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Automatic method for enhancement and detection of curvilinear structure in 2-d geophysical image

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ABSTRACT

The identification of linear structures are done in geophysical images. The problem of identification of curvilinear structures in real and synthetic geophysical images is faced for the first time. Here we propose a method for automatic enhancement and detection of curvilinear structures. The accurate identification of line structures in geophysical images plays an important role in geophysical interpretation and the detection of subsurface structures. The method was applied on geophysical images in an effort to recognize the linear patterns of subsurface architectural structures that exist in archaeological sites. The method efficiently combines a rotation and Scale-invariant filter and a pixel-labelling method, providing a robust enhancement and detection of mostly line structures in 2-D gray scale images. Mainly they are used in archaeological sites.

Introduction

The automatic enhancement and detection of structures on real and complex 2-D images are important tasks on various applications of computer vision, medical analysis, and geosciences. In many of the above applications, the most fundamental feature of image understanding is the recognition of line structures in 2-D images, since line segments occur in various natural and synthetic objects. Upon the identification of the line segments, features can be better delineated. One of the most widely used methods to solve the line detection problem in binary or gray scale images is the Hough transform[1]. According to Hough transform, the detection of line segments is reduced to the detection of the peaks in a voting parameter space. This space is initially estimated by the voting of each original image point to all points in the parameter space that could have possibly produced the image point. Moreover, Hough Transform has been used to detect more complicated shapes like circle[2] and ellipses[3]. However, Hough Transform is difficult to be tuned due to the discretization of the continuous parameter space and due to the determination of the neighbour size that is used for peak estimation. Thus, in many cases, the estimated results are strongly associated to the input parameters.

In [4], curvilinear structures are enhanced by a nonlinear combination of linear filters. The filters are applied in different scales and orientations. The method has been successfully applied in 2-D and 3-D images. In [5], a scheme for the reconstruction of curvilinear structure regions based on skeleton extraction and skeletal segment classification is proposed. The skeleton is extracted from the Euclidean distance map that is constructed based on the edge map of an input image. Other techniques use Gabor filters [6] for estimation of image features. Gabor filter responses are characterized by orientation and spatial frequency selection. The estimated features have been used in the past to detect various complicated image structures like faces, textures, and characters [7]. Matching filters approaches [8], convolve the image with multiple matched filters for the extraction of objects of interest, vessel contours in the vessel extraction domain. Matching filters procedure is usually followed with some other image processing operations like thresholding and then connected component analysis to get the final vessel contours. Combination of local and region-based properties to segment blood vessels in retinal images. Their method examines the image of a matched filter response (MFR) in pieces and applies thresholding using a probing technique. The probing technique classifies pixels in an area of the MFR as vessels and non-vessels by iteratively decreasing the threshold. Tensor voting methods, which associate a tensor field with each edge pixel, are promising methods for contour detection in images [9]. These methods are based on saliency maps that are obtained by iteratively increasing the strength of those edges which have collinear edges in their immediate surroundings, and by reducing the strength of edges that are surrounded by random patterns. Alternatively, Gestalt theory concerns the ability of human observers to group visual stimuli which share certain common characteristics .Statistics is used, in combination with an integration rule that links the locally grouped contour elements into longer contours. A disadvantage of these methods is the high computational cost. Moreover, they need post processing to recognize the patterns of subsurface architectural structures since these contour detection methods will detect two “parallel” contours (pattern boundaries) for each pattern. The main contribution of this research is that it faces the problem of identification of curvilinear structures in geophysical images for archaeological sites, which is faced for the first time.

Concerning the proposed methodology, instead of using Gabor filters for feature estimation and high-computational-cost methods with post processing schemes, a line model filter that is applied into different scales and orientations is proposed, aiming toward the detection of lines of different widths and directions, respectively. The proposed method can be classified into matching filters techniques. Then, the image of maximum

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values of the filter responses is estimated, providing an enhancement of invariant to rotation and scaling curvilinear structures. This procedure is similar to the Hough Transform methodology, where the peaks in voting parameter space are selected. Finally, a pixel-labelling method is applied, yielding the identification of partial curvilinear structures. The above method was employed on different images produced by geophysical measurements in archaeological sites, where a number of linear subsurface structures were suggested. In an earlier work, we have proposed a method for automatic enhancement of partial curvilinear structures on geophysical images. The current work focuses on automatic detection and enhancement, improving the preliminary results by introducing new filters models and the pixel-labelling algorithm. The rest of the paper is organized as follows. Section II describes the geophysical image interpretation and the problem of relic recognition in archaeological sites. Section III presents the proposed scheme. Finally, conclusions are provided.

Geophysical Image Interpretation

Interpretation of 2-D geophysical images comprises the final and most important step of geophysical processing. Interpretation of the images depends mainly on the clarity of the images and on interpreter's experience and very few schemes have been proposed for the automatic feature detection and extraction. These schemes mainly concern horizon tracking across discontinuities in 2-D and 3-D seismic data and image de-noising attempts [10]. With the fast advances in computing technology, there has been considerable and increasing interest in the development of automatic geophysical interpretation and understanding methodologies. Image processing and analysis techniques offer the means to acquire digital information, at different scales quickly and efficiently. The development of an efficient and effective computer-based approach for the automated geophysical image interpretation would allow the selection of more details in subsurface structures and the reduction of misinterpretation. Shallow-depth geophysical prospection suffers from the influence of anthropogenic interventions and activities, both on the surface and below it, creating various difficulties in the presentation and interpretation of the results. For this reason, multiple geophysical techniques are preferably employed since their complementary measurements offer a better insight about the subsurface of the archaeological sites. The combined image constructed from these data, through different graphics and processing techniques, makes it easier to detect the location of the relics and visualize their extent within the subsurface. Still, the interpretation of the geophysical data is a difficult task since measurements are masked by cultural noise originated by then diachronic usage of the landscape or the modern agricultural or construction activities in an area of interest. As a result of the above processes, the image resulting by the interpolation of the geophysical measurements is often of poor quality, containing high percentages of random or systematic noise which hinder the valuable information related to the subsurface targets. The noise in geophysical data has usually high-frequency content and characteristic frequencies depending on the causing sources; while in many cases, it is distributed across all spatial scales.

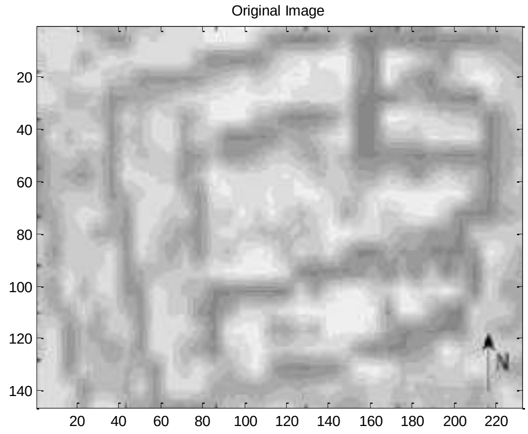

Fig-1 Original image

Proposed Scheme

In this section, first, noise reduction is performed. Next, the multiple filtering provides an enhancement of curvilinear structures. A pixel-labelling method provides the detection of curvilinear structures. Finally we calculate the threshold and find about that area, whether that is shallow or peak area.

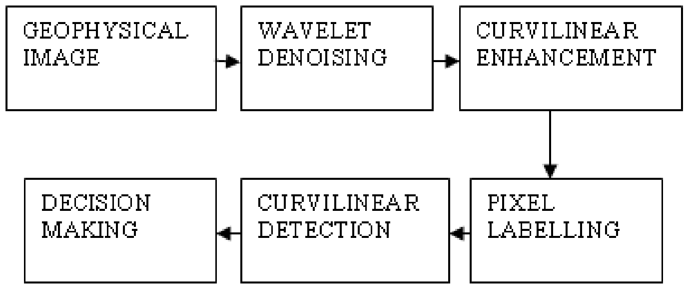

Fig.2 Scheme of the proposed system architecture

A. Noise Reduction

A given geophysical image contains cultural noise, difficult to be modelled; it is originated by the modern agricultural or construction activities. Therefore, in order to smoothen the noise of the image, the first step of the proposed scheme consists of a noise reduction module. Wavelet decomposition is effective in decoupling the high order statistical features of natural images. In addition, it shares some basic properties of neural responses in the primary visual cortex of mammals which are presumably adapted to represent efficiently the visually relevant features of images. For this reason, wavelet decomposition has been successfully applied on image, or geophysical data, de-noising schemes. In this research, de-noising is performed via wavelet thresholding method. It has been shown that wavelet thresholding schemes for de-noising have near-optimal properties in the minimax sense and perform well in simulation studies of 1-D curve estimation. Wavelet thresholding method was implemented by Mat lab, using an symlet filter.This image de-noising algorithm uses soft thresholding to provide smoothness. Hereafter, I and Id denote the original and de-noising images correspondingly.

B. Filter Model

In this section, the proposed filter model is presented. The filtering task aims toward the enhancement of curvilinear structures under various orientations and widths. Different types of zero mean filters can be used for curvilinear structure enhancement. The constraint of zero mean will yield zero response on constant structures. For this reason, the proposed filters were enforced to be zero mean, being able at the same time to model a line of specific orientation Step and Polynomial filter that were used for curvilinear structures enhancement.

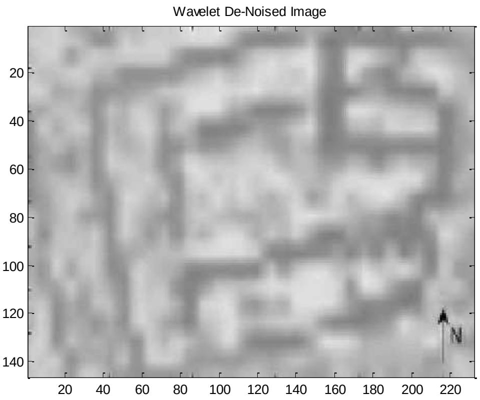

Fig.3 Wavelet De-noised image

Let F(a,w) be a zero mean filter of orientation angle a and width w. The step filter Fs(a,w) is a simple line model that is given by the extension of one dimension filter F1s (x) [see (1)] of width w in 2-D rotated by a degrees. The constant cs is a negative number close to −0.5, estimated by the constraint that the 2-D filter is zero mean. The methodology for cs estimation is described in the Appendix.

$$F1s(x) = \begin{cases} 1, & |x| < w \\ cs, & w \le |x| < r \cdot w \\ 0, & |x| \ge r \cdot w \end{cases} \quad \text{---- (1)}$$

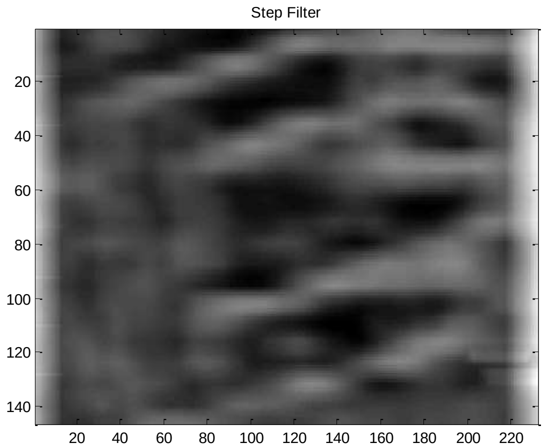

Fig.4 Step filter image

The Polynomial filter Fp(a,w) is a smoothed line model that is given by the extension of one dimension filter *F*1*p* (*x*) [see (2)] of width w in 2-D rotated by a degrees. The constant *cp* is a positive number close to 0.5, estimated by the constraint that the 2-D filter is zero mean. The methodology of *cp* estimation is the quite similar with the methodology of *cs* estimation .

$$F_p^1 = \begin{cases} 1-\left(\frac{x}{w}\right)^2, |x|<w \\ C_p \cdot \left(\left(\frac{x}{w}-2\right)^2-1\right), w \le |x| < r.w \\ 0, |x| \ge r.w \end{cases} \quad \text{----- (2)}$$

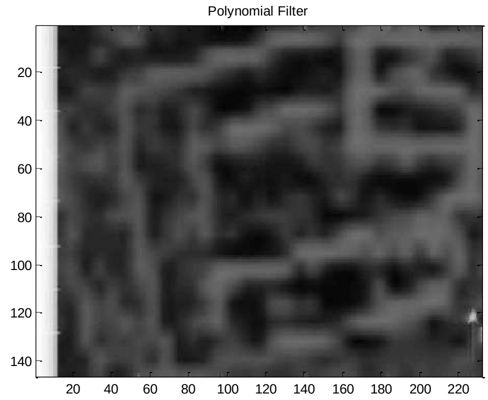

Fig.5 Polynomial filter image

However, experiments that were carried out with real and synthetic data indicated that Gabor filters cannot enhance curvilinear structures as well as the Polynomial or Step filters. This is due to the more than one local maximum of a Gabor filter in the vertical direction of the filter orientation, which is not true in line models, making them more efficient for texture analysis and feature extraction applications.

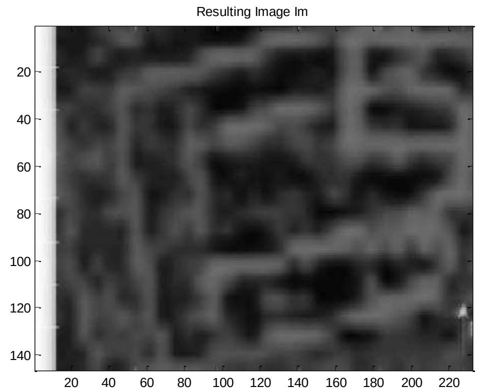

Fig.6 Resulting image Im

C. Multiple Filtering

Let F(a,w) be a zero mean filter of orientation angle a and width w, described in the previous section. According to the proposed method, we estimate the absolute-value image of the convolution of Id with the F(a,w) for different angles a and widths w, getting the images If (a,w) [see (3)]

If (a,w) = |Id ∗ F(a,w)| . (3)

Image If (a,w) hosts an enhancement of the curvilinear structures of orientation a and width w. The use of absolute value takes into account the fact that curvilinear structures can be appeared in Id in local minima or local maxima regions, enhancing both cases. Finally, the resulting image Im is provided by getting the maximum of the corresponding pixel values of images If (a,w) [see (4)]

Im = maxa,w If (a,w). (4)

In the resulting image Im, all curvilinear structures under any orientation have been enhanced. The selection of small angle step and small changes in widths ensure continuity in Im. Two different widths (2 and 4), depending on the width of the expected subsurface structures, and 12 different orientations (15◦ angle step) were used, resulting in a good curvilinear structure enhancement in any orientation. It holds that the response Im using polynomial filtering is smoother with better “balanced enhancement” than the response Im using step filtering.

D. Pixel Labelling

The preliminary goal of initial pixel-labelling method is to classify Im pixels into three classes C1, C2, and C3 with label numbers 1, 2, and 3, respectively:

• C1: The pixels that (surely) belong to curvilinear structures.

• C2: The pixels that we are uncertain if they belong to curvilinear structures.

• C3: The pixels that (surely) do not belong to curvilinear structures.

In the proposed scheme, the thresholds Tl and Th are automatically estimated. Let Med to denote the median value of Im. Then, Tl is given by the mean value of Im pixels that have a value lower than Med. Th is given by the mean value of Im pixels that have a value higher than Med. Let Bi be the image of pixel's initial classification into classes C1, C2, and C3. Let Im(p) and m to denote the value of image Im on pixel p and the median value of nine pixel neighbourhood of pixel p in Im, respectively.

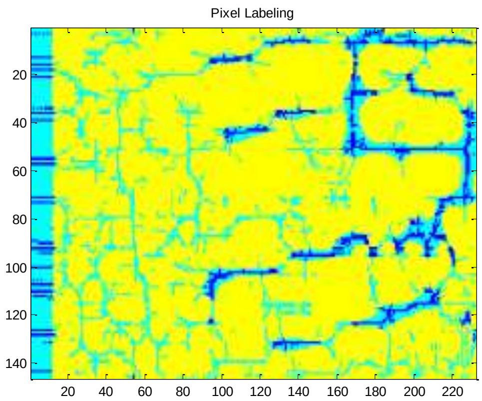

Fig.7 Pixel labelling image

Then, if Im(p) ≥Th and Im(p) >m, p is classified to C1, since its value is very high comparing with the image (Im(p) ≥Th) and with its neighbourhood (Im(p) >m). If Im(p) ≥Th or Im(p) >Tl and Im(p) >m, p is classified to C2 class. If the pixel value is compared with its neighbourhood or reversely, then it is labelled to unknown class. Otherwise, p is classified to C3 class. The algorithmic steps of the method are given hereafter.

Algorithm Initial Pixel Labelling

Input: Im, Tl, Th

Output: Bi

01: for each pixel p of image Im
02: V=set of pixel values of p neighbourhood //9 *values*
03: m = median(*V*); //*Median value of V*
04: if Im(p) ≥ Th && Im(p) > m
05: Bi(p) = 1;
06: else if Im(p)≥Th || (Im(p)>Tl && Im(p)>m)
07: Bi(p) = 2;
08: else
09: Bi(p) = 3;
10: end
11: end

Finally, a region-growing-based method is executed providing the final pixel labelling into classes C1 and C3. So, the goal of this method is to classify the pixels of class C2. Let Bf be the image of final pixel classification into classes C1 and C3. According to the method, the pixels of C2 class are classified to C1 if they are connected to a pixel of C1, otherwise they are classified to C3 class. Thin curvilinear structure detection (Bt) is provided if we change the rule of classification to class C2 of line 06 of initial pixel-labelling algorithm, removing the case of Im(p) ≥ Th. The method sufficiently recognizes all curvilinear structures under various orientations and scales.

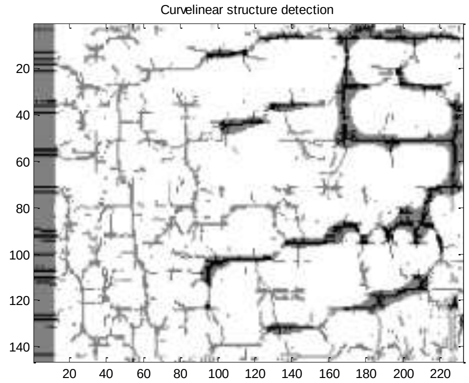

Fig.8 curvilinear structure detected image

Decision Making

Here calculation of the threshold value of the images are done, from that we find the area, which is near to curvilinear structure. After that it check whether that area is shallow or peak area.

Conclusion

In this paper, a fast, effective, and automatic method for enhancement and detection of partly curvilinear structures in 2-D geophysical images has been proposed. The method has been applied on real and synthetic geophysical images (with low and high levels of noise), recognizing the curvilinear patterns of subsurface architectural structures that exist in archaeological sites. The problem of identification of curvilinear structures in geophysical images for archaeological sites is very difficult due to the interpretation and nature of geophysical images and it is faced for the first time in this research. The proposed method efficiently combines a rotation- and scale-invariant multiple filter scheme with a pixel-labelling algorithm. In multiple filtering, we have proposed two different filter models, the step and polynomial models. The proposed multiple filtering schemes seem to be effective in curvilinear structure enhancement.

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