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IMAGE SEGMENTATION USING SOM NEURAL NETWORK WITH DISCRETE COSINE TRANSFORM

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Abstract

Image Segmentation has wide importance in various applications of image analysis like medical diagnosis, pattern recognition, object detection etc. SOM is used to segment images into regions that have similar properties. The Self Organizing Maps (SOM) by Kohenen is an efficient unsupervised Artificial Neural Network method. This paper focuses on improving the performance of SOM by feeding the input that is preprocessed. In this paper the image segmentation is enhanced by using an image compression technique called the Discrete Cosine Transform (DCT) which is implemented by Fast Fourier Transform (FFT) algorithm.

I. Introduction

The process of dividing an image into regions with similar attributes like color, intensity or texture is called image segmentation. An image is a matrix of pixels arranged in rows and columns. Segmentation is the process of partitioning the image into regions or sets of pixels to acquire information for analysis. There are many methods used for image segmentation like Histogram based methods, Edge detection based methods, model based methods, region growing methods, artificial neural network methods, statistical approaches etc. The clustering methods involve algorithms to group elements of similar properties into clusters.

Artificial neural networks are biologically inspired networks. In neural

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network clustering the active neurons reinforce the neighboring regions by suppressing the activities of all other neurons. Algorithms like SOM, ART, MLPs are used in various practical applications like medical diagnosis, segmentation of images, sonar/radar detection etc. The spatial data shows non-linear characteristics that make other conventional statistical methods inappropriate. The goal of this paper is to propose a method for an efficient image segmentation using SOM with DCT for image compression. The next section gives the proposed method and covers DCT for image compression and SOM clustering for image segmentation. The experimental observations and results are presented in the third section.

II. Proposed Method for Image Segmentation

For large sized image data training using SOM neural network becomes cumbersome as it involves huge computations and is computationally very expensive. It requires millions of comparisons to train the network on an ideal sized image [6]. This makes SOM network less efficient in real time application. Hence, a compression technique called the Discrete Cosine Transform is used so that it increases the efficiency. Once the image is compressed, the SOM is trained on the DCT images and then it is decompressed to produce the segmented images. The flow chart of the process is as shown in figure 1.

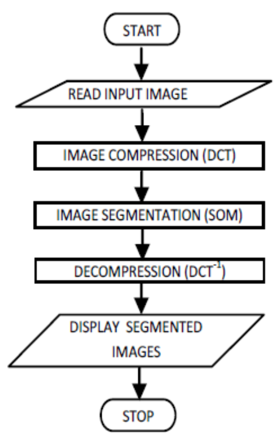

Figure 1. Flow chart for the proposed method.

A. Discrete Cosine Transforms

Discrete Cosine Transform is a Fourier transform where the data is compressed to one eighth of its size that can be used as a preprocessing technique in image segmentation. It is a lossless compression technique. DCT exploits the correlations of the pixel with its neighbors to predict the value of the pixel. The correlated data is transformed to uncorrelated coefficients thus reducing the information size of the pixel. DCT involves three blocks-Transformation block, quantiser block and the entropy encoder block. The transformation block de-correlates the image data by reducing the inter-pixel redundancy. The quantizer exploits the fact that the human eye cannot perceive some information in an image, which can be discarded. The entropy encoder reduces the number of bits with the previously acquired knowledge. The variants of DCT are DCT-1, DCT-2, DCT-3 and DCT-4, all of which are orthogonal transforms. DCT-2 and DCT-4 are applied in image processing [5]. The DCT-2 is implemented using Fast Fourier Transform (FFT) algorithm in this paper.

The major properties of DCT are [7] De-correlation - removes redundancy between neighboring pixels Energy compaction - packs the energy of the co-related image into the low frequency region. Therefore some of the high frequency contents can be discarded without significant quality degradation. Separability - the transformation takes place in two steps, row transform and then the column transform, thus decreases the complexity, and Orthogonality - the DCT basis functions are orthogonal ie., the inverse transform of a matrix is equal to its transpose.

The DCT-2 or 2D-DCT is given by

$$c(u, v) = \alpha(u)\alpha(u)\sum_{x=0}^{N-1}\sum_{Y=0}^{N-1} f(x, y)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2x+1)v}{2N}\right]$$

for $u, v = 1, 2, \ldots N-1,$ and

$$\alpha(u, v) = \begin{cases} \sqrt{\frac{1}{N}} for \ u = 0 \\ \sqrt{\frac{1}{N}} for \ u \neq 0. \end{cases}$$

The inverse transform is defined as

$$f(x, y) = \sum_{x=0}^{N-1}\sum_{Y=0}^{N-1} \alpha(u)\alpha(u)c(u, v)\cos\left[\frac{\pi(2x+1)u}{2N}\right]\cos\left[\frac{\pi(2x+1)v}{2N}\right]$$

for $x, y = 0, 1, 2, \dots N-1,$ The 2-D basis functions can be generated by multiplying the horizontally oriented 1-D functions with vertically oriented set of the same functions [8]. This function is called as the DC coefficient which is a constant.

B. Self Organizing Map

Kohenen's Self Organizing Map is a non parametric unsupervised learning neural network [2]. It is based on the two most important issues, weight adaptation and to preserve the topological properties of the neighboring nodes in the input space [3]. SOM includes two layers, the first one includes the input nodes and the second one represents the output nodes.

SOM finds a set of centroids also called reference vectors and then each pixel in the dataset is assigned to the centroid.

The basic SOM algorithm is as follows [4].

(1) Initialize the centroids.

(2) Repeat.

(3) Select the next object.

(4) Determine the closest centriod to the object.

(5) Update this centroid and the centroids that are close (specified neighborhood).

(6) Until the centroids do not change or the threshold is exceeded.

(7) Assign each object to its closest centroid and return the centroid and the clusters.

In the initialization step the initial centroids are chosen randomly. Now, in the competition step assign the next selected object to the closest centroid the Best Matching Unit (BMU) by using some distance metric like the city block distance or the Euclidean distance $d\{ij\} = \min \| x_i(t) - w_{ij}(t) \|$ which is used often. The input pixel has the least dissimilarity with the BMU. In the updating step only the neighbors are updated, they become more like the BMU than the neurons that are farther away. The change in the weight value is the difference between the input vector and the weight vector [2].

$$w_{ij}(t+1) = w_{ij}(t) + \eta(t)(x_i(t) - w_{ij}(t)).$$

Where w_{ij} is the i^{th} component of the weight vector to the node j, for j in the neighborhood is chosen so that it diminishes with time and it enforces the neighborhood effect. $\eta(t)$ is one of the two functions $\eta(t) = \alpha(t) \exp(dist(r_j, r_k)^2 / 2\sigma^2(t))$ which is the Gaussian function and $\eta(t) = \alpha(t)$ if $dist(r_j, r_k) \leq threshold$ and 0 otherwise. $\alpha(t)$ is the learning rate parameter, $0 < \alpha(t) < 1$, which monotonically decreases with time. The size of the neighborhood and the learning rate decreases, thus decreasing the adaptation rate with time. This causes the network to converge to a solution.

III. Experimental Observations

We have considered some of the examples for segmentation using the proposed method and found the results to be satisfactory. As the discrete cosine transform is lossless when compared to other transforms, it has increased the performance of SOM networks.

Figure 2. Test Images.

We can observe that the proposed method has given better results. 256X256 test images are taken as input shown in Figure 2. The DCT of the test images Lena and cameraman respectively are shown in Figure 3. The DCT operation on the images shows a very good energy compaction. These images exhibit low frequencies with low spatial content.

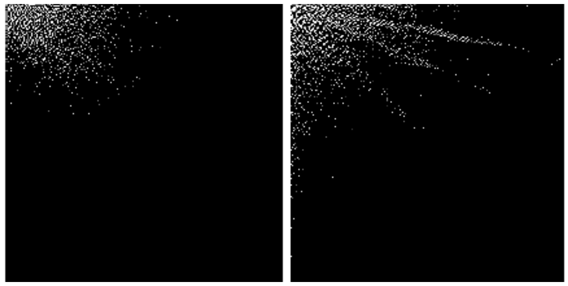

Figure 3. DCT of the Test Images.

Figure 4. Compressed Images.

Figure 4 shows the compressed images. Now the SOM network is trained using the DCT transformed images. The results of segmentation are obtained using a 16X16 SOM.

Figure 5. Segmented Images of Lena 4.

Figure 6. Segmented Images of Cameraman.

The segmented images are presented in figure 5 for the Lena image. Figure 6 shows the segmented images of Cameraman.

The proposed method was implemented using many test images. Table 1 presents the comparison of the proposed method and the existing one for the images of Lena, Cameraman and Mandrill using the generated quantization and topological errors.

Table 1. Error Comparisons.

Image	SOM		Proposed Method	
	q	t	q	t
Lena	0.3127	0.0315	0.4017	0.0097
Cameraman	0.5414	0.0432	0.5604	0.0112
Mandrill	0.4682	0.0193	0.5029	0.0034

The comparison is also shown for the same images in Table 2 based on the running time, in order to evaluate the performance of the proposed method with the existing method. We can clearly observe that the performance of the proposed method is doubled when DCT is used when compared with the existing method where SOM is used directly for segmentation. The above experiments were conducted for various sized images of 204X204, 1024X768 and 1240X1754 also.

Table 2. Running Time.

Images	SOM	Proposed Method
Lena	0.6923	0.3960

Cameraman	0.7458	0.4846
Mandrill	0.7021	0.3996

IV. Conclusion

Segmentation is a very important step in image analysis. The segmentation by SOM is efficient but at the cost of computation. Hence, DCT transform is used for compression as a preprocess technique so as to decrease the cost of computation and increase the performance of segmentation. The DCT is explained briefly and also the working of the SOM network is discussed. The proposed method was applied on images and was found to be better than applying SOM directly to the input images. A number of experiments were conducted on various sized images and the results were found to be highly encouraging.

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