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Wavelet-Based Color Image Segmentation using Self-Organizing Map Neural Network

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Abstract. Image segmentation has been and is likely to be an important component of the content-based image acquisition and retrieval systems. In this paper, we have proposed an image segmentation technique that uses Kohonen's self-organizing map (SOM) neural network for segmentation of color images. It has been observed that, SOM training if performed on the wavelet-transformed image, not only reduces the training time of the SOM but also make more compact segments. Our experiments have shown better results produced by our proposed technique than the previous approaches in practice.

Keywords: Color images segmentation, self-organizing map, neural networks, and wavelets

1. Introduction

Image segmentation is the process of dividing an image into non-overlapping regions based on perceptual information. Applications of image segmentation include Content-Based Image Retrieval (CBIR), object recognition, matching of stereo pairs for 3-D reconstruction, navigation and artificial expert medical diagnosis.

The Content-based image retrieval systems search the repository of images based on features of the digital images rather than labels. Major features include texture, color, object structure or any other selective information that can be extracted from the image itself. According to [1] applications of CBIR systems include, expert medical systems, art collections, photographic archives, retail catalogs, medical diagnosis, crime prevention, military use, intellectual property, architectural and engineering design, geographical information and remote sensing systems. The main bottleneck of CBIR systems is the inability to process high dimensional data. In a color image, where 8 bits for the representation of each color component (R, G, and B) are used, there are 16 million possible colors in that image. We need to decrease these dimensions in order to get meaningful results from the CBIR systems. Image segmentation is a method that helps decrease the number of colors required to represent an image by dividing an image into regions and by assigning each region with the same color. In the past, a number of classical methods e.g. edge-detection [2]-[4], region growing, histogram-based [5]-[7], and graph partitioning were used for image segmentation.

The Human Visual System (HVS) has tremendous ability to segment and extract information from the images. This remarkable ability of the HVS is obviously a great motivation for anyone to apply Artificial Neural Networks in field of image segmentation. ANNs have many advantages over the other methods; such as, massive parallelism, fault-tolerance to missing, noisy or outlier attributes, better adaptability on different datasets and optimal or near optimal performance [8]. For image segmentation, mainly three types of ANNs are used: supervised, unsupervised, and a combination of the both. When segmenting color images, ANNs with unsupervised learning are preferred over the others. Because the former needs training samples for training and in some cases, training data might not be available at all.

Self-Organizing Map (SOM) Neural Network is a type of unsupervised ANN. It has two major characteristics, (i) it reduces the dimensions of data (ii) it groups together similar samples. These two characteristics of SOM help us in segmenting the regions of the image that has similar features, and it reduces the number of colors required to represent an image.

In the proposed method, a SOM is trained on approximation co-efficients of the wavelet transformed image. The main contributions of the proposed method includes:

- Works equally well for non-noisy as well as noisy images since approximation co-efficients of the wavelet transformed image are used.
- Proposed technique is computationally less expensive than [10] technique, since training is performed using only approximation co-efficients.

2. Problem Definition

Image segmentation is the problem of dividing an image into disjoint sets, such that the union of these sets makeup the complete image. An image when divided in K segments, each segment must satisfy 1. The value of K in unsupervised learning is determined at run-time or we can control K by implying maximum limit on K.

$$I = \bigcap_{k=1}^{K} s_k \quad where \;\; s_i \bigcap s_j = \phi, \, for \; i \neq j \qquad (1)$$

A SOM is a two dimensional lattice of neurons. Each neuron has a weight vector associated with it. The weight vector is composed of three components, each representing Red, Green and Blue component of color. SOM can be used to reduce the representative colors of the image. It selects the dominant colors and replaces closely related colors by dominant colors. Fig. 2 is the histogram of the 'lena' image before segmentation and fig. 3 is the histogram after segmentation using SOM. From the comparison of the two histograms, we can easily infer that SOM has reduced the number of colors required to show the image without significant degradation in the quality of the image.

Nowadays, SOM is being widely used in image segmentation literature. In [9] authors propose a SOM-based technique to segment brain MRI images. They use wavelet-transformed images to train SOM. In [10], they use a two-stage SOM to segment medical images.

3. Proposed Method

Each component of the input image, Red, Green and Blue is separated. For each component, we take the wavelet transform upto 2nd level. Then we combine the 2nd level approximation co-efficients of each component to make a color image. This wavelet-transformed image is of 1/8 of the size of original image. Then we use wavelet transformed image for the training of randomly initialized SOM. After training the SOM, we use it to segment the original image. In the forthcoming sections this process is explained in detail.

3.1 Wavelets. Wavelets not only give frequencies of the image but also when these frequencies occur. Wavelets also help us perform multi-resolution analysis of the images. In [9] wavelet transformed images were used for SOM training. SOM is very computationally expensive network. If we train the network of size 16x16 on a 128x128 color image, it will require 12 million comparisons to do the job. This makes SOM less effective in real-time applications. To decrease the number of computations, two level wavelet transform of the input image is taken using 'haar wavelets'. The approximation coefficients are then linearly scaled between 0-255. Then SOM is trained on the scaled coefficients of the wavelet transformed image. After training, we use SOM to segment the original full sized image. This makes our technique computationally economical. An image upto 2nd level wavelet transform is shown in the fig. 6.

3.2 SOM Initialization. Mainly SOM has two types of Initializations. One is linear and the other is random. We have chosen random initialization for SOM because with random initialization our cluster (segment) centers have good chance of searching the maximum color segmentation space available. In Fig. 1 a randomly initialized SOM of size 16x16 is shown. Each color component is represented using 8-bits (24-bits per pixel).

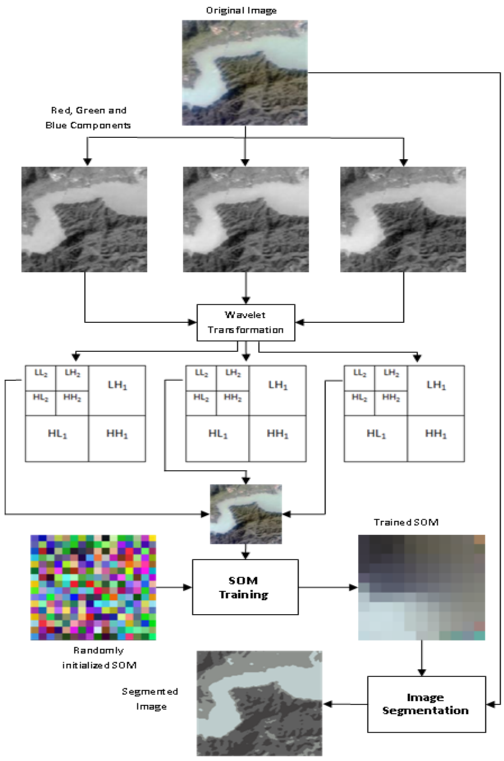

Figure 1: Flow diagram of segmentation process using SOM and wavelets

3.3 SOM Training. For each pixel '*V*' of the image, the Best Matching Unit (BMU) is selected in the SOM. BMU has the least dissimilarity with the input pixel from the rest of the SOM. The weight associated with this neuron is updated according to 2. New weight W_i of the neuron *i* at iteration $t+1$ is calculated. Here L_0 is the initial learning rate, σ_0 is the initial neighborhood size and η is a time constant. For each neuron within the neighborhood of *i*, $\delta_i(t)$ is calculated. Then the weight vector of all neurons within the neighborhood σ(t), at time t, is updated using (2). Neurons nearer to the BMU becomes more alike the BMU then those neurons farther but within the neighborhood. After all the pixels of the image are presented to the SOM then t is incremented by 1. This process is repeated unless t reaches t_{max}. SOM after training on the 'river' image look like the fig. 4.

3.4 Segmentation. After training the randomly initialized SOM using wavelet transformed image. For each pixel in the image, a BMU is found in the SOM. Then the value of the image pixel is replaced by the BMU from SOM. This results in the final segmented image. For SOM training, we use different sizes of lattices i.e.6x6, 8x8 and 16x16 SOM lattice. We train SOM for maximum 15 epochs. Initial learning rate was tested between 0.1 and 0.5, and initial radius started from 2, 3 and 4 for 6, 8 and 16 lattice sizes respectively. The best results were obtained with 16x16 SOM with radius 4 and learning rate 0.5

4. Results. From the results on some of the standard images of image processing, we can easily conclude that our method is better than previous attempts. Fig. 6 is a fruit image and fig. 7 are the segmentation results of our technique and in fig. 8 are the results of [11]. In [11] they have used Spatial FCM with back propagation neural network for color image segmentation. Our approach have preserved the finer details of the image and correct segments are formed. Fig. 9 is a hand and ring image. Fig. 10 is segmented using our method using 8x8 SOM. In our method, the original colors of the image are preserved even after segmentation but with [11] in fig. 11 the colors as well as the image details are lost. Fig. 13 is the result of segmentation of fig. 12. Fig. 14 is segmented with [11]. The technique [11] has wrongly classified grass portion on the bank of the river while in SOM results, water, grass and rocks are preserved. All the results are obtained using 16x16 SOM, or other size lattices, where exclusively mentioned.

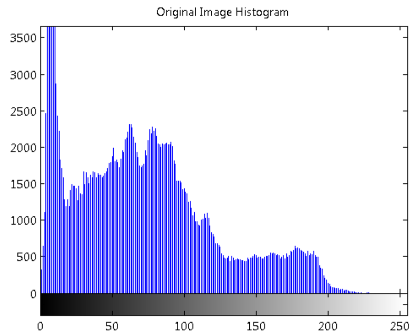

Figure 2: Histogram of original Lena image

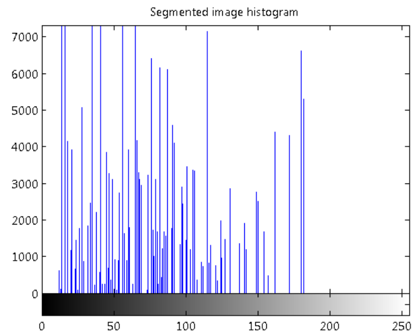

Figure 3: Histogram of segmented Lena image using SOM

$$W_i(t+1) = W_i(t) + \delta_i(t) \cdot L(t) \cdot (V(t) - W_i(t)) \qquad (2)$$

Where

$$L(t) = L_0 \exp\left(-\frac{t}{\eta}\right)$$

$$\sigma(t) = \sigma_0 \exp\left(-\frac{t}{\eta}\right)$$

$$\delta_i(t) = \exp\left(-\frac{\|i - BMU\|^2}{2\sigma^2(t)}\right)$$

$$\eta = \frac{t_{\max}}{\log(\sigma(t))}$$

Figure 4: Trained SOM having similar colors near to each other and dissimilar apart

Figure 5: wavelet transform of lena image upto 2nd level

5. Conclusion

Experiments show that the use of wavelets in the segmentation of color images using SOM neural network had outclassed previous approaches.

6. References

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Figure 6: Original fruits picture with salt & pepper noise


Figure 7: Segmented using SOM and wavelets


Figure 8: Segmented using Spatial-FCM, [11]


Figure 9: Noisy hand and ring picture


Figure 10: Segmented using 8x8 SOM and wavelet transform


Figure 11: Segmented using Spatial-FCM [11]


Figure 12: Original river picture

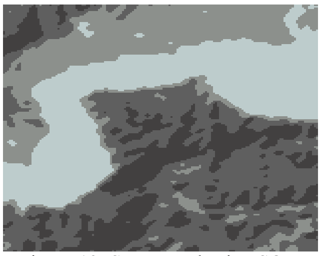
Figure 13: Segmented using SOM


Figure 14: River image segmented using Spatial FCM [11]