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An Embedded PSO Approach to Facial Emotion Recognition

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Abstract: Facial expression recognition system using evolutionary particle swarm optimization (PSO)- based feature optimization employs modified local binary patterns, which conduct horizontal and vertical neighborhood pixel comparison, to generate a discriminative initial facial representation. Then, a PSO variant embedded with the concept of a micro genetic algorithm (mGA), called mGA embedded PSO, is proposed to perform feature optimization. It incorporates a nonreplaceable memory, a small-population secondary swarm, a new velocity updating strategy, a subdimension- based in-depth local facial feature search, and a cooperation of local exploitation and global exploration search mechanism to mitigate the premature convergence problem of conventional PSO. Multiple classifiers are used for recognizing seven facial expressions. Based on a comprehensive study using within- and cross-domain images from the extended Cohn Kanade and MMI benchmark databases, respectively, the empirical results indicate that proposed system outperforms other state-of-the-art PSO variants, conventional PSO, classical GA, and other related facial expression recognition models reported in the literature by a significant margin.

Keywords: Ensemble classifier, facial expression recognition, feature selection, particle swarm optimization (PSO).

I. INTRODUCTION

Facial emotion recognition has opened up a new era for human–computer interaction, and has provided benefits to a wide range of computer vision applications, such as healthcare, surveillance, event detection, personalized learning, and robotics. Robust emotion classification relies heavily on effective facial representation. However, it is still a challenging task for identifying significant discriminative facial features that could represent the characteristics of each emotion because of the subtlety and variability of facial expressions.

This paper aims to deal with such challenges to produce effective and optimized discriminative facial representations to benefit real-time facial expression recognition. In comparison with other feature selection methods, evolutionary computational (EC) algorithms show powerful global search capabilities, and have been widely accepted as efficient techniques for feature selection. Among different EC algorithms, the particle swarm optimization (PSO) algorithm is motivated by the flocking behaviors of birds, and has been extensively used for feature optimization with the benefits of a low- computational cost and a fast convergence speed. However, conventional PSO tends to converge prematurely and, therefore, be trapped in local optima. As a result, in this paper, a PSO variant embedded with the concept of a micro genetic algorithm (mGA) is proposed. Known as mGA-embedded PSO, the proposed algorithm incorporates a nonreplaceable memory, a small-population secondary swarm, a new velocity updating strategy, a subdimension-based regional facial feature search strategy, and a cooperation of local exploitation and global exploration search strategy to overcome both pre- mature convergence and local optimum problems encountered by conventional PSO. The proposed facial emotion recognition system consists of three steps: 1) feature extraction2) feature optimization 3) emotion recognition.

First of all,use modified local binary patterns (LBPs), i.e., horizontal and vertical neighborhood comparison LBP, to extract the initial facial representation. Then, the proposed mGA-embedded PSO algorithm is used to identify the most discriminative and signifi- cant features for differentiating distinct facial expressions. Diverse classifiers (e.g., single and ensemble models) are applied to recognize seven emotions: 1) happiness; 2) sad- ness; 3) anger; 4) fear; 5) surprise; 6) disgust; and 7) neutral. The system is evaluated with two facial expression databases, i.e., the extended Cohn Kanade (CK+)and MMI. State-of-the-art PSO variants, conventional PSO, and classical genetic algorithm (GA) are used to compare with the proposed mGA-embedded PSO algorithm in feature optimization. The empirical results indicate that the proposed system outperforms state-of-the-art optimization methods and other related facial expression recognition research reported in the literature by a significant mar- gin. The main contributions of this paper are summarized as follows.

1) A modified LBP operator that conducts horizontal and vertical neighborhood pixel comparison is proposed, in order to overcome the drawbacks of original LBP by retrieving the missing contrast information embedded in the neighborhood to generate the initial discriminative facial representation.
2) A novel mGA-embedded PSO algorithm is proposed for feature optimization, in order to mitigate the premature convergence and local optimum problems of conven- tional PSO. It provides great flexibility to allow the feature selection process to not only separate facial fea- tures into specific areas for in-depth local search but also combine facial features for overall global search.
3) The proposed algorithm includes a new velocity updat- ing strategy by employing the personal average experi- ence to generate the individual best, pbest, and Gaussian mutation to produce the global best, gbest, in order to increase swarm diversity.
4) The proposed algorithm also applies the diversity main- tenance strategy of mGA to keep the original swarm in a nonreplaceable memory [5], which remains intact during the lifetime of the algorithm, in order to reduce the probability of premature convergence.
5) In order to speed up evolution for convergence, the small population size concept of mGA is used to generate a secondary swarm with five particles. The secondary swarm consists of the swarm leader and four follower particles from the nonreplaceable memory with the lowest or highest correlation with the leader to increase local exploitation and global exploration. These local and global search mechanisms work in a collabora- tive manner to guide the search toward global optima. A subdimension-based search strategy is also conducted, in order to identify optimal features for each facial region.
6) Our proposed system is evaluated with CK+ and MMI databases. It outperforms state-of-the-art LBP and PSO variants, and other facial expression recognition methods reported in the literature significantly.

II. STATE OF THE ART

Previous Works on Facial Emotion Recognition

Feature extraction techniques: A number of LBP variants are available to increase its robustness and discriminative power. As an example, dominant LBP (DLBP) is able to retrieve the most frequently occurred patterns of LBP to improve its texture descriptive capability. According to [3], uniform patterns in LBP can lead to a loss of information with respect to complex shapes despite their effectiveness in capturing fundamental patterns in an input image. Therefore, instead of purely using uniform patterns, DLBP calculates the occurrence frequencies of all the pat- terns extracted by LBP. These patterns are subsequently ranked based on the occurrence frequencies to enable the extraction of dominating patterns in texture images.

Completed LBP (CLBP) [4] employs three key components, i.e., CLBP-center, CLBP-sign, and CLBP-magnitude, to extract the image's local gray level and the sign and magnitude features of local difference, respectively. The final CLBP histogram is formed by fusing these three components. In comparison with LBP which only considers the sign component, CLBP takes the magnitude component and intensity of the central pixel into account for formulating the additional discriminative power. It produces superior texture classification accuracy than those from other state-of-the-art LBP algorithms. Center-symmetric LBP (CS-LBP) [5] aims to solve the lengthy histogram problem of LBP. In order to produce more compact binary patterns, CS-LBP purely employs the center-symmetric pairs of pixels for comparison. Therefore, compared with LBP, it enables a significant reduction in dimensionality while capturing better gradient information. Local derivative pattern (LDP) [6] is a high-order local pattern descriptor, which encodes directional pattern features based on local derivative variations. In comparison with LBP (as a nondirectional first-order local pattern operator), LDP encodes more detailed discriminative information by calculat- ing higher-order directional derivatives. It effectively extracts spatial relationships in a local region. LBP, on the other hand, only defines the relationships between the central point and its neighbors. In LDP, the first-order derivatives from four different directions, i.e., 0◦, 45 ◦, 90 ◦, and 135◦, are calcu- lated. A set of 16 spatial relationship templates is defined for derivative direction comparisons with each template assigned a value of "0" or "1" based on whether it is a "mono-tonically increasing/deceasing" or a "turning point" pattern. The four first-order derivatives are then concatenated to form the second-order LDP. The nth-order LDP, therefore, encodes the (n−1)th-order derivative direction variations.

PSO variants and feature selection techniques: There are many PSO variants in the literature to over- come the local optimum problem of conventional PSO [7]. Mahmoodabadi et al. [8] proposed a PSO variant known as high exploration PSO (HEPSO). In HEPSO, PSO is integrated with a multicrossover mechanism of the GA and the food source finding operator of bee colony optimization for updating the particle velocity and position, respectively. Evaluated with well-known benchmark functions, HEPSO has shown superiority over other PSO variants. Li et al. [9] proposed another hybrid PSO algorithm with the integration of fuzzy reasoning and a weighted particle to guide the swarm. The weighted particle is used to adjust the search direction, whereas other parameters such as the attraction factor and inertia weight controlled by fuzzy reasoning are used to adjust local exploitation and global exploration to guide the search. The proposed model was tested with ten benchmark functions, and was further applied to nonlinear neural network (NN)-based modeling. Jordehi [7] proposed an enhanced leader PSO model known as ELPSO. ELPSO employs Gaussian, Cauchy, opposition-based, and differential evolution (DE)-based mutation to increase the diversity of the swarm leader.

Face and facial emotion recognition: Krisshna et al. [9] developed a face recognition system with a method called threshold-based binary PSO feature selection (ThBPSO). ThBPSO conducts multiruns of conven- tional BPSO and stores gbest identified from each run. Then, a threshold is used to identify the importance of each dimen- sion of the global best solutions. A feature is selected and considered as important if the total number of selections of this feature in the past runs is more than the predefined threshold. The system was tested with seven benchmark datasets, and showed superior performance over other state-of-the-art meth- ods. Liu et al. [10] proposed a deep learning architecture, i.e., action units inspired deep networks (AUDNs), for learning facial expression features. AUDN consists of three sequential processes: 1) a convolutional layer and a max-pooling layer to learn the micro-action-pattern (MAP) representation; 2) feature grouping to integrate correlated MAPs to produce mid-level semantics; and 3) a multilayer learning process to construct subnetworks for higher-level representations.

III.PROPOSED SYSTEM

A. Facial Feature Extraction Using the Proposed LBP

In this paper, in order to improve the discriminative abilities of LBP, we propose horizontal and vertical neighborhood pixel comparison LBP (hvnLBP). It is integrated with the Gabor filter for producing the discriminative facial representation.There are four steps in the feature extraction process: 1) preprocessing for illumination changes and noise invariance; 2) face detection; 3) Gabor magnitude image generation; and 4) the proposed hvnLBP-based textural description. First of all, we apply histogram equalization and bilateral filter to compensate illumination variations and reduce noise in the input image, respectively. We then use a Haar-cascade face detector to detect faces. A 2-D Gabor filter is also applied to produce magnitude pictures. Finally, the proposed hvnLBP operator is used to generate the textural description of facial images.

As a well-known texture descriptor, LBP employs a circular neighborhood for feature extraction. This original LBP operator performs a comparison purely between the central pixel and the eight surrounding neighborhood pixels, therefore likely to lose the contrast information among the neighbor- hood pixels. To solve this problem, we propose hvnLBP to capture missing contrast information among the neighborhood pixels. Instead of comparing with the central pixel as in original LBP, hvnLBP employs horizontal and vertical neighborhood pixels for direct comparison to produce the resulting textural descriptions. As an example, we employ P={ p0,p1,p2,p3,p4,p5,p6,p7}to represent the eight neighborhood pixels in LBP. In either vertical or horizontal comparison, the values of the vertical or horizontal neighboring pixels are compared with one another. A 1 is assigned to the pixel with the highest value and a 0 is assigned to the remaining pixels. This horizontal and vertical comparison process can be conducted in any order, i.e., horizontal comparison followed by vertical comparison, or vice versa. Moreover, in both vertical and horizontal com- parisons, we do not include the center pixel for comparison.For horizontal comparison, we first compare the pixel sets of {p0,p1,p2}, {p7,p3}, and {p6,p5,p4}. Subsequently, we conduct the vertical comparison with the pixel sets of {p0,p7,p6},{ p1,p5}, and {p2,p3,p4}. If a pixel has conflicting outputs in the horizontal and vertical comparisons (e.g., the highest value in the horizontal compar- ison but not in the vertical comparison, or vice versa), then the highest value (i.e., 1) is used as the final output, since the pixel is regarded as important, which contains valuable contrast information in the dimension that generates the highest value. The mathematical representation of this proposed hvnLBPp,r operator is illustrated as follows

$$\text{hvnLBP}=\begin{Bmatrix} S\left(\max(l_0,l_1,l_2)\right),S\left(\max(l_7,l_3)\right) \\ S\left(\max(l_6,l_5,l_4)\right),S\left(\max(l_0,l_7,l_6)\right) \\ S\left(\max(l_1,l_5)\right),S\left(\max(l_2,l_3,l_4)\right) \end{Bmatrix} \tag{1}$$

where p is the number of neighborhood pixels, and r is the radius. li represents the ith neighborhood of pixel while S denotes the comparison operation, as follows

$$S\left(\max(l_j,l_k,l_m)\right)=\begin{cases}1 & \text{if maximum} \\ 0 & \text{if non maximum}\end{cases} \tag{2}$$

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where lj,lk,and lm represent the neighborhood pixels in a row or column. Note that lk is removed if it is the center pixel.Overall, in comparison with the original LBP operator, the experimental results indicate that hvnLBP is more capable of capturing discriminative contrast information such as corners and edges among neighborhoods to inform subsequent PSO- based feature selection and facial expression analysis.

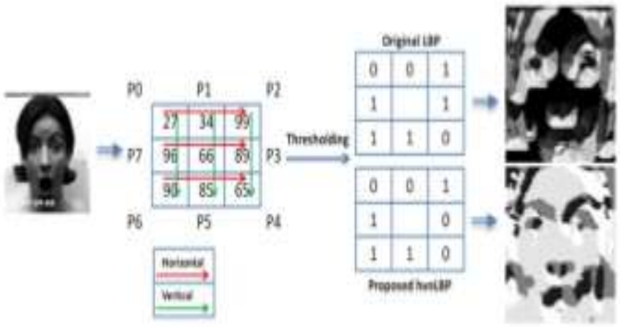

Fig 1: Example output of the proposed hvnLBP operator in comparison with that of the original LBP.

B. Proposed PSO Algorithm for Feature Optimization

To identify the discriminative characteristics of each expression, we propose a PSO variant embedded with the concept of mGA for feature optimization, called the mGA-embedded PSO algorithm. This proposed PSO algorithm mitigates the premature convergence problem of conventional PSO, and shows superior capabilities of discriminative feature selection. The proposed mGA-embedded PSO algorithm employs personal average experience and Gaussian mutation for velocity updating. Furthermore, it integrates the diversity maintenance strategy of mGA to keep the original swarm in a nonreplaceable memory, which remains intact during the lifecycle of the algorithm to increase swarm diversity. Inherited from the con- cept of mGA, a secondary swarm with a small population size of five particles is employed. The swarm comprises a leader and four follower particles with the highest or lowest correlation to the leader from the nonreplaceable memory to increase local and global search capabilities and avoid premature convergence. Moreover, the algorithm separates facial features into specific areas for in-depth local subdimension-based search. Overall, the local exploitation and global exploration search strategies of the algorithm work cooperatively to lead the search process to the global optima.

1) Update of pbest and gbest: In conventional PSO, each solution is represented as a particle in the swarm. Particles move in the search space by following the swarm leader in order to find the optimal solutions. Each particle has a position in the search space represented as xi = (xi1,xi2,...,xiD), whereas it also has a velocity represented as vi = (vi1,vi2,...,viD), with D denoting the dimensionality of the search space. Each particle has a memory of its best experience whose position is represented as pbest. The swarm leader represents the best experience of the overall swarm, whose position is represented as gbest. The position,x_{id}^{t+1} , and velocity, v_{id}^{t+1} , of each particle are updated using the following equation

$$x_{id}^{t+1}=x_{id}^{t}+v_{id}^{t+1} \quad (3)$$

$$v_{id}^{t+1}=w*v_{id}^{t}+c_1*r_1*(p_{id}-x_{id}^{t})+c_2*r_2*(p_{gd}-x_{id}^{t}) \quad (4)$$

where t and d indicate the tth iteration and dth dimension in the search space, respectively. An inertia weight, w, is used to embed iteration influence of the previous velocity. Note that r1 and r2 represent random values within the range of [0, 1] whereas c1 and c2 are the acceleration constants.

Furthermore, p_{id} and p_{gd} indicate elements of pbest and gbest in the dth dimension. In this paper, we modify the velocity updating formula (4) by introducing the averaging search strategy for computing p_{id} and Gaussian mutation for computing p_{gd} specifically, the averaging search strategy takes the personal average experience into account, instead of the conventional personal best experience. The average experience is obtained by averaging the positions found from previous iterations of each individual particle for generating pbest. This enables the algorithm to better look into the search space inbetween to increase local exploitation. Furthermore, instead of using the position of the global best experience directly, Gaussian distribution operation is applied to the swarm leader to generate gbest. This mutation technique enables the generation of offspring further away from its parent to increase global exploration. Therefore, the revised velocity updating strategy possesses more capability of sustaining search diversity. The updated formulas are provided as follows

$$v_{id}^{t+1}=w*v_{id}^{t}+c_1*r_1*(p_{id}^{'}-x_{id}^{'})+c_2*r_2*(p_{gd}^{'}-x_{id}^{t}) \quad (5)$$

$$p_{id}^{'}=\frac{\sum x_{id}}{t} \quad (6)$$

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$$p'_{gd} = p_{gd} + \left(x^d_{max} - x^d_{min}\right)*\phi(0,h) \qquad (7)$$

where p^t_{id} and p^t_{gd} represent the updated pbest and gbest in the dth dimension using personal average experience and Gaussian distribution, respectively, as defined in (6) and (7). Moreover, in (7), ϕ(o,h) indicates the Gaussian distribution and o represents the mean of the distribution with h as the standard deviation which decreases linearly during the execution. Note that x^d_{max} and x^d_{min} indicate the upper and lower bounds of the decision vector in the dth dimension, respectively, d =1,2,...,D.

As indicted in Algorithm 1, we first initialize the original swarm with 30 particles. The modified PSO operation with the proposed velocity updating formula is applied to the initial swarm. It iterates ten times at the beginning of the algorithm to find the best leader. We use a small number of iterations (i.e., 10) for this initial PSO search to accelerate convergence and allow benefits from subsequent search strategies to take place. This mainly aims to find the best balance between computational costs and performance. The following setting (obtained from experimental trials) is applied to this modified PSO operation, i.e., maximum velocity = 0.6, inertia weight = 0.78, population size = 30, acceleration constant c1 = c2 = 1.2, and maximum generations = 500. Moreover, (8) is used to define the fitness evaluation for each particle, C, which consists of two criteria, i.e., classification performance and the number of selected features. Since we apply the proposed PSO algorithm to each emotion category separately, in an attempt to identify the discriminative features for each distinct expression, the classification accuracy score in (8) indicates accuracy of each individual expression, rather than combined accuracy across all emotion categories. This helps avoid bias toward specific emotion categories during optimization.

$$\text{fitness(C)}= w_a * \text{accuracy}_c + w_f * (\text{number} - \text{features}_c)^{-1} \qquad (8)$$

where w_a and w_f are two predefined weights for classification accuracy and the number of selected features, respectively, with w_a =1−w_f. In addition, parameters $w_a$and$w_f$indicate the relative importance of classification performance and the number of selected features, respectively. In this paper, since the classification performance is considered to be more important than the number of selected features, w_a assumes a higher value than w_f , i.e., wa =0.9 and wf =0.1.

2) Construction of Secondary Swarm Embedded With the Concept of mGA :Besides the velocity updating mechanism, the proposed PSO algorithm integrates the concepts of mGA and a secondary swarm, as well as the cooperation of local exploitation and global exploration search strategies to balance between convergence speed and swarm diversity. In summary, the proposed algorithm employs the diversity maintenance strategy of mGA using a nonreplaceable memory. This nonreplaceable memory comprises the initialized swarm to sustain search diversity. Motivated by the small population size concept of mGA, a secondary swarm with five particles comprising the swarm leader and four follower particles from the nonreplaceable memory with the highest or lowest correlation with the leader is constructed to increase local exploitation and global exploration. A subdimension-based search in the secondary swarm is also conducted, in order to identify the discriminative regional facial features. Moreover, the local exploitation and global exploration search strategies of the secondary swarm work in a collaborative manner to avoid stagnation and overcome premature convergence. The details of these strategies are as follows. mGA is a small-population GA with a reinitialization mechanism. It was initially proposed by Goldberg, whose theories suggested that a small population was sufficient enough to achieve convergence regardless of the chromosome length. mGA usually employs a population of 3–6 chromosomes and shows great capability of solving nonlinear optimization problems. Instead of using the mutation operation as in classical GA, mGA employs a restart strategy to maintain genetic diversity in the population. The mGA model is proven to be more capable of avoiding premature convergence and reaching the optimal search region than the classical GA. Because of its impressive performance and fast convergence speed, mGA has been widely used to deal with singleobjective and multiobjective optimization problems. Furthermore, Coello and Pulido proposed a multiobjective mGA with two memories, i.e., population memory and external memory. The population memory consists of replaceable and nonreplaceable aspects. The nonreplaceable fragment of the memory remains intact during the entire lifetime of the algorithm, in order to bring sufficient diversity to the algorithm, whereas the replaceable portion of the memory is used for conventional evolution where the solutions are kept updated in the subsequent evolutionary cycles. The multiobjective mGA shows efficient searchdiversity, and requires less computational cost compared with other algorithms such as Pareto archived evolutionary strategy.

This paper borrows the multiobjective mGA concept with the replaceable and nonreplaceable memories to update the swarm leader (replaceable portion) and preserve diversity of the initialized swarm (nonreplaceable portion), respectively. After initializing the swarm with 30 randomly generated particles at the beginning of the algorithm, this original swarm is stored in the nonreplaceable memory, which remains intact during the lifetime of the algorithm, in

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order to reward swarm diversity when stagnation occurs. To balance between swarm diversity and convergence speed, a secondary swarm embedded with the small population concept of mGA is constructed. It has a typical population size of five, and consists of a swarm leader and four follower particles from the nonreplaceable memory. As illustrated in Algorithm 1, the followers are chosen based on two types of correlation relationships with the leader: 1) the lowest and 2) the highest correlations. Particles with the lowest correlation provide higher variations in the swarm to enable global exploration whereas particles with the highest correlation bring more similarity in the swarm where local exploitation can be observed. Moreover, the correlation relationship between particles using (9) and (10). Since the extracted features using hvnLBP are in the binary format and can be converted into histogram easily, we use the histogram correlation comparison method, as shown in (9) and (10), to identify particles with highest/lowest correlation to the leader

$$\mathrm{corr}(H_1, H_2)=\frac{\sum_I (H_1(I)-H'_1)(H_2(I)-H'_2)}{\sqrt{\sum_I (H_1(I)-H'_1)^2 \sum_I (H_2(I)-H'_2)^2}} \quad (9)$$

where

$$H'_k=\frac{1}{N}\sum_I H_k(I) \qquad (k=1,2) \quad (10)$$

where corr indicates the correlation relationship between two particles with H_1 and H_2 representing the histograms for the swarm leader and a follower particle, respectively. H'_k indicates the mean of the histogram for the kth particle (k=1,2), whereas N represents the number of histogram bins and I indicates the intensity range present in the histogram. Equation (9) produces an output in the range of [0, 1], with 0 and 1 representing the lowest and highest correlations, respectively.

As shown in Algorithm 1, first of all, after identifying the swarm leader by the previous modified PSO process, four follower particles from the nonreplaceable memory with the highest correlation with the leader are recruited to the secondary swarm. The aim of extracting the follower particles from the nonreplaceable memory, instead of using the particles from the main swarm, is to avoid diversity loss as the particles in the main swarm tend to be converged and become identical after ten iterations. Moreover, these follower particles with the highest correlation with the leader provide certain degree of position proximity in the secondary swarm, therefore enabling local exploitation of the search space. Subsequently, we divide each particle in the secondary swarm into five feature subsections, with each subsection representing each facial region to enable an in-depth local search to identify its discriminative features.Search reveals a new swarm leader whose fitness value is compared with that of the previous leader, in order to elect a new leader for the next iteration.

After employing particles with the highest correlation with the leader as followers to conduct an in-depth local optimal facial feature search, the secondary swarm recruits a new set of four particles with the lowest correlation with the leader from the nonreplaceable memory to replace the existing follower particles. Since the new set of follower particles with the lowest correlation recruited from the original swarm inject high variation to the secondary swarm, it boosts the swarm diversity significantly to increase global exploration and avoid premature convergence. Subsequently, the newly updated diversified secondary swarm is also used to conduct a local facial feature search to identify a new swarm leader.

In this way, particles with the highest or lowest correlation with the swarm leader from the nonreplaceable memory are recruited alternately in the secondary swarm to increase local exploitation and global exploration. Moreover, when local exploitation in the subdimension search using particles with the highest correlation with the leader stagnates, our PSO algorithm employs follower particles with the lowest correlation with the leader from nonreplaceable memory to increase swarm diversity and drive the search out of local optimum trap. On the other hand, when global exploration in the subdimension search using particles with the lowest correlation with the leader fails to generate a fitter leader, it recruits follower particles with the highest correlation to the leader from nonreplaceable memory to avoid stagnation. and enable local exploitation. Therefore, the local and global search mechanisms embedded in the secondary swarm work cooperatively to mitigate premature convergence and lead the search toward the global optima.

<u>Algorithm 1 Pseudo-Code of mGA-Embedded PSO</u>

```
Initialize a primary swarm (e.g. 30 particles);
Copy the initialized swarm into a non-replaceable Memory;
For each particle in the primary swarm do //perform modified PSO operator
{
 Evaluate each particle using the defined fitness function;
 Compute the average fitness value of previous runs (if available) for each particle in the primary swarm;
 Perform the proposed Averaging Search operation (Eqn. (6)) to generate pbest for each individual particle;
 Apply the Gaussian mutation operation to the swarm leader to produce gbest (Eqn. (7));
```

9 Update the velocity and position of each particle;
10 Update the best particle gbest in the primary swarm;
11 Until (iterations==10)
12 }
13 Generate a Secondary Swarm
14 {
15 Select the best particle gbest from primary swarm as the leader of the Secondary Swarm;
16 Select 4 particles that have the highest correlation with the leader from the non-replaceable Memory, which contains the original particle swarm, as the followers in the Secondary Swarm; //this is for local exploitation and a high correlation means very similar particles.
17 }
18 Divide each particle in the Secondary Swarm into five feature subsections with each subsection consisting of partial dimensions which indicates a specific facial region (e.g. eye, eyebrow, mouth etc);
19 For each feature subsection representing each facial region do // i.e. the corresponding partial dimensions of each particle in the Secondary Swarm
20 {
21 Apply operations of line 6-10;
22 Update the best solution for the corresponding feature sub- section;
23 Until (stagnation detected);
24 }
25 Replace the particles in the Secondary Swarm
26 {
27 Combine the dimensions of each best solution for each feature subsection to replace the swarm leader in the Secondary Swarm if this newly generated combined leader has a better fitness value;

- Select 4 particles in the non-replaceable Memory of the original swarm that have the lowest correlation with the above swarm leader to replace other particles in the Secondary Swarm; //this is for global exploration, and the lowest cor- relation means particles with high variations to the leader

28 }
29 While (Overall termination criteria are not achieved)
30 {
31 Repeat lines 19-25;
32 Repeat lines 26-30, but change from lowest correlation to highest correlation in a vice versa manner;
33 }
34 End
35 Return the most optimal solution;
36 End

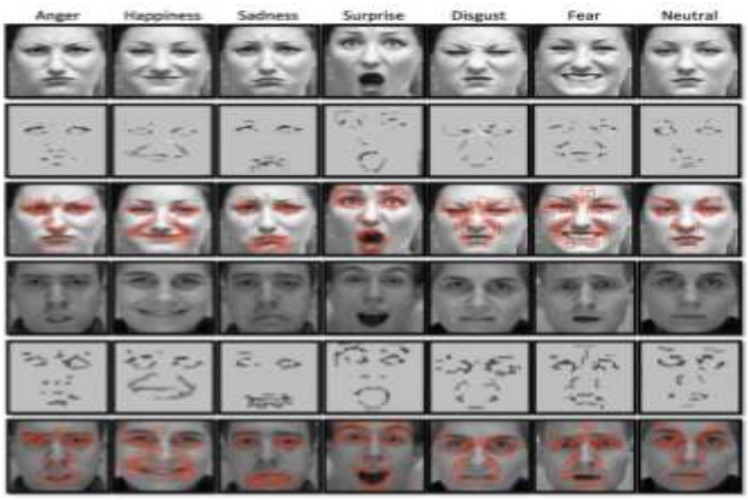

Fig.2: Selected optimal features and their distribution for each expression using the proposed mGA-embedded PSO algorithm (rows 1–3: CK+ images and rows 4–6: MMI images).

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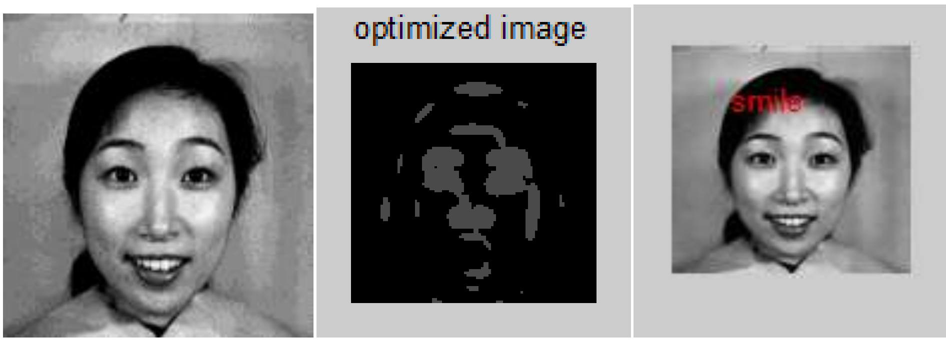
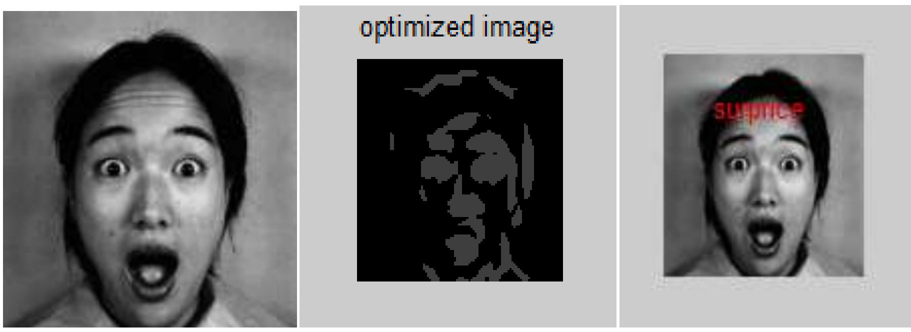
In this paper, we conduct a study of seven-class facial emotion recognition using the features automatically generated by the mGA-embedded PSO. NN with backpropagation, a multiclass SVM , and ensemble classifiers are used for classification. The detailed setting of the classifiers is introduced, as follows. In this paper, the trial-and-error method is conducted to identify the optimal NN structure, whereas a grid-search method is applied to find the optimal parameters of the multiclass SVM with the RBF kernel. After several trials, the NN is equipped with one input layer with 25–40 nodes indicating the optimized features obtained from the proposed PSO algorithm, one hidden layer, and one output layer with seven nodes, respectively, representing seven expressions. For the grid search of optimal settings for the multiclass SVM with the RBF kernel, we use exponentially growing sequences and search the ranges of [2−5−215], [2−10−25], and [2−8−2−1], respectively, for a soft-margin constant, C, a kernel parameter, gamma (γ), and an epsilon (ε) in the loss function since the combination of these three parameters plays very important roles in affecting the SVM’s performance. We also employ tenfold cross validation to identify the best combination of these parameters to avoid over-fitting. The identified optimal setting in the training stage is then applied to the subsequent experiments in the test stage.

Besides these single model classifiers, we also employ ensemble classifiers for expression recognition in order to improve accuracy. We use weighted majority voting for the construction of ensembles because of its impressive performance and suitability for undertaking small datasets (<1000) in this paper. We construct two ensembles with NN and multiclass SVM as the base model, respectively. Also the NN-based and SVM-based ensembles use three basemodels, respectively. The optimal settings identified earlier for NN and SVM are applied for building each base model.

The ensemble classifiers are constructed using an AdaBoost process so that the performance of the three base models within each ensemble classifier is complementary to each other [5]. The training process of each ensemble classifier focuses on misclassified instances. As an example, the weights of misclassified instances by the first base model are increased so that they are more likely to be selected for training the second base model. A similar case is also applied to the construction of the third base model, which employs the instances misclassified by the second base model for training. Therefore, each ensemble classifier is constructed with a number of base models that are complementary to each other [5]. Weighted majority voting is applied to combine the outputs from the three base models to gener- ate the final output for each ensemble. The empirical results indicate that the constructed ensembles outperform NN/SVM-based emotion recognition for both within and across database evaluations.

IV. SIMULATION RESULTS





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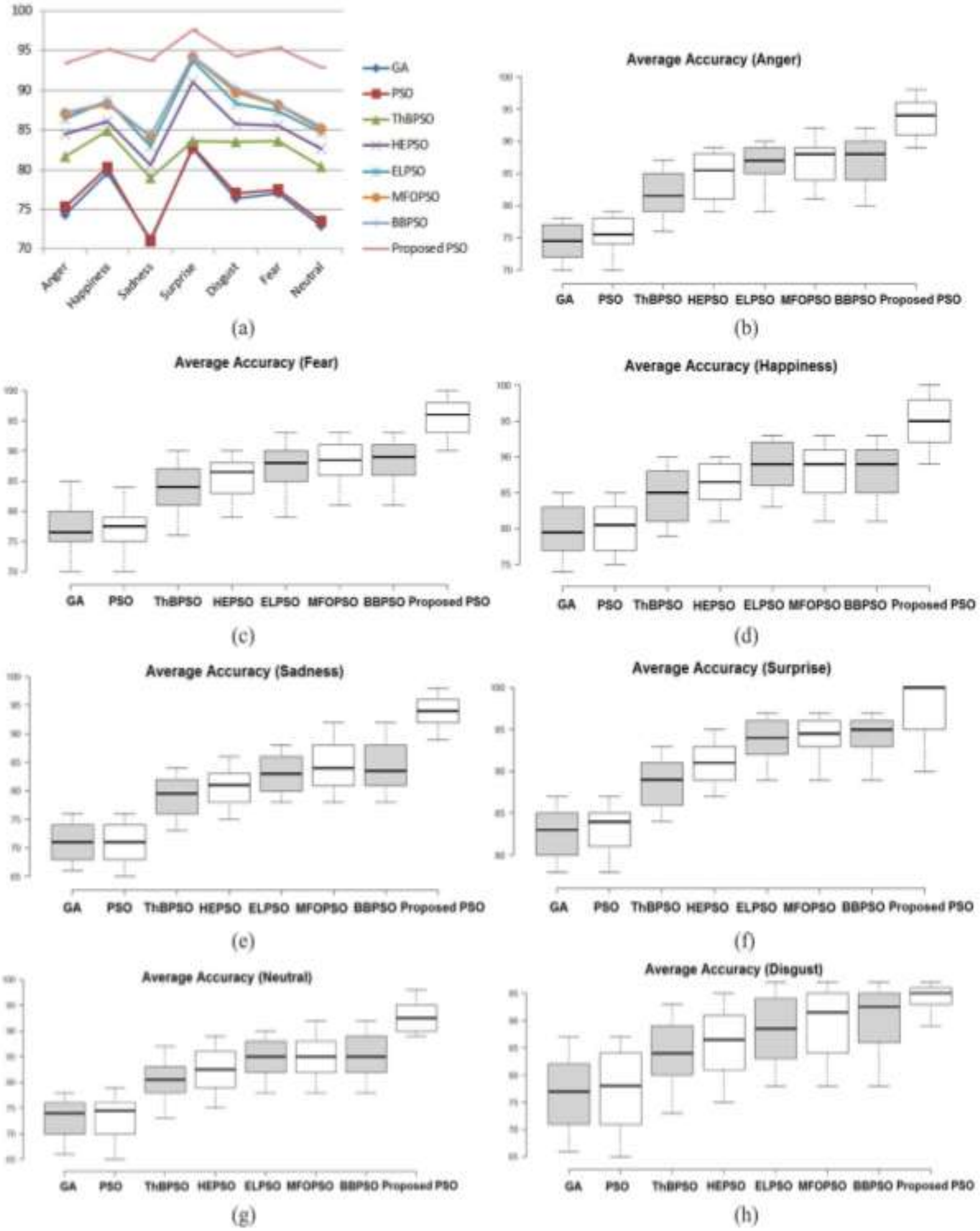

Fig 3 Overall comparison of our system with other methods

V. CONCLUSIONS AND FUTURE SCOPE

In this paper, we have proposed a facial expression recognition system with hvnLBP based feature extraction, mGA-embedded PSO-based feature optimization and diverse classifier based expression recognition. The proposed hvnLBP operator performs horizontal and vertical neighborhood pixel comparison to retrieve the initial discriminative facial features. It outperforms state-of-the-art LBP variants, LPQ, and conventional LBP significantly for texture classification. Moreover, a new PSO algorithm, i.e., mGA-embedded PSO, has been proposed to mitigate the premature convergence problem of conventional PSO in terms of feature optimization. The mGA- embedded PSO algorithm incorporates personal average experience and Gaussian mutation for velocity updating as well as employs the diversity maintenance strategy of mGA by keeping the original swarm in a nonreplaceable memory, which remains intact during the lifecycle of the algorithm to increase swarm diversity. Furthermore, it also maintains a secondary swarm with a small population size of five to host the swarm leader and four follower particles with the highest/lowest cor- relation with the leader from the nonreplaceable memory to increase local and global search capabilities. The algorithm subsequently separates facial features into specific areas for in-depth local subdimension based search. Overall, the local exploitation and global exploration search mechanisms of the algorithm work cooperatively to guide the search toward the global optimal solutions. The empirical results indicate that our PSO algorithm outperforms other state-of-the-art PSO variants and conventional PSO and GA for optimal feature selection significantly. Integrated with the SVM-based ensemble, our algorithm achieves the best average accuracy of 96% over 30 runs for the within (CK+) database evaluation and 94.66% accuracy for the cross-domain (MMI) evaluation. Fire fly algorithm can replace mGA embedded PSO to get 100% accuracy.

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REFERENCES

[1] Kamlesh Mistry,Li Zhang"A micro-GA Embedded PSO feature selection approach to intelligent facial emotion recognition"IEEE Trans.cybernetics,march,2016.
[2] M. Heikkilä, M. Pietikäinen, and C. Schmid, "Description of interest regions with local binary patterns," Pattern Recognit., vol. 42, no. 3, pp. 425–436, 2009.
[3] B. Zhang, Y. Gao, S. Zhao, and J. Liu, "Local derivative pattern versus local binary pattern: Face recognition with high-order local pattern descriptor," IEEE Trans. Image Process., vol. 19, no. 2, pp. 533–544, Feb. 2010.
[4] M. Campos, R. A. Krohling, and I. Enriquez, "Bare bones particle swarm optimization with scale matrix adaptation," IEEE Trans. Cybern., vol. 44, no. 9, pp. 1567–1578, Sep. 2014.
[5] N.-J. Li, W.-J. Wang, and C.-C. J. Hsu, "Hybrid particle swarm optimization incorporating fuzzy reasoning and weighted particle," Neurocomputing, vol. 167, pp. 488–501, Nov. 2015.

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