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Research on High-Accuracy Gait Recognition Technique based on Parallel Genetic Algorithm

Xiaojia Lin
Department of Computing and Information Technology
Fujian Business University, Fuzhou, 350012, China
No. 19 Huang Pu Road, Gulou District, Fuzhou
14759227@qq.com

Fuquan Zhang*
Fujian Provincial Key Laboratory of
Information Processing and Intelligent Control, Minjiang University
School of Software
Beijing Institute of Technology
Room A9. 301, Jiyuan, Juyuan, Jinshan, Fuzhou, 350008, China
*Corresponding author: 8528750@qq.com

Lin Xu
Innovative Information Industry Research Institute
Fujian Normal University
Fuqing Brunch of Fujian Normal University,
Campus County 1., Longjiang Road, Fuqing, Fuzhou, 350300, China
xulin@fjnu.edu.cn

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Abstract. *In the field of sports science, gait recognition has a wide range of applications. However, compared to other biometric technologies, it has the problem of low recognition accuracy. Therefore, a technique combining the parallel genetic algorithm based on hierarchical fair competition with neural network ensemble is proposed to be applied in gait recognition. First, parallel genetic algorithm is adopted to increase individual diversity, and only appropriate features are selected to train each neural network candidate. Then, a set of individual neural networks are selected to complete the neural network ensemble so as to minimize the generalization error and maximize the negative correlation. Experiments on the CASIA gait database demonstrate the effectiveness of the proposed gait recognition method. The results show that the proposed method has a higher recognition rate than the existing methods.*
Keywords: Gait recognition; Parallel genetic algorithm; Hierarchical fair competition; Neural network ensemble; Negative correlation; Generalization error

1. **Introduction.** Each individual has a unique gait which is determined by his or her weight, leg length, shoes, posture and particular movements [1]. As one of the biometric features, gait has many advantages, for instance, it is non-invasive, easy to access from a distance, and even measurable under the condition of low-resolution images. These advantages have led to human gait study becoming a hot topic in many different fields, including athletic training, health care and video games. Yet gait recognition is not as reliable as other biometric identification technologies [2]. Reference [3] presents a BP

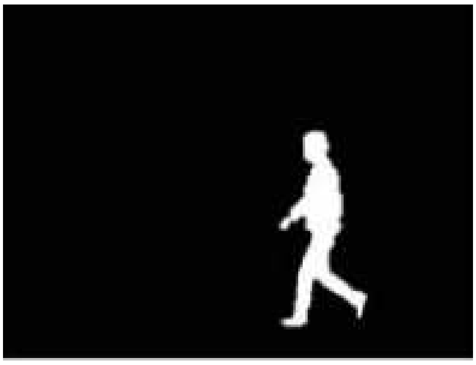

Figure 1. Sample of image silhouette extraction: Background subtraction image,

neural network classifier with optimized genetic algorithm for the purpose of recognizing human gait. But this method requires high accuracy of the transducer. Reference [4] proposes that gait recognition can be achieved by using the mean impact value and the probabilistic neural network. Reference [5] puts forward the algorithm based on the negatively correlated neural network ensemble to be used in the recognition scope. Neural networks can form the non-linear decision boundaries without the statistical distribution of hypothetical data input. In particular they represent the implicit information of given data. However, in general, one single neural network with a limited size needs to load a specific incomplete mapping, and the mapping is usually not sufficiently generalized, which might not be enhanced by increasing the size and amount of the hidden layers in a single neural network. Therefore,the neural network ensemble can be applied to gait recognition effectively, which is a new research direction [6]. Accordingly, a new design method is proposed here, targeted at minimizing generalization errors and maximizing system diversities in gait recognition [7].In this method, parallel genetic algorithm based on hierarchical fair competition (HFC-PGA) [8] is adopted in the generalization of neural network ensemble candidates for increasing the diversity of the network. Furthermore, only a set of appropriate features selected by HFC-PGA are used to train each neural network candidate, instead of all features. Finally, after designing the neural network candidate, we choose a group of individual neural networks so as to minimize the generalization errors and maximize the negative correlation. Experiments on the CASIA-B gait database demonstrate the effectiveness of the proposed gait recognition method. Because negative correlation contributes to increasing individual diversity as well as classification accuracy, the results show that this method has higher accuracy and reliability in gait recognition than the existing methods.

2. **Gait Recognition System.**

2.1. **Pre-treatment.** First, we implement background subtraction to generate a silhouette image from image sequences [9]. We then create a bounding box around the silhouette and adjust it to a fixed size so as to eliminate the scaling effect. Figure 1 shows a sample of a background subtraction image and a normalized silhouette image.

2.2. **Feature Extraction.** Motion silhouette images (MSI) [8] are selected as gait features in normalized silhouette images. MSI is a grayscale image whose pixel intensity represents the temporal movement history of pixels. It contains pivotal space and time information, which can be represented as,

Figure 2. Sample of image silhouette extraction: Normalized silhouette image

Figure 3. Motion silhouette image: a Side view, b. Oblique view, c. Front view

$$MSI(x, y, t)=\begin{cases} 255 & if\ S(x, y, t)=1 \\ \max[0, MSI(x, y, t-1)-1] & otherwise \end{cases} \tag{1}$$

where S(x,y,t) denotes the value of the pixel at (x,y) at frame t, t denotes the time or frame, x and y denote the horizontal and vertical axes of the graph, respectively. S(x,y,t)=1 means that a new silhouette area appears, which is computed to be the gray level of the pixel at (x,y) in the graph. Figure 3 indicates samples of the side view, oblique view and front view of a motion silhouette image.

space is defined by the formula:

$$x_i = P^T m_i = [P_1 P_2 ... P_p]^T m_i \tag{2}$$

Where $P_t|t = 1, 2, ...p$ is the feature vector aggregate of q dimension covariance matrix with the maximum eigenvalue $p\,(p \ll q)$. x denotes the i^{th} low dimension motion silhouette image where i is the number of times, $user2x_i \in \Re^p$.

3. **Proposed method.** As was mentioned above, we suggest using a new design method of neural network ensemble so that higher accuracy and reliability can be achieved in gait recognition. The new design method has two stages. In the first stage, the hierarchical fair competition model based parallel genetic algorithm(HFC- PGA) is adopted to train multiple neural networks to make sure that each neural network has the appropriate features, optimized structure, and adjusted parameters. In the second stage, one group can be chosen from multiple neural networks.

3.1. **Hierarchical fair competition model based parallel genetic algorithm.** In the context of the ensemble, the diversity of the system is a very important factor [7, 8]. Consequently, a simple genetic algorithm may not be a good choice with regards to the

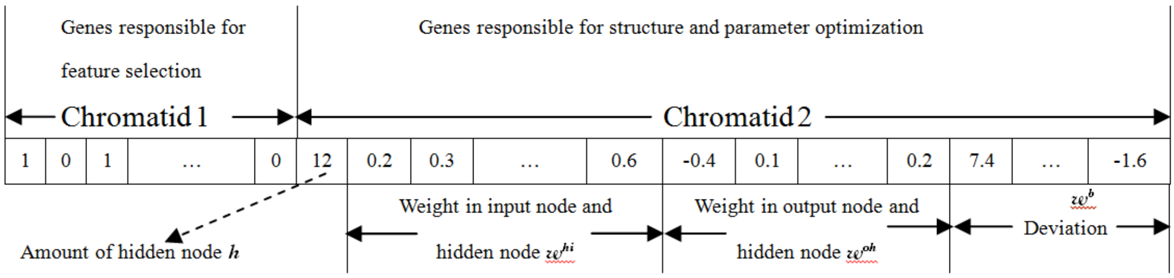

FIGURE 4. Chromosome with the proposed genetic algorithm

training of multiple neural networks because 1) Due to possible early convergence, the algorithm is restricted to the local optimum. 2) In the parent group, individuals with the highest fitness dominate the entire group [8].

Both situations would make individuals so similar that the effect of forming the network ensemble becomes limited. This article suggests solving the problem through the application of HFC-PGA in order to reduce the possibility of premature convergence and maintain the diversity of individuals. In different populations, the hierarchical fair competition model allows young and promising individuals to develop in the early stage, and to join intense competition at a proper time. HFC-PGA has many hierarchically organized sub-populations, and each sub-population is able to contain individuals within the specified range of fitness [13]. The hierarchical fair competition model preserves a lot of various sub-populations, which provides the optimal and the most diversified solution.

As shown in Figure 4, at the first stage, HFC-PGA is implemented to generate individual neural networks each of which is encoded into a chromosome. One chromosome is made up of two chromatids while one is in charge of feature selection and the other is in charge of structure and parameter optimization of the neural network. The first chromatid is encoded as a binary string in which each bit is related to the corresponding feature. To show whether the corresponding feature has been selected, we use1meaning yes and 0meaning no, in Figure 4. p denotes the amount of features in low dimension motion silhouette images.

The second chromatid indicates the structure and parameter of the neural network. It is encoded as presented in Figure 3 where w^{hi} indicates the weight in the input layer and hidden layer while w^{oh} indicates the weight in the hidden layer and the output layer. w^b denotes deviation. p, h and o represent the number of input nodes, hidden nodes and output nodes, respectively. As p and o are both known parameters, the value of h should be affirmed. It is included in the chromosome and its value is between 1 and n^{mh}. n^{mh} is the maximum allowed for hidden nodes. Figure 4 shows a sample of neural network encoding for solving the problem of two hierarchies and four features. Since there are three optional features and two categories, the neural network has three input nodes, four hidden nodes and two output nodes. The lengths of $w^{hi}w^{oh}$ and w^b are 12, 8 and 6 , respectively.

Crossover and mutation are used as genetic operators in the HFC-PGA algorithm. Crossover and bit-reversal mutation are used in chromatids for feature selection. In the second chromatid, arithmetical, simple, heuristic crossover and uniform boundary mutation are utilized. Especially the greatest integer function of the corresponding gene is utilized to determine the number of neurons in the hidden layer.

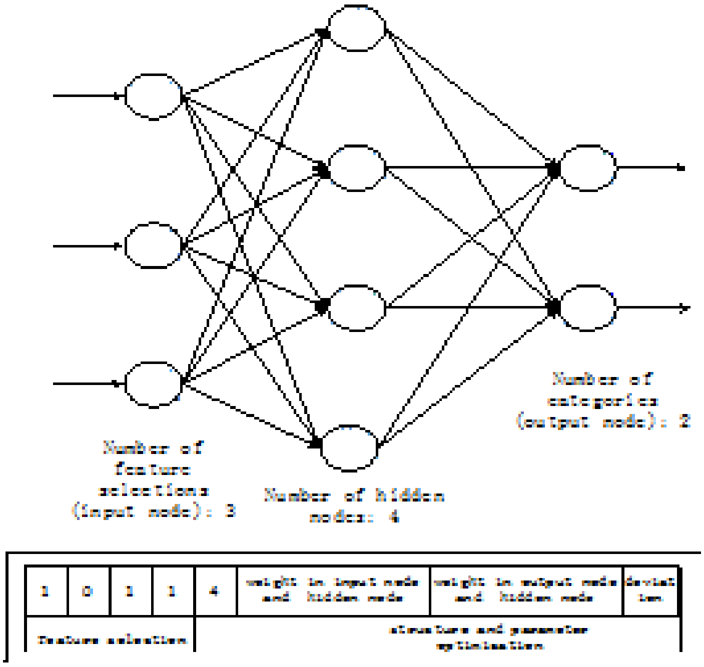

FIGURE 5. Example of neural network

3.2. **Neural network ensemble.** The neural network ensemble can be constructed by combining the multiple neural networks as described in the previous section. To construct an effective ensemble, we need to select a group of appropriate individual neural networks which also have good ensemble generation capability. In other words, we should choose diversified individual networks. Negative correlation prompts the ensemble to choose diverse individual networks which learn from different training data or focus on different aspects of the data. Therefore, we select individual neural networks not only based upon learning error, but also correlations among individuals [7]. Suppose a group of low dimension motion silhouette images are,

$$\{(x_i, c_i)|i = 1, ..., N\}, x_i \in \Re^p \tag{3}$$

Moreover,

$$c_i \in \{1, 2, 3, ..., C\} \tag{4}$$

where c_i denotes the marker for relevant levels.

Theorem 1: Suppose there is a neural network ensemble comprising of J individuals. If we add another individual neural network into it, then the new ensemble will contain J+1 individuals and the error generated by the new one can be presented as the following formula,

$$\widehat{E}_{J+1} = \left(\tfrac{J}{J+1}\right)^2 \widehat{E}_J + \left(\tfrac{J}{J+1}\right)^2 \left(2\sum_{j=1}^{J}\left[C_{j(J+1)} - \lambda K_{j(J+1)}\right] + E_{J+1}\right) = \left(\tfrac{J}{J+1}\right)^2 \widehat{E}_J + \left(\tfrac{J}{J+1}\right)^2 \left(2\sum_{j=1}^{J+1}\left[C_{j(J+1)} - \lambda K_{j(J+1)}\right] - E_{(J+1)}\right) \quad (5)$$

(5)

where $E_{(J+1)}$ denotes the error of the $(J+1)^{st}$ individual neural network, λ denotes controllable variable, C_{jt} and K_{jt} are defined as,

$$C_{jt} = \sum_{i=1}^{N}\sum_{k=1}^{C}\left[\left(f_j^k(x_i) - y_i^k\right)\left(f_t^k(x_i) - y_i^k\right)\right] \quad (6)$$

(6)

$$K_{jt} = \sum_{i=1}^{N}\sum_{k=1}^{C}\sum_{r=1}^{J}\left[\left(f_j^k(x_i) - f_r^k(x_i)\right)\left(f_t^k(x_i) - f_r^k(x_i)\right)\right] \quad (7)$$

where $f_j^k : \Re^p \to [0,1]$ denotes the k^{th} output of the j^{th} neural network, $y_i = (y_i^1 y_i^2 \cdots y_i^C)$ represents the target of c_i. The argument for theorem 1 can be found in reference [7]. As regards to whether or not new individual neural networks should be added into the ensemble, the recursive error equation in theorem 1 can decide it. The reason is that the new ensemble comprises of J+1 individuals, and its deviation can be computed by comparing the error of J individuals ensemble with that of J+1 individuals ensemble. If $\widehat{E}_{J+1} \geq \widehat{E}_J$, then the $(J+1)^{st}$ individual neural network should be added. But if $\widehat{E}_{J+1} \geq \widehat{E}_J$, then the $(J+1)^{st}$ individual neural network should not be added. Consequently, we can determine whether adding a new individual neural network is necessary for an ensemble on the basis of the recursive error equation, and an outstanding ensemble is obtained for solving the raised question.

4. Experiment Result and Analysis.

4.1. Experiment setting.
To verify the validity of the proposed method and its accuracy in gait recognition, we employ the Dataset-B [11] from the CASIA gait database provided by Institute of Automation, Chinese Academy of Sciences in the experiment. This database has been widely applied to the benchmark algorithm in the gait recognition field. Comparing to Dataset-A, Dataset-B has a bigger scale. It is also multi-perspective with more peoples gaits collected and greater applicability. Dataset-B captures gait sequences using digital cameras on tripods, outdoors on two different dates for the purpose of building the CASIA gait database.

The experiment is made using the Windows 7 operating system. The CPU is Pentium Dual-Core E5200 processor with 2GB RAM, and the simulation environment is Matlab R2014a.

Dataset-B has the gait data of 124 people each of whom has been shot from 11 different angles (018365472901081261441 62and 180). Figure 5 illustrates the samples of images from 11 angles. Data are then collected under three different conditions (normal, carrying items and wearing a coat). The image resolution is 320240 with 13640 gait sequences in

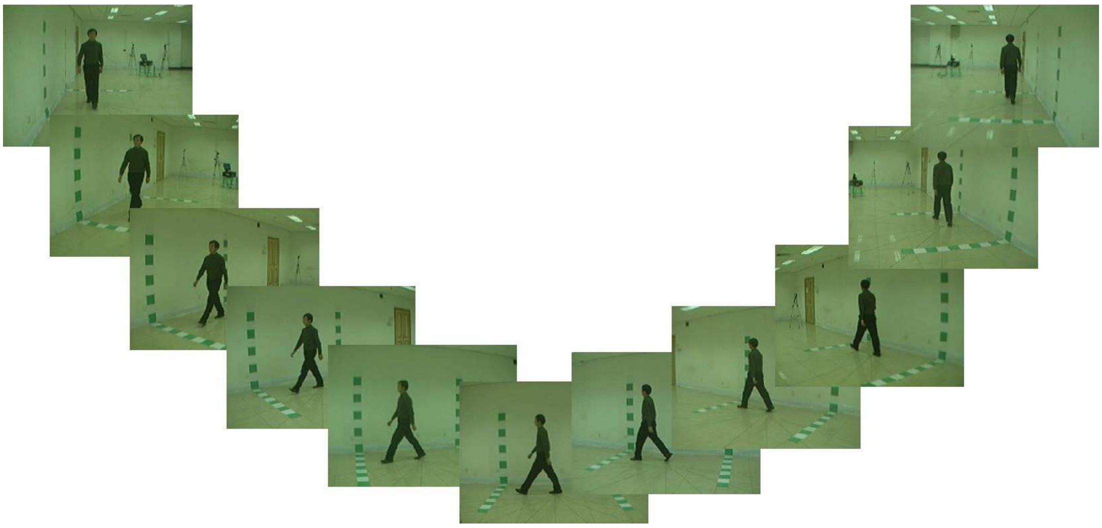

Figure 6. Examples of gait images from 11 different angles

total. The sequence examples from a 0angle under three different conditions are as figure 6,7 and 8.

Sheet 1.Evolutionary optimization parameters

Parameter	Value
Crossover rate	0.60
Mutation rate	0.05
Population quantity	40
Negative correlation coefficient	0.50
Maximum size of the hidden layer	100
Sub-population quantity	4

4.2. **Parameter setting.** In the experiment, twenty principal components are used in motion silhouette images, and the leave-one-out cross-validation (LOOCV) method is employed to test the overall performance of this algorithm. Parameter values applied to evolutionary optimization are summarized in Sheet 1. The parameter values of population quantity, negative correlation coefficient, maximum size of the hidden layer and sub-population quantity in Sheet 1 are all set on the basis of the experiment result in reference [13]. Notice that the sub-population quantity is only one tenth of the population quantity.

4.3. **Result and analysis.** We select the image sequences of the first 20 people shot from three angles (036and 90) under normal conditions and while carrying items, from Dataset-B. The test results are as Figure 9 and 10. Forty independent neural networks are built through hierarchical neural network evolution. Individual neural networks are chosen in the light of the proposed method and then they are used to construct the ensemble.

From Figure 9 and 10, we can draw a conclusion that the recognition rate shot from a 0angle is the highest, that from a 36angle is lower, and that from a 90angle is the lowest.

FIGURE 7. Example of a gait image under normal conditions

FIGURE 8. Example of a gait image with the person wearing a coat from a 0 ° angle

The reason is that the side view obtained from a 0angle contains the most information, while the front view and the oblique view36and 90 have part of silhouette image information covered, so that their gait recognition rates become lower. In addition, the gait recognition rates while wearing a coat are lower than those under normal conditions because a large coat, for instance an overcoat, would affect the eigenvalue during the feature extraction process and increase errors.

This article evaluates the performance of the proposed method with the most common cumulative match scores (CMS) indicator from three different angles. Figure 11 and 12 display the cumulative match scores of 20 people under normal conditions and while

Figure 9. Example of a gait image with the person wearing a coat from a 0 ° angle

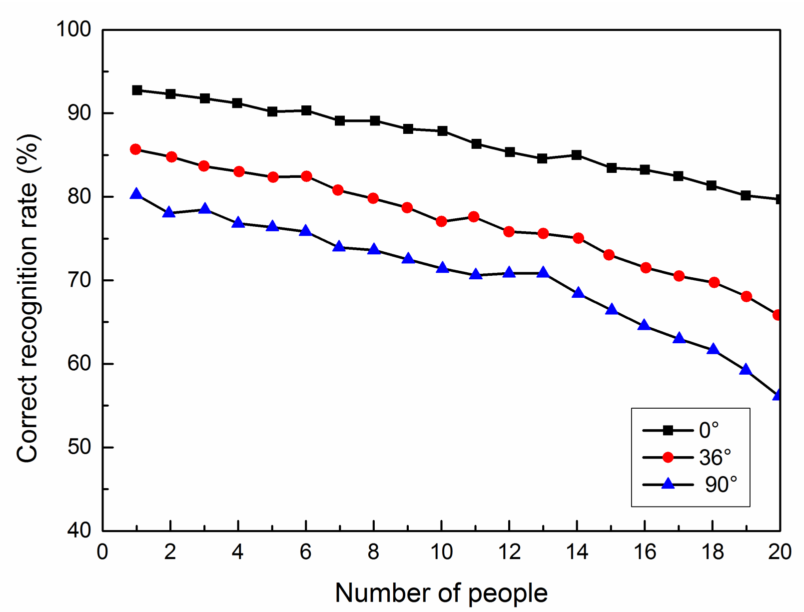

Figure 10. Gait recognition rates under normal conditions

carrying an item. From the curves in Figure 11 and 12, we find that the cumulative match scores under normal conditions outperform those scores while carrying an item, in all three angles. Under normal conditions the 7th, 13rd and 14th order (corresponding to 0, 36and 90) can all achieve 100% of the target, whereas under the condition of carrying items at least the 12th order is required for achieving the target. Besides, in both circumstances, the scores of the data for images from a 0angle are the highest, those from a 36angle are lower, and those from a 90 angle are the lowest.

To demonstrate the performance improving effect of the new method, it is compared to other existing gait recognition methods [6, 11, 12, 13]. We selected image sequences

Table 1. Sheet 1.Evolutionary optimization parameters

Parameter	Value
Crossover rate	0.60
Mutation rate	0.05
Population quantity	40
Negative correlation coefficient	0.50
Maximum size of the hidden layer	100
Sub-population quantity	4

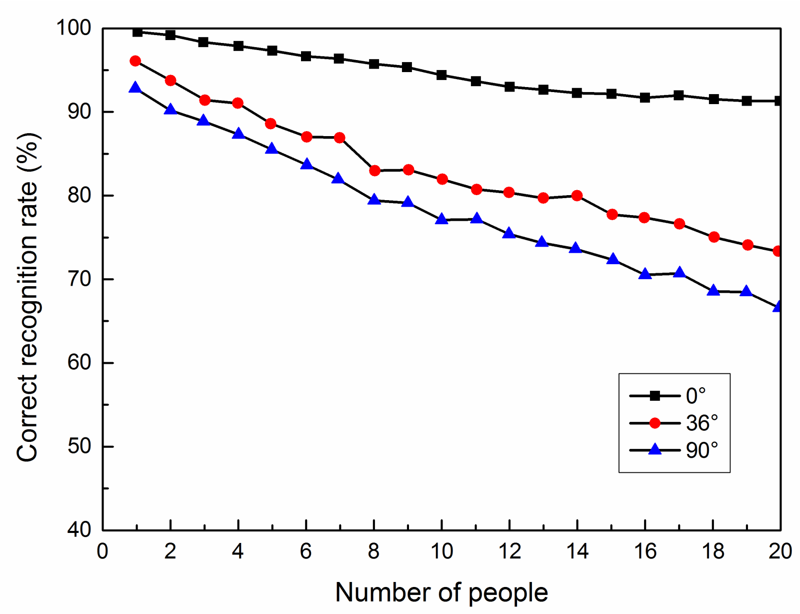

Figure 11. Gait recognition rates while carrying an item

of 20 people shot from seven angles ($0°, 36°, 72°, 90°, 126°, 162°$, and $180°$, respectively) under normal conditions and while carrying items, from Dataset-B as the samples. All the compared parameters are identical to the previous ones. The results are shown in Sheet 2.

As can be seen from the results on Sheet 2, the recognition rate of the technique proposed in the article and that from reference [13] are higher, which are over 90% under normal conditions, with the rate of the proposed method even reaching 93.31%. The recognition rates decline in the circumstance of carrying items. However, the proposed technique still outperforms methods from all the references, with its 82.48% recognition rate, 3 % higher than that of the method described in reference [6]. Hence the comparison proves the superiority of the proposed technique.

5. **Conclusion.** To enhance the accuracy of gait recognition we utilize neural network ensemble and HFC-PGA. Firstly we use HFC-PGA to generate a diversity of individual neural networks, and reasonably select appropriate individual neural networks to minimize the generalization error while insuring negative correlation among individuals. Finally, we make an experiment based on data from the CASIA Gait Databases. The results indicate that the proposed method outperforms all other methods of gait recognition referenced, in recognition accuracy.

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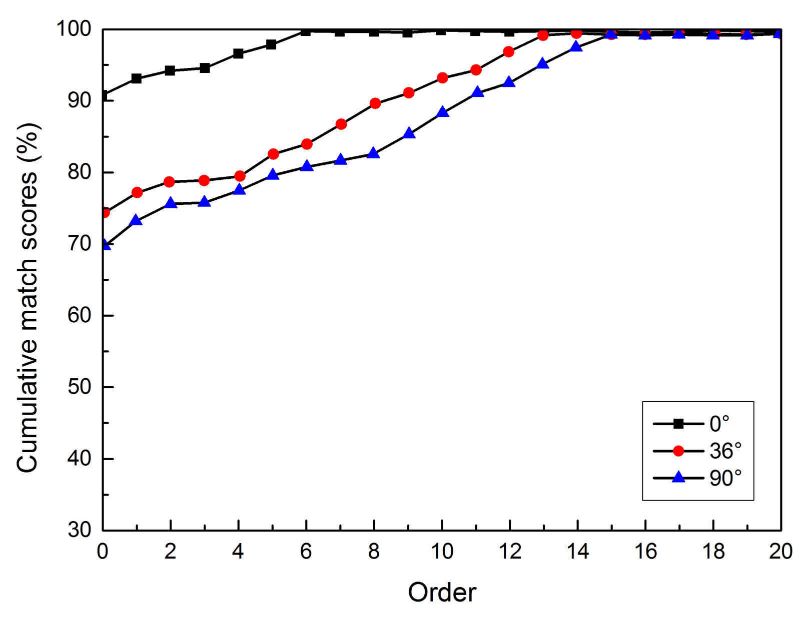

FIGURE 12. Test results under normal conditions

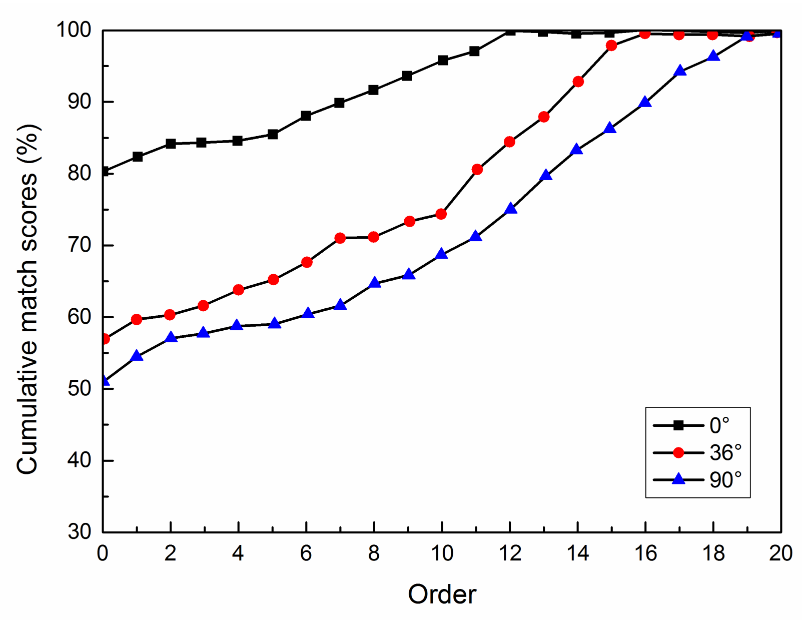

FIGURE 13. Test results while carrying an item

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Sheet 2.Comparison of different algorithms' results

Condition	Algorithm	Recognition rate %
Normal	Reference [6]	86.93
	Reference [11]	88.68
	Reference [12]	87.19
	Reference [13]	91.02
	This article	93.31
Carrying items	Reference [6]	79.49
	Reference [11]	78.36
	Reference [12]	80.03
	Reference [13]	81.79
	This article	82.48

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