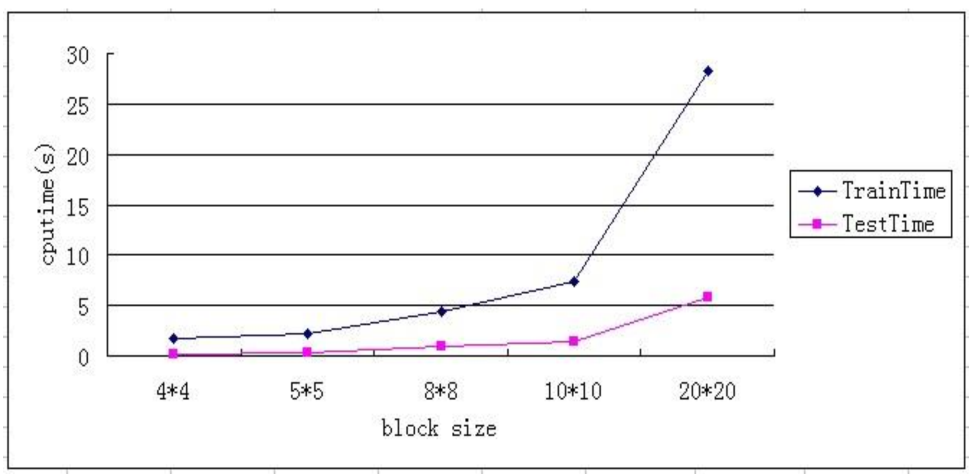

Fig. 9. Consumption time of different block.

4.2.2 Comparison of Different Feature Extraction Methods

Based on the 4*4 block partition, we compare different methods of feature extraction which include LBP, PCA, Gabor and the paper proposed methods LTP_upper and LTP_low with ELM over the Stanford University database. The results are shown in **Table 1**.

Table 1. Different feature extract methods with ELM based on Stanford database.

Methods	LTP_High	LTP_Low	LBP	PCA	Gabor
Test Accuracy	0.95625	0.915	0.9187	0.91625	0.935

From the table, it shows that the average accuracy of LBP is 91.87%, and the average accuracy of PCA is 91.625%, and Gabor is 93.5%,

whereas that of the LTP_upper method is 95.625%, and that of the LTP_low is 91.5%. These results show that the proposed method using LTP_upper for face gender classification is superior.

4.2.3 Comparison of Different Classifiers

We compared different classifiers equipped with LTP_upper. In the classification experiments, we compared ELM with SVM and BP in the Stanford database. The classification accuracies of the BP, SVM, and ELM algorithms are shown in **Table 2**. From the table we can see that the accuracies of the SVM and ELM algorithms are higher than that of the BP, and the accuracy of ELM is similar to the SVM.

Table 2. Recognition accuracies of BP, SVM and ELM on the Stanford database.

Methods	BP	SVM	ELM
Test Accuracy (%)	91.25	94.2857	95.625
Train Accuracy (%)	99.06	100	100

To compute complexity, we calculated the average training time and the average test time of these learning methods by conducting 10 experiments. The average time costing of SVM, BP, and ELM are shown in **Table 3**. From the table, the average total time of ELM, SVM, BP are 1.93, 150.76, 129.99 seconds respectively. Therefore, the ELM method has much fastest speed, which is less than one percent of others.

Table 3. Time cost (seconds) of BP, SVM, ELM based on the Stanford university database.

Methods	BP	SVM	ELM
Train time (s)	121.06	149.81	1.71
Test time (s)	8.93	0.95	0.22
Total time (s)	129.99	150.76	1.93

We compared various algorithms and the result of the comparison is shown in **Fig. 10**. From the figure we can clear see that our proposed methods using LTP_upper for feature

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extraction and ELM for classification can achieve better performance. Though, the accuracy of ELM is a litter higher than the SVM, the training time is much smaller.

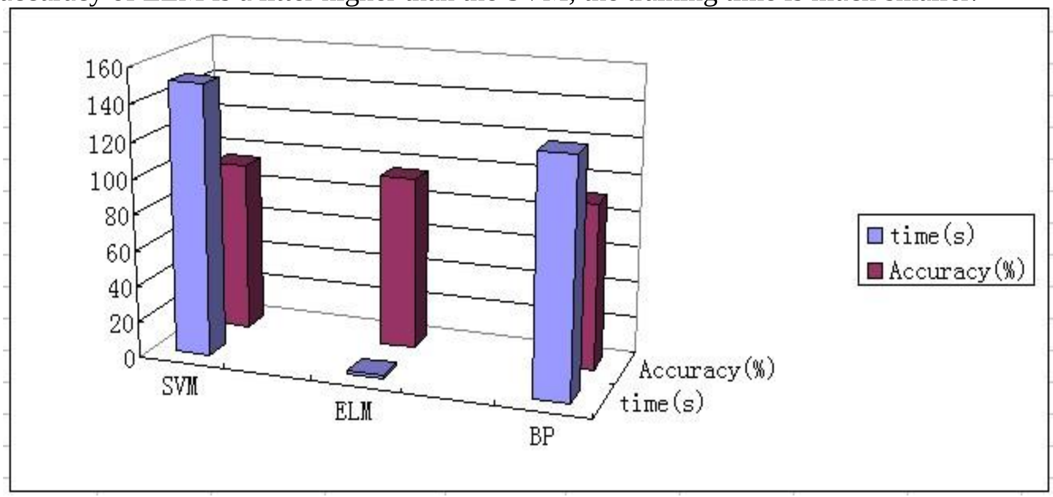

Fig. 10. The performance of three algorithms.

4.2.4 Experiments and Analysis using FERET Database

Experiments were conducted using the proposed algorithm on the FERET database with mean accuracy and time consuming. The results are shown in **Table 4**.

Table 4. Classification results of three algorithms based on the FERET database

Methods	LTP-Upper_BP	LTP-Upper_SVM	LTP-Upper_ELM
TestAccurracy(%)	84.25	87	87.13
Total time (s)	32.8	54.72	1.87

Table 4 shows the comparison of several algorithms using the FERET database. From the table, we can see that the accuracy of ELM (87.13%) is higher than that of the BP algorithm (84.25%) and similar to that of SVM (87%). And the Total time (1.87 second) is also much smaller. So ELM outperformed SVM and BP from overall point of view. It has a significant gain in speed which renders it suitable for the real time system.

5. Conclusions

For better human–computer interaction and in some intelligence environments, it is desirable that face gender classification can be performed in real-time with high accuracy and high speed .This paper described a new face feature based on LTP and used the ELM for face gender classification. The LTP is a generalization of LBP that is more discriminant and less sensitive to noise in uniform regions. LTP operator is used to extract the LTP

Histogram Sequence from the grey-level images. Face recogniton is realized based on the ELM classier for fast processing with high accuracy and high speed. Extensive experiments have been conducted, too. Compared with traditional learning algorithms, such as SVM and BP, ELM has achieved better recognition performance while having a significant gain in speed.

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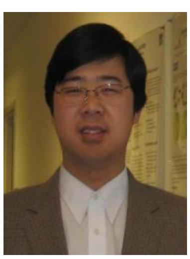

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