Role of Hyperbox Classifiers for Color Recognition

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***Abstract*—In this research work, we explore the application of hyperbox classifier for the color recognition problem. Color is an important cue in computer vision and its recognition plays an important role in many vision tasks. Color boundary separation has earlier been performed by use of traditional classifiers like SVM, Naive Bayes etc. However the intrinsics of color are very delicate and their separation using the traditional classifiers have not achieved acceptable accuracy. In this research work we show the applicability of hyperbox classifiers for color recognition task and perform comparative analysis with traditional classifiers to validate that hyperbox classifiers achieve better color boundary separation results.**

I. Introduction

Hyperbox classifers have been investigated for many pattern classifcation problems. These classifers utilize fuzzy sets as pattern classes [1]. A hyperbox is completely defned by its min point and its max point, and a membership function is defned with respect to these hyperbox min-max points. The hyperbox membership function gives a degree of membership to each pattern for all existing classes. The pattern is assigned to a class with a highest membership value. Amongst Hyperbox classifers Fuzzy Min-Max Neural Network (FMNN) proposed by Simpson [2] and Fuzzy Min-Max Neural Network with Compensated Neuron (FMCN) proposed by Nandedkar and Biswas [3] have significant impact. FMNN learns the underlying structure of data by creating a hyperboxes for each class. The hyperbox size is controlled by a design parameter called expansion coefficient (Θ). In case of overlap amongst the hyperboxes of different classes, a contraction process is used as shown in Fig.1. The advantage of such a topology is that, online learning is possible in a single pass there by avoiding retraining. However, there are many disadvatages like dependence of network complexity on the expansion coefficient (Θ), order of presenting the patterns as well as classification error caused by the contraction process. This drawback was overcome by Nandedkar and Biswas [3] by creating additional hyperboxes as shown in Fig.2. namely Compensatory Neurons to handle overlap which was inspired from human reflex mechanism and the architecture is called Fuzzy Min-Max Neural Network with Compensatory Neurons (FMCN). Fig.2. shows a Overlap Compensatory Neuron (OCN) which mitigates the classicification error shown in the Fig.1. It overcomes most of the drawbacks and achieves better results in comparison to FMNN and GFMNN proposed by Gabrys and Bergiela [4]. **Algorithm 1** gives the FMCN learning process. However, datasets on which these experiments were carried out like

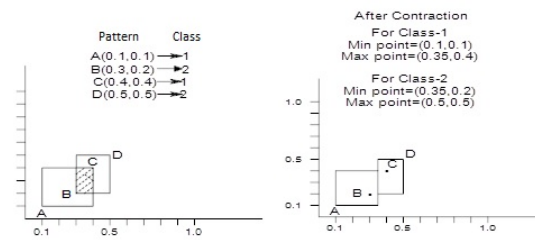

Fig. 1. Overlap removing process of FMNN. After contraction point B is classified as class 1 and pont C is classified as Class 2 which causes a classification error.

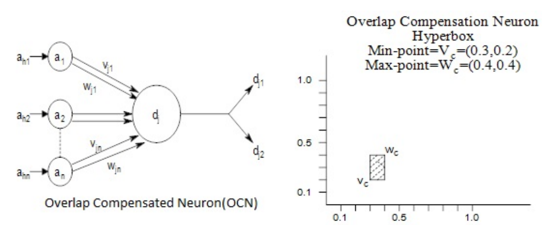

Fig. 2. FMCN creating a Overlap Compensatory Neuron(OCN) to handle Overlap.

Iris, Wine, Ionosphere, Thyroid as well as Synthetic data did not offer enough challenges for such a powerful classifier with capabilities of online learning, single pass training and accurate classification capabilities. Motivated by this, in our research work we are exploring the applicability of Hyperbox Classifiers to a practical and fundamental problems in computer vision namely Color Boundary Separation.

II. Color Recognition Problem

Color is an important cue in human perception and faces many challenges for its recognition. Few among the challenges are color naming (i.e what is Red, Pink and Pink-red etc), presence of shadows and specularities, effect of unknown acquisition system etc. Since color is an integral part of most computer vision systems like autonomous navigation, object detection, tracking and other surveillance applications, a deeper utilization of color cues would simplify most vision tasks. Towards this goal our research is focused on the following objectives:

1) Studying different color models and color spaces for color boundary separation.

Algorithm 1 FMCN Learning Algorithm

1: Hyperbox creation or expansion.
  1) Find a suitable hyperbox b_j that can accommodate the training sample A_h or
  2) Create a new hyperbox for the applied training sample.

2: Creation of Compensatory Neurons (overlap test). Add OCN and CCN to the network using the following tests for the hyperbox expanded in Step 1).
  - **A. Isolation test:** Check whether hyperbox b_j expanded in previous step is isolated or not. If this test is negative, conduct the containment test.
  - **B. Containment test**: Tests whether the hyperbox b_j is contained in or contains any other hyperbox belonging to different class.

3: **If** test is positive, create a **CCN**

4: **Else** create an **OCN**

2) Investigating role of hyperbox classifiers for color boundary separation.
3) Design a vision system with a color camera capable of autonomous navigation by utilizing color cues.

III. Proposed Method

The HSV color space is used for our study as it represents decorrelation of the color data by having Hue (H) and Saturation (S) describing the chroma and Value (V) describing the Intensity (brightness). The Hue (H) of a color refers to which color it is more likely to resemble and is expressed in angle form which ranges from 0° to 360° representing hues of red (starts at 0°), yellow (starts at 60°), green (starts at 120°), cyan (starts at 180°), blue (starts at 240°), and magenta (starts at 300°) as shown marked in the hexagon in Fig.3. The Saturation (S) of a color describes the amount of gray (0 to 100%) in the color and is the distance from center of the hexagon. Value (Brightness) works in conjunction with saturation and describes the brightness or intensity of the color from 0 to 100%. It describes how dark the color is i.e. a value of 0 is black, with increasing lightness moving away from black. Fig.3. shows the hexagon which is widely utilized to represent the HSV color model.

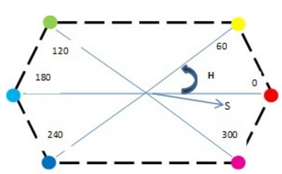

Fig. 3. Color Hexagon of HSV Space

Classifier	% misclassification
Naive Bayes	46
Logistic Regression	46
SVM	46.6
Hyperbox	33.3

Fig. 4. Results on Pink-Pink Red-Red data

Classifier	% misclassification
Naive Bayes	36
Logistic Regression	27
SVM	40
Hyperbox	25

Fig. 5. Results on Yellow-Yellow Green-Green data

Classifier	% misclassification
Naive Bayes	22.2
Logistic Regression	23
SVM	66
Hyperbox	16.67

Fig. 6. Results on Cyan-Cyan Blue-Blue data

As observed from the Hexagon, the three features H, S and V can separate out the colors shown at the vertex of the hexagon i.e red, yellow, green, cyan, blue and magenta. However, when we consider the color space between two adjacent vertices there are a host of other colors which are possible for example between red and yellow which have a separation of 60° on terms of hue angle, one can have many variants of the colors like pink, light pink, dark pink, light yellow, dark yellow, orange etc. depending on the hue,saturation and brightness values. Such a classification task is difficult since there is a overlap between the colors. To solve this problem traditional classifiers both linear and non-linear face challenges since they have been designed without analysing the intrinsics of the data. Here we have tried using the hyperbox classifier namely FMCN and our results show that hyperbox classifiers are typically suited for such problems as they achieve lower classification errors in comparison to the traditional classifiers due to overlap compensation being taken into account by hyperbox classifiers.

IV. Results

Dataset is prepared by taking Hue, Saturation, Value and Luminance (L) creating a table containing numerical values corresponding to the colors to be classified. For example a sample of Pink color has H=350°, S=100, V=88 and L=84. Pink Red has H=348°, S=83, V=47 and L=49. Red has H=0°, S=100, V=50 and L=54. 20 instances for each color is prepared and fed to FMCN classifier. Number of experiments conducted were 200 for each dataset of adjacent colors. Fig.4, Fig.5, Fig.6 shows the preliminary results that have been obtained and its comparative analysis with traditional classifiers on various datasets.

V. Conclusions

We explored the application of Hyperbox classifiers to color recognition problem for situations of overlapped colors which do not have precise boundary between them. It is observed that the proposed application of hyperbox classifiers outperforms the traditional classifiers for overlapping colors. We seek an opportunity to present our work in the doctoral symposium as we have demonstrative results and it will help us getting a feedback on our current work as well as we may get new ideas especially in the feature extraction pipeline.

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