SPATIAL OBJECT RECOGNITION VIA INTEGRATION OF DISCRETE WAVELET DENOISING AND NONLINEAR SEGMENTATION

Zhengmao Ye, Habib Mohamadian

College of Engineering, Southern University
Baton Rouge, LA 70813, USA
zhengmaoye@engr.subr.edu, mohamad@engr.subr.edu

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ABSTRACT:

Spatial digital image analysis plays an important role in the information decision support systems, especially for regions frequently being affected by hurricanes and tropical storms. For the aerial and satellite imaging based pattern recognition, it is unavoidable that these images are affected by various uncertainties, like the atmosphere medium dispersing. Image denoising is thus necessary to remove noises and retain important signatures of digital images. The linear denoising approach is suitable for slowly varying noise cases. However, the spatial object recognition problem is essentially nonlinear. Being a nonlinear wavelet based technique, wavelet decomposition is effective to denoise blurring spatial images. The digital image can be split into four subbands, representing approximation (low frequency feature) and three details (high frequency features) in horizontal, vertical and diagonal directions. The proposed soft thresholding wavelet decomposition is simple and efficient for noise reduction. To further identify the individual targets, nonlinear K-means clustering based segmentation approach is proposed for image object recognition. The selected spatial images are taken across hurricane affected Louisiana areas. In addition to evaluate this integration approach via qualitative observation, quantitative measures are proposed on a basis of the information theory, where the discrete entropy, discrete energy and mutual information, are applied for the accurate decision support.

1. INTRODUCTION

Spatial image processing has many potential applications in the fields of ground surveillance, weather forecasting, target detection, environmental exploration, and so on. The remote taken images will be affected by various factors, such as atmospheric dispersions and weather conditions, thus spatial images contain diverse types of noises, both slowly varying or rapidly varying ones. Discrete wavelet denoising can be designed to eliminate noises presented in images so as to preserve the characteristics across all frequency ranges. It involves three steps, that is, linear wavelet transform, nonlinear thresholding and linear inverse wavelet transform. Using discrete wavelet transform, a digital image can be decomposed into the approximation component and detail components (horizontal, vertical, diagonal). The approximation component will be further decomposed. Information loss between two successive decomposition levels of approximations will be represented in detail coefficients [1-3, 5-6]. The essence of fractal-based denoising in the wavelet domain has been used to predict the fractal code of a noiseless image from its noisy observation. The cycle spinning is incorporated into these fractal-based methods to produce enhanced estimations for the denoised images [7]. The new image denoising method based on Wiener filtering for soft thresholding has been proposed. It shows a high and stable SNR (signal to noise ratio) gain for all noise models used. This process leads to an improvement of phase images when real and imaginary parts of wavelet packet coefficients are filtered independently [8]. Two techniques for spatial video denoising using wavelet transform are used: discrete wavelet transform and dual-tree complex wavelet transform. An intelligent denoising system is introduced to make a tradeoff between the video quality and the time required for denoising. The system is suitable for real-time applications [9].

Image segmentation is a main step towards automated object recognition systems. The quality of spatial images is directly affected by atmospheric medium dispersion, pressure and temperature. It emphasizes necessity of image segmentation, which divides an image into parts that have strong correlations with objects to reflect the actual information being collected [1-3]. Spatial information enhances quality of clustering. In general, fuzzy K-means algorithm is not used for color image segmentation and not robust against noise. In this case, integration of discrete wavelet denoising and nonlinear K-means segmentation provides a suitable solution. Spatial information can be incorporated into the membership function for clustering of color images. For optimal clustering, gray level images are used. The spatial function is the summation of the membership function in the neighborhood of each pixel under consideration. It yields more homogeneous outcomes with less noisy spots. Image segmentation refers to the process of partitioning a digital image into multiple regions. Each pixel in a region is similar with respect to specific characteristic, like color, brightness, intensity or texture. [10-12]. To minimize the effects from medium dispersing, K-means clustering is critical for image processing. It is used to accumulate pixels with similarities together to form a set of coherent image layers. For K-means clustering, optimization can be implemented via the control algorithms such as the nearest neighbor rule or winner-take-all scheme. Nonlinear K-means clustering is presented here for image segmentation [10-14].

To objectively measure the impact of technology integration of image denoising and image segmentation, metrics of the discrete entropy, discrete energy, relative entropy and mutual information can be introduced to evaluate all the measuring outcomes of image processing integration [4].

2. DISCRETE WAVELET TRANSFORM

Two spatial source images were taken in State of Louisiana regions, which are frequently affected by hurricanes. The first image shows the spatial view of New Orleans and the second image shows the spatial view of Baton Rouge. The source images are contaminated by noises. The objective is to identify diverse types of targets involved. Image processing technology integration is proposed, where the nonlinear wavelet denoising is applied at first and nonlinear K-means clustering is used for target identification.

Fig.1 Source Spatial Image of New Orleans Areas

Fig.2 Source Spatial Image of Baton Rouge Areas

Discrete wavelet transform uses a set of basis functions for image decomposition. In a two dimensional case, four functions will be constructed: a scaling function $\varphi(x, y)$ and three wavelet functions $\psi^H(x, y)$, $\psi^V(x, y)$ and $\psi^D(x, y)$. Four product terms produce the scaling function (1) and separable directional sensitive wavelet functions (2)-(4), resulting in a structure of quaternary tree. Here the scaling function and wavelet functions are all determined by Haar Transform.

$$\varphi(x, y) = \varphi(x)\varphi(y) \tag{1}$$
$$\psi^H(x, y) = \varphi(y)\psi(x) \tag{2}$$
$$\psi^V(x, y) = \varphi(x)\psi(y) \tag{3}$$
$$\psi^D(x, y) = \psi(x)\psi(y) \tag{4}$$

The wavelets measure variations in three directions, where $\psi^H(x, y)$ corresponds variations along columns (horizontal), $\psi^V(x, y)$ corresponds to variations along rows (vertical) and $\psi^D(x, y)$ corresponds to variations along diagonal direction. The scaled and translated basis functions are defined by:

$$\Phi_{j,m,n}(x, y) = 2^{j/2}\,\varphi(2^j x - m, 2^j y - n) \tag{5}$$
$$\psi^i_{j,m,n}(x, y) = 2^{j/2}\,\psi^i(2^j x - m, 2^j y - n),\ i=\{H, V, D\} \tag{6}$$

where index i identifies the directional wavelets of H, V, and D. Given the size of image as M by N, the discrete wavelet transform of the function f(x, y) is formulated as:

$$w_\varphi(j_0,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\varphi_{j_0,m,n}(x,y) \tag{7}$$

$$w^i_\psi(j,m,n)=\frac{1}{\sqrt{MN}}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x,y)\psi^i_{j,m,n}(x,y) \tag{8}$$

where i={H, V, D}, j_0 is the initial scale, the $w_j(j_0, m, n)$ coefficients define the approximation of f(x, y), $w^i_\psi(j, m, n)$ coefficients represent the horizontal, vertical and diagonal details for scales $j>= j_0$. Here $j_0 =0$ and select $N + M = 2^J$ so that j=0, 1, 2,…, J-1 and m, n = 0, 1, 2, …, 2^j -1. The f(x, y) can also be obtained via inverse discrete wavelet transform. Discrete wavelet decomposition and thresholding will both be applied in discrete wavelet transform.

Discrete wavelet transform is implemented as a multiple level transformation, where two level transformation is implemented in context. The decomposition outputs at each level include: the approximation, horizontal detail, vertical detail and diagonal detail. Each of them has one quarter size of its original image followed by downsampling by a factor of two. The approximation will be further decomposed into multiple levels while the detail components will not be decomposed. Information loss between two immediate approximations is captured as the detail coefficients. For the denoising using discrete wavelet transforms, only wavelet coefficients of the details at level one will be subject to thresholding, while the approximation components at the level one and higher levels will stay the same for image reconstruction.

In a thresholding process, the selection of the threshold is critical. Soft thresholding is selected instead of hard thresholding, which will shrink nonzero wavelet coefficients towards zero. Considering that a small threshold produces a good but still noisy estimation while in general, a big threshold produces a smooth but blurring estimation, thus the median value stem from the absolute value of wavelet coefficients at each wavelet decomposition level is selected. The shrinkage function of soft thresholding is formulated at each decomposition level as (9), where THR is the median threshold value based on wavelet coefficients. x is the input signal and f(x) is the nonlinear signal after thresholding.

$$f(x)= \mathrm{sgn}(x)(|x| - THR) \quad (9)$$

Using wavelet denoising, two revised images are generated which represent the intrinsic geographical information of two biggest cities of State of Lousiana (Figs. 3-4). These two denoised images will be further analyzed by nonlinear K-means clustering.

Fig.3 Denoised Image of New Orleans Areas

Fig.4 Denoised Image of Baton Rouge Areas

3. NONLINEAR K-MEANS SEGMENTATION

In image nonlinear segmentation, four clusters are proposed for partitioning. Centers of each cluster represent the mean values of all data points in that cluster. A distance metric should be determined to quantify the relative distances of objects. Both Euclidean and Mahalanobis distances are major types of distance metrics. Computation of the distance metrics is based on the spatial gray level histograms of digital images. The Mahalanobis metric distance has been applied, which is formulated as (10), where X_A is the cluster center of any layer X_A, s is a data point, d is the Mahalanobis distance, the K_A^{-1} is the inverse of the covariance matrix.

$$d=(s-X_A)^T K_A^{-1} (s- X_A) \quad (10)$$

K-means clustering assigns each object a space location, which classifies data sets through numbers of clusters. It selects four cluster centers and points cluster allocations to minimize errors. Optimal statistical algorithms are applied for classification, which are categorized as threshold based, region based, edge based or surface based. The distances of any specific data point to several cluster centers should be compared for decision making. For each individual input, winner-take-all competitive learning (11-12) is applied so that only one cluster center is updated. Images will thus be decomposed into four physical entities. In fact, the winner-take-all learning network classifies input vectors into one of specified categories according to clusters detected in the training dataset. All points are eventually allocated to the closest cluster. Learning is performed in an unsupervised mode. Each cluster center has an associated weight that is listed as w's. The winner is defined as one whose cluster center is closest to the inputs. Thus, this mechanism allows for competition among all input responses, but only one output is active each time. The unit that finally wins the competition is the winner-take-all cluster, so the best cluster center is computed accordingly.

$$w_{ij}x = \min(w_i x) \text{ for } j = 1, 2, 3, 4;\ i = 1, 2, 3, 4 \quad (11)$$

$$w_{i1} + w_{i2} + w_{i3} + w_{i4} = 1 \text{ for } i = 1, 2, 3, 4 \quad (12)$$

Assume the cluster center S wins, the weight increment of S is computed exclusively and then updated according to (13), where α is a small positive learning parameter and it decreases as the competitive learning proceeds.

$$\Delta w_{ij} = \alpha(x_j - w_{ij}), \text{ for } j = 1, 2, 3, 4;\ i = 1, 2, 3, 4 \quad (13)$$

The K-means clustering outcomes of two city images are shown in Figs. 5-12, where objects of the highway, river, building and grass lawn are major features in 4 clusters.

Fig.5 K-means Clustering #1 of New Orleans Areas

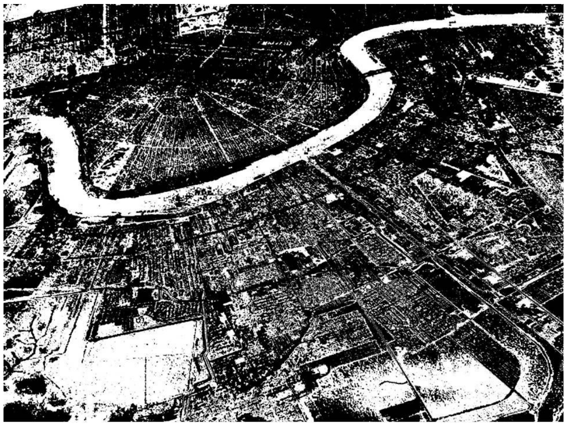

Fig.6 K-means Clustering #2 of New Orleans Areas

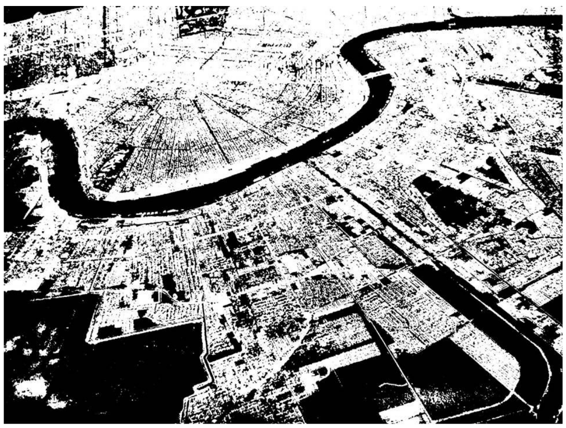

Fig.7 K-means Clustering #3 of New Orleans Areas

Fig.8 K-means Clustering #4 of New Orleans Areas

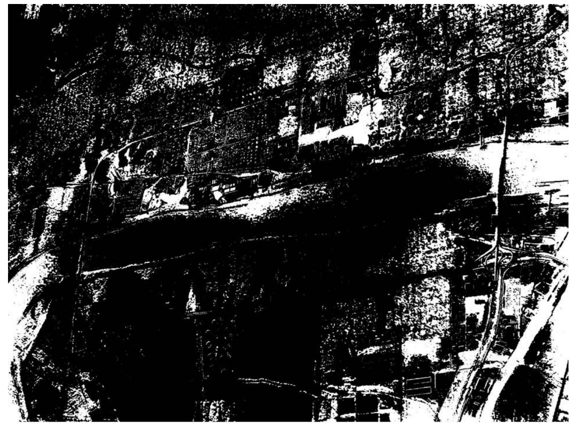

Fig.9 K-means Clustering #1 of Baton Rouge Areas

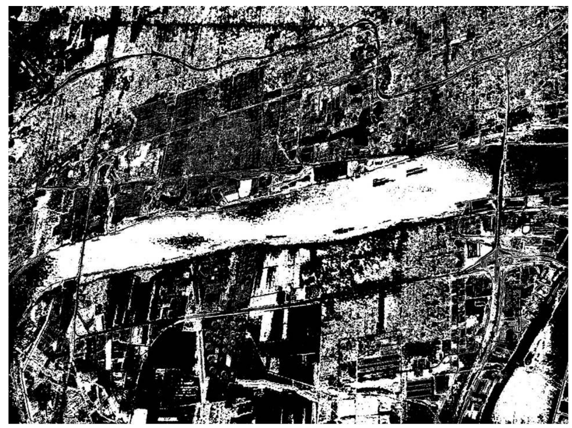

Fig.10 K-means Clustering #2 of Baton Rouge Areas

Fig.11 K-means Clustering #3 of Baton Rouge Areas

Fig.12 K-means Clustering #4 of Baton Rouge Areas

4. QUANTITATIVE ANALYSIS

4.1 Histogram and Probability Functions

For a M by N digital image, occurrence of the gray level is described as the co-occurrence matrix of relative frequencies. The occurrence probability function is then estimated from its histogram distribution.

4.2 Discrete Entropy Analysis

The discrete entropy is a measure of information content, which represents the average uncertainty of the information source. The discrete entropy is the summation of products of the probability of the outcome multiplied by the logarithm of inverse of probability of the outcome, taking into account of all possible outcomes {1, 2, …, n} as the gray level in the event $\{x_1, x_2, \ldots, x_n\}$, where p(i) is the probability at the gray level i, which contains all the histogram counts. The discrete entropy H(x) is formulated as (14) and all corresponding results are shown in Table 1.

$$H(x)=\sum_{i=1}^{k} p(i)\log_2\frac{1}{p(i)} = -\sum_{i=1}^{k} p(i)\log_2 p(i) \quad (14)$$

Table 1 Discrete Entropy of Images

Discrete Entropy	Image A (N.O.)	Discrete Entropy	Image B (B.T.R)
Source Image	6.5630	Source Image	6.7279
Denoised Image	6.9670	Denoised Image	7.2252
Cluster 1	1.4650	Cluster 1	2.2084
Cluster 2	3.1182	Cluster 2	3.1886
Cluster 3	2.9009	Cluster 3	3.0486
Cluster 4	0.5474	Cluster 4	2.0423

4.3 Discrete Energy Analysis

The discrete energy measure indicates how the gray level elements are distributed. Its formulation is shown in (15), where E(x) represents the discrete energy with 256 bins and p(i) refers to the probability distribution functions at different gray levels, which contains the histogram counts. For any constant value of the gray level, the energy measure can reach its maximum value of one. The lower energy corresponds to larger number of gray levels and the higher one corresponds to smaller gray level numbers. The discrete energy of the source, denoised and segmented images are shown in Table 2.

$$E(x)=\sum_{i=1}^{k} p(i)^2 \quad (15)$$

Table 2 Discrete Energy of Images

Discrete Energy	Image A (N.O.)	Discrete Energy	Image B (B.T.R)
Source Image	0.0122	Source Image	0.0112
Denoised Image	0.0090	Denoised Image	0.0077
Cluster 1	0.6705	Cluster 1	0.4802
Cluster 2	0.2684	Cluster 2	0.2609
Cluster 3	0.2788	Cluster 3	0.2938
Cluster 4	0.8965	Cluster 4	0.5411

4.4 Relative Entropy Analysis

Assuming that two discrete probability distributions of the digital images have the probability functions of p(i) and q(i). The relative entropy of p with respect to q is defined as the summation of all the possible states of the system, which is formulated as (16). The relative entropies of the source, denoised and segmented images are shown in Table 3.

$$d=\sum_{i=1}^{k} p(i)\log_2\frac{p(i)}{q(i)} \quad (16)$$

Table 3 Relative Entropy of Images

Relative Entropy	Source Image	Denoised Image A	Source Image	Denoised Image B
Cluster 1	0.0705	0.2944	0.0255	0.1938
Cluster 2	0.0882	0.2835	0.0294	0.1994
Cluster 3	0.0905	0.2846	0.0569	0.2665
Cluster 4	0.0512	0.2707	0.0719	0.3043
Denoised Image	0.3167		0.3088	

4.5 Mutual Information Analysis

Another metric of the mutual information I(X; Y) should also be discussed, which is used to describe how much information one variable tells about the other variable. The relationship is formulated as (17).

$$I(X;Y)=\sum_{X,Y} p_{XY}(X, Y)\log_2 \frac{p_{XY}(X, Y)}{p_X(X)p_Y(Y)}=H(X)-H(X|Y) \quad (17)$$

where H(X) and H(X|Y) are values of the entropy and conditional entropy; p_{XY} is the joint probability density function; p_X and p_Y are marginal probability density functions. It can be explained as information that Y can tell about X is the reduction in uncertainty of X due to the existence of Y. The mutual information also represents the relative entropy between the joint distribution and product distribution. Calculated mutual information outcomes among the source, denoised and segmented images are indicated in Table 4.

Table 4 Mutual Information Between Images

Mutual Information	Source Image	Denoised Image A	Source Image	Denoised Image B
Cluster 1	5.0980	5.5020	4.5194	5.0167
Cluster 2	3.4447	3.8487	3.5392	4.0365
Cluster 3	3.6621	4.0661	3.6793	4.1765
Cluster 4	6.0156	6.4196	4.6855	5.1828
Denoised Image	0.4040		0.4973	

From Table 1 and Table 2, the denoised images cover more useful information than source images and each individual image cluster covers partial information. From Table 1 to Table 4, the quantitative values between the segmented images and original images can be set as measures for target detection when more clusters will be generated. Each cluster will actually represent certain type of objects that need to be identified. This image processing integration approach has been successfully applied to spatial object recognition issues.

5. CONCLUSIONS

This article has presented the outcomes from integration of image processing technologies. Image denoising can be used to maintain the energy of the images and reduce the energy of noises. Being a nonlinear approach, wavelet denoising has advantages of dealing with highly nonlinear spatial images. Using a set of wavelet bases, the wavelet coefficients can be thresholded to reduce the influence from noises. Wavelet denoising has been used to remove noises without distorting important features of images. Image segmentation can be used to identify objects from images. It classifies each image pixel to a segment according to the similarity in a sense of a specific metric distance. To reduce blurring effects of the spatial images stem from atmospheric media, nonlinear region K-means segmentation has been presented for image segmentation, where the competitive learning rule is applied to update clustering centers with satisfactory results. To evaluate the roles of wavelet denoising and nonlinear segmentation approaches, quantitative metrics are proposed. Several information measures of the discrete energy, discrete entropy, relative entropy and mutual information are applied to indicate the effects of integration of two image processing approaches. These methodologies could be easily expanded to other image processing techniques for diverse types of potential practical implementations.

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