Trademarks Cassification by Moment Invariant and FuzzyARTMAP

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Abstract - ***The purpose of automated image classification is to facilitate a machine to classify image patterns without human intervention. There are a variety of approaches proposed to perform the task. In our case, the image chosen is that of trademark. Geometric and Zernike Moment techniques are employed to extract a set of patterns in terms of feature vectors from the image. Fuzzy ARTMAP is then utilized to classify the image patterns. In order to test the invariant properties of the feature vectors, trademark images are manipulated into various orientations in the aspect of rotational, translational and size. The classification performance of Fuzzy ARTMAP is evaluated based on cross validation techniques. It is found that Zernike Moments displayed a higher classification accuracy when compared to Geometric Moments***.

Keywords: Fuzzy ARTMAP, Geometric moment, Zernike moment

I. INTRODUCTION

Trademark symbols are categorised as multi-componet 2-D images that do not have a standard shape, size or design style [11]. A trademark symbol represents a reputation of a company and it is legally required that the symbol must be unque. In a trademark registration office, before a trademark can be registered, the trademark registration officer must ensure that the symbol is not identical to each trademark image that have been registered [12][13]. This is a challenging task due to the large number of trademark images to be examined and the size of individual image is huge. Thus, Geometric and Zernike Moment techniques are utilized to extract the significant feature vectors from each image and Fuzzy ARTMAP is used to classifiy the features. *k*-folds cross validations are used to verify the classification accuracy.

Section II describes Geometric Moment and Zernike Moment techniques that are used to extract features from trademark images. It also explains the normalization procedures that had been carried out to the features extracted. Features classification is described in section III and section IV explains the implementation. Section V is on Results and Discussion and the paper ends with a conclusion in Section VI.

II. FEATURES EXTRACTION

a. Moment Invariants

Given a features vector of G and Z where G ={ GM_1,GM_2,GM_3,GM_4,GM_5,GM_6,GM_7} and Z={ Z_{00}, Z_{11}, Z_{20}, Z_{22}, Z_{31}, Z_{33}}; GM represent Geometric Moment and Z_{ij} , Zernike Moment is given by the (1) and (2) .Where Mij and µij are given by (3) and (4) with respect of image intensity *h(x,y)*.

$$
\begin{aligned}
GM_1 &= (\mu_{20} + \mu_{02}) \\
GM_2 &= (\mu_{20} - \mu_{02})^2 + 4\,\mu_{11}^2 \\
GM_3 &= (\mu_{30} - 3\mu_{12})^2 + (3\mu_{21} - \mu_{03})^2 \\
GM_4 &= (\mu_{30} + \mu_{12})^2 + (\mu_{21} + \mu_{03})^2 \\
GM_5 &= (\mu_{30} - 3\mu_{12})(\mu_{30}+ \mu_{12})[(\mu_{30}+ \mu_{12})^2-3(\mu_{21}+ \mu_{03})^2] \\
&\quad + (3\mu_{21}+ \mu_{03})(\mu_{21}+\mu_{03})[3(\mu_{30}+\mu_{12})^2-(\mu_{12}+\mu_{03})^2] \\
GM_6 &= (\mu_{20}- \mu_{02})[(\mu_{30}+ \mu_{12})^2-(\mu_{21}+ \mu_{03})^2] \\
&\quad + 4\mu_{11}(\mu_{30}+\mu_{12})(\mu_{21}+ \mu_{03}) \\
GM_7 &= (3\mu_{12} - \mu_{03})(\mu_{30} + \mu_{12})[(\mu_{30} + \mu_{12}) - 3(\mu_{21} + \mu_{03})] \\
&\quad - (\mu_{30} - 3\mu_{12})(\mu_{12}+ \mu_{03})[3(\mu_{30}+ \mu_{12})^2 \\
&\quad - (\mu_{21} + \mu_{03})^2] \quad \ldots\ldots\ldots\ldots\ldots\ldots \qquad (1)
\end{aligned}
$$

$$
\begin{aligned}
Z_{00} &= (1/\pi)\, M_{00} \\
|Z_{11}|^2 &= (2/\pi)^2 (M_{10}^2 + M_{01}^2) \\
Z_{20} &= (3/\pi)\, [(2M_{20} + M_{02}) + M_{00}] \\
|Z_{22}|^2 &= (3/\pi)^2\, [\,2(M_{20} - M_{02})^2 + 4M_{11}^2) \\
|Z_{31}|^2 &= (12/\pi)^2[(M_{30} + M_{12})^2 + (M_{03} + M_{21})^2] \\
|Z_{33}|^2 &= (4/\pi)^2[(M_{30} - 3M_{12})^2 + (M_{03} - 3M_{21})^2] \quad \ldots\ldots\ldots\ldots \qquad (2)
\end{aligned}
$$

$$M_{ij} = \sum_{x=-n}^{n} \sum_{y=-m}^{m} (x - \bar{x})^i (y - \bar{y})^j h(x, y) \qquad (3)$$

$$\mu_{pq} = m_{pq} / m_{00}^{\gamma} \qquad (4)$$

Where $\tilde{x} = m_{10}/m_{00}$, $\tilde{y} = m_{01}/ m_{00}$, $\gamma = (p + q)/2 + 1$

b. Normalization of Features vector

FuzzyARTMAP requires input value to lie between 0 to 1. Thus the features vector are normalize using the equation (5). Where x' = normalized features, x = raw features x_{max} = a maximum features value, x_{min} = a minimum features value.

$$x' = 0.8\left(\frac{x - x_{\min}}{x_{\max} - x_{\min}}\right) + 0.1 \qquad (5)$$

c. Mean Absolute Error

Mean absolute error is used to determine the sensitivity of Geometric Moments and Zernike Moments invariant. The equation used is shown in (6).

$$\min \varepsilon(GM) = \frac{\sum_{i=1}^{6} \varepsilon(G.M)}{6} \qquad (6)$$

Where $\varepsilon i(G.M) = |\varphi i(\text{original}) - \varphi i(\text{perturbed})|$, i=1,2,3…6

III. FEATURES CLASSIFICATIONS

FuzzyARTMAP is utilized to perform features classifications. The FuzzyARTMAP is a supervised neural network that incorporated two Fuzzy ART module, ARTa and ARTb as illustrated in Figure 1. Mapfield is used to form predictive associations between categories and to realize the match tracking rule, whereby the vigilance parameter of ARTa increases in response to predictive mismatch ARTb.

Fuzzy ARTMAP learning algorithm consists of five initial steps . The first step is called initialization where weight vector of ARTa, w_{ij}^{a} and ARTb, w_{ij}^{b} are set to '1' while weight vector of mapfield are set to '0'. Learning rate, β and baseline vigilance parameter, $\tilde{\rho}$ are set between [0,1]. The choice parameter, α is set larger

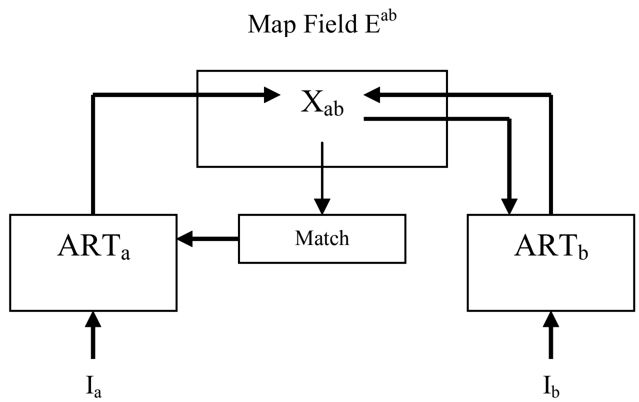

Figure 1 – The architecture of fuzzy ARTMAP neural Network.

$$I = (a_1, a_2, \ldots\ldots, a_1^c, a_2^c, \ldots\ldots, a_M^c) \quad (7)$$

than zero. The second step require the complement of input vector given as (7), where $a^c = 1 - a_i$ with $(1 \leq i \leq M)$.Then the input vector activate each node j in recognition layer of ARTa given by the choice function,(8). Node J with maximal Tj will performed with vigilance test,(9). If test is passed, then the node J is remains active and resonance occurs. Otherwise the next training pair will be presented until another node J passes the vigilance test. If such J node is not exits, an uncommitted node is selected to undergo the vigilance test.

$$Tj = \frac{| I \wedge W_j |}{A + |W_j|} \quad (8)$$

Where $(I \wedge W_j) \equiv \min(I_j, W_j)$, $| W_j | \equiv \sum | W_j |$

$$\rho = \frac{| I \wedge W_j |}{| I |} \quad (9)$$

Once the J category from ARTa module learns to predict K category from ARTb module, the association is permanent and the associative, w_{jk}^{ab} is set to '1'. If incorrect class prediction occur, the vigilance parameter ρ_a is increased slightly to search a new node in the recognition layer of ARTa. This will continue until either an uncommitted node become active or node J that has previously learned the correct class prediction K becomes active. The weight vector of J node in recognition layer is updated according to (10) where for fast learning β is set to 1.

$$Wj = \beta (I \wedge W_j (old)) + (1 - \beta) W_j (old) \quad (10)$$

IV. IMPLEMENTATIONS

In this work 20 classes of trademark images that produced totally 400 features vector were analysed. Firstly each trademark images were transformed into grey-level format. Then each of images are manipulated into various rotations and scale. Then, features vectors are computed using Moment techniques elaborated in Section II. The value of mean absolute error of each member of the image class are computed. Then, the normalized image vectors are classified using

FuzzyARTMAP. The classifications performance of the FuzzyARTMAP been examine using *k*-folds cross validations given by (11).

$$PCC_{G.M} = 100\frac{1}{kN}\sum_{m=1}^{k}\sum_{n=1}^{N}\delta(y_n, O_n) \tag{11}$$

Where δ(y,O) = 1 if the testing vector true, while δ (y,O) = 0 if otherwise. *k* represents the number of class and *N* is the number of data set per class.

V. RESULTS AND DISCUSSION

Figure 2 shows samples of trademark images that were used in this experiment. Table 3 shows the example of raw and normalize features vector for the same image generated. Table 3a) shows the features vectors produce by the Geometric Moment invariant. Table 3b) contains the normalized version of Table 3a). Table 3c) illustrate the features vectors generated by the Zernike Moment. Table 3d) contains the normalized version of Table 3c). Figure 4 indicate the mean absolute error for Geometric Moment and Zernike Moment. Table 5 shows the result of cross validation for *k*=4 and *k*=5. ‘A’ characterize all data were been train and test to FuzzyARTMAP neural network. The log values of the Geometric moment are since the values are too small [9]. The results are shown in Table 3a).

a)

b)

c)

Figure 2-a) Original image b) scale image c) 45° image

Table 3

	GM1	GM2	GM3	GM4
original	-1.45509	-8.99166	-9.19732	-7.97817
0.75X	-1.47729	-8.92668	-9.29626	-8.11589
45'	-1.47187	-8.99406	-9.29047	-8.09065

a)

	GM1	GM2	GM3	GM4
original	0.165357	0.107523	0.44994	0.556746
0.75X	0.155414	0.113465	0.443893	0.548428
45'	0.157844	0.107304	0.444247	0.549952

b)

	ZM3	ZM4	ZM5	ZM6
original	0.466757	0.000124	0.005486	0.000461
0.75X	0.456509	0.000133	0.00478	0.000232
45'	0.458993	0.000124	0.004902	0.000401

c)

	ZM3	ZM4	ZM5	ZM6
original	0.121892	0.100004	0.100584	0.100274
0.75X	0.118352	0.100008	0.100509	0.100138
45'	0.11921	0.100004	0.100522	0.100239

d)

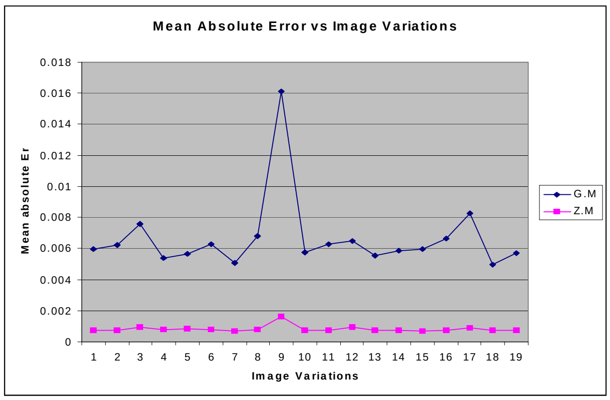

Figure 4

VI. CONCLUSION

This paper had demonstrated that Geometric moments are better than Zernike moments for intraclass classifications. The phenomena are illustrated in Table 5 where the percentage of correct classifications on FuzzyARTMAP is higher when using Geometric Moment invariant. Furthermore the maximum number categories generate by the fuzzy ARTa is less when using the features vector extracted using the Geometric Moment rather than using the Zernike moment. The vigilance parameter of ARTa for Zernike Moment is also higher, which notify that the discrimination of each class in the features space is more difficult compare to Geometric moments. Nevertheless Zernike moments is better than Geometric moment for interclass classifications because of the fact that they are producing less number on mean absolute error as shown in Figure 4.

	Geometric moment		
k	categories of ARTa	ρ_a	$NCC_k/100$
1	28	0.947492	100
2	28	0.947492	100
3	24	0.955261	95
4	23	0.944087	96
		PCC_{GM}	97.75%
A	28	0.947492	100%

	Zernike moment		
k	categories of ARTa	ρ_a	$NCC_k/100$
1	185	0.999866	71
2	186	0.999866	67
3	117	0.999677	53
4	161	0.999866	46
		PCC_{ZM}	59.25%
A	214	0.999866	100%

a)

	Geometric moment		
k	categories of ARTa	ρ_a	$NCC_k/80$
1	24	0.954525	74
2	27	0.947637	79
3	28	0.947492	80
4	28	0.947592	80
5	23	0.943461	76
		PCC_{GM}	97.25%
A	28	0.947492	100%

	Zernike moment		
k	categories of ARTa	ρ_a	$NCC_k/80$
1	174	0.999866	38
2	162	0.99985	37
3	182	0.999866	44
4	193	0.999866	61
5	181	0.999866	46
		PCC_{ZM}	56.50%
A	214	0.999866	100%

b)

Table 5 – a) k=4 b) k=5

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