Segmentation-based Image Compression Using Modified Competitive Network

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Received 21 Jan 2014; Accepted 13 May 2014; doi: 10.5405/jmbe.1806

Abstract

A method that combines watershed segmentation with a modified competitive learning network (MCLN) is proposed for segmentation-based image compression. The watershed algorithm is used to segment a gradient image into several closed regions via region growing. The mean intensity for each region is then calculated for subsequent classification. After classification, vector quantization with MCLN is applied to these regions with different compression rates according to the importance of the regions to simultaneously preserve important features and reduce the size of images. The results indicate that the proposed method is promising in comparison with the generalized Lloyd algorithm and the MCLN algorithm.

Keywords: Segmentation-based compression, Watershed segmentation, Modified competitive learning network (MCLN)

1. Introduction

The process of codebook design from training vectors is an important step in vector quantization (VQ) of the coding process in image compression. A number of VQ algorithms have been proposed [1-7]. The purpose of VQ is the creation of a codebook for which the average distortion caused by the approximation of a training vector and a codevector in the codebook is minimized. Codebook design can be considered as a clustering process in which the training vectors are classified into specific classes based on the minimization of the average distortion between the training vector and codebook vectors. Clustering algorithms then update the codebook at each iteration to improve the performance.

Neural-network-based techniques have been applied for VQ [8]. Unlike the generalized Lloyd algorithm (GLA), which is a batch method, methods based on competitive learning, an on-line approach, update the codebook whenever a training vector is presented. In VQ, the whole image is divided into n blocks and mapped onto a two-layer competitive learning network with each input representing a training vector and each output neuron representing a codevector of the codebook. In the modified competitive learning network (MCLN), the competitive learning rules and the stopping criterion of the original competitive learning neural network [5] are modified so that on-line learning with hardware devices for performing VQ is feasible.

In region-based techniques, pixels with common image properties are partitioned into a region. The region-based watershed algorithm is an automated and unsupervised technique that is extensively used for segmentation. Several efficient algorithms have been devised for the determination of watersheds [9-13]. For medical image segmentation applications, Grau *et al*. [14] proposed a marker-based watershed method for knee cartilage segmentation and white matter/gray matter segmentation for magnetic resonance images. Beare [15] introduced the Minkowski path cost, which can be used to describe watershed segmentation. Huang and Chen [16] introduced an integrated technique that combines the advantages of neural network classification and morphological watershed segmentation to extract precise contours of breast tumors from medical ultrasound images. Shojaii *et al*. [17] presented a technique for segmenting lungs in computed tomography images, in which markers are combined with the gradient image and applied in an automated method. Adiga and Chaudhuri [18] proposed a region-based segmentation method that includes seeded volume growing, constrained erosion-dilation techniques, and a watershed algorithm for three-dimensional (3D) histo-pathological images.

In this study, a method that combines watershed segmentation and MCLN is proposed. The image is segmented into two regions via the watershed technique. The segmented regions are then compressed via MCLN.

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2. Methods

2.1 Image segmentation with watershed transform

Watershed segmentation is a powerful tool for morphological image segmentation. Band [19] presented the first algorithmic approach that uses the topographical concept in image segmentation. The intensity value in a grayscale image can be considered from a topographical point of view, with the grayscale image representing a surface in 3D Euclidean coordinates of all the points within the surface [20]. The topographical point represents the intensity value in the grayscale image. Low and high intensity values are analogous to hills and valleys, respectively, of a landscape. The analogy is extended by imagining rain pouring over the landscape. The water flows from high altitude (high-intensity region) along the steepest descent until it reaches the lowest basins (lowest-intensity region). The grayscale landscape can therefore be partitioned or segmented according to watersheds of the image; that is, the concepts of watersheds and catchment basins from topographical analysis are applied as a tool of mathematical morphology for image segmentation [21].

There are many advantages to using these algorithms, such as the partitioning of images into connected regions. Therefore, the watershed approach is commonly applied for image segmentation [22,23]. In order to obtain more accurate results, image pre-processing and the gradient image are commonly used in watershed segmentation techniques. They are used to improve image quality and alleviate the problems of disconnected contours and false edges [9]. Gradient operators are employed to improve segmented contours [24]. In this study, the watershed segmentation method proposed by Vincent [9] is adopted; this method is based on immersion simulation. The principle is briefly described as follows. For original grayscale image I, the gradient image ∇I is computed. Watershed lines separate catchment basins that belong to different minima. When the rainwater flows down into a catchment basin, the amount of rainwater in the basin increases, resulting in increased grayscale values. If the rainwater keeps flowing into the basin, the intensity will reach the local maximum values. A dam is therefore built to prevent the basins from merging when two floods originating from different catchment basins meet.

2.2 Image compression with modified competitive learning network

A vector quantizer maps Euclidean $\ell \times \ell$-dimensional space $R^{\ell\times\ell}$ into a set $\{\mathbf{W}_x,\ x = 1, 2,..., n\}$ of points in $R^{\ell\times\ell}$, called a codebook. A vector quantizer approximates a training vector from $R^{\ell\times\ell}$ with as little distortion as possible using one of the codevectors in the codebook. Suppose that an image is divided into n blocks (vectors of pixels) and that each block occupies $\ell \times \ell$ pixels. The performance of a system in terms of the average distortion $E[d(\mathbf{X}_x, \mathbf{W}_x)]$ between the input sequence of training vectors $\{\mathrm{X}_x,\ x = 1, 2,..., n\}$ and the output sequence of codevectors (centroid vectors) $\mathbf{W} = \{\mathbf{w}_1, \mathbf{w}_2,..., \mathbf{w}_c\}$ is defined as:

$$D_{x,y} = E[d(X_x, W_x)] = \frac{1}{n}\sum_{x=1}^{n} d(X_x, W_x) \tag{1}$$

The distortion measure $d(\mathbf{X}_x, \mathbf{W}_x)$, the squared Euclidean distance between vectors, is defined as:

$$d(X_x, W_x) = \left|X_x - W_x\right|^2 = \sum_{k=1}^{\ell\times\ell}\left(x_k - w_k\right)^2 \tag{2}$$

A vector quantizer is optimal if the average distortion converges to a minimum value. Neural networks have been studied extensively due to their simple architecture and potential for parallel implementation [8]. In this study, a modified competitive learning network for VQ in image compression is adopted. It is an unsupervised competitive learning network that uses the modified competitive learning rules and stopping criterion.

The MCLN has the same architecture as that of a conventional competitive learning network. The structure of the MCLN provides a crisp relation between the output neurons $\mathbf{W} = \{\mathbf{w}_1, \mathbf{w}_2,..., \mathbf{w}_c\}$ and input samples $\mathbf{X}$. It has a single layer of output neurons, each of which is fully connected to input nodes with interconnection strengths.

A two-dimensional (2D) image is divided into n blocks (a block represents a training vector that captures $\ell \times \ell$ pixels) and is directly mapped to the input layer of the MCLN. For an image of n training vectors and c codevectors in the codebook defined in advance, the network architecture can be conceived as a 2D neuron array. Each vector is trained with the nearest neighbor condition and the winner's codeword is iteratively updated. Instead of updating the interconnection strengths using the winner-take-all scheme, as done in the conventional competitive learning network, the MCLN only modifies the output states (cluster centrodis) to simplify the hardware architecture. After several iterations (when the total energy of the MCLN converges to a minimum solution), the output neurons remain in a stable state.

The objective function for the MCLN, J_{CMLN}, is the same as that for the c-means algorithm and similar to that for the conventional competitive learning network:

$$J_{MCLN} = \frac{1}{2}\sum_{j=1}^{c}\sum_{i=1}^{n}\left\|x_i - w_j\right\|^2 \tag{3}$$

where $\mathbf{x}_i$ is the training vectors and $\mathbf{w}_j$ is the winner's codeword. For a given cluster $\boldsymbol{cj}$, $\mathbf{w}_j$ is the representative of the samples in cluster $\boldsymbol{cj}$ in the sense that it minimizes the sum of the squared error vector $\mathbf{x}_i - \mathbf{w}_j$. Therefore, J_{MCLN} represents the measure of the least sum of squared error between n training vectors $\{\mathbf{X}_x,\ x = 1,2,..., n\}$ within a cluster and produces c cluster centers $\mathbf{W} = \{\mathbf{w}_1,\mathbf{w}_2,...,\mathbf{w}_c\}$. Gradient descent on the objective function yields:

$$\left\langle \Delta w_j \right\rangle = -\eta\frac{\partial J_{MCLN}}{\partial w_j} = \eta\sum_{i=1}^{n}\left(x_i - w_j\right) \tag{4}$$

The standard competitive learning rule is replaced by:

$$w_j(t+1)=\begin{cases} w_j(t)+\eta(x_i-w_j) & \text{if } |x_i-w_j|\le|x_i-w_k|, \forall k \\ w_j(t) & o.w. \end{cases} \tag{5}$$

Therefore, the MCLN algorithm for VQ only modifies output neurons and omits updating the interconnection strengths. A 256 × 256 simulated image was divided into 4096 blocks with a size of 4 × 4 pixels. The condition "iter > 4096" is thus used to determine whether all 4096 training vectors completed the learning loop. In addition, it does not influence the performance of learning for different block sizes.

2.3 *Combination of watershed and modified competitive learning network*

The flowchart of the proposed approach is illustrated in Fig. 1. The watershed transform is sensitive to the noise in image segmentation, which can lead to over-segmentation.

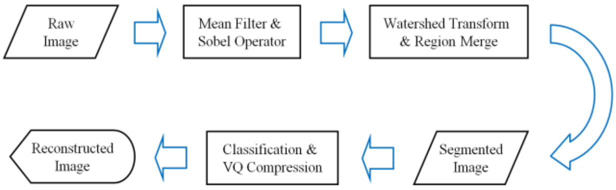

Figure 1. Flowchart of proposed method.

Hence, the mean filter, which can effectively reduce the effect of noise, is used in this study to smooth the images before segmentation. The Sobel operator, which is based on the convolution of images with a separable and integer-valued filter in the horizontal and vertical directions, is then used to detect edges in smoothed images. After the components of the gradient in the horizontal (G_x) and vertical (G_y) directions are calculated, the magnitude of the gradient is evaluated as:

$$G=\sqrt{G_x^2+G_y^2} \tag{6}$$

The watershed transform is then performed on the gradient images. Several closed regions are obtained after image segmentation. In addition, regions are merged to further refine the results of segmentation according to their characteristics, such as mean, standard deviation, and edge information. The mean intensity for each segmented region is defined as the threshold T_i. Each region is then divided into two sub-regions based on T_i. Finally, the codebook is calculated by the MCLN method to achieve image compression.

3. Results and discussion

3.1 *Image segmentation*

The watershed transform can be used to achieve morphological image segmentation. To demonstrate the results of proposed segmentation method, several images were adopted in the experiments. The size of all the images was 1024 × 1024 pixels. The procedure of the proposed segmentation method is illustrated in Fig. 2. The test images are shown in Fig. 2(a), with the corresponding smoothing results shown in Fig. 2(b). Figure 2(c) shows the gradient magnitude obtained from Fig. 2(b). Finally, the results of the watershed transform and image merging are shown in Fig. 2(d).

Figure 2. Procedure of proposed segmentation method. (a) Test images, (b) smoothed images, (c) gradient images, and (d) segmentation results.

3.2 *Image compression*

Codebook design is the primary problem in image compression based on VQ. In this study, the quality of images reconstructed from the codebooks obtained using GLA, MCLN, and the proposed method was compared. The training vectors were extracted from 256 × 256 images, which were divided into 4 × 4 blocks to generate 4096 non-overlapping sixteen-dimensional training vectors. Three codebooks, of sizes 64, 128, and 256, respectively, were built using this training data. In the experiments, the compression rates were 6/16 = 0.375, 7/16 = 0.438, and 8/16 = 0.5 bits/pixel, respectively. The test images had 8-bit gray levels. The resulting images were evaluated using the peak signal-to-noise ratio (PSNR), defined for $N \times N$ images as:

$$PSNR=10\log_{10}\frac{255\times255}{MSE} \tag{7}$$

where the mean square error (MSE) is defined as:

$$MSE=\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\left(x_{i,j}-\hat{x}_{i,j}\right)^2 \tag{8}$$

where $x_{i,j}$ and $\hat{x}_{i,j}$ are the gray levels of pixels from the original and reconstructed images, respectively. The peak value of the gray level is 255. The test images and reconstructed results for codebook sizes of 64, 128, and 256 obtained using the proposed method are shown in Fig. 3.

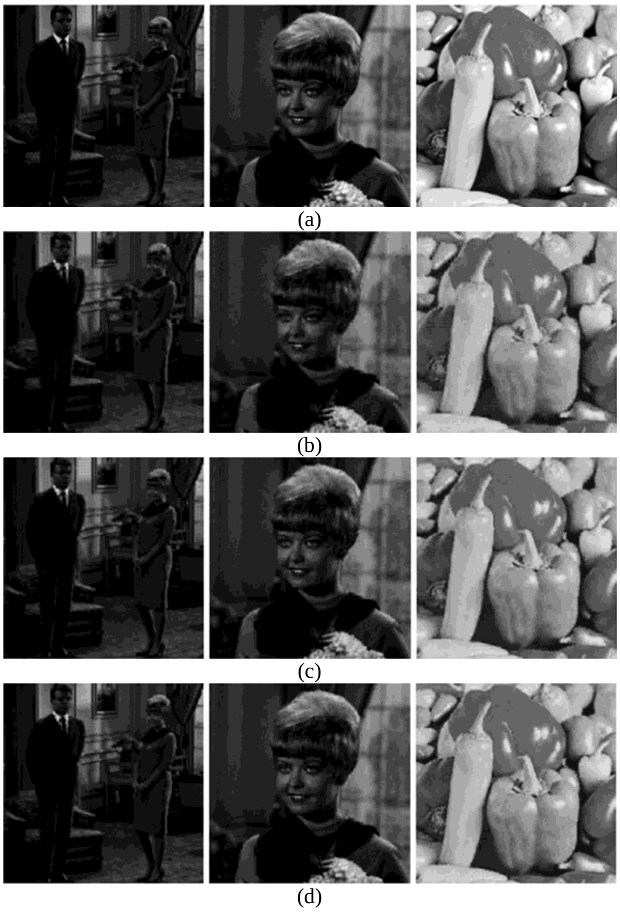

Figure 3. Reconstruction results. (a) Test images and images reconstructed using compression rates of (b) 0.375, (c) 0.438, and (d) 0.5.

Table 1 lists the PSNR values of images reconstructed using codebooks with sizes of 64, 128, and 256 obtained using GLA, MCLN, and the proposed method. The results indicate that the proposed method outperforms GLA and MCLN in terms of image compression and reconstruction.

Table 1. PSNR values of images reconstructed from codebooks of three sizes obtained using GLA, MCLN, and proposed method.

PSNR values		Codebook size		
Image	Method	64	128	256
Boy-girl	GLA	28.264	29.403	31.198
	MCLN	29.820	30.222	31.603
	Proposed	30.356	31.495	32.593
Lena	GLA	25.256	26.374	27.064
	MCLN	26.294	27.551	28.700
	Proposed	26.990	28.169	29.389
Pepper	GLA	24.821	25.593	26.779
	MCLN	25.670	26.829	28.157
	Proposed	27.670	28.814	29.883

4. Conclusion

A method that combines watershed segmentation with VQ was proposed. The watershed transform is first used to segment the image into several closed regions, and then the MCLN algorithm is applied. High-quality image reconstruction is achieved because the regions are compressed with different compression rates, which simultaneously preserves important features and reduces the size of images. The results indicate that the proposed method is effective in image compression and reconstruction.

Acknowledgements

The authors would like to express their sincere appreciation to the Ministry of Science and Technology of Taiwan for supporting this study under grants NSC102-2633-E-194-002, MOST103-2410-H-194-070-MY2 and NSC103-2622-E-194-003-CC2.

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