Optik 126 (2015) 3132–3134

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

New facial expression recognition based on FSVM and KNN

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ARTICLE INFO

Article history:
Received 11 June 2014
Accepted 14 July 2015

Keywords:
Facial expression recognition
Fuzzy Support Vector Machine
K-Nearest Neighbor
Principle Component Analysis

ABSTRACT

To improve the recognition accuracy, a new approach for facial expression recognition based on Fuzzy Support Vector Machine (FSVM) and K-Nearest Neighbor (KNN) is presented in this paper. At first, the feature of the static facial expression image is extracted by the Principle Component Analysis (PCA), then, the algorithm divide the region into different types, and combine with the characteristic of the FSVM and KNN, switch the classification methods to the different types. The results of the experiment show that proposed algorithm can achieve good recognition accuracy and simplify the computation complexity.

1. Introduction

Facial expression is an important way for communication of emotion and interpersonal relationship, and it is also one key part of the body language and an effective method for communication without speaking. Based on features of the human vision, the computer technology for classifying the facial expression feature has been becoming one important research subject.

Facial expression recognition consists of three key parts: detection and location, extraction and representation, and recognition and classification. In them, the design of categorizer in the continuous research, the improve phase is one hot and difficult problem. Now, there are some traditional classifiers such as KNN [1,2], SVM [3,4] and FSVM [5,6]. The FSVM algorithm well solve the problem of the unclassifiable region of multi-classification and improve the accuracy of the classification, but increase the amount of calculation due to the introduction of Fuzzy subordinate function. Classification algorithm KNN with non parametric classification, calculation is simple, but the use of Euclidean distance formula to calculate the distance to represent the similarity between two objects is not exact, the classification accuracy is not high [7,8]. In view of this, in order to improve the classification accuracy and reduce the computational complexity, a classifier combining FSVM and KNN is proposed in this paper.

2. Classifier combining FSVM and KNN

The classifier main idea is: as for the area to be classified in this new classifier, firstly calculate the input samples to the Euclidean distance of all categories, secondly discriminate the candidate classes and the input sample discrimination classifier output through the discrimination function, and adaptively switch FSVM and KNN classification algorithm based on distinction degree at last. The emphasis of the algorithm on the discrimination, and the rationality of discrimination make influence on the classification accuracy and speed.

2.1. Distinction degree

Based on the research of reference [9–12], the wrong situation of classifying samples is usually divided into two types: as for one type, the distance between sample and many candidate classes is close and multiple output closely related with the input sample x simultaneously; as for the other type, the distance between sample and the optimal candidate class is also close, in other words, the input samples is away from all the candidate classes. We can calculate the distance between the sample x and each candidate class and make sure the distinguishing degree of the candidate to sample x by using following formula:

$$\varphi_{i_j}(x) = \frac{\left|d_i(x) - d_j(x)\right|}{\gamma}, \quad j = 1, \ldots, n, \quad i \neq j \tag{1}$$

where $\varphi_{ij}(x)$ is the discrimination function. The candidate class owning mini-distance ($d_i(x)$) is defined as the optimal candidate class and the second mini candidate is defined as the secondly optimal candidate and so on. γ is the distance threshold, which

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http://dx.doi.org/10.1016/j.ijleo.2015.07.073
0030-4026/

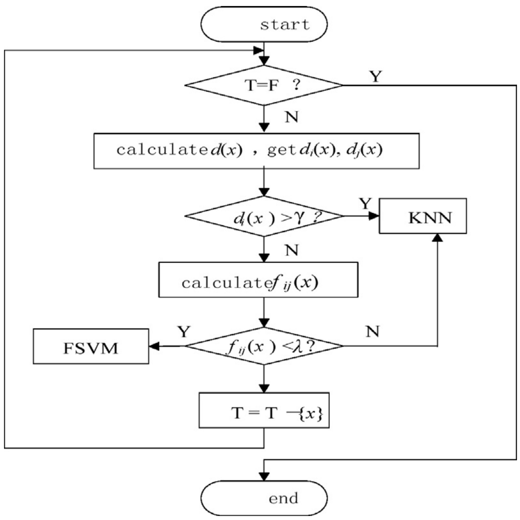

Fig. 1. The algorithm process of combination classifier.

can be used to control the deviation degree of the sample x away from the optimal candidate class.

If $d_i(x) > \gamma$, sample x is away from all the candidate class and FSVM is not suitable for the classification of sample x. If $d_i(x) < \gamma$, $\varphi_{ij}(x)$ can be calculated by the distinction degree function and the x area can be further made clear by comparing the specified discrimination degree threshold with $\varphi_{ij}(x)$.

In one condition of $\varphi_{ij}(x) \geq \lambda$, only one output is independent with sample x, and the classification results can be derived directly and exactly. In the other condition of $\varphi_{ij}(x) < \lambda$, the conclusion can be put out that when the area of sample x covers the unclassifiable region of the sample space, FSVM classifier can be used in the unclassifiable region.

Detailed proof will be given in this section. As for the three-class problem (i,j,k), given that $\lambda \in [0,0.15]$ and i and j are the optimal and suboptimal candidate classes respectively, $|d_i(x) - d_j(x)|$ decreases with λ and the absolute value τ of distance between x and the optimal hyper-plane of i and j classes relatively small and the absolute value τ meets the condition of $0 \leq \tau < 1$ (if $\tau \geq 1$, x only belongs to one class and this situation contradict the precondition of uncertainty of x type). As shown the decision blind area E' in Fig. 1, given that $x' \in E'$, the absolute value $\tau'$of any of two classes' distance between $x'$and the optimal hyper-plane of i, j and k classes meets the condition of $0 \leq \tau' < 1$, because x' is in the unclassifiable region. Based on above analysis, it is easy to get a conclusion that the area of sample x covers the unclassifiable region of samples in the condition of $E' \subseteq E\ (\varphi_{ij}(x) < \lambda)$.

2.2. Description of the algorithm of the classifier combining FSVM and KNN

Given that $x \in T$ and T is the set of test sample, the Euclidean distance of x to all categories is $d(x)$, the optimal and suboptimal candidate are $d_i(x)$ and $d_j(x)$ respectively, γ is the distance threshold, and λ is the discrimination threshold, the algorithm process is shown in Fig. 1.

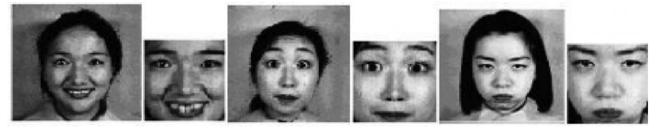

Fig. 2. The original images and the images after processing in JAFFE database.

3. Experiments and analysis

JAFFE facial expression database is applied in experiment, which consists of 7 different expressions of 10 Japanese women containing surprised, happy, angry, disgust, fear, sadness and neutral facial expression and 2–3 facial images with the same expression of everyone exists. 210 facial expression graphs are selected as the data objects in experiments. In order to eliminate noise, before expression feature extraction, the facial expression in database should to be cut, made size normalization and gray normalization and other preprocesses. The image after processing (30×24) is shown in Fig. 2.

The Principle Component Analysis (PCA) [13] is utilized to extract the facial expression feature parameters. Experimental results of SVM, KNN, FSVM and combination method are compared. $\mathrm{Exp}(-\mathrm{sqrt}((u-v) \times (u-v)')/(256 \times P1^2)$ and linear function are used as the kernel functions of FSVM and SVM, respectively. $K = 1$ in KNN. In order to get the correct identification rate of each expression, each image (total number with 70) of every expression of every people (total number with 10) is randomly selected as the training sample, and other 140 images as the measured samples. Computers used in experiments are P4 2.26 G CPU, 1 G internal memory and the procedure words are written by MATLAB7.0. The list of facial expression recognition rate and running time for 4 types of classifiers is shown in Table 1.

As for the average discrimination rate, KNN owns the lowest value of 83.91%, SVM 85.74% and FSVM 87.75%. The similarity of both objects calculated by Euclidean distance formula applied in KNN is not exact. It is more accurate in SVM due to the application of the linear kernel function in classification, but not effective on the multi-class problems. Resolution precision is further improved in FSVM due to the introduction of Fuzzy subordinate function. As for combination method, regional analysis based on the discrimination function is applied. KNN and FSVM classifications are applied in the weak and strong relevance regions, respectively, so the average discrimination rate is improved and similar to FSVM.

As for the running time, KNN owns the shortest value of 0.2 min and FSVM has the longest time of about 43 min. This is because that KNN is a non parametric classification method and its algorithm is very simple, but Fuzzy subordinate function in FSVM further increase the amount of calculation. In proposed method, KNN and FSVM are used in different regions and the amount of calculation has been reduced relatively.

As for the specific facial expression discrimination rate, "Angry", "Happy" and "Surprised" are on high level in 4 kinds of

Table 1
Facial expression recognition rate and running time for 4 types of classifiers.

Classifier	Discrimination rate (%)								Running time (min)
	Angry	Happy	Sadness	Surprised	Disgust	Fear	Neutral	Average	
FSVM	96.43	97.24	76.29	91.12	78.86	75.08	85.21	85.74	35
KNN	89.29	83.33	83.87	83.33	82.76	78.13	86.67	83.91	0.2
FSVM	95.78	96.62	81.35	92.13	82.26	80.78	85.33	87.75	43
Proposed	95.34	97.02	81.13	92.24	81.96	80.35	85.84	87.70	

classifications and others are relatively lower. The main reason is that the former expression changes greatly, relatively easy to distinguish; the latter is the opposite, easily confused. Compared with SVM and FSVM, the discrimination rates of “Sadness”, “Hate” and “Fear” are improved by combination method due to the introduction of Fuzzy subordinate function.

4. Conclusion

By using the characteristics of FSVM’s accurate classifying for multi-class problems with fuzzy membership function and KNN’s simplicity of Euclidean distance calculation algorithm, we proposed facial expression recognition method based on a combination of FSVM and KNN. For the regions to be classified, we compute the Euclidean distance from all categories to the input samples, and distinguish the distinction degree of the candidate samples to the input samples with distinguishing function, then adaptive switching the classification algorithms of FSVM and KNN according to the degree of distinction. Experiments show that this method can effectively improve the human face recognition rate, and can effectively reduce the computational complexity.

Acknowledgements

These problem serves as “National Natural Science Foundation of China” (61203257), and “Hunan Province Education Department Natural Science Research Item” (10C0578).

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