GABOR FILTER AND NEURAL NET APPROACH FOR BUILT UP AREA MAPPING IN HIGH RESOLUTION SATELLITE IMAGES

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ABSTRACT:

In the satellite images, built up area is manifested as texture. Therefore, built up area analysis can be approached using texture concepts. It is observed in many gray scale high resolution satellite images that building tops , ground, vegetation and roads have almost same gray value variations and also sometimes texture of the image surface is not very well defined. So when built up area analysis is performed based on only either gray level variation or texture of the image alone, it does not always give satisfactory results, The proposed approach in this paper involves a multi level processing which uses both texture information as well as tone variation of the image to perform analysis for built up area mapping. The approach is based on Gabor filters and neural networks to extract built up areas in satellite images such as IRS 1C/1D and IKONOS. The main issues addressed in this process are – functional characterization of the filter bank and number of filters, extraction of appropriate texture features from the filtered images, the relationship between filters (dependent vs. independent) and the texture feature extraction. The paper addresses all these issues and proposes a texture feature to reduce the computational time required for Gabor Filter based texture classification. The classification of texture features is done using artificial neural networks. In the second layer of processing, built up area extracted in first layer is segmented using Fuzzy C means clustering resulting in extraction of individual buildings. The output of the approach results in layout of the urban areas which can be used for updating the GIS information or the maps.

1. INTRODUCTION

In present scenario, built up areas change very fast. In order to monitor these changes as well as to update the information on regular basis, it is very much required to automate the process of mapping built up area from satellite images. Research work in this area has been carried out for automatic building extraction in aerial images(Busch 1999 ; Fraser et al 2000; Grun 1997**;** Schilling et al 1997) where buildings are clearly visible and their contours can be extracted. In IRS1C/1D panchromatic images having resolution 5.8 meters, individual buildings are not seen, but boundaries of built up area can be marked and this information can be used for updating maps or Geographic Information System (GIS). There are very few publications dealing with satellite images having resolution same as that of IRS1C/1D for built up area extraction (Lacroix et al 2004; Lacroix et al 2006).

In the satellite images, built up area is manifested as texture. Therefore, built up area analysis can be approached using texture concepts. The areas of modeling, synthesis, description, segmentation and classification of texture require intensive research and a series of methods have been developed (Zhang 2002). However, due to the variety of different types of texture present, there is as yet no overall solution for any of these topics. The problem becomes even more complex in case of texture in satellite images.

Many methods have been developed to extract texture features, which can be loosely classified as statistical, model – based and signal processing methods. In statistical approaches such as the co-occurrence or autocorrelation statistics of the gray levels of pixels (Tuceryan 1993; Zhang 2002). These have disadvantage of small window size and are not suitable for built up area analysis as it can capture only micro level texture. Model based methods characterize texture images based on probability distributions in random fields, such as Markov chains and Markov random fields (MRFs) (Li, 1995;Tuceryan 1993). MRFs are widely used because they yield local and economical texture descriptions (Li, 1995). However, they require intensive computations to determine the proper parameters. Signal processing methods also known as multi channel filtering methods are attractive due to their simplicity (Randen et al 1999). In these methods, a textured input image is decomposed into feature images using a bank of filters such as Gabor or wavelets. Among the filter based approaches, multi-channel filtering approach using Gabor filters (Jain et al 1991; Simona et al 2002) is intuitively appealing because it allows to exploit differences in dominant sizes and orientations of different textures. The other advantage of this approach is that one can use simple statistics of gray values in the filtered images as texture parameters. The present paper proposes a multi level approach based on Gabor filters and neural networks to analyze built up areas in satellite images such as IRS 1C/1D and IKONOS. Section 2 of the paper contains the proposed approach. Results and analysis is presented in section 3. Section 4 and 5 consists of conclusion and references.

2. PROPOSED APPROACH

Built up area and building extraction in satellite images has been proposed as a hierarchical approach which involves both texture information as well as tone variation of the image to perform classification for built up area mapping. The flow of the steps of the approach is as shown in Figure 1. The major steps involved are :

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- Texture Feature Computation
- Neural Net based Classification
- Image masking and gray level based Segmentation

In first level of processing, texture classification is used to classify the image in built up and non built up regions. Coggins and Jain have demonstrated the use of Gabor filter for texture classification as well as texture segmentation. In the proposed approach texture features are computed in spatial domain using real valued even symmetric Gabor Filter in different orientation and frequency. These features are used to classify the image as built up and non built up area. The classification is done through Multi layer Perceptron (MLP) neural network. The network passes through two phases namely training and testing. During training phase network is initialized with random weights and the texture features computed using Gabor filter are used as training data set of built up and non built up area. These training sets are fed randomly as input to network. Error is calculated by taking the difference between desired output and the network output. This error is fed back to the network and the connection weights of the network are updated appropriately. After a number of iterations the network converges to a minimum error solution. These connection weights of the network are encoded with input space information. For testing purpose part of training set data is applied as input to the network and its result is verified for accuracy. In second level of processing, the non built up area is masked in the original image and intensity based segmentation is applied only on built up regions based on its image gray value variation using Fuzzy C-Means (FCM) clustering technique. This followed by morphological processing results in individual buildings as regions.

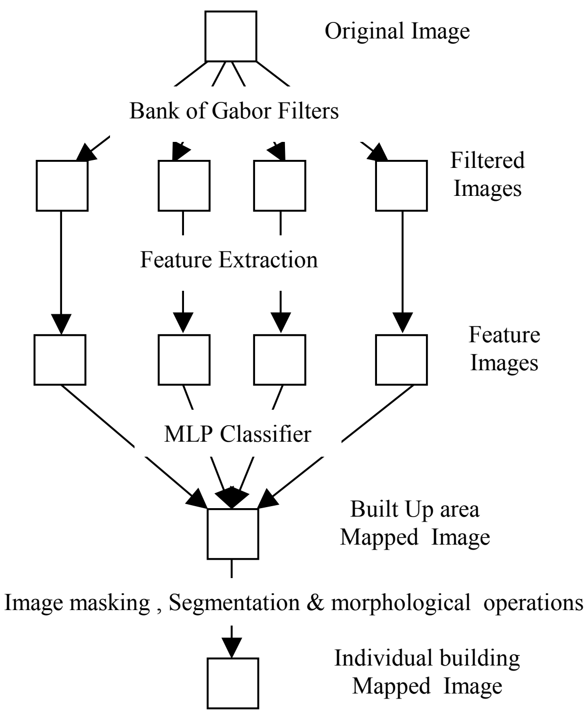

Figure 1. Block schematic of the proposed Approach.

2.1 Texture Classification Using Gabor Filters And Neural Network :

The main steps involved in Gabor Filter based texture classification are (a) Gabor filter characterization (b) Feature computation and (c) Neural Net based classification. The size of the window used for each response image is determined using a formula involving the radial frequency to which the corresponding filter is tuned.

2.1.1 Gabor Filter Characterization:

Channels are represented with a bank of Gabor filters. Gabor function is a Gaussion modulated sinusoid. A complex Gabor filter as a 2-D impulse response is represented as in equation (1).

$$h(x,y) = \frac{1}{2\pi\sigma_x\sigma_y}\exp\left\{-\frac{1}{2}\left[\frac{x'^2}{\sigma_x^{\,2}} + \frac{y'^2}{\sigma_y^{\,2}}\right]\right\}\exp(j2\pi u_0 x')\text{...(1)}$$

Gabor filter with its real component is given in equation (2)

$$h(x,y) = \exp\left\{-\frac{1}{2}\left[\frac{x'^2}{\sigma_x^{\,2}} + \frac{y'^2}{\sigma_y^{\,2}}\right]\right\}\cos(2\pi u_0 x')\text{...(2)}$$

Where $x' = x\cos\theta + y\sin\theta$

$y' = -x\sin\theta + y\cos\theta$

u_0 is the frequency of the sinusoidal plane wave along the x axis,

σ_x and σ_y are the space constants of the gaussian envelop along the x-axis and y-axis.

Value of θ is obtained by rotation of the x-y coordinate system. Six values of orientations used while implementing this filter are 0^o, 30^o, 60^o, 90^o, 120^o and 150^o. The restriction to 6 orientations is made for computational efficiency of the current implementation and is sufficient for discriminating built up and non built up texture. Radial frequency u_0 takes values from the set

$$\{\, 1\sqrt{2},\ 2\sqrt{2},\ 4\sqrt{2}\ \ldots\ldots\ldots\ (Nc\ /\ 4)\sqrt{2}\ \}$$

Where Nc is the image width.

Window size T used for Gabor filter characterization is given by equation (3)

$T = \alpha\, Nc/u_0$………(3)

Where α is a parameter to control the window size. For generating the gabor filter bank the value of α is taken as 0.5. The total number of Gabor filtered images when the image size is 256 width is 42 (6 orientations and 7 radial frequencies). We have used the filters at 30 degree separation which captures most of the texture characteristics of built up area in the image and produces accurate results. In our experiment with satellite images it has been found that to distinguish built up and non built up areas in satellite images only the last 2 frequencies are sufficient. Filters with low radial frequencies form very big window, where they capture spatial variations that are too large to explain texture variations in an image. In order to ensure that the filter do not respond to homogeneous regions, mean value of each filter is set to 0. Because of this reason mean value of each filtered image is also zero.

2.1.2 Feature computation:

In the proposed approach, the texture features are extracted using a non linear function given in equation (4). This transformation is applied on all the 12 filtered images to compute the measure of energy ψ for the feature value t in a window around each pixel.

$$\psi(t) = \frac{1}{1+e^{-t}} \quad \ldots\ldots\ldots\ldots(4)$$

The average absolute deviation of the pixel energy values from mean in a small overlapping window is computed as texture feature. This sigmoidal function based feature extractor given in equation (4) produces good result and takes less computation time . Window size used is as given in equation (3) but the value of parameter α is taken as 1.0. In our experiments we have found that when the window size is slightly larger in texture feature computations as compared to the window size used in Gabor filter computations, results are more accurate. In present case we have taken the window size for texture feature computation to be twice of window size given by equation. While computing Gabor filter based texture features (Jain 1991) filter outputs are smoothed using Gaussian smoothing operation. This helps to suppress the variations within the same texture region. We have found that for satellite images this smoothing operation is not required as it over smoothes the texture features and also consumes lot of computational time.

2.1.3. Neural net based built up area classification

Neural networks are designed to mimic the human mind by using multiple artificial neurons working in parallel to learn to recognize certain pattern and be able to generalize this learning to new data (Haykin 1999) A three layer perceptron model of neural network has three layers of neurons, an input layer, a hidden layer, and an output layer. All neurons are interconnected with each connection having a unique weight. These weights are adjusted through a error back propagation mechanism until the neural network has successfully learned the data. Neural networks are not restricted to linear relationships and are much more robust when dealing with complex data relationships. In the present implementation, neural network is built with 12 input units, 22 hidden units and 2 output units to classify any given image to 2 classes i.e. built up and non built up. The 12 input units correspond to 12 Gabor filter features selected for classification to discriminate built up and non built up classes.

During training phase the training set consists of built up and non built up samples. They are fed to the network randomly one at a time. Learning rate is set to 0.5 and momentum to 0.6 the decay rate for learning rate and momentum is 0.999. Error for output and hidden nodes are computed. Connection weight is updated using back propagation algorithm (Haykin 1999) after each training data is presented. Error calculated after the first iteration is 21.649675 after performing 1000 iterations network converges to an error 0.000521. This weight file is saved so that it can be used whenever classification of build up and non built up area is required.

To test the network first network is built and weight file is loaded. Part of the training set is fed to the network and tested for accuracy. After the testing the network is used to classify any given IRS1C,1D images or high resolution IKONOS images into built up and non built up class. The classification results using neural net are more accurate than the conventional classifiers as neural net can handle the data where the distribution has complex boundary.

2.2 Building Extraction

After the image is classified into built up and non built up classes, the built up area portion is replaced with original image and non built up portion is masked so that it is not processed further. This image is subjected to intensity based segmentation using fuzzy c-means clustering procedure. Fuzzy c-means (Gath 1989) is an iterative procedure. It attempts to cluster the measurement vectors by finding local minima of the generalized within group sum of squared error objective function with respect to a fuzzy c-partition of data set and to a set of c-prototypes. It starts with the initial cluster seeds. At each iteration it partitions the image into clusters where each image pixel belongs to each cluster with a membership value. The new cluster centers are calculated as weighted average of cluster pixels weighted by the membership value. The new partitions are generated using these new cluster centers. The process is repeated till the cluster seeds stabilize and the objective function is minimized. It results in intensity based image segmentation where building pixels form one particular class. At this stage segmented image is binarized, and only the class, which belongs to building, is made foreground rest other classes are made background. Post processing consisting of morphological opening and closing operations is used to fill the holes and remove the gaps in buildings. An area threshold facilitates the extraction of buildings based on their sizes.

3. RESULTS AND ANALYSIS

The proposed approach has been tested on large number of satellite images and gives good results. Figure 2 shows a test image of IRS1C satellite. Built up area is classified in this image and the result is as shown in figure 3 where built up area is depicted in orange colour and non-built up area is shown in green colour. Second test image shown in figure 4 is of IKONOS single band. The proposed approach has been applied on this image. Figure 5 shows the built up areas marked in orange colour. The test image 4 is masked (as shown in figure 6) using built up area extracted in figure 5 so that image corresponding to built up area is left and non built up area is converted into background and the background pixels are not considered for further processing. Building extraction procedure is applied on figure 6 image and results in individual buildings as shown in figure 7.

Figure 2.Test Image1 IRS1D Single Band

Figure 3. Built Up Area Extraction In Test Image1

Figure 4.Test Image2 IKONOS Single Band

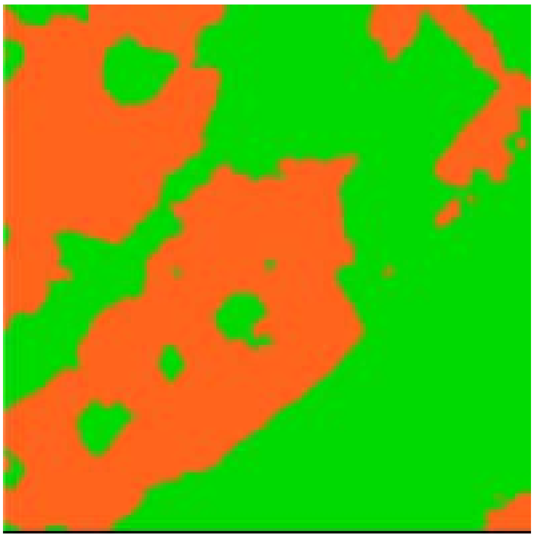

Figure 5. Built Up Area Extraction in Test Image2

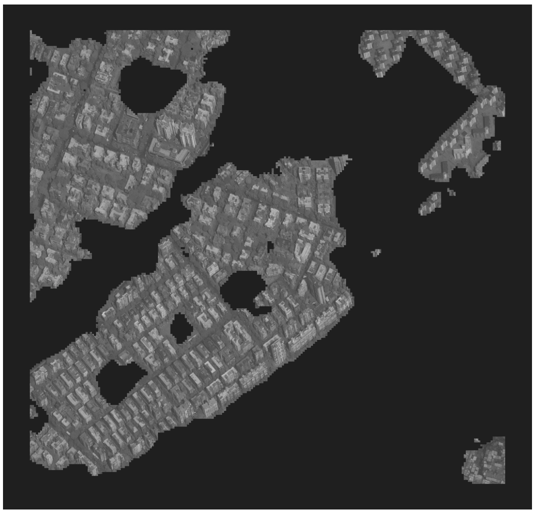

Figure 6. Masking in Test Image2

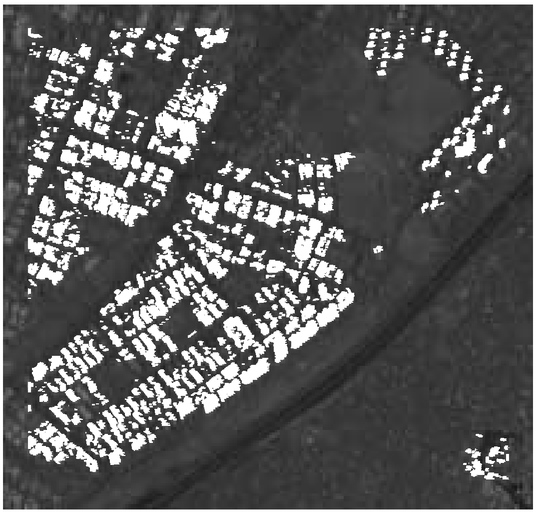

Figure 7. Buildings Extraction in Test Image2

4. CONCLUSION

The multi layer approach proposed in the paper is capable of extracting the built up areas in IRS1C/1D and built up ares as well as buildings in IKONOS single band images. The output of the approach results in layout of the urban areas which can be used for updating the GIS information or the maps. The salient points of the approach are:

a) For Gabor filter based texture feature computation filters at 30 degree separation capture most of the texture characteristics of built up area in the image and produced accurate results.

b) For texture feature extraction the use of sigmoidal logistic function produces good results and takes less computation time.

c) The use of neural net based classification results in robust classification in case of complex class boundaries.

Thus the proposed approach saves lot of computational time. Though initial training of MLP neural net takes time but once it is trained and weights are saved, built up area mapping is performed in less than 10 sec on a Pentium 4 machine with 512 MB RAM. The complete procedure to map individual buildings in IKONOS image takes less than 15 seconds, which makes it computationally feasible. As for processing large size images, the number of filters increases tremendously; our future work involves incorporating multi resolution image representation using wavelet transform in the present approach to handle large size images.

REFERENCES

References from Journals:

Busch Andreas, 1999, Revision of built up areas in a GIS using satellite imagery and GIS data, *International Archives Of Photogrammetry And Remote Sensing, ISPRS Commission iv Symposium On GIS Between Vision And Applications*, Stuttgart, Germany.

Fraser, C S. , Baltisavias E and Gruen A , 2002, Processing of IKONOS imagery for sub meter positioning and building extraction, *ISPRS Journal Of Photogrammetry And Remote Sensing*, 56(3), pp 177-194.

Gath I and Geva A B, 1989, Unsupervised optimal fuzzy clustering, *IEEE Trans. Pattern Analysis And Machine Intelligence*, vol PAMI-11, no 7 , pp 773-781.

Jain A K, Farrokhnia F, 1991, Unsupervised texture segmentation using Gabor filters, *Pattern Recognition* 24(12), pp 1167-1186.

Lacroix V, Hincq Arnaud, Mahamadou I, Bruynseeds and Swaxtenbroekx O , 2004 , Spot5 Images For Urbanization Detection , *ACIVS* 2004, Belgium,

Lacroix V, Hincq Arnaud, Mahamadou I, Bruynseeds and Swaxtenbroekx O , 2006, Detecting urbanization changes using Spot5, *Pattern Recognition Letters*, 27, pp 226-233.

Randen T and Husoy J H, 1999, Filtering for texture classification: A comparative study, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol 21, no. 4 pp. 291-310.

Schilling K J and Vogble T, 1997, An approach for the extraction of settlement areas, In: *Grun et al 1997*, pp 333-342.

Simona, Grigorescue E, Nicolai Petkov, and Kruizinga Peter, 2002, Comparision of texture features based on Gabor filters, *IEEE Tran. Image Processing*, vol11,no. 10.

Zhang Jianguo, Tan Tieniu, 2002, Brief review of invariant texture analysis methods, *Pattern Recognition* ,35, pp 735-747.

References from Books:

Grun, A., Baltisavias, E. P. and Henricsson, O (eds) 1997, *Automatic extraction of Man-made objects from Aerial and space images (II)*, Birkhauser Verlag,Basel.

Haykin Simon, 1999 , *Neural networks A comprehensive foundation,* Pearson Education(Singapore), Pte Ltd. pp 159-175

Li S Z, 1995, *Markov Random Field Modeling in Computer Vision*, Springer Verlag NewYork.

Tuceryan M and Jain A K, 1993 *"Texture Analysis", Handbook Pattern Recognition and Computer Vision,* C. H. Chen, L F Pau & P S Wang, eds Singapore: World Scientific, pp 235-276.

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