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Soft Computation Based Topographic Map Legend Understanding Prototype System

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Abstract— ***The goal of the study is to devise an intelligent system to understand topographic map automatically. This paper explains the design of a system to automatically interpret information from scanned Indian topographic map legends set.***

A method based on perception of shape provides a collective understanding of size, form and orientation as that of human psycho-visual approach, is required towards development of a topographic map legends understanding system. The fundamental of the system are map legend analysis algorithms- Edge detection algorithm and line thinning algorithm to extract patterns and shape features from images of scanned topographic map legends and describe it as primitives which is building entity of shape of legend. An approach is based on feature extraction model and back propagation neural network which allows efficient and coherent management of map legends, recognition processes, recognition results. The system incorporates shape feature and uses back propagation neural network for recognition. The experimental results show that developed system performs well in recognition and understanding of map legends.

Index Terms—***Back propagation neural network, Edge detection, Legend primitives, Map understanding, Syntactic pattern recognition, Thinning algorithm,.***

I. INTRODUCTION

A topographic map is characterized by large-scale detail using the topography of land. It shows both natural and man-made features. Topographic maps essentially consist of color point, linear, and area features to represent geographic information about the earth, or part of it. It has been in use since long for a variety of purposes where frequent reference to a map is required, e.g. routing and scheduling applications, site location, geographical analysis, for military purposes, etc. The use of a map of such applications is tedious and time-consuming. People involved in map reading need to have a good level of ability to undertake the task. Effectiveness of perception and the human mechanism for processing information has a finite capacity as it is directly related to the ability of an individual to interpret the information. So for every kind of aspect to be interpreted with the map understanding it is sensible to assume map reader's assumption. Culturally trained map legend understanding system can make good use of maps for practical problem solving. Psychological studies prove that humans can recognize an object using outline (shape) is one of the important feature which carries characteristic information about it even though they are different in texture or color [1].

Therefore, it is an interesting scope for an automated understanding of map to reproduce psycho-physical capabilities of human vision admitting very complex task by computer treatment.

The work of map understanding system starts with a cartographic pattern recognition system using homogeneous parallel algorithms [15], automatic map recognition system [7] and query-driven map recognition based on template matching [11]. Yamada et al. [16] focused on extracting specific features such as points and lines based on a computationally intensive multi-angled parallelism method, whereas Samet and Soffere [12-13] reported a legend driven map recognition system. But the legend driven map recognition system is based on weighted bounded several nearest-neighbor classifier which is noise sensitive and requires separate map layers as inputs. Top-down approaches [4,18] suggested especially suitable for recognizing symbols or letters from maps or technical drawings. Research has also been done by separating the layers of scanned maps by colors as in [10].

Research on automated map interpretation has been going on for many years and obtains certain achievements. In the automatic symbol and line recognition Hausdorff distance and multilayer neural network for recognition is proposed. In this case, the found candidates are passed through the network for user-guided training or for recognition once trained [6]. A research is presented to automatically extract information from paper-based maps and answer queries related to spatial features and structure of geographic data. This paper proposes a set of map legend analysis algorithms to extract spatial features from images and query processor to analyze the queries presented by the user [11]. A method for automatic data acquisition from colored topographic maps is proposed in which a semantic net is used as a formalism for representation of corresponding knowledge [10]. In the contour line extraction to overcome the difficulty of the gaps and thick line's introduction of linear feature extraction from a gray version of the input color image and local window segmentation method is proposed [10]. In the Handwritten numerals recognition topic multilayer cluster neural network is adopted [12]. Other systems mostly consider the extraction of one or more types of features and primitives of complex maps [3,5,8] but do not address the problems of non-horizontal symbols in different orientations. No work on recognition and understanding of the legends in the Indian topographic map based on ANN has been reported so far in the literature.

The approach described in this paper is different from those described in the literature. In this approach the information is extracted from scanned map legends using map legend analysis algorithms in the form of primitives i.e. element that is to be accepted as a part of shape and having specific pattern and given as input vector to back propagation neural network.

Recognizing legend is the first step in using a topographic map.

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Though prerequisite for extraction of information from topographic map, automated understanding of the legend is a challenging task. Hence, the study of a soft computation based Indian topographic map legend understanding prototype system mainly focused on two aspects: one concentrates on seeking efficient methods to detect the legend image and then identifying specific legend image pattern, the other focuses on transferring legend image pattern into a neural network. In this paper, a topographic map legend understanding system based on shape representation in the form of primitives and shape interpretation using neural network is explained. In the next section, feature extraction model to form primitives which acts as primitives, is described, while Section III gives detailed description of back propagation algorithm. Section IV explains working of the system. Section V reports the experimental results. Finally, Section VI concludes this paper.

II. A FEATURE EXTRACTION MODEL

Edge detection is itself acts as a segmentation technique based on detection of discontinuity. An edge or outline always leads to changes in intensity of an image. A major motivating factors behind the use of syntax or sequential order of primitives or primitives for legend understanding is that our collective understanding about the object lies in the shape of legend. The human biological psycho-visual system always uses the edge detection technique instead of threshold or intensity based measures for the recognition of different objects.

A. Edge Detection Algorithm

One of the main tasks of this application is to detect the specific syntactic pattern in a legend image. The edge detection is processed in the gray color amount of the pixels. The Prewitt operator is used within the edge detection algorithm is used to develop proposed system.

A Prewitt's edge detector is used to find edges in smoothing topomap. Then the map is binarized using local adaptive thresholding technique. Prewitt's outlines are dilated for filtering. Prewitt edge detection computes an approximation of the gradient of the image intensity function. The Prewitt operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction. Mathematically, the operator uses two 3×3 kernels which are convolved with the original image to calculate approximations of the derivatives - one of horizontal changes, and one for vertical.

$$1/3^* \begin{matrix} 1 & 0 & -1 \\ 1 & 0 & -1 \\ 1 & 0 & -1 \end{matrix} \qquad 1/3^* \begin{matrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{matrix}$$
$$x \qquad\qquad\qquad y \qquad (1)$$

The pixel number in the 3X3 sub-domain of image in the form of window is defined by:

A0	A1	A2
A7	[i,j]	A3
A6	A5	A4

where, A0 to A7 are the gray levels of each pixel about the pixel [i,j]. The partial derivatives can be computed by,

$$dx = -1^*A0 + 1^*A2 - 1^*A7 + 1^*A3 - 1^*A6 + 1^*A4 \qquad (2)$$
$$dy=1^*A0 +1^*A1+1^*A2 -1^*A6 -1^*A5 -1^*A4 \qquad (3)$$
$$Z = \sqrt{dx^2 + dy^2} \qquad (4)$$

where, Z is the Prewitt gradient. All pixels are filtered to determine edge points [17].

III. THINNING ALGORITHM

The shape of a legend is one of the features for recognition. Thus, it is necessary to identify the shape and its pattern. The Prewitt edge detection algorithm detects edge points. A thinning algorithm converts the edge obtained from the threshold technique to a one-pixel wide line [2].

The thinning algorithm iteratively deletes pixels inside the shape to shrink it without shortening it or breaking it apart. To decide whether an edge pixel A0 should delete,sider its 8 neighbors in the 3 by 3 neighborhood, A1, A2, A3, A4, A5, A6, A7. Special method neighbor() is implemented that returns the offset of a neighbor pixel to x, y in the specified direction j. Another method match_Patterns () is developed that checks if a specified pattern matches the actual position x, y of the array. This method is mainly used by the thinning algorithm. The edge data is converted into an ordered primitives to describe a syntax or structure of legend.

IV. LEGEND PRIMITIVE

The central part of this system is the syntactic pattern recognition of each legend image in the form of primitives, which are found after the map legend processing. The cosine and sine angles of the shape represent the criteria of a recognition pattern in order to transfer the legend image shape into a neural network usable form. Fig. 1 shows a part of a legend image that was already processed through above mentioned edge detection and thinning algorithms. Methods are implemented to calculate the cosine & sine to identify the direction of a line. Thus a primitive is specified by the coordinates of the line and its cosine & sine angle.

Here Red Line represents the shape of the legend image after a successfully edge detection and thinning.Red Square represents this square represents a point in the shape of the legend image from which a line of the next square is drawn.

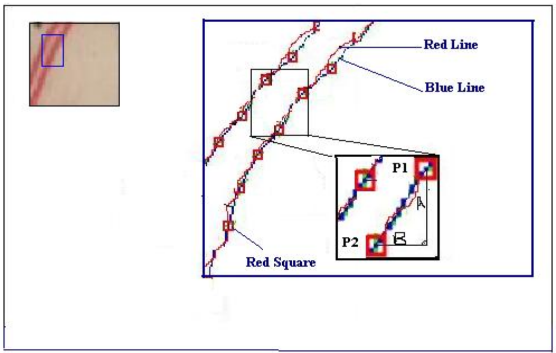

Fig. 1 Legend image primitives

Blue Line represents the compound in the center of two squares from which the cosine and sinus angle are computed. Such a blue line is a representation of a legend primitive. The small right angled triangle represents a primitive of a single legend image. The summary of all triangles of a legend image represents the primitives of a legend from which the calculations of neural network can be started. The direction of hypotenuse can be represented from point P1 to P2.

V. THE BACK PROPAGATION ALGORITHM

Another important part of this work is the integration of a feed-forward back-propagation neural network. The proposed neural network has one input, hidden and output layers.

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Back propagation computing element structure is shown in Fig. 2. The inputs for this network are the individual pattern which is represented in the form of primitive. A primitive is defined by a cosine and the sine angle hence the amount of input neurons for this network are the two times the amount of primitives.

The number of output neurons is normally specified by the amount of different legend types that we want to recognize. The network parameters are defined by the mathematical framework of a back-propagation network [14]. The network uses the performance index: mean square error. The algorithm is provided with a set of legends primitives and desired output for proper network behavior.

$$\{i_1,t_1\},\{i_2,t_2\},......,\{i_K,t_K\} \tag{5}$$

where, i_k is an input to the network and t_k is the corresponding target output.
If $e_k = t_k - O_k$ then the network's energy function i.e. the total output error is:

$$E(x)=\frac{1}{2}\sum_{k=1}^{K}[(t_k-O_k)^2] \tag{6}$$

where, x is vector containing all network weight and biases, t_k the target output, and O_k the actual output. The E is the sum of squares of all patterns. The algorithm should adjust the network parameters in order to minimize the mean square error. During the first step the input i_k is propagated forward. For multilayer networks the output of one layer becomes the input to the following layer [9]. Following are the equations showing net input for hidden and output layer respectively.

$net_j = \sum_{j=1}^{m} \omega_{ij} o_i + b_i$ is used between input and hidden layer

where, ω_{ij} represents the weight connecting the input neuron to the hidden layer neuron and b_i is a bias. The net input is used by its activation function.

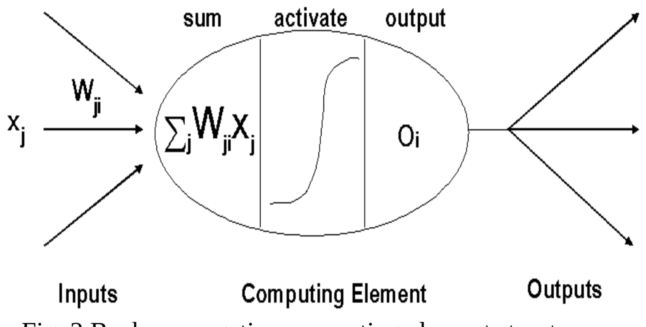

Fig. 2 Back-propagation computing element structure

$net_k = \sum_{k=1}^{m} \omega_{jk} o_i + b_k$ is used between hidden and output layer where, ω_{jk} represents the weight connecting the input neuron to the hidden layer neuron and b_k is a bias. $O_j = f(net_j)$ and $O_k = f(net_k)$ are the output equation of hidden and output layer respectively.

The sigmoid activation function is $f(x)=\frac{1}{1+e^{-x}}$

According to Delta learning principle,

$$\Delta\omega_{jk} = -\eta\frac{\partial E}{\partial \omega_{jk}} \tag{7}$$

$$\delta_k = e_k.g'(O_k) \tag{8}$$

is used for adjusting weight. Here, g' is derived activation function.

Defining that $\delta_k = -\frac{\partial E}{\partial net_k}$

Then Equation (3) can be calculated:

$$\Delta\omega_{jk} = -\eta\frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial \omega_{jk}} = -\eta\delta_k O_j \tag{9}$$

where, η is a positive constant called as learning rate. Then calculate δ_j for preceding layers.

The network is initialized with random numbers using random (-1.0,1.0) function. [14].

$$\delta_j = \eta.g'(O_k)\sum_{k=0}^{k}\delta_k\omega_{jk} \tag{10}$$

$$\Delta\omega_{ij} = -\eta\frac{\partial E}{\partial \omega_{ij}} = -\eta\frac{\partial E}{\partial net_i}\frac{\partial net_i}{\partial \omega_{ij}} = -\eta\delta_j O_i \tag{11}$$

This correction step is needed to transform the back propagation algorithm into a learning method for neural network.
In order to update the connection weight matrix in turn,

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \alpha\Delta\omega_{ij}(t) \tag{12}$$

$$\omega_{jk}(t+1) = \omega_{jk}(t) + \alpha\Delta\omega_{jk}(t) \tag{13}$$

is used where, t+1 represents a new set of weights/biases, α is momentum coefficient that can have a value between 0 and 1. Learning rate determines how much the link weight and biases can be modified. Higher learning rate i.e. max of 1 leads to faster training process but it can also lead to no guarantee converging. With small learning rate, number of iterations will increase resulting in slow converging processing.

VI. WORKING OF THE SYSTEM

A. Map Legend Processing

The initial part of a system is the map legend processing. Without finding primitives we cannot convert the shape of legend into neural net parameters. The left Road map legend in Fig. 3 is a view of the original legend image in the image file and the right one is the map legend processed which is generated after pressing "Find Primitive". Three configurable sliders are used to set the threshold for the detection of the edge, the distance of the syntactic pattern generated in the form of primitives (red square) and a number of pixels in a line that should be recognized as a pattern which cannot be subdivided further to recognize it successful.

The different types of legend images can be added and deleted from the hierarchical list at the right upper side window.

B. Neural Network

Another main part of this application is the back-propagation neural network. The inputs for a network are the individual detected syntactic pattern in the form of primitives of a legend image.

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The following network information can be obtained from Fig. 3: there are 200 legend images in the training set and 10 legend types. Also there are maximum 52 primitives got from the first step. The network parameters are shown in Table 1. The single pattern is defined in terms of cosine and sine angle to input that pattern in neural network it requires two neurons per pattern. The number of output neurons is the number of different legend types that is to be recognized. The result shows that when the step kept at 500, the error will reach about 0.129.

C. Recognition

The last of three parts in this system is the recognition as shown in Fig. 4. Recognition result tested for only 4 legends are shown in fig. 4. The probably approximately correct learning model is applied for 10 different legends set. A set of x is a conceptual set of primitives of a legend image and a set of subsets of x i.e. primitives of a legend of a particular type are called a concept class. An element of a concept is an object in the domain of interest together with a class label. If the element is a member of the concept, then refer to it as a one else as a zero [14]. It is implemented using learn_vector() function. A concept in which elements are provided is called a target concept. The result of this recognition is displayed with a value whose closeness to one determines its legend type. It shows that the primitive of loaded legend is similar about 0.990 to a legend type Road. It is concluded that the loaded legend is most similar to the legend type Road.

VII. RESULTS

To demonstrate the effectiveness of the proposed map legend understanding prototype system, numerical simulations have been performed. The system described in this paper was tested for 10 different types of symbol data sets in which each set contains 20 samples for the training set and 20 samples for the testing set. The small parts of a toposheet image of sizes 350X300, 800X600, 1500X400, and 2700X2900 scanned at 300dpi was taken for both training and testing. The testing sets are used to test the accuracy of the developed system. Each kind of legend is loaded from a training set for testing and is recognized correctly. For each kind of legend in training set the performance metric in terms of accuracy is 100%. In order to analyze how method will perform in practice, 5-fold cross validation technique was used. The map legends were grouped into 5-fold cross validation.

Table 1. Network operation parameters

Input Neuron	Hidden Neuron	Output Neuron	Lear n rate	Momentum	Max. Steps
104	20	10	0.3	1.0	500

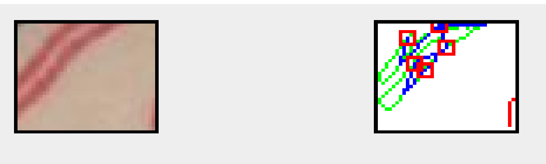

Fig. 3 Primitive formations using map legend processing operations

Each iteration was carried out with one subset as a test set and the rest of the subsets have been combined to form training set. The result is shown in Table 2. It provides a percentage of correct recognition of 10 diffetent types of symbols. An overall recognition rate of 91.24% is achieved. It is found that tree, antiquities, broken land and grass is having a higher recognition rate as compared to the rest due to their distinctive shape. The recognition error rate is higher for Hut, Road, River. The primitive generation algorithm results in the external spatial representation of symbols in terms of sub-patterns. During training process neural network has learnt the pattern of corresponding sample images of training set and in recognition process it found that primitives obtained are exactly same as the previously learnt primitives. The trained models are used to recognize symbols appeared in training as well as testing image with an overall success rate of 91.24%.

It has been found that Road legend test images are recognized correctly giving 88.82% accuracy. 20 sample images from testing set are tested out of which 17 sample images are recognized correctly as a cart-track providing 90.77% accuracy. The accuracy of Antiquities recognition is 95.68% For Well legend testing, the system gives 87.49% accuracy. Thus a system provides overall accuracy rate of 91.24%. The experimental results can be summarized as in Table 2.

VIII. CONCLUSION

Topographic map provides valuable information to a planner or surveyors, but their understanding remains a time-consuming and subjective task. The shape representation using primitives provides a shape description paradigm for improving the traditional approach of overlying for symbol recognition. The system incorporates shape feature and uses back propagation neural network for recognition which emulates human understanding process. The result gives 91.24% of accuracy.Although the performance of the system is good enough, only shape cannot be single criteria for recognition. As topographic map reveals lots of information using colors, the system should incorporate a color feature in the recognition process. Also, an automatic understanding of digital maps remains an open problem due to the complexity, wide variability of the characteristics and heavily interconnected objects and labels and different features of topographic maps which will be researched in the future.

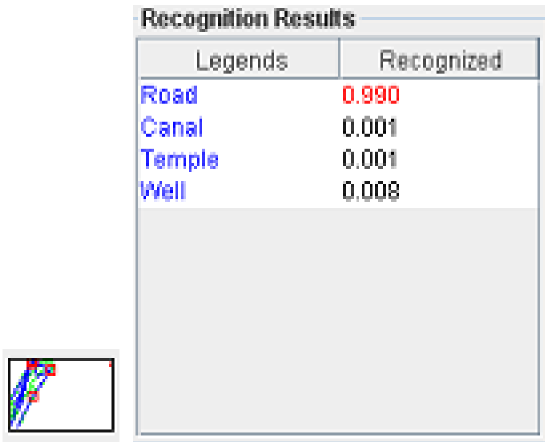

Fig. 4 Recognition process

Table 2. System performance in terms of accuracy

Legends	5-fold cross validation					Overall recognition
	Fold-1	Fold-2	Fold-3	Fold-4	Fold-5	
Hut	87.90	93.04	82.30	82.67	86.00	86.38
Tree	100	92.89	96.03	100	100	97.78
Grass	90.83	92.90	89.00	91.45	91.58	91.15
Antiquities	92.56	100	100	93.01	92.85	95.68
Road	86.90	92.90	90.54	82.00	99.00	88.82
Dry Stream	90.76	90.70	89.87	91.98	87.99	90.26
Cart-Track	89.87	90.77	91.45	92.78	89.02	90.77
River	90.67	88.43	91.32	90.70	87.90	89.80
Broken Land	92.30	90.54	92.89	96.03	100	94.35
Well	89.02	82.67	89.00	86.90	89.87	87.49
Overall Recognition	91.08	91.48	91.24	90.75	91.69	91.24

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