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Face Gender Classification by Using Improve Binary Particle Swarm Optimization and K-Nearest Neighbors

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Abstract **–** This paper studies the application of the Binary particle swarm optimization (BPSO) algorithm to the optimal search for facial features and gender classification by K-Nearest Neighbors (K-NN) model. The results show that the accuracy and processing time of the model is much better than that of VGG16, VGG19, Resnet50, Senet50, Face Net, Open Face and FbDeep Face models. a large-scale GenderFace80K dataset with 80,000 facial images with gender annotation used in the research model.
Keywords**— Binary particle swarm optimization, BPSO, K-Nearest Neighbors, K-NN. Levy flight.**

INTRODUCTION

Applying the uniqueness of face anthropometry to gender identification for security purposes, e-commerce, finance and banking. Big brands like Universal Pictures, Samsung, LG, Philips, Unilever, P&G, Ford, Badoo recognize customers by face. The US Department of Defense, Singapore's Ministry of Home Affairs, and the National Forensic Service of Korea apply facial gender recognition to criminal investigation. Companies use facial recognition systems to take attendance of employees entering and leaving the company, daily attendance.

In fields such as commerce, marketing, healthcare, and hospitality, the potential for using facial gender-based technology is huge. Currently, the results of the accuracy of facial analysis studies are not high. Specifically, due to the surrounding environment such as light, environmental luminance, the image of a human face is often not fixed when moving, these factors interfere with the image of a human face when it is included in the computational analysis system. To improve facial recognition accuracy, researchers are aiming to recognize 3D faces instead of 2D images as it is currently difficult to detect and recognize faces with incomplete details such as faces that have partially obscured.

To limit the noise of the face image. Previous studies have performed feature extraction methods such as Local binary pattern (LBP), Gabor filter, Edge histogram descriptor, Color Correlograms, Scale invariant feature transform (SIFT). Selecting the attribute after extracting from the image to include in the K-Nearest Neighbors (K-NN) classifier determines the accuracy of the model, reducing the processing time.

This study introduces a feature selection model using BSPO algorithm combined with levy flight model in Local search for the purpose of quickly finding features provided to BPSO. The reason, BSPO has fast convergence. This article brings the following benefits:

(1) Optimization of feature selection extracted by Local binary pattern from face images using Binary particle swarm optimization (BPSO).

(2) Reducing the error due to the fast convergence factor of BPSO by levy flight method in Local search optimization.

(3) Improved facial gender recognition accuracy compared to previous similar studies.

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The research paper is organized as follows: Section 2 presents the Raw material and methodology. Section 3 shows the content of the experiment result and Section 4 shows the content of conclusion and future work

RAW MATERIAL AND METHODOLOGY

Face image feature extraction

The research model of face sex classification is performed as follows: The Local Binary Pattern (LBP) method is used for image feature extraction. BPSO method combines Levy flight feature optimization and K-Nearest Neighbors (K-NN) method used for feature recognition for gender classification. See Figure 1.

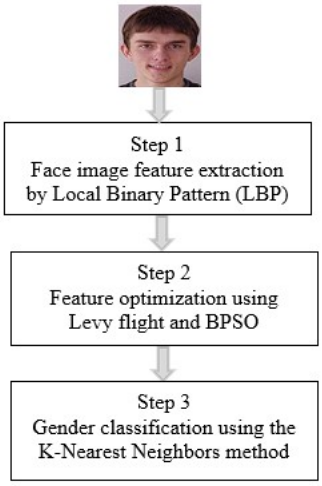

Figure 1: The Research model

Step 1 performs image detection and feature extraction analysis. The face image is reduced to 128 x 128 size and converted to grayscale according to formula (1) for the purpose of reducing image signal noise.

gray(i;j)={0.29×rgb(:;:;1)+0.59×rgb(:;:;2)+0.11×rgb(:;:;3)}

(1)

The image converted to a histogram $f_1(x,y)$ is described as follows:

$$H_i = \sum_{x,y} I\{f_1(x,y) = i\}, \quad i = 0,1,\dots,n-1 \qquad \textbf{(2)}$$

When n different labels are generated by the Local Binary Pattern (LBP) it is expressed as follows:

$$I(A) = \begin{cases} 1, & A \text{ is True} \\ 0, & A \text{ is False} \end{cases} \qquad \textbf{(3)}$$

The histogram shows the local microsample distribution of the entire image, see Figure. 2. Such as edges, points, and flat areas. Spatial information is retained so that the face is fully represented. The image is divided into regions. The spatial histogram expansion is shown by the following expression:

$$H_{i,j} = \sum_{x,y} I\{f_l(x,y) = i\} \times I\{(x,y) \in R_j\} \qquad \textbf{(4)}$$

Where $i = 0,1,\dots,n-1$ and $j = 0,1,\dots,m-1$.

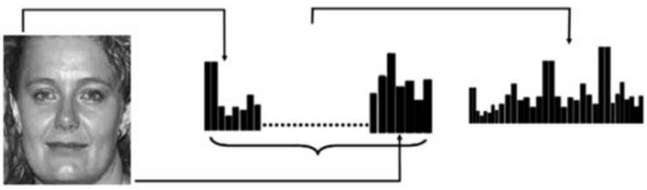

Figure 2. Histogram analysis of image

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The position of the eyes on the face is extracted by geometric normalization, cropping, and histogram normalization. The local binary sample of the image is subdivided into blocks of size k x k, see Figure 3. The vector fed to the classifier is composed of vectors concatenated into rectangular blocks. Multi-sample and multi-view mode, respectively LBP faces belong to GenderFace80K dataset.

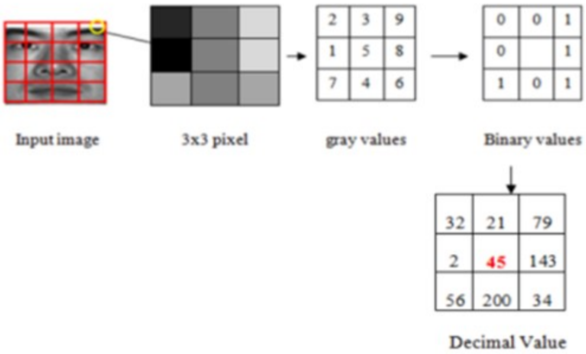

Figure 3: Local Binary Pattern Face

Ojala et al developed the Local Binary Pattern method, the pixels of the image are assigned in a 3 x 3 pattern each pixel according to the central mean using LBP. Neighborhood x 3 3 is difficult to zoom in to make the properties stand out. The expanded LBP is shown, see Figure 4.

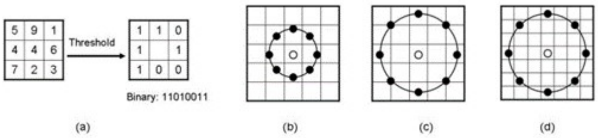

Figure 4: The basic Local Binary Pattern. (a) The basic LBP operator. (b), (c), (d) The circular

Binary Particle swarm optimization (PSO)

Binary Particle Swarm Optimization (BPSO) is inspired by nature. The goal of BPSO optimization is to find the optimal function to maximize accuracy or precision or minimize loss. A swarm is a collection of particles in the search space. (1) x-vector : current position of particle. (2) p_{best} : individual best position found by individual county and (3) g_{best} : global best location found by swarm. Initialize the particle's best fitness value, p_{best} and the herd's best fitness value, g_{best} to infinity. each with two distinct properties, position (x) and velocity (v).

$$x_i^{t+1} = x_i^t + x_i^{t+1} \quad \textbf{(5)}$$

$$v_{i+1}^{t+1} = w \times v_i^t + c_1 \times r_1 \times (P_{best\,i}^t - x_i^t) + c_2 \times r_2 \times (G_{best} - x_i^t) \quad \textbf{(6)}$$

With: P_{best}: individual best solution, the solution with the best fitness function in the t iteration. G_{best}: global best solution with current best fitness function value. w: coefficient of inertia in the range from 0 -> 1. c_1, c_2: coefficient of acceleration. r_1, r_2: random numbers generated by homogeneous distributions, and their weights are in the range [0;1]. The decoding of the BPSO is shown in Algorithm 1, See Figure 5.

Algorithm 1: Binary Particle Swarm Optimization (BPSO)	
1:	Initialize c_1, c_2, v_i and x_i
2:	$P_{ibest} \leftarrow x_i$
3:	Select from x_i, P_{gbest}
4:	Repeat

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5:	Obtain velocity v_i with Equation (6)
6:	Update position x_i with Equation (5)
7:	if f (x_i) < f (P_{ibest}) then
8:	$P_{ibest} \leftarrow x_i$
9:	If f (P_{ibest}) < f (P_{gbest}) then
10:	$P_{gbest} \leftarrow P_{ibest}$
11:	End if
12:	End if
13:	Until The stopping condition is met

Figure 5: Binary Particle Swarm Optimization (BPSO)

Regular BPSO has each solution updated according to G_{best} guidelines. If G_{best} is located far away from the optimal solution, it affects the optimal performance of the algorithm. Levy flight-based local search is incorporated into the BPSO to improve efficiency. Levy flight is a stochastic star walk method with a multi-component distribution that searches for the shortest distances and the uncommon long distances. Local search based on Levy flight's capabilities does the following equation 3.

$$G_{best}^{new} = G_{best} + \alpha \times Levy(\delta) \quad \textbf{(7)}$$

With, δ: step factor and its value depends on the application.

$$Levy(\delta) = u = t^{-\delta} \quad (1 < \delta < 3) \quad \textbf{(8)}$$

K-Nearest Neighbor Classification (K-NN)

K-Nearest Neighbor Algorithm uses the classification of nearest trained objects in feature space. K-NN is the simplest algorithm in machine learning algorithm. During the classification process, the query point is not labeled but only needs to be labeled with its K nearest neighbors. Classified objects are based on the labels of K-Nearest Neighbor by majority selection. In case K=1 the object is classified in the nearest feature class. In case there are only 2 classes, then K must be an integer. However, there will also be cases of multi-class implementation where K is an odd integer. After forming vectors of fixed length, see Figure 7. We use the distance function of K-NN in terms of Euclidean distance.

$$d(x, y) = \|x - y\|^2 = \sum_{i=1}^{K} (x_i - y_i)^2 \quad \textbf{(9)}$$

Algorithm 2: Improvement Binary Particle Swarm Optimization (IBPSO)	
1:	Define and initialize the related parameter: population size N_{pop}, solution dimension N_{dim}, maximum iteration t_{max} and fitness function;
2:	Map the searching agents into spaces by using equation (5) and equation (7);
3:	Calculate the fitness function values of mapped particles and sort these particles in ascendity orders;
4:	For t=1 to t_{max} do

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5:	For i=1 to N_{pop} do
6:	Update each searching agent particles by using equation (5);
7:	Apply the local search operator to update G_{best} by using equation (7);
8:	If G_{best}^{new} is better than G_{best} then G_{best} is replaced by G_{best}^{new};
9:	End;
10:	Else
11:	Remain G_{best};
12:	End;
13:	End;
14:	Calculate the fitness function values of mapped particles;
15:	End;
16:	Return x_{best}; //x_{best} is the best solution obtained by the algorithm;

Figure 6: Improve Binary Particle Swarm Optimization

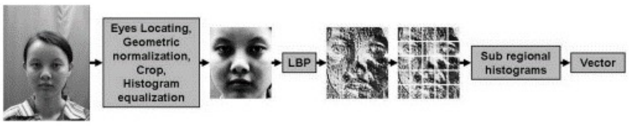

Figure 7: The LBP is divided into blocks, histograms fitted together form a vector

The proposed identification system

The gender recognition system is shown in Figure 1, showing three main contents: (1) Extracting facial features using the Local Binary Pattern (LBP) method. (2) Optimizing face set by levy flight method combining Binary Particle Swarm Optimization (IBPSO) and (3) gender classification using K-Nearest Neighbors method (K-NN).

In step 1, the face image is extracted features and converted into cells with the center pixel compared with 8 neighboring pixels. In step 1, the face image is extracted features and converted into cells with the center pixel compared with 8 neighboring pixels. The surrounding space is arranged in a circular shape. Neighboring pixels have a greater gray level value than the central pixel. The central pixel value connects to neighboring pixels in a counter-clockwise direction. Each cell corresponds to each histogram, and the interconnectedness of all pixel cells forms the LBP image of the face. The recognition system validates a number of different pixel cells to find the feature with the best accuracy.

In step 2, the Face Image is organized as a matrix of size 128 and features are used to create the face image. The features in the pixel matrix are updated position by position from the Binary Particle Swarm Optimization method, the Levy flight method helps to find good features at different square positions and updates to the BPSO method to speed up the face image update time and increase the feature selection accuracy of the BPSO method. BPSO achieves fast convergence. However, if the features are far from the center pixel in time, the BPSO has converged, so there is a possibility that it may not be accurate. The levy flight search method helps to increase the feature search feature to update the BPSO algorithm.

In step 3, the good features from the face image obtained from the IBPSO optimization method are divided into train feature and test feature. The train feature is used to let the model learn and the test feature is used to evaluate the model. Gender classified from the set of points extracted from the

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tested face images matched their labels. Conversely, If the tested characteristics do not match or are incorrect, then the gender is not determined.

EXPERIMENTAL RESULTS

Dataset

To evaluate the proposed approach model, a dataset was collected from a social network, namely GenderFace80K including 40318 male face images and 40318 female face images. All images are cropped and annotated manually. Some images are extracted illustratively from the data set. See Figure 7. The experiment is implemented on Python 3.8, Tensorflow-GPU, Keras, and Visual Studio Code.

Figure 8: Several images from GenderFace80K dataset

Experimental results and discussion

K-Nearest Neighbor Algorithm performed the classification with GenderFace80K including 40318 male face images and 40318 female face images. The images using training accounted for 70% (28223 images of men and 28223 images of women) and images used for testing accounted for 30% (12096 images of men and 12096 images of women). Experimental results show that the processing time is 330.3451 minutes. The result of K runs between 2 and 10 (Tab. 1) and the highest accuracy observed result is 95.34% (Tab. 2) at K = 9 and resulting in gender classification from the actual picture, see Figure 9.

TABLE I

K-NN ALGORITHM FOR GENDER CLASSIFICATION

K	TP	TN	FP	FN	CC	ACC(%)
2	19	20	4	3	40	83
3	18	21	5	2	40	83
4	18	21	5	2	40	83
5	18	22	5	1	41	85
6	20	21	3	3	42	86
7	20	23	3	1	44	89
8	19	22	5	2	42	88
9	20	24	3	1	45	**95**
10	19	23	4	2	43	92

Where:

TP = True , FP = False Position , CC = Correctly Classified , ACC = Accuracy , TN = True Negative , FN = False Negative , K = Incorrectly Classified.

TABLE II

COMPARE RESULT OF FEATURE EXTRACT

No	Feature extract	Classification	Accuracy (%)	Time (minu

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				tes)
1	LBP	K-NN	86.44	220.5271
2	LBP+BPSO	K-NN	91.75	298.9853
3	LBP+IBPSO	K-NN	**95.34**	**330.3451**

(a) (b) (c)
(d) (e) (f)

Figure 9: Experiment the model on real images captured from the camera

TABLE III
COMPARE RESULT OF ACCURACY CLASSIFICATION

Picture	Feature extract	Accuracy (%)
(a) and (d)	LBP	86.44 / 84.68
(c) and (e)	LBP+BPSO	91.75 / 89.59
(d) and (f)	LBP+IBPSO	**95.34** / 96.46

Analysis and selection of face image extraction features 3 methods as follows: Local Binary Pattern (LBP), Local Binary Pattern combining Binary Particle Swarm Optimization (BPSO) and Local Binary Pattern combining Levy flight and Binary Particle Swarm Optimization. Features are selected and included in the K-Nearest Neighbors (K-NN) method of sex classification. Experimental results, Feature extraction and feature selection optimization using the Local Binary Pattern method combining Levy flight and Binary Particle Swarm Optimization gave the classification results with the highest accuracy, reaching 95.34%. However, the processing time is still slow, reaching 330.3451 minutes.

Feature extraction by the Local Binary Pattern method gives relatively good processing time, reaching 220.5271 minutes, but the classification accuracy of the model is not high, reaching 86.44%. Similarly, Feature Extraction by Local Binary Pattern and Binary Particle Swarm Optimization method gives the results in relative processing time, reaching 298.9853 minutes, but the classification accuracy of the model is not high, reaching 91.75%. The convergence of Binary Particle Swarm Optimization is fast and the feature search is not complete, the BPSO has converged, so the accuracy of the classification model is not high.

Compare the results with previous research models of Mai's team, using the same GenderFace80k dataset (Tab. 4). The accuracy of the proposed model is higher than that of previous research models. However, the processing time of the research model is much slower. The results of the OpenFace model's processing time reached 3.0074 minutes, however, the accuracy of the OpenFace model was not high, reaching 71.38%. This is a big challenge for further studies that need to build models with faster processing time.

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TABLE IV
A COMPARISON BETWEEN OUR PROPOSED GENDER IDENTIFICATION METHOD AND SOME RELATED METHODS IN TERMS OF, FEATURE EXTRACTION, CLASSIFICATION, ACCURACY AND PROCESSING METHODS

Authors	Feature extract methods	Classification method	Result (%)	Time process (minutes)
Mai et al	CGG16	K-NN	62.51	196.1951
	VGG19	K-NN	61.76	210.0669
	FaceNet	K-NN	83.07	24.4372
	Resnet50	K-NN	91.05	25.4826
	VGG16	K-NN	63.29	453.0137
	SENet50	K-NN	92.10	21.4503
	OpenFace	K-NN	71.38	**3.0074**
	FBDeepFace	K-NN	50.61	77.5128
Our proposed system	LBP +IBPSO	K-NN	**95.34**	**330.3451**

Conclusion and future work

In this study, we use facial images to classify gender. The system uses 3 methods of feature extraction and selection as follows (1) Local Binary Pattern, (2) Local Binary Pattern combining Binary Particle Swarm Optimization and (3) Local Binary Pattern combining Levy flight and Binary Particle Swarm Optimization to improve the ability to eliminate noise compared to ambient conditions such as illumination, blurred images, and face orientations. The K-Nearest Neighbors (K-NN) method performs the gender classification process. The experimental results of the model used on GenderFace80K and the classification accuracy results are as follows. For Men, it is 86.44%, 91.75% and 95.34%. For Females, it is 84.68%, 89.59% and 96.46%. (Tab. 3)

The limitation of this study is that the processing time is slow, reaching 330,3451 minutes, and the fuzzy image has not yet resulted in low classification accuracy and wrong gender recognition. To improve recognition accuracy for noisy, blurred images, it is necessary to add another Bio-Inspired optimization method after the K-NN classification method to optimize unclassified or undefined features. it's future research flavor.

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