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A Novel 2D Texture Classifier For Gray Level Images

B.S. Mousavi

[1] Young Researchers Club, Zahedan Branch, Islamic Azad University, Zahedan, Iran.

ABSTRACT

In this paper a new fuzzy method for 2D texture classification is proposed. A fuzzy rule base system is designed based on computed Geometric Moments (GMs), which are rotation, scale and translation invariant, for each texture class. Although GMs are applied to classify texture, utilizing fuzzy inference system (FIS) to make decision, develops much more robust classifier. Where GMs are inputs and likelihood of belonging to one class is the output of fuzzy system, the optimized threshold value is obtained by Genetic Algorithm, to make final decision. 90.8% classification rate proves the system efficiency.
KEY WORDS: Texture,Fuzzy System,Gray Level Images,Classifier.

1. INTRODUCTION

Texture analysis plays an important role in computer vision and pattern recognition, and is widely applied in areas of industrial application; bio medical image processing; remote sensing; and image retrieval for classification, detection or segmentation of images based on spatial variation [1].Texture classification is a branch of texture analysis which results particularly well suited for the automatic grading of products such as ceramic tiles, marble and granite tiles, parquet slabs, etc. Based on this fact, an increasing attention from industry has recently emerged. Since in practical applications it is uncommon that texture images are captured under invariant viewing conditions, it is of great importance that texture classification be rotation, translation and scale invariant. Another issue in texture classification is about the role of colour [2]. Even if many approaches to texture analysis have been proposed in the last three decades, in most cases such methods are applied to grayscale images. A comprehensive review of these techniques can be found in Petrou and García Sevilla work [3].

The aim of this work is to present a rotationally invariant descriptor for gray level textures. After studying various texture classification methods, Geometric Moment (GM), that is scale, position and orientation invariant, is chosen and fuzzy rule base system is applied for classification.

Geometric invariant moment was first introduced in 1962 by Hu. It was derived from the theory of algebraic invariant [6].

GM technique attempts to extract Rotation/ Scale/ Translation (RST)-invariant visual features. GM has been successfully applied in aircraft identification, texture classification and radar images to optical images matching [7]. Two-dimensional moments of a digital image $f(x,y)$ is given as:

$$m_{pq} = \sum_x \sum_y x^p y^q f(x,y) \qquad (1)$$

for $p,q = 0,1,2,\ldots$.

The corresponding central moment is defined as:

$$\mu_{pq} = \sum_x \sum_y (x-\bar{x})^p (y-\bar{y})^q f(x,y) \qquad (2)$$

where:

$$\bar{x} = \frac{m_{10}}{m_{00}} \;\&\; \bar{y} = \frac{m_{01}}{m_{00}} \qquad (3)$$

The normalized central moment of order (p+q) is defined as:

$$\eta_{pq} = \frac{\mu_{pq}}{\mu_{pq}^{\gamma}} \qquad (4)$$

***Corresponding Author:** B.S. Mousavi, Young Researchers club, Zahedan branch, Islamic Azad University, Zahedan, Iran.
Email: bbmoosavi@gmail.com

where:

$$\gamma = \frac{p+q}{2} + 1 \tag{5}$$

In particular, Hu defines seven values, computed by normalizing central moments through the third order, that are scale, position, and orientation invariant. In terms of the central moments, these seven moments are [6]:

(1) $\varphi_1 = \eta_{20} + \eta_{02}$ (6)

(2) $\varphi_2 = (\eta_{20} - \eta_{02})^2 + 4{\eta_{11}}^2$

(3) $\varphi_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$

(4) $\varphi_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} + \eta_{03})^2$

(5) $\varphi_5 = (\eta_{30} - 3\eta_{12})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} - \eta_{12})^2 - (\eta_{21} + \eta_{03})^2]$

(6) $\varphi_6 = (\eta_{20} - \eta_{02})[(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03})]$

(7) $\varphi_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})[(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2] + (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03})[3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2$

Fuzzy sets theory provides a framework to materialize a fuzzy rule-based system which contains the selection of fuzzy rules, membership functions, and the reasoning mechanism. Such systems have been applied to many disciplines such as control systems, decision making and pattern recognition [4], and in this paper it is supposed that such a system could overcome the complexity of the texture classification problems, mainly are known as: variable conditions. Fuzzy logic if-then rules are formed by applying fuzzy operations to these membership functions for given inputs. The resulting output membership functions are added together using desired weights yielding a sort of probability function. This function can then be used to estimate the expected value of the output variable. Mamdani type is one the most commonly used fuzzy inference method which is employed in this study as well [5].

In this paper, accurately designed Mamdani fuzzy rule base system is proposed for gray scale texture classification. GMs are employed as inputs and different texture clusters are outputs. More details about various steps of system designing and its characteristics are presented in following sections. The reminder of paper is organized as follows. Proposed method is analyzed in section 2. Section 3 and 4 present obtained result and conclusion, respectively.

2. PROPOSED METHOD

After various investigation GMs are found as one of the most reliable methods to texture classification. Table 1 shows obtained GM values for six different texture depicted in Fig. 1. These images are from Outex [8] texture image database. The number of each category and the number of texture in that category (in parentheses) could be seen at the bottom of each image. It should be noted, GM values in table 1 are the absolute values of log of results, obtained by applying equation (6). Using log, dynamic range would be reduced and the absolute values avoids having to deal with the complex numbers that result when the log of negative moment invariant is computed. As it is more difference between Φ_5 to Φ_7 values for different categories, these values are chosen to classify. Instead of using crisp threshold,

fuzzy rule base system is applied. This fuzzy system is a Mamdani type, with three inputs (Φ_5-Φ_7) and one output which is the likelihood of belonging to special category for any input texture.

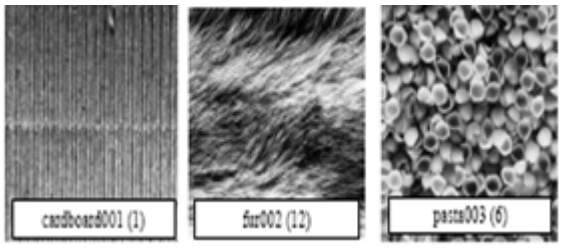


Fig.1. Texture images from Outex database

Table 1. GM values for textures shown in Fig. 1.

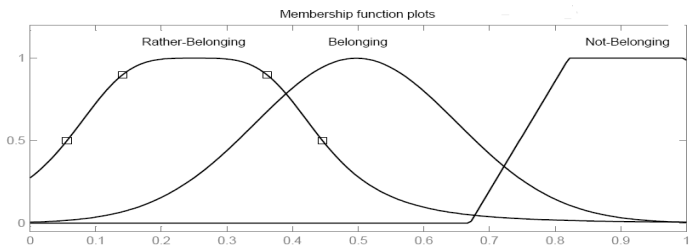
GM	*Image 001(1)*	*Image 002(12)*	*Image 003(6)*
Φ_1	6.50	6.40	6.56
Φ_2	15.50	15.33	15.81
Φ_3	26.77	23.21	28.24
Φ_4	25.31	26.01	29.66
Φ_5	53.99	51.06	58.94
Φ_6	33.31	33.68	37.72
$\Phi 7$	51.36	50.98	59.17

As an example, to show the robustness of proposed method, a system is designed to select and classify the first category in Outex database. Subtractive clustering [9] is applied on input space (contain 600 various texture image) to decide on the number of membership functions (MF's) and rules. Utilizing the obtained three clusters information and experimental knowledge, input and output MF's are designed. The semantic meaning is assigned to each cluster for better understanding. The achieved rule in texture classification FIS is:

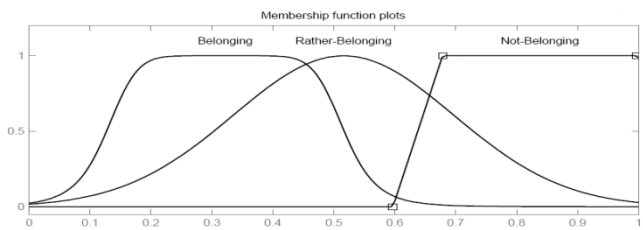
IF input is *Z*, THEN output is *Z*

where *Z* €{ *Belonging, Rather-Belonging, Not Belonging* }

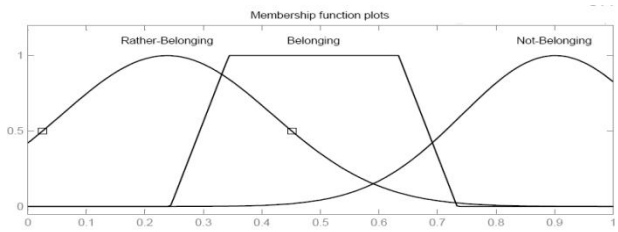
MF's of inputs and output is depicted in Fig. 2. To achieve the crisp output, centroid method is chosen, which is the most widely used one among all defuzzification approaches [5]. The output is the texture-likelihood, between 0 to 1. This value reveals the probability of belonging to desired texture group, for each arbitrary input texture image sample.



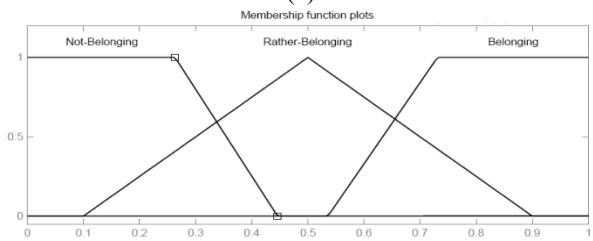
(a)



(b)



(c)



(d)

Fig.2. (a-c) input and (d) output MF's.

To make final decision a suitable threshold value should be selected. To find an optimized value, genetic algorithm (GA) is applied. GA is the most extended group of evolutionary technique known, which rely on the use of a selection, crossover and mutation operators [10]. The threshold is the chromosome of the GA, whose fitness function attempts to maximize the output likelihood for texture belonging to desired texture group.

Over 100 randomly selected texture samples, the obtained threshold is 0.78. It means that the texture with likelihood more than 0.78 are regarded as texture belonging to one class.

3. RESUNLTS AND DISCUSSI

To show the system efficiency and evaluate its performance, the proposed method is applied on Outex texture database. This image database contains a large collection of textures, both in form of surface textures and natural scenes. The collection of surface textures exhibits well defined variations to a given reference in terms of illumination, rotation and spatial resolution [8]. A large collection of texture classification, retrieval and segmentation problems, both supervised and unsupervised, is constructed using the image database. The diversity of the surface textures provides a rich foundation for building the problems. For example, in addition to standard texture classification, problems of illumination/rotation/resolution invariant texture classification, or their combinations, are also available. Different misclassification cost functions and prior probabilities of classes are also incorporated.

The described system in previous section is applied on 1000 texture image of Outex database, suite ID from *Outex_TC_0000* to *Outex_TC_0009,* with window size from 32x32 to 128x128.

The designed fuzzy inference system showed successfully 90.8% correct classification rate over these image textures. Considering wide range of various image textures, specially textures with different size and rotation angles, it can be said that proposed system is nearly rotation and size invariant. This feature is valuable characteristic for a texture classifier.

4. Conclusion and Future Works

In this paper we presented a novel fuzzy inference system to classify texture. GMs were used as system inputs to design a rotation, scale and translation classifier. As the system output shows likelihood of belonging to the special class, an optimized threshold value was achieved using Genetic Algorithm. Utilizing fuzzy method and selecting optimizing threshold value, a reliable classifier was designed, whose correct classification rate (90.8%) proved this idea. Adding colour information to this system, for colour texture classification, is our next aim.

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