FEATURE FUSION BASED ON DEMPSTER-SHAFER'S EVIDENTIAL REASONING FOR I MAGE TEXTURE CLASSIFICATION[1]*

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ABSTRACT:

A new multi-feature fusion technique based on Dempster-Shafer's evidential reasoning for classification of image texture is presented. The proposed technique is divided into three main steps. In the first step, the fractal dimension and gray co-occurrence matrix entropy are extracted from a texture image. In the second step, we focus on how to design a probability assignment function m(A) representing the exact belief in the proposition *A* depicted by one of features. A combining rule, which synthesizes probability assignment functions representing the fused information, is proposed based on Dempster-Shafer's evidential reasoning. The formulas for calculating the belief function Belief(*A*), the plausibility function Plausibility (*A*) and uncertainty probability are given. In the decisive step in which image texture is classified, a set of decision rules is provided. An example is provided, and the performance is investigated with some aerial photos. Texture classification is considered, with the following classes: inhabitant area, water field, grassland and woodland. As a reference for evaluating the performance of multi-feature fusion technique based on Dempster-Shafer's evidential reasoning in texture classification, classification accuracies using the single-feature and fused features are calculated. Compared with the results obtained from the single feature, the results obtained from multi-feature fusion indicate the multi-feature fusion technique based on Dempster-Shafer's evidential reasoning for classification is stable and reliable, and efficiently improves the accuracy of classification.

1. INTRODUCTION

The aims of texture analysis are texture recognition and texture-based shape analysis. A variety of statistical methods such as primitive length features [Galloway M., 1975], edge frequency method, autocorrelation [Haralick R. 1979], co-occurrence approach [Haralick R. 1986], fractal dimension and Markov random field method [Huang Guilan, Zheng Zhaobao, 1998a, 1998b], etc., have been proposed for texture analysis which are based on capturing the variability in gray scale images. One of the best methods is that parameters of Markov random field model, features of gray scale co-occurrence matrix and fractal dimensions extracted from image are combined, and then fuzzy clustering analysis are applied for image texture classification [Huang Guilan, Zheng Zhaobao, 1998a, 1998b]. But it has two shortcomings, the one is its complexity and incompleteness in obtaining parameters of Markov random field model by Bayesian decision; the other is not concerned features whether are related or are the best combined. Extraction and selection of image texture features in classification are very important, classification according to only one feature has its localization in accuracy, and can't satisfy the requirement of identifying image targets. So a multi-feature fusion technique based on Dempster-Shafer's evidential reasoning for image texture classification is presented. The remainder of this paper is organized as follows. The methodology is explained in section 2. The experiments and discussion are given in section 3. Finally, the conclusions are summed up in section 4.

2. FEATURE FUSION BY DEMPSTER-SHAFER'S EVIDENTIAL REASONING FOR I MAGE TEXTURE CLASSIFICATION

2.1 Measurement of fractal dimensional feature

A variety of methods measuring fractal dimension from image texture have been proposed. Here is given a method of measuring Brown's fractal dimension.

Supposing $X\in E^n$ (E^n is a n-dimensional space), *f*(*X*) is a real random function. If a constant H(0<*H*<1, called self-similar parameter) exist, function F(t) is a distributing function having nothing with *X* or ΔX, then f(*X*) is called Brown's fractal function. Its expression is

$$F(t) = P_r\{\frac{f(X+\Delta X)-f(X)}{\|\Delta X\|^H} < t\} \qquad (1)$$

And its fractal dimension is

$$f_1 = n+1-H \qquad (2)$$

Eq. (1) can be rewritten as

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$$E[\ |f(X+\Delta X)-f(X)|\ ]\cdot\|\Delta X\|^{-H}=C \quad (3)$$

Therefore

$$lgE[\ |f(X+\Delta X)-f(X)|\ ]-H\cdot lg\|\Delta X\|=lgC \quad (4)$$

Where H= a self-similar parameter
C= a rational constant

Therefore Eq.(4) is a linear equation. If the Brown's fractal function $f(X)$ is used to simulate gray scale surface of image texture, the sum of squared errors is

$$e^2=\sum_{\min\|\Delta X}^{\max\|\Delta X|}\{\lg E[|f(X+\Delta X)-f(X)|]-H*\lg\|\Delta X\|-\lg C\}^2 \quad (5)$$

where $X\in(x,y)\in E^2$,
$f(X)$= gray scale at X.

The fractal dimension f_1 can be obtained by the following steps: First of all, $E[\ |f(X+\Delta X)-f(X)|\ ]$ (ΔX=1，2，…, K) can be respectively calculated, where $|f(X+\Delta X)-f(X)|$= **Error!**[$|f(x,y+\Delta y)-f(x,y)|$ + $|f(x+\Delta x,y)-f(x,y)|$ +$|f(x+\Delta x,y+\Delta y)-f(x,y)|$]; Then H and lgC of the isomorphic fractal model are calculated according to the least-square method; finally f_1 is obtained according to Eq. (2).

2.2 Measurement of entropy feature based on gray co-occurrence matrix

The co-occurrence matrix $P(i,j,\delta,\theta)$ (or $P(i,j,\Delta x,\Delta y)$) of a image $f(x,y)$ describes the probability for gray scale i and j ($i,j\in[0;g-1]$) to occur at two pixels separated by distance δ and direction θ (or by displacement Δx and Δy), it can be written as

$$P(i,j,\delta,\theta)=P(i,j,\Delta x,\Delta y)=P\{f(x,y)=i \text{ and } f(x+\Delta x,y+\Delta y)=j\} \quad (6)$$

Separated co-occurrence matrices can be established for each combination of distance and direction. A set of 14 features based on a co-occurrence matrix was proposed by Halarick etc.. Once the co-occurrence matrix has been formed, texture feature can be computed. Since we are interested in rotationally invariant texture feature for classification, first, we specify the distance $\delta_4=max[\ |\Delta x|,\ |\Delta y|\ ]$, and the co-occurrence matrixes of all directions ($\theta=0^\circ,45^\circ,90^\circ,135^\circ$) are computed; Then features are computed from co-occurrence matrixes; finally the average features can be obtained for texture classification. Some co-occurrence matrix-based texture features correspond to characteristics that are recognized by the eyes, but many do not. Experiments show entropy feature of gray scale co-occurrence matrix is one of the feature having the best discriminatory power. Here is given the entropy formula

$$f_2=-\sum\sum P(i,j,\delta,\theta)\log_2 P(i,j,\delta,\theta) \quad (7)$$

2.3 Feature fusion based on Dempster-Shafer reasoning theory for texture classification

2.3.1 Dempster-Shafer reasoning theory: The Bayesian theory is the canonical method for statistical inference problems. Dempster-Shafer decision theory is considered a generalized Bayesian theory. It allows distributing support for a proposition not only to the proposition itself but also to the union of propositions. In a Dempster-Shafer reasoning system, all possible mutually exclusive context facts (or events) of the same kind are enumerated in "the frame of discernment ."

Each texture feature f_i will contribute its observation by assigning its belief. This assignment function is called the "probability mass function" of the feature f_i, denoted by m_i. So, according to feature f_i's observation, the probability that "the detected texture is A" is indicated by a "confidence interval":

$$[Belief_i(A),\ Plausibility_i(A)] \quad (8)$$

The lower boundary of the confidence interval is the belief confidence, which accounts for all evidence A_j that supports the given proposition " texture A":

$$Belief_i(A)=\sum_{A_j\subseteq A} m_i(A_j) \quad (9)$$

The upper boundary of the confidence interval is the plausibility confidence, which accounts for all the observations that do not rule out the given proposition:

$$Plausibility_i(A)=1-\sum_{A_j\cap A=\phi} m_i(A_j) \quad (10)$$

For each possible proposition, Dempster-Shafer theory gives a rule for combining feature f_i's observation m_i and feature f_j's observation m_j:

$$(m_i\oplus m_j)(A)=\frac{\sum_{A_i\cap A_j=A} m_i(A_i)m_j(A_j)}{1-\sum_{A_i\cap A_j=\phi} m_i(A_i)m_j(A_j)} \quad (11)$$

$(m_i\oplus m_j)(A)$ is called combined probability mass function.

This combining rule can be generalized by iteration: if we treat m_j not as feature f_j's observation, but rather as the already combined (using Dempster-Shafer combining rule) observation of feature f_k and feature f_l.

Compared with Bayesian theory, Dempster-Shafer theory of evidence feels closer to our human perception and reasoning processes. Its capability to assign uncertainty or ignorance to propositions is a powerful tool for dealing with a large range of problems that otherwise would seem intractable.

2.3.2 Designing for the basic assignment function: Designing for the basic assignment function $m_i(j)$ is: first, we set up a model base of texture image by selecting a variety of texture training samples according to prior knowledge; then we extract features f_i (i=1,2) from unknown texture, and match them with features of image texture in model base respectively to obtain correlation coefficients $P_i(j)$, here j represents the class number of texture in the model base; finally $m_i(j)$ which feature f_i assigns texture j can be constructed by $P_i(j)$. Its expression [Yang Jingyu, Wu Yongge, Liu Leijian Etc. 1994] is given as follow:

$$m_i(j) = \frac{p_i(j)}{\sum_j p_i(j) + n(1-\gamma_i)(1-\alpha_i\beta_i)} \tag{12}$$

Where

$\alpha_i = \max_j P_i(j)$ is the maximum correlation coefficient between feature f_i of unknown texture and that of texture j

$\beta_i = \frac{\alpha_i}{\sum_j p_i(j)}$ is distributing coefficient of feature f_i

$\gamma_i = \frac{\alpha_i\beta_i}{\sum_i \alpha_i\beta}$ is reliable coefficient of feature f_i;.

Therefore

$$m_i(\theta) = \frac{n(1-\gamma_i)(1-\alpha_i\beta_i)}{\sum_j p_i(j) + n(1-\gamma_i)(1-\alpha_i\beta_i)} \tag{13}$$

Here $m_i(\theta)$ is an uncertainty probability which feature f_i assigns frame of discernment θ.

According to Eq. (12), we can compute the single feature (fractal dimension or entropy) probability mass function, then fuse according to Eq.(11) probability mass functions of all features to get the combined probability mass function.

2.3.3 Decision rules for texture classification: Based on the analysis of the combined probability mass function, we adopt four decision rules to classify textures:

- The target should have the largest probability mass function;
- The difference between the target probability mass function and any other target's should be greater than threshold t_1, namely that the supporting degrees of all textures by each possible proposition should have difference enough.
- The uncertainty probability $m_i(\theta)$ must be smaller than threshold t_2.
- The target probability mass function must be greater than $m_i(\theta)$.When we seldom know a target, the classification can't be preceded.

Above all, the processes of image texture classification based on the Dempster— Shafer reasoning theory are given as follows: First of all, $m_i(A)$,$Belief_i(A)$, and $Plausibility_i(A)$ of each feature are computed; Secondly, according to the combining rule, compute the fused probability mass function m_i and its $Belief_i$ and $Plausibility_i$; Finally, according to decision rules to choose the maximum hypotheses in the action of fusion.

3. EXPERIMENT AND DISCUSSION

The performance of the method is investigated with some aerial photos on some area. A Four-class texture classification is considered, with the following classes: inhabitant area, water field, woodland and grassland. 10 test samples from each texture are obtained; the size of the test sample is 100 by 100 pixels. As a reference for evaluating the performance of multi-feature fusion technique based on Dempster-Shafer's evidential reasoning, the same decision rules (t_1=0.1,t_2=0.3) are utilized, classification accuracies with the single-feature (fractal dimension or entropy of co-occurrence matrix) and the fused feature are calculated. See Table 1. Compared with the results obtained from the single feature, the results obtained from multi-feature fusion have higher accuracy of classification, single feature, either the fractal dimension or entropy of gray co-occurrence matrix, is not sufficient for descripting texture. This indicates the multi-feature fusion technique based on Dempster-Shafer's evidential reasoning for classification is stable and reliable, and efficiently improves the accuracy of image texture classification.

Feature	Fractal feature	Entropy of grey co-occurrence matrix	Multi-feature fused
Accuracy of classification	72.5%	80%	95%

Table 1. The accuracy of texture classification based on Dempster-Shafer evidential reasoning.

Texture	Feature	$m(\theta)$	Confidence interval [*Belief*(*A*), *Plausibility*(*A*)]								Identified result
			Woodland		Grassland		Inhabitant area		Water field		
Woodland	Fractional	0.482	0.280	0.762	0.089	0.571	0.050	0.532	0.110	0.592	Unknown
	Entropy	0.162	0.678	0.840	0.087	0.249	0.032	0.194	0.051	0.212	Woodland
	Fused	0.105	0.727	0.832	0.081	0.187	0.030	0.136	0.060	0.165	Woodland
Grassland	Fractional	0.446	0.132	0.578	0.225	0.671	0.119	0.565	0.177	0.623	Unknown
	Entropy	0.233	0.115	0.348	0.355	0.588	0.072	0.305	0.164	0.397	Unknown
	Fused	0.162	0.121	0.283	0.481	0.643	0.066	0.228	0.170	0.332	Grassland
Inhabitant area	Fractional	0.543	0.137	0.680	0.126	0.669	0.283	0.826	0.101	0.644	Unknown
	Entropy	0.475	0.062	0.527	0.089	0.564	0.263	0.728	0.140	0.615	Unknown
	Fused	0.234	0.080	0.314	0.137	0.371	0.341	0.635	0.154	0.388	Inhabitant area
Water field	Fractional	0.426	0.145	0.571	0.181	0.607	0.119	0.545	0.238	0.664	Unknown
	Entropy	0.192	0.113	0.305	0.183	0.375	0.148	0.340	0.464	0.656	Water field
	Fused	0.182	0.095	0.277	0.171	0.353	0.110	0.292	0.463	0.645	Water field

Tabel 2. Part of confidential intervals and uncertainty probability

Table 2 is part of confidence intervals and uncertainty probabilities. The confidence interval obtained from the fused feature is smaller than that from the single feature correspondingly, Belief and Plausibility obtained from the fused feature are higher than that from the single feature correspondingly, the multi-feature fusion technique based on Dempster-Shafer's evidential reasoning for classification is apt to identify textures correctly. Comparison with uncertainty probability $m(\theta)$, the feature fusion technique reduces $m(\theta)$ and enhances the power of identify.

4. CONCLUSION

A new multi-feature fusion technique based on Dempster-Shafer's evidential reasoning for classification of image texture is presented. The proposed technique is divided into three main steps. An example is provided. The performance of the method is investigated with some aerial photos in some area. Compared with the results obtained from the single feature, the results obtained from the multi-feature fusion indicate the multi-feature fusion technique based on Dempster-Shafer's evidential reasoning for classification is stable and reliable, and efficiently improve the accuracy of classification.

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