Automatic Lineament Detection from Geophysical Grid Data Using Efficient Clustering and Weighted Hough Transform Algorithms

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An automated lineament detection method based on a weighted Hough transform is presented. The method utilizes the result of unsupervised classification based on Kohonen's self-organizing maps, for vector quantizing the input data space, followed by neuron clustering. It then post-processes the classification result with classical image processing techniques and finally applies the modified Hough transform in order to identify lineaments. The capabilities of the method are described using geophysical (airborne magnetic and electromagnetic) data from the Vammala area in Finland. The results of the automated analysis show major geological faults in the selected area. Finally, comparisons with the classical Hough transform algorithm show the advantages of our proposed modifications.

INTRODUCTION

Lineaments are line features or patterns on earth's surface which reflect geological structure such as faults or fractures and should be discriminated from other line features (e.g. roads, airports) that are not due to geological structures. Detection and mapping of lineaments is an important operation in Environmental Geology for the study of the structural or tectonic history of a region, to aid detection of seismic horizons, investigation of active fault patterns, mineral deposits, water resources, etc.

Most lineament mapping is done visually using regional scale aeromagnetic surveys and/or remotely sensed images. However, visual analysis has several disadvantages the most important of which are: a) it is time consuming to visually identify lineaments, and b) the results are somewhat subjective and sometimes hardly to be followed by other interpreters.

As an aid to save time and improve the objectivity of lineament analysis we developed a novel method based on fast and efficient *unsupervised classification* followed by a modified implementation of the *Hough transform*. Starting from images corresponding to ancillary data from the areas of interest, unsupervised classification is achieved by first using Kohonen's *Self Organizing Map* (SOM) algorithm for vector quantization of the input data space and then by clustering the neurons of the map. As was observed using images obtained from grided magnetic and electromagnetic (real and imaginary) data, categories with a relatively small number of pixels correspond to significant linear formations. Therefore, a *threshold* is imposed on the classification map. In the resulting black and white image, only categories with a small number of pixels are kept as foreground, with the rest of the categories considered as background. At this stage, usually many linear formations are present, along with regions that do not correspond to linear formations.

At this point, further processing is needed in order to extract the significant information corresponding to lineaments from the unwanted information corresponding to correlated or uncorrelated noise. To this end, we have originally applied variants of the Hough transform (Duda and Hart, 1972), which is a well known method for detecting linear formations in the presence of noise. These variants have been applied with some success to the delineation of lineaments (Wang and Howarth, 1990). However, we noted that in most data sets, interference from unwanted pixels was very prominent.

A novel, general purpose method is proposed for detecting linear formations in highly noisy images which proved much more successful for the delineation of lineaments. According to this method, the image is decomposed into connected regions following a fast, one pass, label assignment procedure which is outlined in Sonka et al., 1993. While in the original Hough transform all foreground pixels contribute the same amount to all accumulator array points that correspond to lines passing through them, our method achieves preferential weighting of certain pixels by introducing a suitable voting kernel, which depends on shape descriptors of the connected regions of the image. In particular, to form the voting kernel, we take into account the elongation of each connected region, its area and the angle formed by a candidate linear formation and the principal axis of the region. The method is successful in removing both correlated and uncorrelated noise and find lines and prevalent orientations in very noisy images (Perantonis et al., 1998). The whole procedure for the delineation of lineaments (application of self organizing map for unsupervised classification, suitable thresholding and application of the novel line detection method) is outlined in Figure 1. The major steps of this approach are analyzed in the subsequent sections.

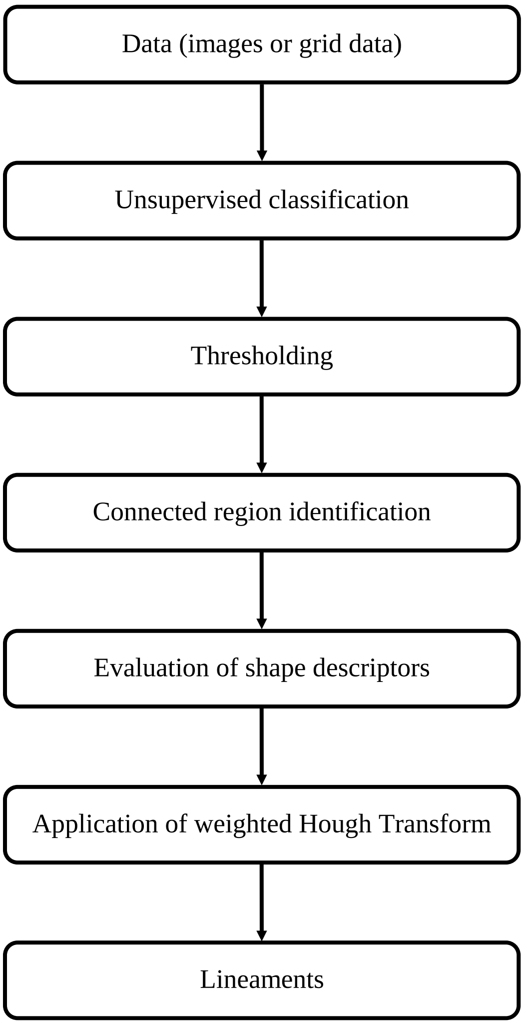


Figure 1: Outline of the procedure for the delineation of lineaments.

UNSUPERVISED CLASSIFICATION

A new methodology for efficient clustering and automatic classification of images or grided spatial data was used (Vassilas and Charou, 1999; Vassilas et al., 1999). Significant clustering and classification speedup was achieved by: a) using a self-organizing map for vector quantization of the data space, b) clustering the neurons of the map instead of the pixels of the original image, and c) using fast indexing techniques for efficient classification. Moreover, the computational speedup allows the user to optimize the results through repeated classifications with different number of clusters each time. Application of the proposed methodology to aeromagnetic and satellite images shows speedup of several orders of magnitude with respect to conventional clustering and classification techniques with no significant loss in terms of final performance.

The unsupervised classification techniques are mainly used when no training sets are available and constitute a valuable objective alternative since they do not depend on previous knowledge and photointerpreter's experience. These techniques, first cluster the data according to some similarity criterion, then assign a label to each cluster (usually a gray level or color) that corresponds to a (thematic) category and, finally, substitute each pixel of the original image with the cluster label to which it belongs (Figure 2). Among the most popular statistical clustering algorithms, we mention the Isodata algorithm (Duda and Hart, 1973) and those based on statistical analysis of multidimensional histograms (Goldberg and Shlien, 1978). It is worth noticing that a number of other statistical clustering algorithms, such as the various hierarchical algorithms (Duda and Hart, 1973) and algorithms based on scale-space analysis (Wong and Posner, 1993) can not be used in applications involving large volumes of data due to their computational complexity. As far as the non conventional algorithms are concerned, we mention the Fuzzy Isodata algorithm (Bezdeck, 1981; Cannon et al., 1986) from the fuzzy logic discipline and the neural algorithms such as the self-organizing maps (Cappellini et al., 1995; Kohonen,1989), a variant of the Adaptive Resonance Theory (ART) neural network (Baraldi and Parmiggiani, 1995) and the hybrid BatchMap algorithm (Kohonen, 1995).

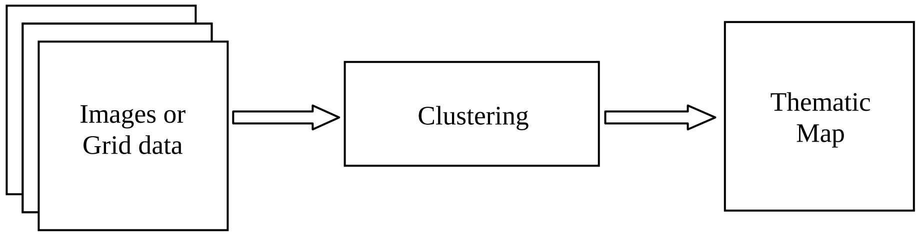


Figure 2: Traditional automatic classification.

Kohonen's self-organizing maps (SOM) (Kohonen, 1989; Kohonen, 1995; Ienne et al., 1997), is one of the most popular neural algorithms for clustering and vector quantization. SOM is a competitive algorithm used for unsupervised training of single-layered neural networks (1-D or usually 2-D lattices of neurons), whereby, a sequence of inputs is randomly presented to the network (map) and its weights are then updated so as to reproduce the input probability distribution as closely as possible. The weights self-organize in the sense that neighboring neurons respond to neighboring inputs (topology preserving mapping of the input space to the neurons of the map) and tend toward asymptotic values that quantize the input space in an optimal way. Using the Euclidean distance metric, the SOM algorithm performs a Voronoi tessellation of the input space (Kohonen, 1989; Kohonen, 1995) and the asymptotic weight vectors can then be considered as a catalogue of representatives or prototypes, with each such prototype representing all data from its corresponding Voronoi cell.

In the sequel, we present our methodology for automatic classification with the following advantages: a) memory savings through data quantization, b) clustering speedup, due to the relatively small number of prototypes, allowing the use of even the most computationally demanding algorithms, and c) classification speedup by using fast indexing techniques. For the presentation, we will assume MxN images obtained from n grided data sets. The input space $\mathbf{R}^n$ is used to represent the image as a set of MxN points whose coordinates are the corresponding values of each data set.

The first stage of the proposed methodology involves vector quantization of the input space using a 2-D lattice of neurons trained with the SOM algorithm. Following a random presentation of these n-dimensional points, the result is to obtain a catalogue of prototypes (the asymptotic weights of the neurons) that quantize the image.

Next, we use indexing techniques for mapping the pixels of the original image to their corresponding prototypes. To this end, an MxN *index table* is constructed to store pointers from pixels to their closest prototypes. The replacement of the original image with the catalogue of prototypes and the index table (Figure 3) constitutes the indexed representation of the image and results not only in data compression but also in a significant speedup of both data clustering and classification.

In general, the larger the number of neurons of the map is, the better the approximation of the original data space will be, due to a smaller quantization distortion (provided that the map self-organizes). However, according to experience, map sizes of no more than 16x16 neurons should suffice in most applications. In the case of large volumes of data from *n* data sets with 256 values/data set, compression ratios of approximately *n*:1, when 256 prototypes are used, are readily attainable.

Typically, automatic classification involves clustering of the data space followed by label assignment. However, due to the large number of data points (up to MxN different values), clustering performed on the original image data is inefficient in terms of both memory and time requirements. On the other hand, in our methodology clustering is performed on the neurons of the map (i.e., the catalogue of prototypes), thus, achieving orders of magnitude a speedup, allowing us to use even the most computationally complex methods

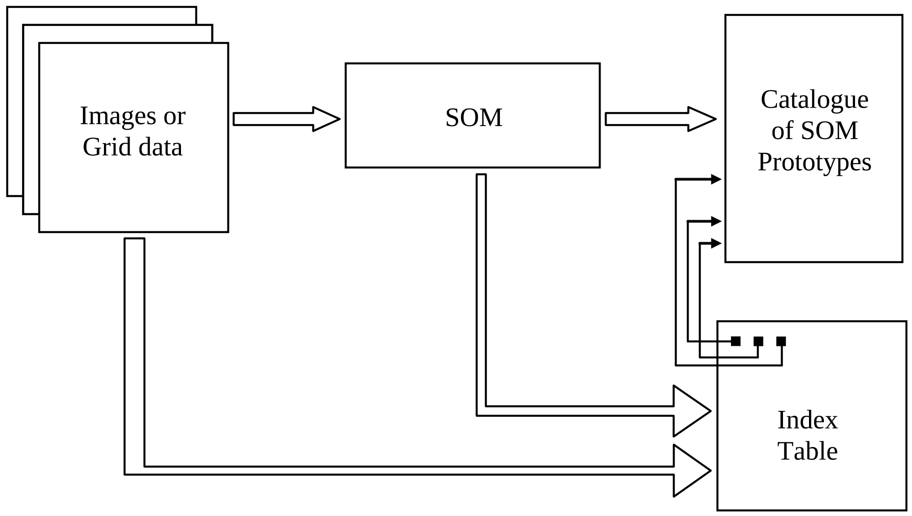


Figure 3: Indexed representation.

such as the hierarchical algorithms (Duda and Hart, 1973). Following clustering, the next step assigns labels to each cluster. These clusters along with their labels will represent the automatic classification categories. At the final stage of the proposed methodology, first the catalogue of prototypes is classified to obtain a corresponding catalogue of labels (Figure 4) and then by using fast indirect addressing through the index table (its pointers to the prototypes also point to their labels) the final classification result (thematic map) is obtained (Figure 5).

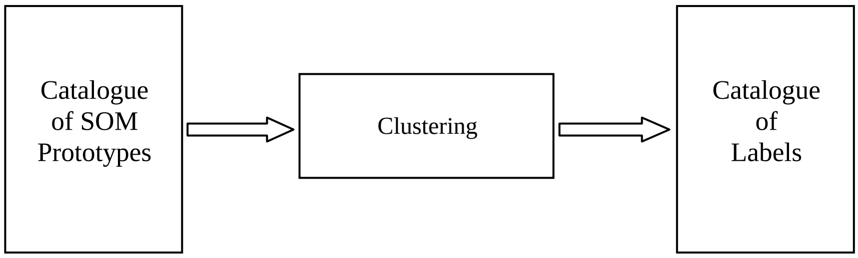


Figure 4: Creation of the catalogue of labels.

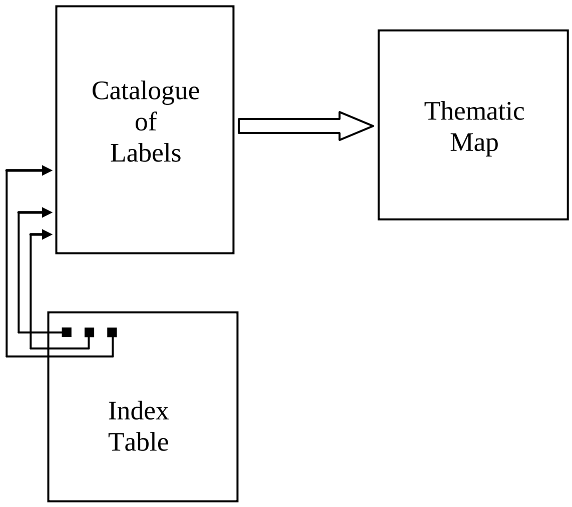


Figure 5: Fast indexed classification

THRESHOLDING OF THE CLASSIFICATION RESULT

A thresholding method was used as the binarization method of the classified image. A histogram of the image is plotted in order to assist on the specification of one of the four following thresholding methods:

- *Percentage Threshold (0-100%):* Gray levels whose percentage of pixels with respect to the total number of pixels in the image are below the threshold, are assigned to the foreground. Otherwise they are assigned to the background.

- *Gray Level Threshold (0-255):* This is the traditional thresholding method in image processing. All gray levels above the threshold are assigned to foreground, otherwise, they are assigned to background.

- *Foreground Gray Levels:* Explicitly defined values of grays to be assigned to foreground.

- *Background Gray Levels:* Explicitly defined values of grays to be assigned to background.

CONNECTED REGION IDENTIFICATION - SHAPE DESCRIPTOR EVALUATION

The connected regions of the binary image were specified by using the label assignment procedure outlined in (Sonka et al., 1993), whereby a linked list is constructed for storing simultaneously the following:

1. labels belonging to different regions using vertical pointers, and

2. equivalence classes, i.e., labels assigned to pixels of the same region using horizontal pointers.

The image is scanned top to bottom and left to right, skipping background pixels, until a new foreground pixel is found. If all the top and left connected neighbors (e.g. assuming 4- or 8-connectedness) belong to the background, a new label is added to the bottom of the linked list and the pixel points to this label (the pointers from pixels to labels are stored in a 2-D array with the same dimensions as the original image). Otherwise, the pixel is made to point to the first label found among the foreground top and left neighbors. Inconsistencies due to two different neighboring pixels having different labels are easily resolved as follows: the second found label is first removed from the vertical label list, then placed to the equivalence class (horizontal list) of the first found label and finally changed to the first found label (also specifying the equivalence class). Such a technique has the advantage of speed, since it does not require a second image scanning in order to assure uniformity in region labeling, i.e., changing all equivalent labels to one.

For each connected region we then calculate three shape descriptors, all of which can be evaluated in terms of the central moments m_{ij} of the region:

1. The area:

$$A = m_{00}. \quad (1)$$

2. The angle ϕ of the principal axis relative to the x-axis, given by the equation:

$$\phi = \frac{1}{2} \tan^{-1} [2\, m_{11}/(m_{20} - m_{02})]). \quad (2)$$

3. The elongation of the region. This is evaluated by finding the ellipse that best fits the region (in the sense that it has the same moments of inertia). The elongation ε is then equal to the major to minor axis length ratio (so that $\varepsilon > 1$) and can be found as:

$$\varepsilon = | I_{max}/I_{min} |^{1/2}, \quad (3)$$

where

$$I_{min} = m_{20}\sin^2\phi + m_{02}\cos^2\phi - m_{11}\sin 2\phi \quad (4)$$

and

$$I_{max} = m_{20}\cos^2\phi + m_{02}\sin^2\phi + m_{11}\sin 2\phi. \quad (5)$$

Details on the derivation of these formulae can be found in (Jain, 1989).

MODIFIED HOUGH TRANSFORM

The Hough transform is a popular and powerful method for detecting parametrically described shapes in images. However, even in its simplest application, which is the detection of straight lines, the original Hough transform is susceptible to the presence of both random and correlated noise that may give rise to spurious maxima in the accumulator array (Leavers, 1993). The problem is especially acute in cases where the required lines are axes located in the interior of objects, so that edge detection followed by Hough transform application is not appropriate for locating them (Gatos et al., 1996). It is thus highly desirable to have methods of hindering irrelevant pixels from contributing to the accumulator array. In the original Hough transform all foreground pixels contribute the same amount to all accumulator array points that correspond to lines passing through them. Preferential weighting of certain pixels can be achieved by introducing a voting kernel (Palmer et al., 1997). Here we present a novel method that employs a suitably defined voting kernel to reduce interference effects and avoid spurious accumulator array maxima even in very noisy images. The kernel depends on the shape descriptors of the connected regions of the image described in the previous section. The method is highly successful in finding linear directions in demanding image processing and computer vision applications.

Given a binary image, we are interested in the detection of straight lines whose points (x,y) are parameterized by $r = x \cos\theta + y \sin\theta$, where r is the distance of the origin from a particular line and θ is the angle formed by the normal to the line and the x-axis (Figure 6). For each connected region, we consider its geometrical center and increment for various values of θ the corresponding cells in the accumulator array. To evaluate the contribution of each region to various cells in the accumulator array we take into account its related shape descriptors and express the dependence formally by introducing a voting kernel.

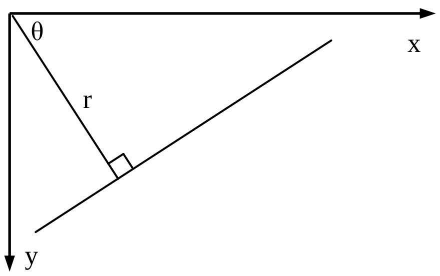


Figure 6: Parametrization of a straight line for application of Hough transform.

The voting kernel is a continuous function of the shape descriptors and is constructed by taking into account the following considerations. The presence of an elongated region is taken as strong evidence for the existence of a line parallel to the principal axis of the region. Thus, the contribution to the accumulator array should increase with ε. Moreover, for a given value of ε, this contribution should be maximum for $\phi = \theta$ and drop with increasing $|\phi - \theta|$. The rate of change with increasing $|\phi - \theta|$ should clearly depend on ε**.** For very elongated regions, only the direction $\phi = \theta$ should be incremented. On the other hand, nearly circular regions ($\varepsilon \approx 1$) should be allowed to vote equally for all directions. Finally, a dependence of the kernel on the area A should be introduced in order to minimize interference effects and avoid spurious accumulator array maxima. Contributions from regions of large A and relatively small ε should be suppressed. These regions are a major source of correlated noise, because spurious lines can be formed from points lying in their interior. At the other extreme, regions of very small A should also be discarded as random noise. In-between these extreme cases, regions of small ε whose area is comparable to a characteristic intermediate area scale A_0 may be part of a chain of regions contributing to a disrupted linear structure and should be taken into account.

To summarize, given a connected region whose center is located at $(\bar{x}, \bar{y})$ and a value of the angle θ, the contribution to the accumulator array cell (r, θ) is of the form $f(A, \varepsilon, \phi - \theta)$ where f must fulfill the following conditions:

1. should be asymptotically proportional to ε as $\varepsilon \longrightarrow \infty$
2. f should not depend on θ as $\varepsilon \longrightarrow 1$ and should tend to $\delta(\phi - \theta)$ as $\varepsilon \longrightarrow \infty$
3. for $\varepsilon \approx 1$, we should have $f \longrightarrow 0$ as $A \longrightarrow 0$ or A $\longrightarrow \infty$

The following function is modeled to conform with the above conditions:

$$f = \varepsilon\, exp[\, -(\varepsilon - 1)\,(\phi - \theta)^2\,]\;\; A\, exp[\, -(A - A_0)/(A_0\, \varepsilon^2)] \tag{6}$$

The factor ε weights elongated regions in accordance with condition 1; the factor $exp[\, -(\varepsilon - 1)\,(\phi - \theta)^2\,]$ is inserted to conform with condition 2; and the factor $A\, exp[\, -(A - A_0)/(A_0\, \varepsilon^2)]$, which has a maximum at $A = A_0$ for given ε, plays the role of a band-pass filter for values of ε close to 1 (so that condition 3 is fulfilled). A_0 can be chosen as the average area of regions whose elongation exceeds a threshold. However, our simulations have shown that the method is robust, exhibiting stable performance for a wide range of values for A_0.

EXPERIMENTAL RESULTS AND DISCUSSION

The automatic lineament detection method has been applied with success on different combinations of geophysical airborne magnetic and electromagnetic (real and imaginary) data from the Vammala area in Finland. For visualization purposes, the original 601x801 grid data were first linearly mapped in [0, 255], then quantized to the nearest integer and finally shown as images. In the sequel, we show the results produced by a combination of magnetic and real electromagnetic data (Figures 7a and 7b).

All programs were run on a SUN ULTRA II Enterprise workstation (64MB, 167MHz). A map of 16x16 neurons was trained with 10^5 random presentations of the 2-D grid data in 20.35sec. Following SOM training, the storage of asymptotic weights into the catalogue of SOM prototypes (256 prototypes x 2 floats/prototype x 4 bytes/float x 8 bits/byte = 2^{14} bits) and the index table construction (601 x 801 indices x 8 bits/index $\approx$ 1.8 x 2^{21} bits) required 87.06sec. The SOFM prototypes and index table can also be used for representing the original data (2 data sets x 601 x 801 integers/data set x 32 bits/integer $\approx$ 1.8 x 2^{24} bits) in a compressed form. The compression ratio achieved in this case is about 8 while higher ratios can be obtained for more data sets and/or smaller maps, although, caution should be exercised with the latter since small maps may lead to large quantization distortions.

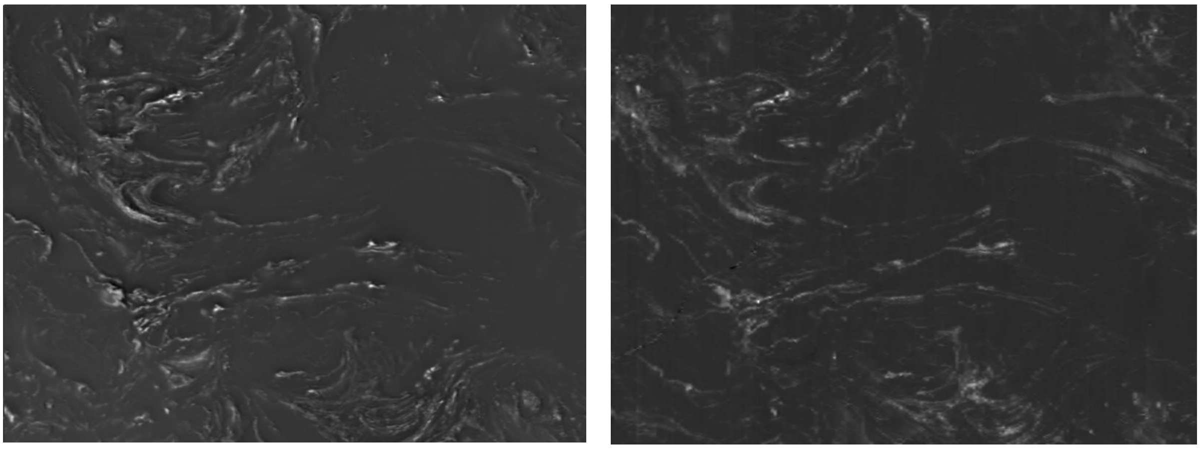
Automatic classification in 10 categories was then performed by clustering the neurons of the map using the Fuzzy Isodata algorithm. The algorithm was terminated after a preselected maximum number of 100 iterations in 0.58sec and the classification result is shown in Figure 8a. The additional indexed classification time was 0.40sec. Direct application of the Fuzzy Isodata algorithm to the original data is possible at a cost of about 1880 times (601x801/256) longer clustering time per iteration. In fact, original data clustering in 10 categories required 1153.34 sec (100 iterations) while classification required 3.75sec.

From the above, the clustering speedup per iteration, achieved by using the proposed methodology with Fuzzy Isodata, is about 1153.34/0.58 = 1988 while the classification speedup, due to the indexing techniques, was 3.75/0.4 = 9.375. At this point, it is important to notice that if SOM training and index table construction (requiring 107.41sec) are not off-line computations, the speedup in the first user trial will be smaller. However, for any additional classification trials (with different number of clusters) performed by the user for optimizing the results, the speedup will be as stated above.

Following unsupervised classification, the image is then binarized in 0.03sec using a variant of the first thresholding criterion, whereby, the foreground pixels inlude the smallest categories that cummulatively do not exceed 20% of the total image area (see Figure 8b). The 8-neighbors connected regions along with the *area*, *principal axis angle* and *elongation* shape descriptors of each region are then computed in 0.67sec. Finally, the lineaments are found using the proposed weighted Hough transform in 5.96sec and are shown superimposed on the binarized classification result in Figure 9a.

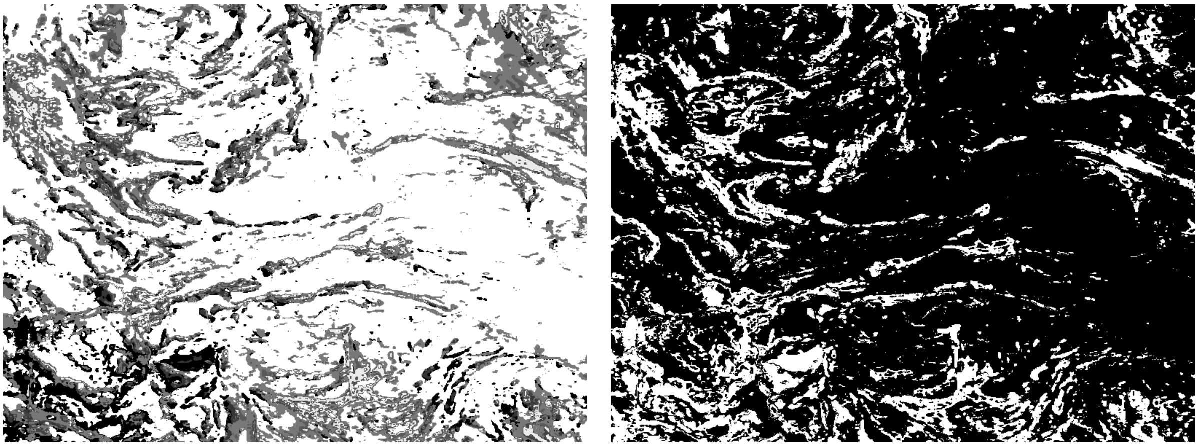
Figure 9b shows the lineaments found by the original Hough method superimposed on the binarized classification result. It is apparent that interference from unwanted pixels (mainly from the large regions found in the bottom of the image) was very prominent and that this method fails to delineate lineaments. On the other hand, the result obtained with the proposed (modified) Hough transform following extraction of the appropriate shape descriptors clearly shows significant linear formations (see Figure 9a). Similar results are also obtained by applying the original Hough transform to the image of Figure 10a which contains the edges of the binarized classification result. As most of the edge pixels lie in the bottom of the image, the method fails to detect the true linear formations (see Figure 10b).

In short, we believe that our proposed method for automatic lineament detection can prove a useful tool not only to those involved with environmental informatics but also to geologists and geophysicists who would like to have a first glance on a digital lineament map without significant time investment. Such a map can then serve as the starting map of a series of improved lineament maps produced within a Geographical Information System (GIS), whereby, existing lineaments can be modified, new ones added and wrong ones removed, by the use of pointing devices, incorporating additional geological and/or geophysical information.



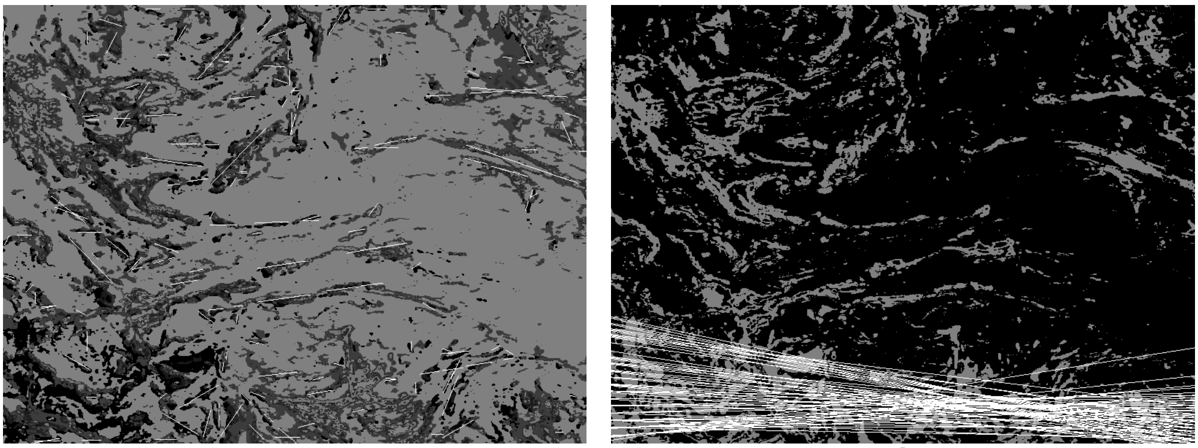
(a) (b)

Figure 7: Original geophysical grid data from Vammala area visualized as 601x801 gray level images: (a) magnetic data, (b) real part of electromagnetic data.



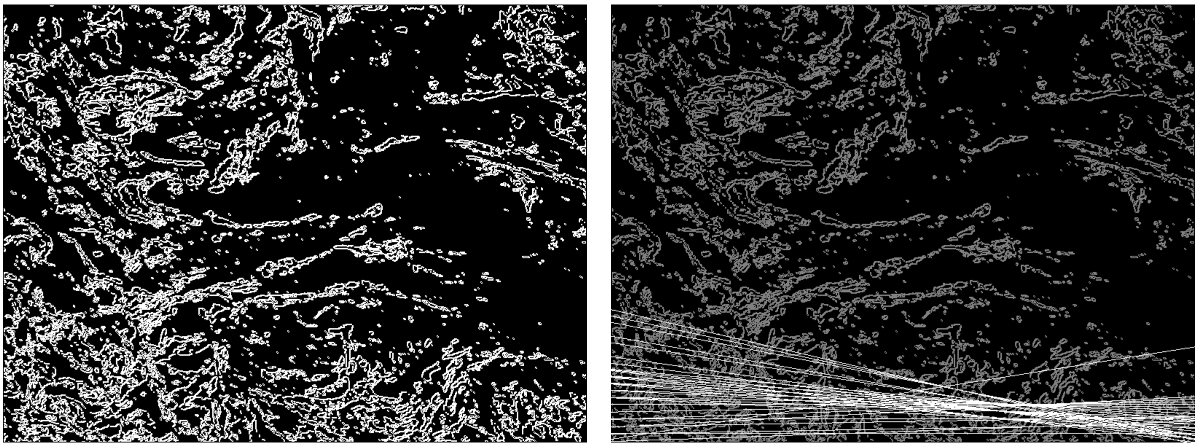
(a) (b)

Figure 8: (a) Classification result in 10 categories using a self-organizing map and Fuzzy Isodata neuron clustering, and (b) binarized classification result.



(a) (b)

Figure 9: Lineament detection from the Vammala area, superimposed on thresholded classification result using (a) the modified Hough transform, and (b) the original Hough transform.



(a) (b)

Figure 10: (a) Binary image produced by extracting the edges of Figure 8b, and (b) the most prominent lines found by the original Hough transform.

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