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Color Object Recognition Using General Fuzzy Min Max Neural Network

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Abstract - A hybrid approach based on Fuzzy Logic and neural networks with the combination of the classic Hu & Zernike moments joined with Geodesic descriptors is used to keep the maximum amount of information that are given by the color of the image. These moments are calculated for each color level and geodesic descriptors are applied directly to binary images to get information about the general shape of the object. The extracted features are given as input to the General Fuzzy Min-Max Neural Network architecture. General Fuzzy Min-Max Neural Network is The fusion of clustering and classification resulted in an algorithm that can be used as pure clustering, pure classification, or hybrid clustering classification.

Keywords – *Component, Neural Network, Zernike moments, Hu moments, Geodesic descriptors, Object recognition and Coil-100 Database.*

1. Introduction

Color provides powerful information for object recognition. The work makes a significant contribution in introducing color for object recognition. Object recognition system is inspired from the human brain to recognize the object from an image. Object recognition broadly involves two steps namely, feature extraction and pattern classification. Pattern classification extracts the underlying structure in the data[1]. Fuzzy interpretation of patterns is very natural in cases where precise partitions of data are not known. Zadeh elaborated the importance of fuzzy logic for pattern classification in his seminal paper. "Fuzzy Min Max Neural Network"(FMNN) is proposed by Simpson [2][3]. It is the combination of fuzzy logic and neural network. Gabrys and Bargilela proposed General Fuzzy Min-max Neural network" (GFMN)[4]. It is the merge of FMNN classification and clustering algorithms. This hybridization allowed learning under partial supervision. Semi-supervised learning is of high importance for the practical implementation of pattern recognition systems, as it may not be always feasible to get a fully labeled dataset for training or cost of labeling all the samples is not affordable.

The proposed Object Recognition System (ORS) uses a new set of features. Transforming the input data into the set of features is called features extraction. In feature extraction different techniques have been used, but the most commonly used are the invariant descriptors. In this system we choose to use the Zernike & Hu moments and combined them with geodesic descriptors. Recognition is carried out using "General Fuzzy Min Max Neural Network " (GFMN). The rest of the paper is organized as follows. Section II discusses Feature Extraction. Classification is discussed in Section III. In section IV architecture of GFMN is described. The paper is ended by a conclusion.

2. Feature Extraction

Feature extraction part extracts the features. Feature can be defined as quantitative description of input. Feature extraction plays an important role in object recognition systems (ORS) since the information related to an object is contained within the extracted features[6]. In this section invariant moments Zernike, Hu and Geodesic distance as a shape descriptor is described.

2. 1 Zernike Moments

The Zernike polynomials were introduced in 1934 by Zernike. Zernike moments can represent properties of an image with no redundancy or overlap of information between the moments. Thus, they can be utilized to extract features from images. Zernike introduced a set of complex polynomials which form a complete orthogonal set over the interior of the unit circle, i.e.,$x^2+y^2\leq 1$[8]. Let the set of these polynomials be denoted by $\{V_{nm}(x,y)\}$.The form of these polynomials is:

$$V^*_{nm}(x,y)=V_{nm}(\rho, \Theta)=R_{nm}(\rho).\exp(jm\Theta) \quad (1)$$

Where:
N : a positive integer (or null).
M : an integer with |m|<=n.

ρ : Length of vector from origin to (x, y) pixel
r : The vector length (distance between the origin and the pixel at (x,y)).
Θ : Angle between vector p and x axis in clockwise direction.
R_{nm} : radial polynomial.

V*(x,y) : complex polynomial, which is the projection of f(x,y) on the complex polynomials space.

To compute the Zernike moments of a given image, the center of the image is taken as the origin and pixel coordinates are mapped to the range of unit circle, i.e.,$x^2+y^2\leq 1$. Those pixels falling outside the unit circle are not used in the computation. Zernike moments are invariants under rotation. These moments reduces noise and redundancies.

2. 2 Hu Moments

The Hu moments were introduced in 1962 by Hu. In physics, the moments are used to get the distribution of mass in a body. Here, we used Hu moments to describe the distribution of gray levels in an object[4]. Let I(x, y) is the grey level of one pixel of image I, the moment of (p + q) order (p, q > 0) of an image I is denoted:

$$M_{pq}=\int_R^2 x^p y^q \; I(x,y)dx\, dy \qquad (2)$$

The central moment of order (p + q) of the function I(x, y) is given by:

$$V_{pq}=\int_r^2 x^p y^q \; I(x+x_0,y+y_0)dx\, dy \qquad (3)$$

The normalized moment is defined as follow:

$$\mu_{p,q} = \frac{v_{p,q}}{v_{0,0}^{\gamma}} \qquad (4)$$

Where:
γ =1+(p+q)/2

$$\phi_1=\mu_{2,0}+\mu_{0,2}$$
$$\phi_2=(\mu_{2,0}+\mu_{0,2})^2+4\mu^2_{1,1}$$
$$\phi_3=(\mu_{3,0}-3\mu_{1,2})^2+(3\mu_{2,1}+\mu_{0,3})^2 \qquad (5)$$

These moments are invariants under translation, rotation and scaling. The moments of Hu are calculated via the normalized moments and they remain invariant under translation, rotation or scaling.

2. 3 Geodesic Descriptors

Geodesic descriptors that are invariant under geodesic isometries, and quasi-invariant to shape articulations and bendings.

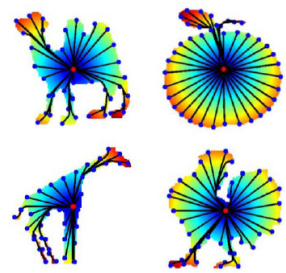

Fig.1. Example of geodesic distance between the center and boundary points.

We first define a reference point by Poisson equation i.e ,the center of the Object ,which remains almost invariant under rigid transform. Then, the geodesic distance from shape boundary to reference point(Center point) is calculated. Geodesic distance shows distinct advantage over the Euclid distance due to its robustness under rigid transformation. Geodesic descriptor can achieve better matching precision. Fig 1 give an example of geodesic distance and between the center and boundary points. Geodesic Descriptors are the vector composed by the different geodesic distances between the center and boundary points.

As shown in Fig 2, Input image is taken from the dataset. Then the nine Zernike and three Hu moments are calculated from three level of gray RGB. Geodesic descriptor is applied on binary image of the color input image and first twenty distances are calculated. Hence the total feature vector length used in the proposed ORS is 56 (27 zernike + 9 Hu + 20 Geodesic).

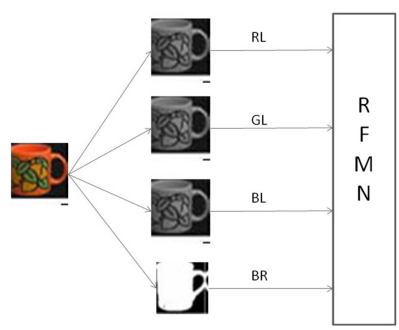

Fig. 2. Zernike, Hu moments and Geodesic descriptors in series with RFMN

RL: Zernike & Hu moment of the Red level of gray.
GL: Zernike & Hu moment of the Green level of gray.
BL: Zernike & Hu moment of the Blue level of gray.
BR: Geodesic descriptors on binary image.

3. Classification

Pattern classification is the key element for extracting the underlying structure of the data. Classifier is used to determine the input output relationship. Fuzzy min max classification neural network is supervised machine learning method that has been proposed by Simpson in

1992. It can be used for classification purposes.A fuzzy set hyperbox is used, a fuzzy set hyperbox is an n-dimensional convex box defined by min point (V) and max point (W) with a corresponding membership functions.

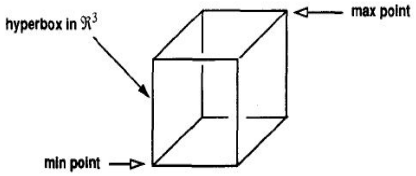

Fig 3. Hyperbox with min and max point

Hyperbox is as shown in Fig 3..The min points are stored in matrix V and the max points are stored in matrix W. Hyperboxes are created and adjusted during the training phase, and in the test phase these hyperboxes and their membership function are used to assign an input sample to a class and classify them. There are several properties that a pattern classifier should possess. They are on-line adaption, non-linear separability, overlapping classes, training time, soft and hard decision, verification and validation, tuning parameters, non-parametric classification. Fuzzy min max neural network is composed of three different layers namely, input node (FA), hyperbox node (FB) and class node (FC). These layers are as shown in the below Fig 4.

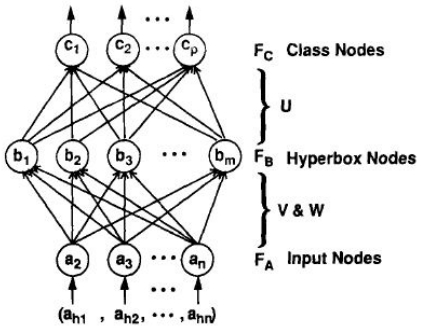

Fig 4. The three layer neural network

All the hyperboxes are created and adjusted during the training phase. For each the sample Ah is checked, if this sample is situated inside any of hyperboxes or not, if there is no such hyperbox then the below described three step process has been executed.

1. Expansion: Identify the hyperbox that can expand and expand it. If an expandable hyperbox cannot fount then add a new hyperbox for that class.
2. Overlap Test: Determine if any overlap exists between hyperboxes that belongs to different classes.
3. Contraction: If overlap exists between hyperboxes that belongs to the different classes then eliminate the overlap by minimally adjusting the hyperboxes.

4. General Fuzzy Min Max Neural Network

A general fuzzy min-max (GFMM) neural network is a generalization and extension of the fuzzy min-max clustering and classification algorithms. The GFMM method combines the supervised and unsupervised learning within a single training algorithm. The fusion of clustering and classification resulted in an algorithm that can be used as pure clustering, pure classification, or hybrid clustering classification.

There are two main training strategies for pattern classification procedures: supervised and unsupervised learning. In supervised learning, often referred to as a pattern classification problem, class labels are provided with input patterns and the decision boundary between classes that minimizes misclassification is sought. In unsupervised learning, often referred to as a cluster analysis problem, the training pattern data is unlabeled and one has to deal with the task of splitting a set of patterns into a number of more or less homogenous clusters with respect to a suitable similarity measure. Patterns which are similar are allocated to the same cluster, while the patterns which differ significantly are put in different clusters. Regardless of the clustering method the final result is always a partition of patterns in disconnected or overlapped clusters[4].

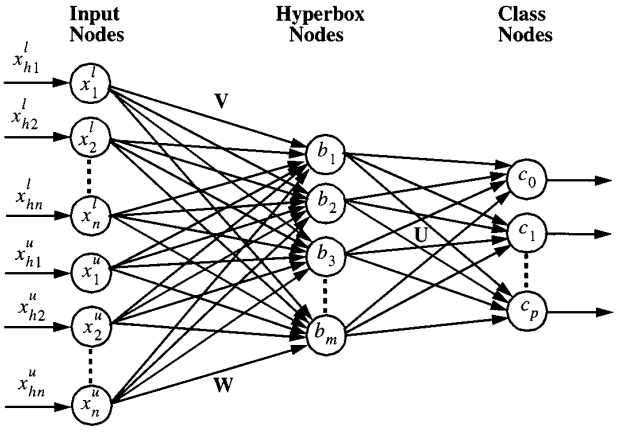

Fig.5 The three-layer neural network that implements the GFMM clustering/classification algorithm.

The neural network that implements the GFMM clustering/ classification algorithm is shown in Fig. 5. It is a three-layer feedforward neural network. The input layer has processing elements. Each second-layer node represents a hyperbox fuzzy set where the connections of the first and second layers are the min-max points and the transfer function is the hyperbox membership function. The min points matrix is applied to the first n input nodes representing the vector of lower bounds of the input pattern and the max points matrix is applied to the other input nodes representing the vector of upper

bounds of the input pattern. The connections between the second and third-layer nodes are binary values. They are stored in the matrix U.

GFMN Algorithm

1) Initialization:
When a new hyperbox needs to be created its min V_j and max W_j points are initialized in such a way that the hyperbox adjusting process used in the expansion part of the learning algorithm can be automatically used. The V_j and W_j are set initially to

$$V_j = 0 \text{ and } W_j = 0 \qquad (6)$$

This initialization means that when the th hyperbox is adjusted for the first time using the input pattern $X_h=[X_h^l X_h^u]$ the min

$$V_j = X_h^l \text{ and } W_j = X_h^u \qquad (7)$$

and max points of this hyperbox would be identical to the input pattern.

2) Hyperbox Expansion:
When the hth input pattern is presented, the hyperbox B_j with the highest degree of membership and allowing expansion (if needed) is found. The expansion criterion, that has to be met before the hyperbox B_j can expand to include the input X_h

3) Hyperbox Overlap Test:
If the hyperbox B_j , expanded in the last expansion step, belongs to one of the existing classes then test for the overlap only with the hyperboxes not being part of the same class as B_j. This allows to overlap the hyperboxes belonging to the same class.

4) Hyperbox Contraction:
Hyperbox overlap causes ambiguity and creates possibility of one pattern fully belonging to two or more different clusters/classes, a contraction process is utilized to eliminate any undesired hyperbox overlaps.

In summary, the General fuzzy min-max neural network learning algorithm is a four-step process consisting of Initialization, Expansion, Overlap Test, and Contraction with the last three steps repeated for each training input pattern.

5. Conclusion

Simple moments are not orthogonal, thus it is difficult to reconstruct the image from them. To overcome this drawback and to get the distribution of gray levels in the color image combination of Zernike and Hu moments is used. Zernike moments are used for less information redundancy. It allow a better description of objects than simple moments. These moments are joined together with Geodesic descriptors to get boundary of the object. Recognition section consists of a General Fuzzy Min-Max Neural Network architecture.

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