Volume 7, Issue 2, February 2017 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

A Review on LBPV for Crop Recognition

[1]Ashwin Shinde, [2]Viiay Masne, [3]Dinesh Gawande, [4]Mayuri Marawar, [5]Madhuri Dubey

[1, 2, 3, 4] CSE Department, RTMNU, Nagpur, Maharashtra, India

[5] IT Department, RTMNU, Nagpur, Maharashtra, India

DOI: 10.23956/ijarcsse/V7I2/0125

Abstract— ***Earlier the Government Ministries was used to make surveys about crops produced by farmers, condition and its productivity. Predictions are made region wise by making comparative analysis of previous year's results. This means that these traditional surveys are both time-consuming and expensive that's why farmer's eye estimates are remarkably close to actual crop production figures. Remote sensing has been identified as an objective, standardized, possibly cheaper and faster methodology for crop production surreys than conventional field investigation. The aim of this research is to evaluate crop discrimination using satellite image data by following remote sensing approach. This research illustrates the use of Local Binary Pattern Variance on satellite images to classify the land in to crop land and non-crop land and to classify different crops. The input image is first enhanced then Local Binary Pattern Variance is used to extract features from the crop images specifically extracting green colors. After identifying the LBPV pattern of each pixel (i,j) in the given image the whole texture image is represented by building a histogram showing intensity values for uniform and non uniform patterns. A texture image database of different crops is created. The texture features of the input image are then compared with texture features obtained from the image database of different crops and the different types of crops are identified.***

Keywords— ***Crop Identification, Remote Sensing, Local Binary Pattern Variance, Histogram, Image Enhancement, Feature's Extraction and Crop Classification.***

I. INTRODUCTION

This Remote sensing has played a significant role in crop classification, crop health and yield assessment. Since the earliest stages of crop classification with digital remote sensing data, numerous approaches based on applying supervised and unsupervised classification techniques have been used to map geographic distributions of crops and characterize cropping practices. Depending on geographic area, crop diversity, field size, crop phenology, and soil condition, different band ratios of multispectral data and classifications schemes have been applied. Nellis (1986), for example, used a maximum likelihood classification approach with Land sat data to map irrigated crop area in the U.S. High Plains. Price et al. (1997) further refined such approaches, using a multi-date Land sat Thematic Mapper (TM) dataset in southwest Kansas to map crop distribution and USDA Conservation Reserve Program (CRP) lands in an extensive irrigated area.

Remote sensing can play an important role in agriculture by providing timely spectral reflectance information that can be linked to biophysical indicators of plant health. Quantitative techniques can be applied to the spectral data, whether acquired from close-range or by aircraft or satellite-based sensors, in order to estimate crop status/condition. The technology is capable of playing an important role in crop management by providing information like fraction of vegetative cover, chlorophyll content green leaf area index, and, other measurable biophysical parameters.

The satellite image processing is becoming increasingly available for vegetation mapping and to decision makers for future growth and development. Remote sensing is identified as a tool to assess performance more than a decade ago [1] [2]. In the last decade, remote sensing has been increasingly identified an efficient, reliable, possibly beneficial and faster methodology for crop production surveys than conventional field investigation [3] [4].

Also for the process of identifying crop types and classifying them an appropriate feature extraction algorithm and classification algorithm are very important. These classification algorithms include Multiple Classifiers [5] [6], Neural Network [7] [8], Support Vector Machine [9], fuzzy classification [10] and other biologically inspired algorithms [11]. These classifications were based on various features such sub-pixels, wavelet functions and texture features etc.

II. LBP & LBPV

The Local Binary Pattern operator is an operator that describes the surroundings of a pixel by generating a bit-code from the binary derivatives of a pixel. The operator is usually applied to grey scale images and the derivative of the intensities.

83	75	126
99	95	141
91	91	100

→

0	0	1
1		1
0	0	1

Binary: 0011101
Decimal: 57

Figure 1 Example of Basic LBP Operator

In its simplest form the LBP operator takes the 3- by-3 surrounding of a pixel and generates a binary 1 if the neighbour of the centre pixel has larger value than the centre pixel. The operator generates a binary 0 if the neighbour is less than the centre. The eight neighbours of the centre can then be represented with an 8-bit number such as an unsigned 8-bit integer, making it a very compact description. Fig.1 shows an example of an LBP operator. [12]

When calculating a LBP code for an image, the edges that do not have enough information are ignored since these would produce false information. The LBP operator is, however, not bound to describe only the eight closest pixels. Further development of the operator support pixels relations over greater distance from the centre, covering larger areas, and uses other thresholds. Some support angles on sub- pixel level where the values are interpolated.

The LBP operator was first introduced as a complementary measure to the contrast in the neighbourhood of a pixel called LBP/C [13]. The LBP component was calculated like the one shown in fig. 1. Thereafter the contrast component C was calculated as the average of the pixels over the threshold minus the average of the pixels under the threshold. An arbitrary circular derivation for a LBP operator with any radius and number of neighbours with the centre as threshold has been given by T. Ojala and is presented in [13]. Equation based on that of Ojala can be given as below We define the local neighbourhood of a pixel by equation 1.

$T=t\ (g_c,g_0---,g_p-1)$

where gc is the grey-value of the centre pixel and g0 - gP-1 corresponds to the P number of neighbours value.

The samples have the same distance to their next neighbour given by equation 2.

$$[x_p, y_p] = [x_c + R\cos(2\pi p/p), y_c + R\sin(2\pi p/p)$$

The grey-level-coordinates that are located between pixel values are interpolated. T. Ojala suggests bilinear interpolation but in many applications "nearest neighbour interpolation" is sufficient and also faster. The LBP operator corresponds to the nearest neighbour interpolation. By definition texture is the changes of values which mathematically correspond to a derivative. By subtracting the neighbours with the centre value and divide by R we get the first discrete derivative in each direction as in equation 3. The changes could also be defined as the difference as by T. Ojala but the result will be the same.

$$T \approx t(g_0 - g_c/R, --- g_{p-1} - g_c/R)$$

The gc value does not contain any information about the texture since it only contains the local grey level of the region so the loss of gc does not mean any loss of texture information.

The same above mentioned concept of basic LBP operator is applied on the input crop images where each input crop image is divided into no. of pixels, considering each pixel as the center pixel and taking into account its 3 X 3 neighbourhood and successive LBP codes or Patterns are formed. Some of these patterns are dominant in nature and are termed as Uniform Patterns. These Uniform Patterns are then checked accordingly against rotation invariance so that rotation should not affect the quality of image in order to extract its features and identify the crop in turn.

III. UNIFORM PATTERN

Uniform patterns are a based on important observations of the LBP code in natural images. The observation is that the majority of LBP codes only contain, at most, two transitions from one to zero or zero to one in a circular defined code. In other words all the binary ones and zeros are connected in the code if it is defined circular. A circularly defined code means also that the last and first bits are connected. A simple algorithm for measuring the uniformity of a LBP code is to summarize the absolute value of the difference between the code and the code circularly shifted one bit, which is shown in equation 4 below:

$$U(G_p) = \left|S(g_p - g_c) - s(g_0 - g_c)\right| + \sum_{p=1}^{p-1} \left|S(g_p - g_c) - s(g_p - 1 - g_c)\right|$$

A code that has the value equal or less than 2 are considered uniform. In practice this can be done with the binary XOR function between the codes. A more practical solution is to use a look-up table of the uniform LBP codes. The number of possible codes by only using uniform codes is reduced to P (P-1) +2, where P is the number of points of the neighbourhood. In addition to number of possible codes, a code could be used to represent codes not designated uniform. In the 3x3 case that means that the code is reduced from 256 to 58, making feature vectors much smaller and also reducing the number of codes inflicted by high frequency noise. One way to study the occurrence of uniform codes is to count the number of uniform codes in an image with white noise that is filtered with a low-pass filter.

IV. ROTATION INVARIANCE

The rotation of the LBP code is a method to make the LBP codes more invariant to the orientation of the texture and to make texture identification much more efficient by reducing the number of LBP codes possible. A rotation of a code is quite a simple operation and is easily derived from a circular defined code. The grey-values are rotated around the centre pixel. In practice this is done with a bit- shift operator, where the code is circularly shifted until it reaches its minimum value as in equation 5.

$$LBP_{P,R}^{ri} = \min\{ROR(LBP_{P,R}, i) \mid i = 0,....P-1$$

In the algorithm the ROR function represents the circular bit-shift operator and LBP^{ri} is the rotation invariant code. One weakness of the LBP^{ri} is that if the code originally was an 8-bit code, the code is rotated 45° at each shift, which is quite a crude quantisation of the data. One possible solution is to introduce more sample points (P) to the binary code However this does not necessary introduce more data for small areas such as 3-by-3 areas since it only contains nine pixels and more information could be redundant.

V. LBPV

The LBP variance (LBPV) is proposed to characterize the local contrast information into the one-dimensional LBP histogram. The experimental results on representative databases show that the proposed LBPV operator and global matching scheme can achieve significant improvement. The LPBV descript or proposed offers as solution to the above problems of BP; R=VARP; R descriptor. The LBPV is a simplified but efficient join t LBP and contrast distribution method. As can be seen in Equation (6), calculation of the LBP histogram H does not involve the information of variance VARP; R. That is to say, no matter what the LBP variance of the local region, histogram calculation assigns the same weight 1 to each LBP pattern. Actually, the variance is related to the texture feature. Usually the high frequency texture regions will have higher variances and they contribute more to the discrimination of texture images. Therefore, the variance VARP; R can be used as an adaptive weight to adjust the contribution of the LBP code in histogram calculation.

The LBPV histogram is computed as:

$$LBPV_{p,r}(k) = \sum_{i=1}^{N} \sum_{j=0}^{M} w(LBP_{p,r}(i,j,k))k \in 0$$

The Histogram basically shows the intensity values of the Uniform Patterns in the crop image. The paper is organized according to research methodology formulated below.

Table 1 Research Methodology Flow

Image Aquisition
Image Preprocessing • Image Resizing • Image Enhancement
Feature's Extraction using LBPV
Land Classification
Crop Identification

The paper is organized into following sections Section 3 contains the image enhancement, Section 4 contains a feature extraction using Local Binary Pattern Variance, Section 5 Land classification and Section 6 explains Crop Identification part, followed by the conclusions drawn from the work with the proposed system. The proposed flow can be given as below:

VI. IMAGE ENHANCEMENT

The Image enhancement produces an output image that subjectively looks better than the original image by changing the pixel's intensity of the input image. Generally, image enhancement enlarges the intensity differences among objects and background. The input crop land image is being enhanced to improve its visibility and interpretability for human visibility system.

Image enhancement techniques are designed to improve the quality of an image as perceived by a human being to improve the interpretability of the information present in images. Image enhancement is one of the most interesting and important issues in digital image processing field. The main purpose of image enhancement is to bring out details that are hidden in an image, or to increase the contrast in a low contrast image. The Enhancement procedure is basically followed for removing unwanted noise and errors from the image, which shows the enhanced version of the image where it can be noted that green colored portions of the given crop land image are enhanced to the extent so that they are clearly visible according to the human vision.

VII. FEATURE'S EXTRACTION

In Crop Type classification appropriate feature selection from satellite images is important. Local Binary Pattern Variance is an advanced feature extraction algorithm which extracts the green color from the crop images in order to classify it later by comparing the extracted part with that of the template patterns stored in the texture database, specifically green color is extracted using Local Binary Patten code. While the green color is being extracted using LBPV, GETMAPPING method is used which returns a mapping table for LBP codes. After this, numbers of patterns in the resulting LBP code are generated, uniform well as rotation invariant patterns are generated to complete features extraction part. The LBP and VAR feature extractors are first reviewed. To address the limitation of VAR, the LBPV is then proposed, as LBP ignores sensitive features of the image such as edges and boundaries. Finally, the matching dissimilarity metric in this work is presented. LBPV is a texture operator which characterizes the spatial structure of the local image texture. Given a central pixel in the image, a pattern number is computed by comparing its value with those of its neighborhoods.

The extracted green colored features and its intensity values of uniform patterns in the image can be shown by a stem plotted histogram. And the extracted crop image can be given as below.

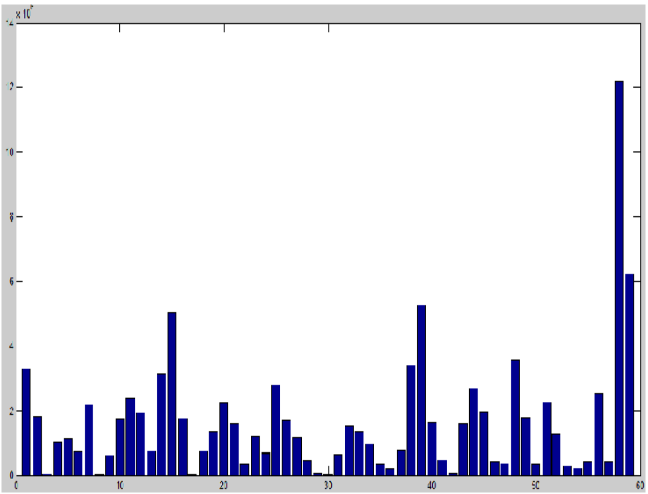

Fig. 1 Histogram Showing Uniform Patterns

VIII. CROP IDENTIFICATION

Crop Identification can be done labelling each extracted green coloured crop by specific colour codes and this can be done by classifying each crop type according to the intensity of green colour in it. Another approach is that the texture database is used in the experiments which consist of different texture classes. A query pattern is any one of the image in the database. This image is then processed to compute the LBPV feature vector. The distance d (i, j), where i is the query pattern and j is a pattern from the database, is computed. The distances are then sorted in increasing order and the closest set of patterns are then retrieved and grouped together for identification of crop type.

IX. CONCLUSIONS

In this research, Local Binary Pattern Variance method is used. A texture based classification method will be used for the classification of land as well as for the classification of different crops and then the method can be applied for the monitoring of the different crops throughout the year.

.

REFERENCES

[1] Abernethy, C.l.; and Pearce, G.r. 1987. Research needs in third world irrigation, Hydraulics Research Limited, Wallingford, England.

[2] Saha, S.k., 1999. "Crop yield modelling using satellite remote sensing and GIS-current status and future prospects", Processing Geo informatics-Beyond 2000, an international conference on Geo informatics for natural resources assessment, monitoring and management held at IIRS Dehradun during 9-11March, 1999.

[3] Singh, Randhir and Ibrahim, AEI, 1996.,"Use of spectral data in markov chain model for crop yield forecasting", Jr. Indian Socy. of Remote Sensing 24 No.3, 145-152.

[4] Bauman, B.A.M., 1992, "Radiometric measurements and crop yield forecasting-some observations over Millet and Sorghum experimental plots in Mali", International Journal of Remote Sensing, 9(10):1539-1552.

[5] Defries, R.S., Chan, J.C.W., "Multiple Criteria for Evaluating Machine Learning Algorithms for Land Cover Classification from Satellite Data", RSE (74), No. 3, 2000, pp. 503-515.

[6] Steele, B.M., "Combining Multiple Classifiers. An Application Using Spatial and Remotely Sensed Information for Land Cover Type Mapping", Remote sensing of environment (74), No. 3, 2000, pp. 545- 556. 0102.

[7] Ji, C.Y., "Land-Use Classification of Remotely Sensed Data Using Kohonen Self-Organizing Feature Map Neural Networks", PhEngRS (66), No. 12, December 2000, pp. 1451-1460.

[8] Kavzoglu, T., Mather, P.M., " Pruning artificial neural networks: an example using land cover classification of multi-sensor images", JRS(20), No. 14, September 1999, pp. 2787.

[9] Huang, C., Davis, L.S., Townshend, J.R.G., "An assessment of support vector machines for land cover classification", JRS(23), No. 4, February 2002, pp. 725-749.
[10] Omkar . S.N. Senthilnath . J. et al. 2008 "Crop Classification using Biologically-inspired Techniques with High Resolution Satellite Image", - Journal of the Indian Society of Remote Sensing, 36 (2). pp. 175-182.
[11] Islam, Z., Metternicht, G., "The Performance of Fuzzy Operators on Fuzzy Classification of Urban Land Covers", PhEngRS (71), No. 1, January 2005, pp. 59-68.
[12] Timo Ahonen, Matti Pietikainen and T.Maenpaa," Multiresulation gray scale and rotation invariant texture classification with local binary pattern", IEEE Transactions on pattern analysis and Machine Intelligence Volume 24, No 7, pp 971-987, 2002.
[13] Topi Mäenpää & Matti Pietikäinen, "Texture analysis with Local Binary Patterns", Dept. of Electrical and Information Engineering, University of Oulu, Finland, 2004.

