An Interactive Shadow Detection and Removal Tool using Granular Reflex Fuzzy Min-Max Neural Network

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Abstract— **This work proposes an interactive tool to detect and remove shadows from colour images. The proposed method uses a Granular Reflex Fuzzy Min-Max Neural Network (GrRFMN) as a shadow classifier. GrRFMN is capable to process granules of data i.e. group of pixels in the form of hyperboxes. Granular data classification and clustering techniques are up-coming and are finding importance in the field of computer vision. Shadow detection and removal is an interesting and a difficult image enhancement problem. In this work, a novel granule based approach for colour image enhancement is proposed. During the training phase, GrRFMN learns shadow and non-shadow regions through an interaction with the user. A trained GrRFMN is then used to compute fuzzy memberships of image granules in the region of interest to shadow and non-shadow regions. A post processing of pixels based on the fuzzy memberships is then carried out to remove the shadow. As GrRFMN is trainable on-line in a single pass through data, the proposed method is fast enough to interact with the user.**

Index Terms— **Granular computing, Granular Fuzzy Neural Network, shadow detection and removal.**

I. Introduction

HUMAN vision system is very immune to shadows. We do not find any difficulty in recognizing, tracking objects even with shadows. But in the case of computer vision, shadows create problems and reduce the reliability of the system. In addition, shadows are also responsible to degrade the image quality. Therefore, shadow removal is an important pre-processing step for computer vision and image enhancement algorithms [1]. It is noted that standard approaches, software, and evaluation datasets exist for a wide range of important vision tasks, from edge detection to face recognition; there has been comparatively little work on shadows during last four decades [2].

The proposed methods in the literature can be classified into two categories, (1) automatic shadow detection, and (2) shadow detection with user interaction. The automatic shadow detection mainly takes the help of multiple images for identifying shadows i.e. prior knowledge about shadow is necessary. Such approaches that use multiple images [3], time-lapse image sequences [4, 5] are available in the literature. An explicit focus on the shadows cast by objects onto the ground plane can be found in [2]. This approach consists of three stages. First, it computes edges in an image, then it extracts features around the edges, and finally these features are used with a trained decision tree classier to detect whether an edge is shadow or not. Training of this classier required in total 170 selected images from LabelMe [6], Flickr, and the dataset introduced in [7], with the only conditions being that the ground must be visible, and there must be shadows. It may be noted that training of such classifier in the above method is a crucial and a difficult task.

In the second approach such as [1, 8, 9] attempt is made to remove shadow from given single image. To acquire knowledge about the shadow in the image, a user interaction is needed and is found helpful to refine the output in the intended manner. Wu and Tang's method [8, 9] remove shadows when given user-specified shadow and non-shadow regions. It adopts a continuous optimization method that requires lot of iterations to converge. As a result, it is not straightforward to use their method in an interactive and incremental manner [1]. The approach in [1] solves this problem by formulating the problem in an MRF framework. It is observed that this method requires more number of strokes for a complicated image.

This work proposes an application of image granules for shadow detection and removal. Granulation of information is an inherent and omnipresent activity of human beings carried out with intent of better understanding of the problem [10]. In fact, information granulation supports conversion of clouds of numeric data into more tangible information granules. The concept of information granulation within the frame work of fuzzy set theory was formalized by Zadeh in his pioneering work [11]. He pointed out that humans mostly employ words in computing and reasoning; and information granulation is a part of human cognition [11]. This paper is a small step towards implementation of this concept for shadow detection and removal in colour images. To implement the concept of data granulation, this work uses Granular Reflex Fuzzy Min-Max Neural Network (GrRFMN) proposed by Nandedkar and Biswas in [12].

The major advantage of this work is that it incorporates user's knowledge for shadow removal and works at an interactive speed. The rest paper is organized as follows. Section 2 briefly discusses GrRFMN architecture and its learning. Section 3 elaborates the proposed method. Section 4 presents experimental results and conclusions.

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II. GrRFMN For Classification

A. *Review Stage*

The detection of shadow and non-shadow region in the proposed method is carried out using GrRFMN (Figure 1). GrRFMN learns different classes by aggregating hyperbox fuzzy sets [12].

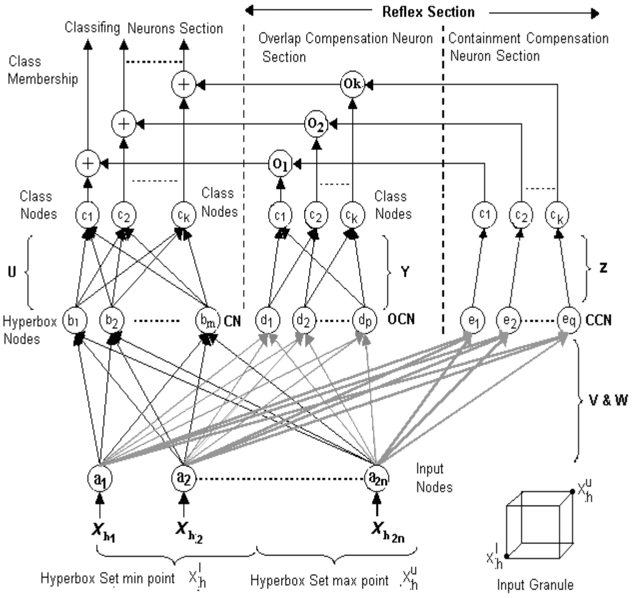

Fig 1. GrRFMN Architecture

A hyperbox is a simple geometrical object which can be defined by stating its min and max points (e.g. is shown in Figure 1). The architecture of GrRFMN is divided into three sections, 1) Classifying neurons (CNs), 2) Overlap compensation neurons (OCNs) and 3) Containment compensation neurons (CCNs). CNs deal with class regions and OCNs and CCNs tackle overlap regions amongst classes. The Advantage of GrRFMN is that it is capable to handle data granules of different sizes efficiently, *on-line* in a single pass through data.

Here it is assumed that all input features are scaled in the range [0-1]. An n-dimensional input granule is represented by, $X_h=[X_h^u,X_h^l]$ where X_h^l, $X_h^u=(x_{h1},x_{h2,....,}x_{hn})$ are min and max point vectors of the input granule respectively. A point data is a special case with $X_h^l=X_h^u$. Appending min and max point vectors, the input is connected to the nodes x_{h1}-x_{h2n}. Training algorithm for GrRFMN and other details regarding activation functions are detailed in [12]. The output of this network is fuzzy membership of input vector to different classes.

III. Granular Shadow Detection and Removal System

Shadow detection and removal (SDR) from a colour image is an important issue in the field of computer vision as well as in commercial photography. Here the problem of SDR is solved using granular computing. This method utilizes capability of GrRFMN to acquire knowledge through granules of data. The proposed SDR system is shown in Figure 2.

The proposed SDR system can be divided into six steps: 1) User interaction to acquire information about shadow and non-shadow regions, 2) extract features of shadow and non-shadow regions, 3) Train GrRFMN using these features, 4) find out fuzzy membership of pixels in the Region of Interest (ROI) indicated by user to shadow and non-shadow regions, 5) use extracted properties of non-shadow region to correct pixels in shadow region, and 6) present output to user for further strokes (interaction) till complete shadow is removed. The details of each step are as follows:

User interaction to acquire information about shadow and non-shadow regions: In this step a user interact with the system in form of strokes and to point out shadow and non-shadow regions and ROI from which shadow is required to be removed. The system uses RGB colour space to represent a colour image.

Feature extraction of shadow and non-shadow regions: Image samples of shadow and non-shadow region provided by the user in the previous step are sub-divided into grids of size (k x k) and granules are produced to represent each grid in the form of hyperboxes which is represented by simply stating its min and max vertices. Thus, a hyperbox is computed by finding min-max values of the pixels in that grid, i.e.

$$V=[R_{min}, G_{min}, B_{min}]\ ,\quad W=[R_{max}, G_{max}, B_{max}] \qquad (1)$$

Along with this information, a mean value of the grid for the three planes is also computed and added to the min-max vector as, i.e.

$$V=[R_{min}, G_{min}, B_{min,} R_{mean}, G_{mean}, B_{mean}]\ ,\quad W=[R_{max}, G_{max}, B_{max}, R_{mean}, G_{mean}, B_{mean}] \qquad (2)$$

Such granules are used to train GrRFMN for shadow and non-shadow region.

To classify the given ROI, around each pixel a neighborhood of size (n x n) is considered and granules are formed using Eq. 2. These granules are then fed to GrRFMN for computing membership of pixels to shadow (μ_S) and non-shadow classes (μ_{NS}).

For the improvement of pixels in shadow region, a correction factor is computed based on the difference between mean RGB values of non-shadow and shadow regions as,

$$\Delta R=R_{NS\_mean} - R_{S\_mean}$$
$$\Delta G=G_{NS\_mean} - G_{S\_mean}$$
$$\Delta B=B_{NS\_mean} - B_{S\_mean} \qquad (3)$$

where NS- non-Shadow, S-Shadow

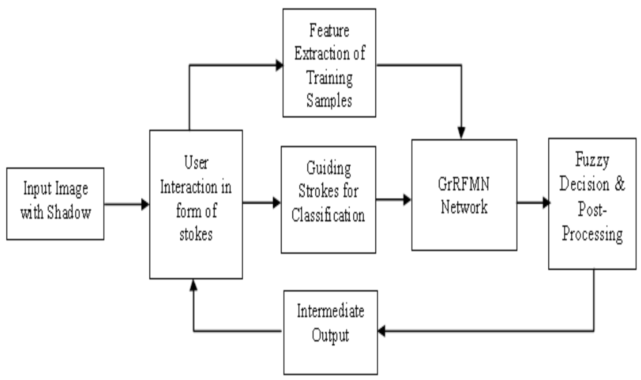

Fig 2. Proposed SDR System

Each pixel P(R,G,B) in ROI is corrected if ($\mu_{PS} > 0$) and

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($\mu_{PNS} < 0.7$) and ($I_{mean\_NS} > I_P$); where I_{mean_NS} is mean intensity of non-shadow region and I_P is the intensity of the pixel. They are calculated as:

$$I_{mean\_NS} = (R_{NS\_mean} + G_{NS\_mean} + B_{NS\_mean})/3;$$
$$Ip = (R_p + G_p + B_p)/3 \qquad (4)$$

The correction to a pixel is done as follows:

$$R_{correct} = (R + \Delta R),$$
$$G_{correct} = (G + \Delta G),$$
$$B_{correct} = (B + \Delta B) \qquad (5)$$

Once correction of ROI is done, the enhanced image is presented to the user. User can give a new ROI for shadow removal. The above steps (4-6) are repeated till the user interacts with the system for corrections. The following section demonstrates detailed procedure and results for the proposed system.

IV. Experimental Results

Here aim is to 1) illustrate the system working, and 2) test the proposed system on some real life images consisting of shadows.

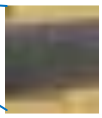
A. System working:

Initially an image is presented to the system (Figure 3(a)). User interacts with the figure to point out the shadow and non-shadow regions required to train GRRFMN (Figure 3(b-c)). After this step, the shadow and non-shadow regions are granulized as per Eq. 2 for a (3x3) grid size. These granules are used to train GrRFMN. The expansion coefficient (θ) of GrRFMN is 0.15. After completion of the training, pixels of ROI (Figure 3(d)) are enhanced using a (3x3) neighborhood as per steps 4 and 5. The user further interacts and may give next ROI for SDR. In this way, user interacts till complete removal of shadow as shown in Figure 3(e) is obtained. Results on few other images are shown in Figure 4.


(a)


(b)


(c)


(d)


(e)

Fig 3. Shadow removal using proposed system.


(a)


(b)


(c)

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(d)

(e)

V. Conclusion

An interactive tool for shadow detection and removal is proposed. Granular computing is a powerful tool and is found suitable in shadow detection and removal. It is observed that due to on-line learning capability of GrRFMN, the system operates at an interactive speed. In future this method may be extended for unsupervised mode of operation.

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(f)

Fig 4, (a-f). Results on other images.

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