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Application of fixed classifier fusion rules in phacoemulsification operation[1]

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Abstract. In cataract ultrasonic phacoemulsification operation, a key problem is controlling frequencies of the ultrasonic wave emitted from the emulsification pinhead. The solution of it depends on the accurate recognition of hardness of lens nucleus. At present, fixed rules for classifier fusion are the most used and widely investigated ones in the field of pattern recognition. These rules have no second-level training and can compete with the more sophisticated rules. In this paper, six common fixed rules were applied to cataract classification. Different color components of cataract images were used to train corresponding classifiers and the fixed rules were used to make the final decision after the classifiers' outputs taking a weighed transform. The error rates of six rules have no obvious differences and meet the actual demand of the cataract ultrasonic phacoemulsification operation.

Key words. Cataract, classification, multiple classifier fusion, fixed rules.

1. Introduction

Age-related cataract is the leading cause of blindness in the world. Up to now, operation is the only effective method to cure the cataract blindness. The ultrasonic phacoemulsification operation is considered to be the main treatment of cataract and is widely accepted for its small cut, short operation time, no suture, no need of being in hospital, no limitation for any activities, and fast recovery of eyesight.

The problem of "how to correctly implement proper oscillation frequency according to different lens nucleus" needs long term operation practice in order to accumulate rich operation experience for reaching the best operation results. Image processing and pattern recognition technologies can be applied in cataract ultrasonic

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phacoemulsification operation to correctly recognize the hardness of the cataract lens nucleus, thus to lower operation difficulty level, shorten study period and improve the safety of the operation. In such a cataract recognition system, one of the major tasks is to extract the relevant features of the part that is being touched by the emulsification pinhead and judge it is cataract tissue with certain hardness or normal tissue. For the former, according to different hardness levels, different signals are emitted to control the ultrasonic frequency. For the latter, no ultrasonic can be sent out. The key problem in the process is to find a suitable recognition method in order to ensure the accurate judgment for the hardness of the lens nucleus.

In recent years, multiple classifier fusion gains increasing attention and has become a research hotspot of pattern recognition. Creating a group of classifiers is one of the ways to improve the classification accuracy in the recognition process [1]. When the member classifiers are diverse or complementary, multiple classifier systems can usually obtain higher classification accuracy compared with a single classifier [2]. Through a great deal of experiments and applications, it has been proved that fusing classifiers' decisions can achieve better performance than the best single classifier and improve the efficiency and robustness of the pattern recognition system. Currently, many application areas have adopted the methods of multiple classifier fusion, such as intrusion detection [3], character recognition [4], remote sensing image recognition [5], character recognition [6] and so on. Multiple classifier fusion supposes that all classifiers are equally "experienced" in the whole feature space. So, all the outputs of the classifiers are fused in a certain way to achieve the final decision. Classifier fusion rules can be divided into two groups: trainable rules and fixed rules [7]. The former considers the fusion also as a classification problem and regards the fusion rule as a second-level classifier who takes the multiple classifier outputs as its input. This kind of rules have to be trained for classification after the classifiers are chosen, e.g., Support Vector Machine (SVM) fusion [8], Neural Networks fusion [9], Dempster-Shafer theory [10]. The latter means that the fusion rule is a function or an algorithm and can do classification without any training after the trained classifiers for decision fusion are selected. Product, Sum, Max, Min, Median and Voting are familiar fixed rules.

Fixed fusion rules are the most used and widely investigated ones. This paper applied six common fusion rules to the cataract classification to test if these rules are effective for this practical application. Since the existence of classifier's performance difference, a statistical vector is used to measure the performance of various classifiers and the outputs of classifiers take a weighed transform before a fusion rule is used.

The rest of the paper is organized as follows: Section 2 describes the relative expressions and six fixed fusion rules. Experiment including the experiment description and test results are reported in section 3 and conclusions are drawn in the last section.

2. Relative expressions and rules

Let $X = [x_1, x_2 ..., x_n]^{\mathrm{T}}$ be the n-dimensional feature vector and R^n be the n-dimensional feature space. Let $\Omega = \{\omega_1, \omega_2, ..., \omega_m\}$ be a set of potential class labels, and $C = \{C_1, C_2, ..., C_n\}$ be a set of trained classifiers for decision fusion. Given the input pattern $X \in R^n$, the output of the i-th classifier is denoted as

$$C_i(X) = [c_{i,1}(X), c_{i,2}(X), ..., c_{i,m}(X)]^{\mathrm{T}}, \tag{1}$$

where $c_{i,j}(X)$ stands for the classifier C_i considering the probability that X belongs to the class ω_j. The value given by diverse classifiers has distinct representations, e.g., the posterior probability from Bayes classifiers, the Euclidean distance produced by some distance classifiers, etc.

The fused output of the first classifiers is constructed as

$$C(X) = F(C_1(X), C_2(X), ..., C_l(X)), \tag{2}$$

where F is a fusion rule.

The classifier outputs can be organized as an $l \times m$ matrix

$$DP(X) = \begin{bmatrix} c_{1,1}(X) & ... & c_{1,j}(X) & ... & c_{1,m}(X) \\ ... & & & & \\ c_{i,1}(X) & ... & c_{i,j}(X) & ... & c_{i,m}(X) \\ ... & & & & \\ c_{l,1}(X) & ... & c_{l,j}(X) & ... & c_{l,m}(X) \end{bmatrix}. \tag{3}$$

Here, the ith row is the measure layer output of ith classifier $C_i(X)$ which is given according to (1). And the jth column is the possibility measure value that l classifiers consider the input pattern X belonging to class ω_j. Fusion result $C(X)$ is also an m-dimensional vector represented by the measure layer form, which is denoted as:

$$C(X) = [d_1(X), d_2(X), ..., d_m(X)]^{\mathrm{T}}, \tag{4}$$

where $d_i(X), i = 1, 2, ..., m$ shows the possibility measure value that X belongs to class ω_i after fusion.

To judge the class which the input pattern belongs to needs a certain rule. It usually adopts the maximum method:

If $d_K(X) = \max_{i=1}^{m} d_i(X)$, then $X \in \omega_K$ (5).

Fixed fusion rules (Product, Sum, Max, Min, Median and Voting) acquire system output by operating every column of $DP(X)$. The fixed fusion rules are described as follows:

1) Product rule

$$d_j(X) = \prod_{i=1}^{l} c_{i,j}(X), \quad j = 1, 2, ..., m. \tag{5}$$

The Product rule computes the product of every $DP(X)$ column as the fused output $C(X)$.

2) Sum rule

$$d_j(X) = \sum_{i=1}^{l} c_{i,j}(X), \quad j = 1, 2, ..., m\,. \tag{6}$$

The Sum rule computes the sum of every $DP(X)$ column as the fused output $C(X)$. It is also called as the Mean rule when it computes the mean, which are just two forms of the same rule.

3) Max rule

$$d_j(X) = \max_{i=1}^{l} c_{i,j}(X), \quad j = 1, 2, ..., m\,. \tag{7}$$

The Max rule takes the maximum of every $DP(X)$ column as the fused output $C(X)$.

4) Min rule

$$d_j(X) = \min_{i=1}^{l} c_{i,j}(X), \quad j = 1, 2, ..., m\,. \tag{8}$$

The Min rule takes the minimum of every $DP(X)$ column as the fused output $C(X)$.

5) Median rule

$$d_j(X) = \underset{i=1}{\overset{l}{median}}\, c_{i,j}(X), \quad j = 1, 2, ..., m\,. \tag{9}$$

The Median rule takes the median of every $DP(X)$ column as the fused output $C(X)$. If l is an even number, the mean of two medians is taken as the result of a column.

6) Voting rule

The class label assigned to is the one that is most represented in the set of m class labels $\Omega = \{\omega_1, \omega_2, ..., \omega_m\}$. Using the matrix$DP(X)$, the Voting method is implemented by summing up the $DP(X)$ columns and taking the index of the column with the highest score as the class label of X. Ties are broken randomly.

Since the existence of classifier's performance difference, even using the same classifier, the distinguishing capacity for different classes of data is different. For the problem, a statistical vector is used to measure the performance of various classifiers and the outputs of classifiers take a weighed transform. The steps are as follows:

The classification error of the kth classifier C_k can be represented by a m-dimensional statistical vector V^k :

$$V^k = [n_1^k, n_2^k, ..., n_m^k]^{\mathrm{T}}\,, \tag{10}$$

where the element n_i^k, $i = 1, 2, ..., m$ represents the number of the ith class of training samples which are correctly recognized by classifier C_k. Let the total amount of training samples be N. The vector V^k is normalized by dividing N. At this time, the meaning of each element changes into its corresponding percentage. The normalized vector is then represented as

$$V^{k/N} = [n_1^{k/N}, n_2^{k/N}, ..., n_m^{k/N}]^{\mathrm{T}}\,. \tag{11}$$

Here, the reliability of output vector of classifier C_k can be weighed by $n_h^{k/N}$, and the value of h should satisfy the following condition: $c_{k,h} = \max_{j=1}^{m}(c_{k,j})$.

Thus the reliable output of classifier C_k can be represented as $C_k^{'}(X) = n_h^{k/N} C_k(X)$. From (1), we obtain

$$[c_{k,1}^{'}(X), c_{k,2}^{'}(X) ..., c_{k,m}^{'}(X)] = n_h^{k/N} [c_{k,1}(X), c_{k,2}(X), ..., c_{k,m}(X)] . \qquad (12)$$

Thus, a new matrix $DP^{'}(X)$ can be acquired:

$$DP^{'}(X) = \begin{bmatrix} c_{1,1}^{'}(X) & ... & c_{1,j}^{'}(X) & ... & c_{1,m}^{'}(X) \\ ... & & & & \\ c_{i,1}^{'}(X) & ... & c_{i,j}^{'}(X) & ... & c_{i,m}^{'}(X) \\ ... & & & & \\ c_{l,1}^{'}(X) & ... & c_{l,j}^{'}(X) & ... & c_{l.m}^{'}(X) \end{bmatrix} . \qquad (13)$$

In this paper, fixed fusion rules get the system output by operating every column of $DP^{'}(X)$.

3. Experiment

3.1. Experiment description

The image features of the lens nucleus need to be selected and extracted in order to recognize its hardness. The hardness of the lens nucleus is mainly based on the Emery and Little's hardness grade standard, which judges the color of the lens nucleus to grade its hardness according to the examination results under the slit lamp. Different color models are used to represent and describe the color feature for different research purposes and objects. This paper uses the RGB model.

The image of the area near the emulsification pinhead was partitioned into $m \times n$ pieces and the color value of a piece was the average of all the pixels in the piece. This paper selected $m = 15$, $n = 5$ as the parameters. Thus, each image was partitioned into 75 pieces and each piece had a similar number of pixels. The average of R, G, B value of all the pixels in a piece was separately calculated as the feature value of this piece. That is to say, every image corresponds to a 225-dimensional feature vector.

On the training set, three k-NN classifiers were separately trained by using R, G, B feature, i.e. the input of each classifier is a feature vector of 75 dimensions. The decisions of three single feature classifiers were fused by the fixed fusion rules. For comparison, a k-NN classifier was trained by using RGB feature, i.e. the input of the classifier is a 225-dimensional feature vector.

The images used in the experiment were intercepted from the operation videos provided by Beijing Tongren Hospital. The size of the image had three categories: 20×20, 30×30 and 40×40. The training image set had 649 images and the test image set had 647 images. Each set had 6 kinds of images, normal tissues and nucleus of I to V hardness level. The class of each image had been confirmed by the ophthalmologists from Beijing Tongren Hospital. The number distribution of different classes of images is shown in Table 1.

Table 1. Number distribution of different classes of images

Hardness level of the tissue	The number of training images	The number of test images
I	293	296
II	184	183
III	37	33
IV	28	30
V	12	14

3.2. Test results

When the parameter $k = 3, 5, 8$, the test results of single classifiers and fixed fusion rules are shown in Table 2.

Table 2. Test results of single classifiers and fixed fusion rules

Feature	Method	Error rate (%)	Method	Error rate (%)	Method	Error rate (%)
R	3-NN	13.75	5-NN	13.75	8-NN	14.47
G	3-NN	7.48	5-NN	6.88	8-NN	7.15
B	3-NN	10.96	5-NN	10.12	8-NN	11.65
RGB	3-NN	8.36	5-NN	6.98	8-NN	8.36
	Product	6.53	Product	6.36	Product	6.61
	Sum	6.42	Sum	6.14	Sum	6.56
	Max	6.67	Max	6.48	Max	6.71
	Min	6.72	Min	6.47	Min	6.75
	Median	7.14	Median	7.07	Median	7.22
	Voting	6.58	Voting	6.44	Voting	6.65

It can be seen from Table 2 that the classifiers using R feature have the highest error rates. While the classifiers using G feature have the lowest error rate among the single color feature classifiers, which are slightly lower than the classifiers using RGB feature. One problem with fixed rules is, that although they have good overall performance, it is not clear which one is good for a particular data set. In the experiment, the error rates of six rules have no obvious differences and are lower than that of all the single classifiers. The experiment results show the effectiveness of the six rules to this practical application. The Median rule has the highest error rate among six rules. But, the average recognition rate of it is 92.86 %, which still reaches the actual demand of the cataract ultrasonic phacoemulsification operation.

When the parameter k takes different values, the error rates change accordingly. While the size-relationship is similar, the conditions can be seen more clearly in Fig. 1.

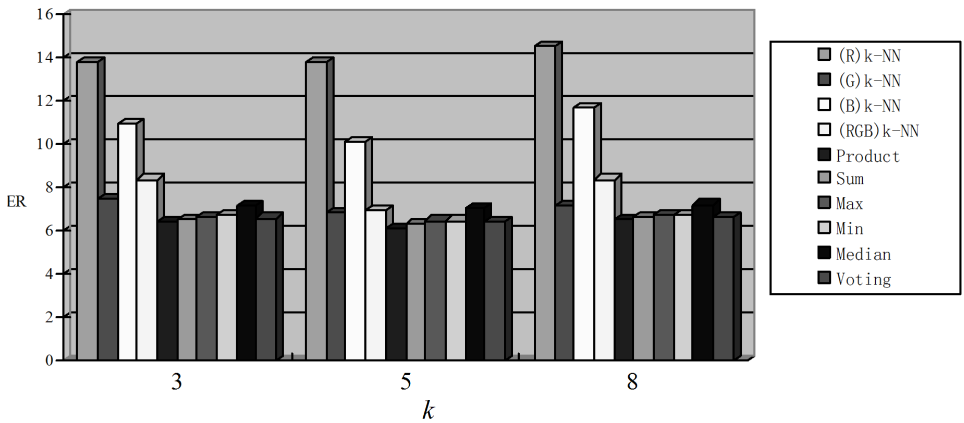

Fig. 1. Comparison of single classifiers and fixed fusion rules (ER, Error rate)

4. Conclusion

In this paper, six fixed rules were applied to the recognition of the lens nucleus's hardness. Different color components of cataract images were used to train corresponding classifiers and the fixed rules were used to judge the hardness after the outputs of classifiers taking a weighed transform. It can be seen through the experiment the error rates of six rules have no obvious differences and are lower than that of all the single classifiers. The experiment results show the effectiveness of the six rules to this practical application. The recognition rates of all the rules reach the actual demand of the cataract ultrasonic phacoemulsification operation.

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