ANALELE UNIVERSITĂȚII
"EFTIMIE MURGU" REȘIȚA
ANUL XVIII, NR. 2, 2011, ISSN 1453 - 7397

Costăchioiu Teodor, Niță Iulian, Lăzărescu Vasile, Datcu Mihai

Unsupervised Clustering of EO-1 ALI Panchromatic Data Using Multilevel Local Pattern Histograms and Latent Dirichlet Allocation Classification

Over the last years huge amounts of remotely sensed data have been acquired. Among remote sensing satellites we can mention the EO-1 ALI mission, designed as a platform for testing and validation of new technologies that will be incorporated in the forthcoming Landsat LDCM satellite. In this paper we propose a method for unsupervised clustering of the panchromatic band of EO-1 data using multilevel local pattern histograms to capture local and spatial information by recording the size and distribution of bright, dark and homogenous area within a moving window. For classification task we propose the use of Latent Dirichlet Allocation, a method that can discover complex patterns in data, providing results with a high semantic meaning, close to expectations of the human user.

***Keywords**: EO1-ALI, Multilevel Local Pattern Histogram, Latent Dirichlet Allocation*

1. Introduction

Over the last decades huge advances were made in the field of remote sensing. New satellite missions allow us to observe the Earth with an ever increasing spectral and radiometric resolution, combined with better spatial resolution. As aresult, huge quantities of data were gathered in the archives. However, our ability to process this data has not improved, at thepresent moment only 5% of the aquired data being procesed. Manual processing of data is subjective to user errors, slow and and expensive in terms of human time and effort. As such, new innovatory methods for remote sensing data analysis have to be developed.

Developped as a testing platphorm for technologies that will be embedded on the new Landsat LDCM mission, EO-1 ALI remote sensing platform features a set of multispectral bands with 30m spatial resolution, matching the previous Landsat satellites and panchromatic band with a spatial resolution of 10m. Unlike its predecessors, EO-1 ALI has a radiometric sensitivity of 16 bits, allowing the observation of a wider dynamic range.

As ground truth information is difficult and expensive to acquire, it comes of a great signifficance to develop methods for unsupervised classification of remotely sensed data. However, the classes discovered by such unsupervised methods often do not match the expectations of the human user, leading to a phenomenon known as the ”semantic gap”, generated by the difficulty of mapping the low-level features extracted from data to the high-level results that users expect.

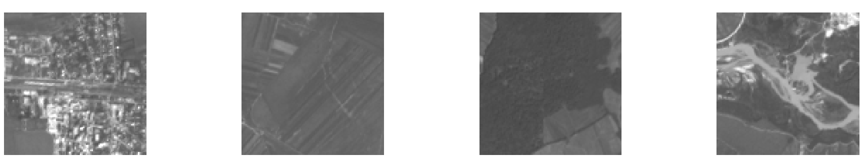
Several tools designed originally for the semantic analysis of large text archives have been adapted for classification of remotely sensed data. Among these methods, the use of Latent Dirichlet Allocation provided good results on high resolution panchromatic Quickbird data [1] as well on Rapid Eye and WorldView-2 color scenes [2].

In this paper we propose a novel method for unsupervised analysis of EO-1 ALI panchromatic data by using the Multilevel Pattern Histogram texture descriptors and LDA classification, obtaining land cover maps with an increased semantic meaning.

This paper is structured as follows: section 2 introduces short theoretical presentation of the MLPH texture descriptor; section 3 describes the Latent Dirichlet Allocation algorithm and its applications in analysis of other types of discrete data. Experiments on EO-1 ALI data are presented in section 4, while section 5 ends the paper with conclusions.

2. Multilevel Pattern Histogram

The Multilevel Pattern Histogram (MLPH) is a novel texture descriptor that uses a sliding window method to capture the distribution of bright, dark and homogenous areas, at various threshold levels [3]. This way, for a given pixel MLPH records information regarding both size and contrast levels of its surrounding area. Such differences in size and contrast for different land cover and land use types can be observed in fig.1.



a) b) c) d)

Figure 1. Different land cover and land use types: a) urban areas; b) agriculture; c) forests; d) water bodies

The basic element of the MLPH is the Local Pattern Histogram (LPH), which captures information in the surrounding neighborhood at a given contrast level.

LPH is computed in three simple steps: image quantization, matrix splitting and histogram computation.

In the quantization stage the intensities I_i of all the pixels within the window are compared with the intensity I_C of the center pixel. Considering a threshold t_j, for a sliding window of size h the result of the quantization step is the matrix s, where each element s_i of this matrix is given by:

$$s_i = \begin{cases} 1 & I_i > I_C + t_j \\ 0 & I_C - t_j \le I_i \le I_C + t_j \\ -1 & I_i < I_C - t_j \end{cases}; \; i \in \left[1,...,h^2\right] \tag{1}$$

The quantized matrix is then split into three separate matrices that record the position of positive, negative and zero values. The positive matrix PM records the position and size of brighter patterns and is defined as:

$$PM_i = \begin{cases} 1 & s_i = 1 \\ 0 & otherwise \end{cases}; \; i \in \left[1,...,h^2\right] \tag{2}$$

The equal matrix EM records the size and position of homogenous areas and is defined as:

$$EM_i = \begin{cases} 1 & s_i = 0 \\ 0 & otherwise \end{cases}; \; i \in \left[1,...,h^2\right] \tag{3}$$

In a similar way the negative matrix NM records the size and position of darker areas:

$$NM_i = \begin{cases} 1 & s_i = -1 \\ 0 & otherwise \end{cases}; \; i \in \left[1,...,h^2\right] \tag{4}$$

A subhistogram recording size of homogenous groups is created from each of these matrices. For a square sliding window of size h, the size of individual groups can range from 1 to h^2. To avoid an unnecessary sparse representation, we use a more compact representation, by selecting a number of bins $K < h^2$. Based on empirical observations we divide the interval $\left[1,...,h^2\right]$ into bins of different sizes, the size of each bin being defined as:

$$vol(k) = B \cdot vol(k-1), \; k \in \left[2,...,K\right] \tag{5}$$

where $vol(k)$ is the size of the k-th bin and B is a hand-tuned parameter.

The Local Pattern Histogram is then obtained by combining these three sub-histograms.

For example, we consider a 9x9 window extracted from an EO-1 ALI panchromatic scene and a threshold level $t_j = 5$. Fig.2 shows the original values in this window and the quantized matrix s.

3020	1641	1799	1923	1608	1427	1372	1430	1444
2421	1876	2716	2410	1645	1551	1684	1867	2128
1676	2223	3042	2563	1911	1836	1877	2086	2145
1744	2474	2905	2208	2020	2017	1970	1835	1785
1632	2700	2761	1737	1895	2043	2112	2022	1698
1674	2756	2812	1716	1832	1772	1860	1961	1666
2224	2525	2423	1904	1829	1664	1671	1833	1820
2313	2289	2209	2278	1858	1588	1760	1916	1834
1840	1766	2197	2501	1583	1402	1602	1685	1519

a)

1	0	0	0	0	-1	-1	-1	-1
1	0	1	1	0	0	0	0	1
0	1	1	1	0	0	0	1	1
0	1	1	1	1	1	0	0	0
0	1	1	0	0	1	1	1	0
0	1	1	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0
1	1	1	1	0	0	0	0	0
0	0	1	1	0	-1	0	0	0

b)

Figure 2. a) Example of a 9x9 window extracted from an urban area;
b) The corresponding quantized matrix showing groups of homogenous pixels

Based on the quantized matrix we extract the three matrices PM, EM and NM:

0	0	0	0	0	1	1	1	1
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0
0	0	0	0	0	1	0	0	0

a)

0	1	1	1	1	0	0	0	0
0	1	0	0	1	1	1	1	0
1	0	0	0	1	1	1	0	0
1	0	0	0	0	0	1	1	1
1	0	0	1	1	0	0	0	1
1	0	0	1	1	1	1	1	1
0	0	0	1	1	1	1	1	1
0	0	0	0	1	1	1	1	1
1	1	0	0	1	0	1	1	1

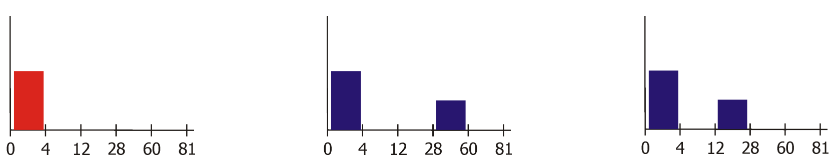
b)

1	0	0	0	0	0	0	0	0
1	0	1	1	0	0	0	0	1
0	1	1	1	0	0	0	1	1
0	1	1	1	1	1	0	0	0
0	1	1	0	0	1	1	1	0
0	1	1	0	0	0	0	0	0
1	1	1	0	0	0	0	0	0
1	1	1	1	0	0	0	0	0
0	0	1	1	0	0	0	0	0

c)

Figure 3. Matrices obtained from splitting the matrix s.
a) the negative matrix NM; b) the equal matrix EM; c) the pozitive matrix PM

For building the subhistograms we choose a nonlinear bin allocation, with the value for the first bin $vol(1) = 4$ and a growing factor $B = 3$, resulting the following bin edges: $\{0, 4, 12, 28, 60, 81\}$. With the above bin definition we start building the subhistograms that record the size of individual groups:



a) b) c)

Figure 4. Subhistograms corresponding to groups in matrices from fig.3

By concatenating the three subhistograms in fig.4 we obtain the LPH:

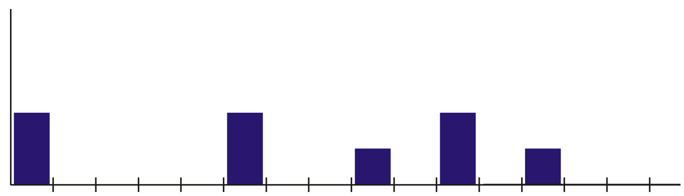


Figure 5. The LPH descriptor for an urban area, computed for a threshold level $t_j = 5$

In order to better differentiate between different ground cover and ground use classes multiple threshold levels have to be considered. Considering a starting threshold level t_1 and a maximum threshold level t_{max}, a method of defining the threshold levels t_j can be expressed as:

$$t_j = T \cdot t_{j-1}, \;\; j = [2,..,M] \tag{6}$$

subject to the constrain:

$$t_M \le C < t_{M+1} \tag{7}$$

where C is the maximum contrast level.

The total size of MLPH is $3 \cdot M \cdot K$, with values for M and K obtained based on the three user-defined parameters: the growing factor for the histogram bins B, the initial threshold value t_1 and the growing factor for the threshold levels T.

3. Latent Dirichlet Allocation

Originally developed for analysis of large text collections, Latent Dirichlet Allocation [4] is a complete generative model that uses a three-level Bayesian hierarchical model to allow generation of an infinite number of samples according to a given mixture of probability distributions. In this model each "document" is modeled as a collection of words belonging to a set of "topics". Each topic is a multinomial probability distribution over the set of words, and the mixture of topics within a document is modeled as a Dirichlet distribution.

In text modeling, given a vocabulary $V = \{w_1, ..., w_N\}$ and *k* topics the generative process of LDA can be summarized as follows:

1. Choose a *k*-dimensional Dirichlet random variable $\theta = Dir(\alpha)$

2. For each of the words $w_j,\ j \in \{1,...,N\}$
    a. Choose a topic $z_j \sim Multinomial(\theta)$
    b. Generate the word w_j from $p(w_j \mid z_j, \beta)$

Considering the above generation process, the likelihood of a document W considering the LDA model can be expressed as:

$$p(W \mid \alpha,\beta) \int p(\theta \mid \alpha)\left(\prod_{n=1}^{N}\sum_{z_n} p(z_n \mid \theta) p(w_n \mid z_n,\beta)\right) d\theta \qquad (8)$$

For learning of a LDA model given a collection of data we need to find the corpus-level parameters α and β that minimize the log-likelihood of the entire collection.

Unfortunately the above equation is intractable, but an approximate solution for inference can be found using methods such as variational expectation maximization or Gibbs Sampling.

The use of LDA is not limited only to text domain, but other type of discrete data can be analyzed with LDA under the assumption of the "bag-of-words" model, in which only the presence and the word count having importance, the order of words within a document being ignored.

In our application we make the following correspondence between text domain and texture features extracted wih MLPH:

- the *corpus* is the image to be analized
- a *document* is the MLPH descriptor extracted for a given pixel in the scene.
- a *word* is a bin of the MLPH

By the proposed correspondence a word has the following semantic meaning „a group of pixels that are in a certain relation with the center pixel according with the threshold level t_j and whose size falls into a bin interval controlled by the user parameter B".

4. Experiments and results

The study area for this paper is a 1500 x 1000 pixels area extracted from a EO-1 ALI panchromatic scene covering the city Titu and its surroundings areas. Several ground cover and land use types were considered: urban areas (including residential and industrial areas), agriculture, forests and water bodies (Fig.6).

Ground truth information required for testing the effectiveness of the proposed method was derived using the 2006 Corine Land Cover vector sets [5].

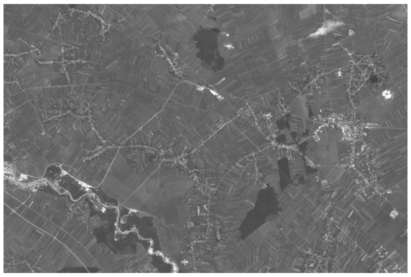
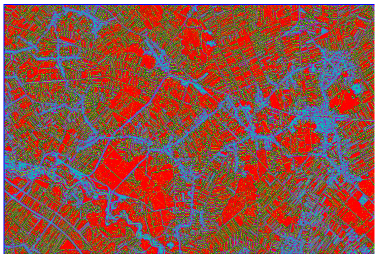


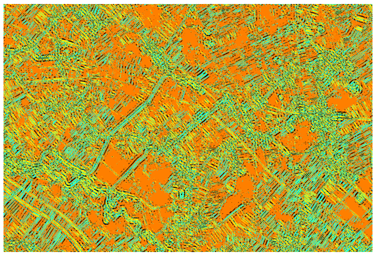
Figure 5. The studied area. Several ground cover and land use types can be observed.

Based on experimental work we found that the following parameters of MLPH provide the best results: threshold levels $t \in \{10, 30, 90, 270, 810\}$ corresponding to a factor $T = 3$ and a bin configuration of the subhistograms with the following bin edges $\{0, 4, 12, 28, 60, 81\}$, which corresponds to a factor $B = 3$. As a result the MLPH has 75 bins, each bin corresponding to a word in the LDA model.

As a comparison we choose a method based on the use of Gabor filter banks [6] followed by unsupervised k-means classification. Fig.6 shows the classification results for a number of 5 classes. We can notice that the proposed method allows a better separation of urban (blue) and non-urban (green and red) areas.



a)



b)

Figure 5. Classification results: a) the proposed method; b) Gabor filter

5. Conclusion

In this paper we have presented a novel method for semantic classification of EO-1 ALI panchromatic data that uses semantic analysis tools from text domain and texture features derived with Multilevel Pattern Histogram texture descriptor to create maps delivering a higher user-level semantic meaning. We found that the proposed method outperforms other texture-based methods such as those using

Gabor filters, and, with proper parameter estimation, the proposed method is able to take full advantage of the higher dynamic range of the new remote sensing platforms such as EO-1 ALI.

6. Acknowledgement

This work has been funded by the Sectoral Operational Programme Human Resources Development 2007-2013 of the Ministry of Labour, Family and Social Protection through the Financial Agreement POSDRU/6/1.5/S/19 and by CNCSIS UEFISCSU project number PNII-IDEI 1247/2008.

References

[1] Lienou, M.; Maitre, H.; Datcu, M.; "*Semantic Annotation of Satellite Images Using Latent Dirichlet Allocation*," Geoscience and Remote Sensing Letters, IEEE , vol.7, no.1, pp.28-32, Jan. 2010.

[2] Bratasanu, D.; Nedelcu, I.; Datcu, M.; , "*Bridging the Semantic Gap for Satellite Image Annotation and Automatic Mapping Applications*," Journal of Selected Topics in Applied Earth Observations and Remote Sensing, IEEE, vol.4, no.1, pp.193-204, March 2011

[3] Dengxin D, Wen Y., Hong S., "*Multilevel Local Pattern Histogram for SAR Image Classification*", Geoscience and Remote Sensing Letters, IEEE, vol.8, no.2, pp.225-229, March 2011

[4] Blei, D.M., Ng, Y.A., Jordan, M.I., "*Latent Dirichlet Allocation*", Journal of Machine Learning Research, vol.3, pp. 993-1022, 2003

[5] ***** Corine Land Cover 2006 datasets [online] http://eea.europa.eu

[6] Ilonen, J., Kamarainen, J.-K., Kälviäinen, H., *Efficient Computation of Gabor Features*, Research Report 100, Lappeenranta University of Technology, Department of Information Technology, 2005

Addresses:

- Drd. Eng. Costăchioiu Teodor, Politehnica University of Bucharest, B-dul Iuliu Maniu 1-3, 061071, Bucharest, cteodor@nspg.pub.ro
- Drd. Eng. Niță Iulian, Politehnica University of Bucharest, B-dul Iuliu Maniu 1-3, 061071, Bucharest, iulian_florin@yahoo.com
- Prof. Dr. Eng. Lăzărescu Vasile, Politehnica University of Bucharest, B-dul Iuliu Maniu 1-3, 061071, Bucharest, vl@vala.elia.ub.ro
- Prof. Dr. Eng. Datcu Mihai, DLR – German Aerospace Center, Oberpfaffenhoffen, Germany, mihai.datcu@dlr.de