16th European Signal Processing Conference (EUSIPCO 2008), Lausanne, Switzerland, August 25-29, 2008, copyright by EURASIP

SEMANTIC REGION LABELLING USING A POINT PATTERN ANALYSIS

Sahbi Bahroun, Ziad Belhadj, Nozha Boujemaa

École Supérieure des Communications de Tunis (SUP'COM), Unité de Recherche en Imagerie Satellitaire et ses Applications (URISA), Cité Technologique des Communications Rte de Raoued Km 3,5. Ariana, Tunisia.
Phone: + (216) 98650582, fax: + (216) 71856829, Email: ziad.belhadj@supcom.rnu.tn, nozha.boujemaa@inria.fr

ABSTRACT

Several recent studies and researches focused on the combination of global and fine local region description using points of interest. The main benefit of global approach is that homogenous parts of the image can easily be described by means of global attributes whereas small details are ignored. In the other hand, as the region gets smaller and with high photometric variability, points of interest are more appropriate to carry local description. In this paper, we propose a new semantic labelling of regions using their interest point spatial dispersion. We introduce a point-based criterion to label regions into homogeneous and textured classes. Our point based criterion is based on a point pattern analysis study and has been validated on a multispectral satellite image database. In our work, we combine the region and point description by constructing a descriptor provided by a new semantic labelling of regions for boosting the object recognition.

1. INTRODUCTION

Global query is considered when retrieving entire image based on the overall visual aspect. On the other hand, when the user focuses on a small part of the image or a relevant detail, several local approaches are used [1]. We can distinguish 2 dual schemas: Region-based and Point-based descriptions. Region-based queries tend to focus on visually homogenous patches and large regions; while point-based queries rely on features extraction by means of interest point detection [2, 3]. The latter description is carried out when searching precise objects or describing locally variable characteristics. A region can be defined as a large set of pixels sharing almost similar visual attributes. In other words, a region is assimilated to a large homogenous area in the image that can be well described by global photometric features. At the opposite, as the region gets smaller and with high photometric variability, local description is more appropriate because it catches small salient areas with characteristic details.
Unfortunately, a simple visual descriptor will classify regions without any distinction between homogenous and textured ones. To do so, local and global descriptions are taken into account during the indexing process. Thus our approach tends to add semantic knowledge information on low level features by labelling regions into homogenous and textured classes. This dual region/points description is evaluated on single coarse regions using Harris colour points detector that catches the local photometric variability on small sites. The use of points of interest was motivated by their ability to finely describe coarsely segmented region.
In this paper, we use the technique of point pattern analysis [4, 5]. This technique is based on point of interest dispersion. This technique leads to label regions through topological and spatial dispersion of points of interest. Historically, Point Pattern Analysis was first noted in the works of botanists and ecologists in the 1930s. However, in the following years, many different fields have also started to use point pattern analysis, such as archaeology, epidemiology, astronomy, and criminology. In general, Point Pattern Analysis can be used to describe any type of incident data.
This paper is structured as follows. In Section 2, we explain the visual content description. First the clustering process for region generation and the Harris colour points extraction method for region description. In section 3, we present the point pattern analysis technique and the methods that we used in our work. Section 4 introduces our proposed technique that labels regions according to their spatial interest point topology. Some discussed evaluations are presented in the experimental setup.

2. COHERENT REGION DETECTION AND FINE DESCRIPTION

The construction of visual descriptors assumes that the regions are relevant and also that their description is confident to their effective visual content. Accordingly, two crucial steps guide descriptors generation: coherent regions and fine local region description. The first step implies that the clustering algorithm could reliably catch the visual photometric content of the region. In the second step, the regions have to be finely described in order to be well categorized.

2.1 Coherent region detection

The Competitive Agglomeration (CA) fuzzy partitional algorithm [6] has the major advantage of determining the optimal number of final classes according to a stability criterion by minimizing the following objective function:

$$J = \sum_{i=1}^{C} \sum_{j=1}^{N} u_{ij}^{2} d^{2}\left(x_i, \beta_j\right) - \alpha \sum_{i=1}^{C} \left[\sum_{j=1}^{N} u_{ij} \right]^{2} \quad (1)$$

Subject to

$$\sum_{i=1}^{C} u_{ij} = 1, \; j = 1,\ldots, \; N$$

In (1), $X = \{x_i, i = 1,...,N\}$ is a set of N data representing the image, $d^2(x_i, \beta_j)$ represents the distance from feature vector x_i to the cluster prototype β_j, u_{ij} represents the degree of membership of feature point x_i in cluster β_j and $[u_{ij}]$ is a C*N matrix called constrained fuzzy C-partition matrix. It should be noted that the number of clusters C in (1) is dynamically updated in the CA algorithm. The weighting factor α reflects the compacity of each cluster and balances the relative influence of each term in (1). It has a decreasing exponential and adaptive expression.

2.2 Fine region description

Once the regions are defined by [6], our purpose is to describe them as informatively as possible in order to generate a reliable visual Descriptor that best summarizes the region content. Thus, we use the Harris invariant points of interest detector [3] to have a point-based local description of regions because it is more appropriate to catch tiny details.

Gouet and Boujemaa [2] proposed a color version of the Harris detector [3] for image description. The idea of the Harris detector is that interest points are local maxima related to the second moment matrix $\mu(x, \sigma_1, \sigma_D)$ (2) and the gradient distribution in a local neighbourhood of a point *x*.

$$\mu(x, \sigma_1, \sigma_D) = g(\sigma_1) * \begin{bmatrix} L_x^2(x, \sigma_D) & L_x L_y(x, \sigma_D) \\ L_x L_y(x, \sigma_D) & L_y^2(x, \sigma_D) \end{bmatrix} \quad (2)$$

where σ_1 is the integration scale, σ_D is the derivation scale, *g* the Gaussian (3) and *L* the image smoothed by a Gaussian (4) for each channel $i \in \{R, G, B\}$.

$$g(\Sigma) = \frac{1}{2\pi\sqrt{\det \Sigma}} \exp -\frac{x^T \Sigma^{-1} x}{2} \quad (3)$$

$$L_i(x, \Sigma) = \frac{\partial}{\partial_i} g(\Sigma\sigma) * I(x) \quad (4)$$

The Harris color extractor is defined as the positive local extrema of the following operator:

$$\det(\mu(x, \sigma_1, \sigma_D)) - \alpha * trace^2 \mu(x, \sigma_1, \sigma_D) \quad (5)$$

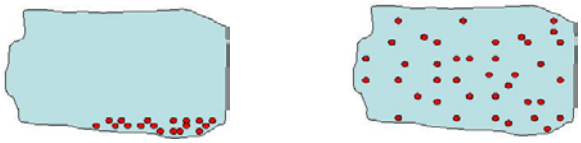
This description is more accurate than with global features (mean color, color distribution...) since it catches the local and slight gradient variations around a pixel.

3. POINT PATTERN ANALYSIS

Point Pattern Analysis is a class of techniques that involves the ability to describe patterns of locations of point events and test whether there is a significant occurrence of clustering of points in a particular area. In general, a spatial data set takes the form: $X = \{x_k / x_k \in R^m, m \in \mathrm{N}\}$.

Our interest will lie in quantifying the dispersion of interest points within a confined region. We apply a point pattern analysis technique to unsupervised label regions into homogenous or textured classes. In fact, the major property of this technique is that points contribute to a global dispersion criterion that encapsulates the following cases:

- If a region has few extracted points of interest, or concentrates some points on the contours due to the coarse segmentation and rough contours, it is more likely to be labelled as homogenous (Figure 1(a)).
- If a region is covered with high number of interest points, more or less regularly dispersed in the region, it is more likely to be labelled as textured. The region is characterized by an important photometric variability (Figure 1(b)).



(a) (b)

Figure 1 - Many points are located on the contours and confined in a small part of the region in (a). The points in (b) are dispersed in the region.

The point pattern analysis is based on comparing the distribution of interest points detected in a given region with randomly distributed points in the same region. The Complete Spatial Randomness (CSR) model assumes that points are distributed at random, which often display features that look like clumping. In addition, this model assumes that the mean density of points per unit area is known.

There are several methods and algorithms to describe pattern for a collection of points. The most popular and best established mathematical and statistical methods used in the literature are the *Quadrant Count Method* [7] and the *Nearest Neighbour Distance* [8].

3.1 Homogeneous Poisson Process

The random model that will serve as our standard of comparison is the *Complete Spatial Randomness* (CSR) model [5, 9, 10]. The CSR model has two basic characteristics:

(i) The number of points in any planar region *A* is with area |*A*| follows a Poisson distribution with mean λ |*A*|.

(ii) Given there are n points in *A*, those points are independent and form a random sample from a uniform distribution on *A*.

The constant λ is the mean number of points per unit area. Also, by (i), the intensity of points does not vary over the plane. According to (ii), CSR also implies the events are independent of each other and there is no interaction between them.

The mathematical construct that we will use to simulate a CSR model is the homogenous Poisson process. Please recall that the Poisson distribution was preferred to the Binomial and the Geometric distributions. Mathematically, this is expressed in the fact that for a Poisson distribution, the variance of the sample is equal to its mean. The geometric distribution has a variance to mean ratio VMR > 1, while the binomial distribution has VMR < 1.0. In probability theory and statistics, the variance-to-mean ratio (VMR) is a good measure of the degree of randomness of a given phenomenon. Therefore, to assess if a set of points are distributed or if there is some clusters in a given region we will compare the VMR of our distribution of interst points to the VMR of the homogeneous poisson distribution. It is well

known that for a Poisson distribution, the variance and the mean are the same. For this reason, random variables with a variance to mean ratio greater then one are called over dispersed and those with a variance to mean ratio less then one are under dispersed [10]. If the set of interest points are randomly distributed then, the VMR is about 1.0.

3.2 Quadrant Count Method

The Quadrant Count Method can be described simply as partitioning the data set into *n* equal sized sub regions; we will call these sub regions quadrants. In each quadrant we will be counting the number of interest points that occur and it is the distribution of quadrant counts that will serve as our indicator of pattern. After partitioning the data set into quadrants (see Figure 2), the frequency distribution of the number of points per quadrant has been constructed. The Variance (6) and Mean are then computed to calculate the Variance-to-Mean Ratio (VMR). The following is the way we will interpret the VMR:

- If VMR > 1.0, this implies that the set of interest points has one or more groups of points in clusters and large quadrants without points. This implies that the region can be labelled as homogeneous.
- If VMR < 1.0, this implies that the set of interest points are distributed more or less regularly over the region. This implies that the region can be labelled as textured.
- If VMR ≈ 1.0, this implies that the set of interest points are randomly dispersed. They have no dominant trend towards clustering or dispersion.

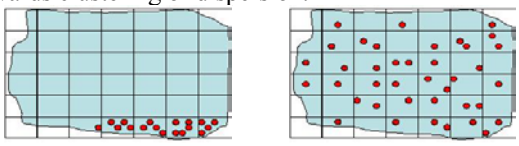


Figure 2 – Example of applying the Quadrant Count Method. Building of quadrants with the same size

The variance and Mean was computed as follows:

$$Variance = \frac{\sum_i n_i^2 - \frac{\left(\sum_i n_i\right)^2}{NQ}}{NQ - 1} \quad (6)$$

Where NQ is the number of quadrants and n_i is the number of interest points in quadrant i. The Mean is the number of interest points in the region divided by the number of quadrants. The VMR compares the number of points in each quadrant with the average of the points on all the quadrants.

The main disadvantage of this method is the choice of the quadrant size because it can greatly affect our analysis. We test different quadrant sizes; we notice the smaller number of quadrants corresponds to larger variance. But as we divide the region into smaller quadrants, the variance starts decreasing to one. We choose the following quadrant size because we want to have a quadrant size proportional to the regions size: $Size = (n / Area) * 2$, where *n* is the number of all interest points detected in a given region. Another disadvantage of this method is where we have VMR close to 1.0. Then, we can't be confident about the label that we will attribute to the region.

Moreover, it has been mentioned in [7] that the Quadrant Count Method is not the most accurate method for identifying clustering of data points. The Nearest Neighbor Analysis would help us to be more confident about the label that we will attribute to all regions.

3.3 Nearest Neighbour Distance

The Nearest Neighbour method was initially introduced by J. G. Skellam [11] where the ratio of expected and observed mean value of the nearest neighbour distances is used to determine if a data set is clustered. Further work was done by P. J. Clark and F. C. Evans [8] to introduce a statistical test of significance of the nearest neighbour statistic in order to quantify the departure of the pattern from random. This test is of great importance because even randomly generated data could be labelled as clustered, but the significance test would reveal if the evidence for this classification is lacking.

Not surprisingly, the nearest neighbour method is based on comparing the distribution of the distances that occur from a data point to its nearest neighbour in a given data set with the randomly distributed data set. The Complete Spatial Randomness (CSR) model assumes that interest points are distributed at random, which often display features that look like clumping. In addition, this model assumes that the mean density of interest points per unit area is known. After reviewing the derivation of the nearest neighbour method we will calculate the test statistic which determines whether the distribution is randomly distributed, uniformly distributed or clustered. After computing the test statistic we would like to know whether our result is due to a sampling error, so we would like to see how reliable our result is. The basic idea from Skellam [11] is to devise a test that would compare the distribution of the nearest neighbour distances for a given data set with nearest neighbour distances of a randomly distributed data set in a CSR model. The Poisson distribution will be used to develop a CSR model for a randomly distributed set of data points. For a set of interest points distributed in a given region A, we calculate the average distance from each point to his nearest neighbour [8]:

$$d_A = \frac{\sum_i d_i}{N} \quad (7)$$

For a random distribution of points generated by the homogeneous process the average distance is equal to [11]:

$$d_{poisson} = \frac{1}{2\sqrt{\frac{N}{A}}} \quad (8)$$

Finally, we compute the ratio R:

$$R = \frac{d_A}{d_{poisson}} \quad (9)$$

The ratio R is interpreted as follows:

- R < 1.0: Existence of clusters. The points are more grouped than the points generated by the random distribution. Therefore, the region can be labelled as homogeneous.
- R > 1.0: the points are more dispersed than the points generated by the random distribution. The region can be labelled as textured.

- R ≈ 1.0: the points have no trend to be clustered or dispersed.

For values of R very close to 1.0, it is necessary to do statistic test of significance to judge the robustness of the result.

3.4 Test of Significance

Clark and Evans [8] proposed a test to indicate whether the observed average nearest neighbour distance was significantly different from the mean random distance. The test is between the observed nearest neighbour distance and that expected from a random distribution and is given by:

$$T = \frac{\overline{d}_A - \overline{d}_E}{\sigma}, \quad (10)$$

T is the significance of departure from random expectation.

σ is a standard deviation of expected mean distance to the nearest neighbour

$$\sigma^2 = \frac{\sigma^2_A + \sigma^2_{poisson}}{N} \quad (11)$$

Where N is the number of interest points in the given region. There have been other suggested tests for the nearest neighbour distance as well as corrections for edge effects (for more details see [10]). However, equations (10) and (11) are used most frequently to test the average nearest neighbour distance.

After having carried out the test of total significativity, it is interesting to carry out the test of partial significativity. We have to choose a degree of confidence which corresponds to a probability in the table of Student, P=0.05 for example. The value T observed is compared with the value from the table of Student. If $|T_{observed}|$ is greater than the corresponding value in the table of student, the difference between the two means is to 95% significant. The number of degrees of freedom for the distribution of points is N-1.

4. OUR PROPOSED APPROACH

In this paragraph, we present the decision algorithm that we introduced to label regions into homogeneous or textured. We have used both the Quadrant Count Method and the Nearest Neighbour Distance. We have also used the significance test if we obtain different labels by these two methods.

To label regions into homogeneous and textured, we have to follow these steps:

1) *Apply the quadrant Count Method and attribute a label L_{QCM} to the given region A.*
2) *Apply the Nearest Neighbour Method and attribute a label L_{NNM} to the given region A.*
3) *If $L_{NNM} = L_{QCM}$ then final label $L_{Final} = L_{NNM} = L_{QCM}$*
   Else apply the Fisher Student's test
   If $|T_{observed}| > T_{Student}$ then $L_{Final} = L_{NNM}$
   Else $L_{Final} = L_{QCM}$

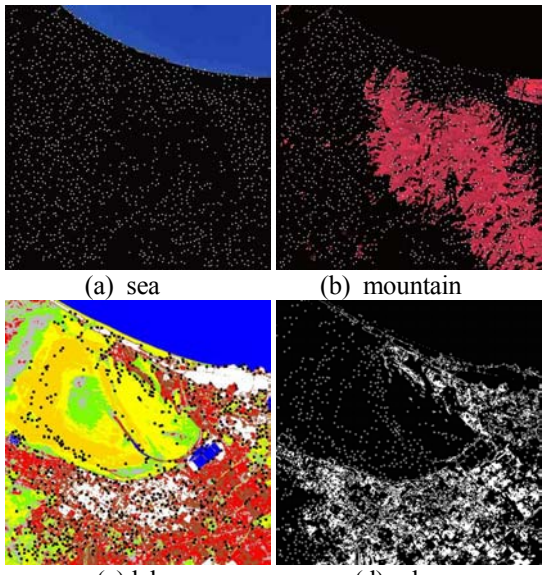
5. EXPERIMENTAL SETUP

In our evaluation, we first segmented a generic database containing about 1500 Multispectral satellite images with different spectral resolutions and spatial resolutions ranging between 1m and 20m. This process provides about 7 regions per image, and then we apply our criterion on about 10000 regions. Points are detected using the Colour Harris detector [2]; each image with size 512*512 pixels is described by about 1000 points of interest. Many types of areas (urban, Mountain, sea, lake …) are present in our database (see Figure 3).

Accordingly, two crucial steps guide our method: coarse and coherent regions; and fine local region description. The first step implies that the segmentation could be rough regarding contours sharpness but reliable enough to catch the visual photometric content of the region. When applying the Competitive Agglomeration algorithm [6], we tried to eliminate the small regions.

In the second step, the regions detected have to be finely described by interest points in order to be well labelled. We have used Harris detector [2] for region description: starting from a multispectral image *i*, we extract N_i points of interest. Given the segmentation mask obtained by the CA algorithm, for each region *j*, we extract N_i^j points.

We present in Figure 3 an example of 4 images where we tried to label respectively the following regions: sea in Figure 3.a (blue colour), mountain area in Figure 2.b (red colour), lake in Figure 3.c (yellow colour) and urban area in Figure 3.d (white colour).



(a) sea (b) mountain

(c) lake (d) urban

Figure 3 – Example of different regions (sea, mountain, lake, urban) respectively in figures (a), (b), (c) and (d)

In Figure 3, we have Examples of homogenous labelled regions: they encapsulate perceptually homogenous regions as well as those resulting from point's accumulation over borders and grouping on small details. We also have Examples of textured labelled regions: they gather textured patches and fully covered regions denoting of an important photometric variation. We compute in Table1 the VMR, R and the label determined by our proposed algorithm for the regions presented in Figure 3. Notice, from Table 1 that for region 1 and region 4 which represent Figure 3.a and Figure 3.d, we have

got the same label by the QCM and the NNM. For all regions in our database where we obtained the same label by the two methods we have made test of significance to judge the robustness of the point 3) of our proposed approach and it was found that in 91% of the regions tested we obtained the good label.

	Number of interest points	VMR	R	Label
Region 1	37	2.891	0.315876	homogeneous
Region 2	228	1.393	1.689345	textured
Region 3	136	1.227	1.775689	textured
Region 4	467	0,172	3.136781	textured

Table 1: VMR, R and label computed for the regions presented in Figure 3

For region 2 and region 3 which represent Figure 3.b and Figure 3.c, we have got different labels. The values of VMR and R were close to 1.0. In order to see whether this result is statistically significant we conduct a test of significance
For region 2 and region 3 we obtained $|T_{observed}| > T_{Student}$. Then regions were labelled textured. It's the label given by the Nearest Neighbour Method. For region 2, the size of the quadrant was 16*16 pixels and for region 3 18*18 pixels. Combining these two methods allowed us to attribute the label textured to these two regions with 95% of confidence.
For visual Descriptor construction, we used a colour histogram for homogeneous labelled regions and correlogram [12] for textured labelled regions.

6. CONCLUSION

In this paper, we presented a new approach based on point pattern analysis to label regions into homogeneous or textured. The Complete Spatial Randomness (CSR) model is one way to simulate data points that occur at random and the Poisson distribution provides a convenient tool for this model. The computation of a test statistic was used for classifying the distribution of interest points as being randomly distributed, uniformly distributed or clustered. A test of significance was found that provided a measure of how far removed the observed result is from the random model. We proposed a new algorithm to label regions. It was then applied to a set of multispectral satellite images with different spatial and spectral resolutions. Our new method encapsulates the coarse description of regions and the fine localization of interest points to label regions according to their structure depicted by spatial topology and dispersion of interest points. Many directions can derive from the coupled use of points/regions description. One possibility is boosting technique for object recognition.

REFERENCES

[1] H. Houissa and N. Boujemaa, "Region labelling using a point-based coherence criterion" IST/SPIE conference on Multimedia Content Analysis, Management and Retrieval, 2006.

[2] V. Gouet and N. Boujemaa, "Object-based queries using color points of interest," In Workshop on Content-Based Access of Image and Video Libraries (CVPR), 2001.

[3] C. Harris and M. Stephens. *A combined corner and edge detector.* In Alvey Vison Conference, pages 147–151,1988.

[4] Dale, Mark R. T., "Spatial Pattern Analysis in Plant Ecology", Cambridge University Press, 1999.

[5] Diggle, Peter J. Statistical Analysis of Spatial Point Patterns. New York: Oxford University Press Inc., 2003.

[6] Hichem Frigui, New approaches for robust clustering and for estimating the optimal number of clusters, thése de doctorat, December 1997.

[7] Cressie, Noel A., "Statistics for Spatial Data (revised edition)", John Wiley & Sons, 1993.

[8] Clark, P. and F. Evans. Distance to Nearest Neighbour as a Measure of Spatial Relationships in Populations, *Ecology*, 35, 445-453 1954.

[9] Miles, R. E. (1970). On the homogeneous planar Poisson point process. Mathematical Biosciences, Vol. 6, pp, 85-127.

[10] Daley, D.J, AND Vere-Jones, D., (1988) Introduction to the theory of poisson process. Springer-Verlag.

[11] Skellam, J.G. (1952). Studies in statistical ecology. I. Spatial pattern, Biometrica, 39, 346-362.

[12] Bahroun S., Belhadj Z., Boujemaa N., "Correlogram in multispectral satellite Image Indexing". In: First International Conference of E-medical Systems. Fez, Morocco, October 2007.