2D Shape Recognition System Using Fuzzy Weighted Mean by Statistical Information

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Abstract

A fuzzy weighted mean method on a 2D shape recognition system is introduced in this paper. The bispectrum based on third order cumulant is applied to the contour sequence of each image for the extraction of a feature vector. This bispectral feature vector, which is invariant to shape translation, rotation and scale, represents a 2D planar image. However, to obtain the best performance, it should be considered certain criterion on the calculation of weights for the fuzzy weighted mean method. Therefore, a new method to calculate weights using means by differences of feature values and their variances with the maximum distance from differences of feature values, is developed. In the experiments, the recognition results with fifteen dimensional bispectral feature vectors, which are extracted from 11,808 aircraft images based on eight different styles of reference images, are compared and analyzed.

Keyword : Bispectral feature vector, Fuzzy weighted mean, Statistical information

I. Introduction

In this paper, the bispectrum based on third order cumulant is applied to the normalized boundary sequence of a 2D image as a means of feature extraction, and a triangular fuzzy membership function and a fuzzy weighted mean method using means by differences of feature values and their variances with the maximum distance from differences of feature column set, are utilized as a classifier. The characteristics and advantages of feature vectors extracted from bispectrum can be founded in [1] and Han's previous works[2]-[4] in 2D image recognition system. These bispectral feature vectors have enough shape information and the property to be invariant in size, shift, and rotation. The fuzzy weighted mean classifier for the recognition process has a relatively simple structure than the neural classifiers[2][5][6] and it can easily improve the classification results by adjustment of weights based on analyses of the feature vectors. More details on the fuzzy classifier are shown in [7].

The other important factor should be considered for the high performance result, such as the choice of appropriate weights for the fuzzy weighted mean method. During the recognition process, weights by statistical information of feature column sets might be an important role. However, there is no certain criterion on the calculation of the weights. Thus, in this paper, a new method for the calculation of weights based on statical information such as means by differences of feature column sets and their variances with the maximum distance from differences of feature column sets, is proposed to achieve the high performance result.

II. Boundary Representation and Bispectral Feature Extraction

For the feature extraction, the boundary of a closed planar shape is characterized by an ordered sequence that represents the Euclidean distance between the centroid and all contour pixels of the digitized shape. Clearly, this ordered sequence carries the essential shape information of a closed planar image. The bispectral feature extraction from a closed planar image is done as follows. First, the boundary pixels are extracted by using contour following algorithm and the centroid is derived[8][9]. The second step is to obtain an ordered sequence in a clockwise direction, b(i), that represents the Euclidean distance between the centroid and all boundary pixels. Since only closed contours are considered, the resulting sequential representation is circular as equation (1).

$$b(i)=\sqrt{(x_i-x_c)^2+(y_i-y_c)^2}$$
$$b(i+PN)=b(i)\quad i=1,2,3,\ldots\ldots,PN \quad\cdots\cdots\cdots (1)$$

where (x_c,y_c) : the centroid of an image, (x_i,y_i) : the contour pixel, and *PN(period)*: the total number of boundary pixels.

This Euclidean distance remains unchanged to a shift in the position of original image. Thus the sequence b(i) is invariant to translation. The next step is to normalize the contour sequence with respect to the size of image. Scaling a shape results in the scaling of the samples and duration of the contour sequence. Thus scale normalization involves both amplitude and duration normalization. The normalized duration of the sequence, 256 points fixed, is obtained by resampling operation and function approximation. This is shown in equation (2).

$$c(k)=b(k^{*}N/256)\quad k=1,2,3\ldots\ldots,256 \quad\cdots\cdots\cdots (2)$$

where *c(k)*: the duration normalized sequence.

After duration normalization, amplitude is divided by sum of contour sequence and removed the mean. It is shown in equation (3) and (4).

$$d(k)=c(k)/s\quad k=1,2,3,\ldots\ldots,256 \quad\cdots\cdots\cdots (3)$$
$$d(k)=d(k)-mean(d(k)) \quad\cdots\cdots\cdots (4)$$

where $s=c(1)+c(2)+c(3)+\ldots\ldots\ldots+c(256)$.

The sequence d(k) is invariant to translation and scaling. In a fourth, bispectral feature measurement is taken into the contour sequence. The spectral density of the sequence *d(k)* is derived by using a third order cumulant, called a bispectrum. In this study, the bispectrum of contour sequence *d(k)*, instead of power spectrum, is investigated for feature vectors because of its better noisy-tolerant characteristic[2][10]. The third order cumulant spectrum of contour sequence d(k) is defined as

$$H_3(\omega_1,\omega_2)$$
$$=\frac{1}{(2\pi)^2}\sum_{\tau_1=-\infty}^{+\infty}\sum_{\tau_2=-\infty}^{+\infty}C_d(\tau_1,\tau_2)e^{-j(\omega_1\tau_1+\omega_2\tau_2)} \quad\cdots\cdots\cdots (5)$$
$$=F(\omega_1)F(\omega_2)F^{*}(\omega_1+\omega_2)$$

where $C_d(\tau_1,\tau_2)=E[d(k)d(k+\tau_1)d(k+\tau_2)]$: a third order cumulant of *d(k)*, and

$|\omega_1|\le\pi, |\omega_2|\le\pi, |\omega_1+\omega_2 RIGHT|\le\pi$

If the observed contour sequence *d(k)=s(k)+n(k)* where *s(k)*: the zero mean contour sequence without noise, n(k): the zero mean white Gaussian noise sequence and they are independent, equation (5) becomes

$$H_3(\omega_1,\omega_2)=\frac{1}{(2\pi)^2}\sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty}C_s(\tau_1,\tau_2)e^{-j(\omega_1\tau_1+\omega_2\tau_2)}$$
$$+\frac{1}{(2\pi)^2}\sum_{\tau_1=-\infty}^{\infty}\sum_{\tau_2=-\infty}^{\infty}C_n(\tau_1,\tau_2)e^{-j(\omega_1\tau_1+\omega_2\tau_2)} \quad\cdots\cdots\cdots (6)$$

$$=H_s(\omega_1,\omega_2)+H_n(\omega_1,\omega_2)\;=H_s(\omega_1,\omega_2)+\gamma_n$$
$$=H_s(\omega_1,\omega_2)+E[n^3(k)] \quad\cdots\cdots\cdots (7)$$

where $C_s(\tau_1,\tau_2)=E[s(k)s(k+\tau_1)s(k+\tau_2)]$ and $C_n(\tau_1,\tau_2)=E[n(k)n(k+\tau_1)n(k+\tau_2)]=\gamma_n\delta(\tau_1,\tau_2)$

In equation (7), the noisy bispectrum $H_n=E[n(k)^3]=\gamma_n$ becomes zero because of skewness of noisy density function, which means the bispectrum suppress the white noisy portion and the extracted feature vectors have better noisy tolerance than the feature vectors from the power spectrum. The performance comparisons between them are shown in [2]. The magnitude of bispectrum derived in a fourth step, $|H_3(\omega_1,\omega_2)\|$, is unchanged even after the sequence d(k) is circular shifted because the magnitude of Fourier transform, $|F(\omega)\|$, is not changed[11]. Thus $|H_3(\omega_1,\omega_2)\|$ is invariant to the rotation of an image. Finally, the two dimensional bispectral magnitude(256 by 256) is projected to vertical axis(ω_1) by taking mean value of each column for feature extraction. It is shown in equation (8).

$$h[k]=[mean(k_{th}\text{ column of }|H_3(\omega_1,\omega_2)|)] \qquad (8)$$

where $k=1,2,\ldots.256$.

The first column and the row in the magnitude of bispectrum contain all zero values because the normalized contour sequence has a zero mean. It means h(1) is always zero. And the projected bispectral components exceed to the sixteenth have very small values (near zero). Thus, for fast classification process with reliable accuracy, the projected bispectral components from the second to the sixteenth (*h(2), h(3),.....h(16)*) are chosen for the possible use of feature values to construct a feature vector. More details on bispectral feature extraction are found in [2].

III. The Proposed Fuzzy Weighted Mean Classifier

In this paper, the triangular type of fuzzy membership function[7] and the fuzzy weighted mean whose statistical information are utilized for weights, are used as a classifier. The process of the proposed method and the classification of images are processed as follows.

First, fuzzy membership functions for each reference image are established by their feature values. The fuzzy membership functions are defined by equation (9).

$$\mu_{ij}(x_j) = 0.01(x_j - f_{ij}) + 1 \quad \text{if } x_j < f_{ij}$$
$$\mu_{ij}(x_j) = -0.01(x_j - f_{ij}) + 1 \quad \text{if } x_j \geq f_{ij} \quad \cdots\cdots (9)$$
$$\mu_{ij}(x_j) = 0 \quad \text{if } \mu_{ij}(x_j) < 0$$

where 0.01 is the selected slope for fuzzy membership functions, xj is a j^{th} feature value of an input image, f_{ij} and $\mu_{ij}(x_j)$ are a j^{th} feature value of a reference feature vector and a membership grade of x_j for an image a_i, respectively.

In a second, the variances for each normalized feature column set by reference images are derived by equation (10), (11) and the variances are normalized by equation (12).

$$m_j = \frac{1}{c}\sum_{i=1}^{c} x_{ij} \quad \cdots\cdots (10)$$

where m_j is a mean of j^{th} feature column set for the reference images, c is the number of kinds of images(classes), and x_{ij} is a j^{th} feature value for reference image a_i.

$$vr_j = \frac{1}{c}\sum_{i=1}^{c}(x_{ij} - m_j)^2 \quad \cdots\cdots (11)$$

$$vr_j = \frac{vr_j}{\sum_{j=1}^{n} vr_j} \quad \cdots\cdots (12)$$

where vr_j is a variance of j^{th} feature value set for the reference images(classes to be classified).

In a third, means(md_j) for differences of each reference feature set are calculated and the means are normalized by equation (13) and (14). And then maximum differences(max_diff_j) for each reference feature set are calculated by equation (15).

$$md_j = \frac{1}{c-1}\sum_{i=1}^{c-1}(x_{(i+1)j} - x_{ij}) \quad \cdots\cdots (13)$$

$$md_j = \frac{(md_j - min\ of\ md_j)}{(max\ of\ md_j - min\ of\ md_j)} \quad \cdots\cdots (14)$$

$$max\_diff_j = max(x_{(i+1)j} - x_{ij}),\ i = 1..c \quad \cdots\cdots (15)$$

where all of x_{ij} are sorted by ascending order in advance.

In a fourth, the feature values of the incoming test image are applied to the corresponding fuzzy membership functions for reference images, and the membership grades are computed by equation (9). The membership grades for any one of reference images present the degree of similarity with that reference image.

In a fifth, the weighted mean values of the membership grades for each of reference image are computed by equation (16) and (17), and a reference image having the largest weighted mean value (the largest h_i) is chosen as a classification result.

$$w_j = md_j + vr_j / max\_diff_j \quad \cdots\cdots (16)$$

$$h_i = \sum_{j=1}^{n} \mu_{ij}(x_j) \cdot w_j,\ i = 1..c \quad \cdots\cdots (17)$$

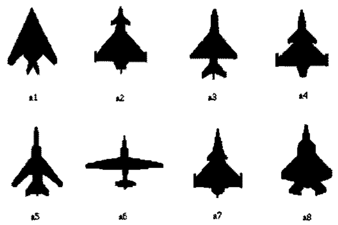
where w_j is a weight for a j^{th} feature value, μ_{ij} and w_j are a membership grade and a weight for a j^{th} feature value, x_j, respectively, and n is the dimension of an incoming feature vector.

By using equation (17), any of reference image with the largest fuzzy weighted mean value is selected as a classification result for an incoming test image.

The one advantage of the fuzzy weighted mean classifier is the use of statistical information for weights. In general, it is hard for the neural classifiers to improve the performance results because they are highly depend on the architectures, learning algorithm and training order[2][5][6][12]. But in the fuzzy weighted mean classifier, the improvement of classification results can be easily achieved by using various statistical information of feature values as weights.

IV. Experiments and Performance Analyses

The proposed method was evaluated with eight different shapes of reference aircraft images shown in Figure 1. From each reference shape of aircraft, 36 noisy-free patterns were generated by rotating the original image with 30 degree increment and scaling with three factors (1, 0.8 and 0,6). And forty noisy corrupted patterns were made by adding four different levels of random Gaussian noise (25dB, 20dB, 15dB, 10dB SNR : ten noisy patterns for each SNR) to 36 noisy-free patterns. Thus the data set for each reference aircraft image has 36 noisy-free patterns and 1440 (40×36) noisy corrupted patterns. The number of total test patterns becomes 11,808 (1,476×8 reference images).



〈Figure 1〉 Eight different styles of reference aircraft images

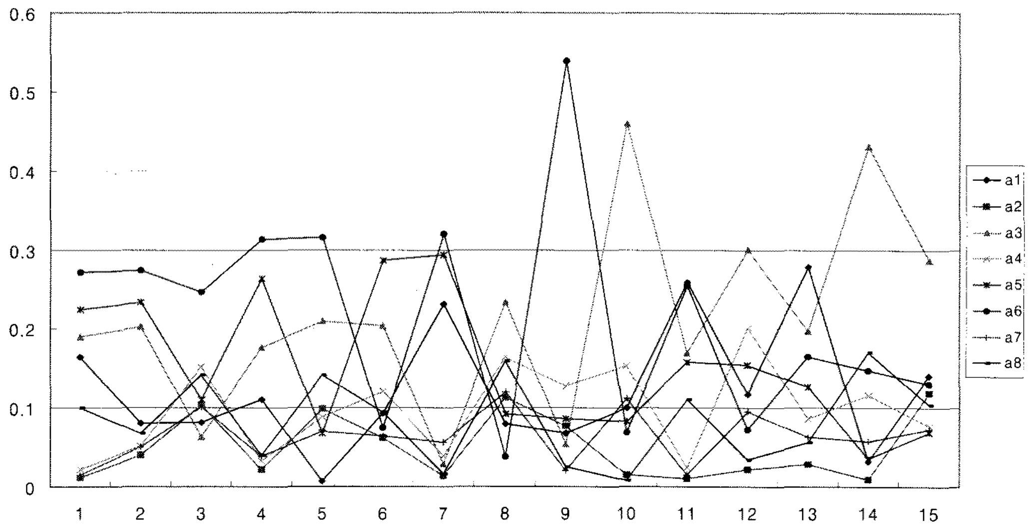
The normalized feature values from reference images are shown in Figure 2 and their weights, weights by only variances used in [13], and ranks of the two methods are shown in Table 1. Comparison of weight distribution by the conventional method with the proposed method is shown in Figure 3.

In the experiments, three different types of reference data set were used for the construction of membership functions. These are as follows.

Reference data set 1: feature values extracted from only the 8 reference aircraft images shown in fig. 1.

Reference data set 2: averaged feature values extracted from 8 reference patterns and 32 noisy patterns (4 noisy patterns with 25dB SNR generated from each of 8 reference images).

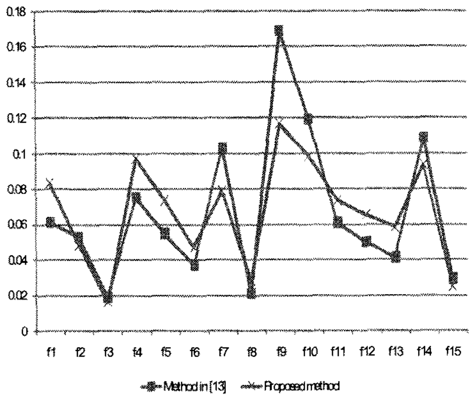
Reference data set 3: averaged feature values extracted from 8 reference images and 32 noisy



〈Figure 2〉 Normalized bispectral feature values (*h(2),h(3),....,h(16)*) for eight aircraft images patterns (4 noisy patterns with each of 25dB, 20dB, 15dB and 10dB SNR generated from each of 8 reference images).

<Table 1> Weights and ranks by feature sets

feature order	Weight	Rank(proposed)	Rank[13]
1	1.007640	5	6
2	0.579658	11	9
3	0.197567	15	15
4	1.177310	3	5
5	0.890021	8	8
6	0.564538	12	12
7	0.954518	6	4
8	0.339517	13	14
9	1.411180	1	1
10	1.190330	2	2
11	0.890710	7	7
12	0.789154	9	10
13	0.703019	10	11
14	1.128200	4	3
15	0.302892	14	13



<Figure 3> Comparison of weight distribution by the conventional method with the proposed method

In our experiments, 11,808 of total test patterns (1,476 patterns for each reference image) were evaluated with each of three different reference data set for the proposed method and the conventional method[13]. The overall classification results with reference data set 1-3 are summarized in Table 2-4. In the recognition process with reference data set 2 and 3, the membership functions for each of eight reference shapes are constructed with a noise-free pattern and four of randomly selected noisy patterns. It means the classification results slightly depend on the selection of noisy patterns. Therefore the five independent experiments with random choice of noisy patterns keeping the same SNR were evaluated. The average results are shown in Table 3, 4.

<Table 2> Number of misclassified patterns in the recognition process with reference data set 1.

Type of data sets (total # of tested patterns)	The proposed method	The conventional method[13]
Noise-free(288)	0	0
25dB(2880)	0	0
20dB(2880)	0	0
15dB(2880)	0	0
10dB(2880)	61	74

<Table 3> Average number of misclassified patterns in the recognition process with reference data set 2 after five independent simulations.

Type of data sets (total # of tested patterns)	The proposed method	The conventional method[13]
Noise-free(288)	0	0
25dB(2880)	0	0
20dB(2880)	0	0
15dB(2880)	0	0
10dB(2880)	55	58

<Table 4> Average number of misclassified patterns in the recognition process with reference data set 3 after five independent simulations.

Type of data sets (total # of tested patterns)	The proposed method	The conventional method[13]
Noise-free(288)	0	0
25dB(2880)	0	0
20dB(2880)	0	0
15dB(2880)	0	1
10dB(2880)	25	20

Table 3 and 4 show that the classification results can be increased by adding some various types of noisy patterns to the construction of membership function. As mentioned in before, under the same experimental environments, the classification performance can be improved by adjustment of weights using appropriate statistical information. It is shown well in experimental results of Table 2-3.

In the experiment results using reference data set 3(Table 4), however, the misclassified number of the proposed method is more than the conventional method in the data set of 10dB patterns. We think this is caused by using all of the same membership functions based on the means of reference data set only except intra-class or inter-class variances for building the membership functions.

V. Conclusion

The experimental results show that the appropriate calculation of weights in the fuzzy weighted mean classifier based on the statistical characteristics of feature values, should be considered to achieve the best performance in image recognition systems. Therefore the proposed fuzzy weighted mean method can be applied to some other types of pattern recognition problems, such as off-line signature verification, vehicle plate recognition systems, or biomedical image understanding systems.

In the future, we would like to extend our approach to construct membership functions using intra-class and inter-class variances for better classification performance.

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