DETECTION OF ALIGNED OBJECTS FOR HIGH RESOLUTION IMAGE UNDERSTANDING

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ABSTRACT

In this article we present a method for extracting groups of aligned objects from a labeled image. Our method is based on fuzzy measures of relative direction between the objects, leading to a fuzzy approach for defining alignment as a spatial relation. The method is able to capture the ambiguities presented when defining alignment between objects of different sizes. Two definitions of alignment are presented; *local* and *global*. The *local* alignments are first extracted and are used as candidates for the *global* alignments. Applications of the alignment relation on real images illustrates its interest for high level image interpretation.

Index Terms— alignments, fuzzy spatial relations, high resolution remote sensing images.

1. INTRODUCTION

Satellite images provide a huge amount of geographical information. The extraction of structural information, such as groups of aligned objects, may help in the interpretation and object recognition tasks for such images. For instance in cartography, it is necessary to find groups of aligned buildings for map generalization [1]. This provides information about the structure of buildings arrangement, and can contribute to determining whether they belong to a urban, rural or residential area. As another example, in object detection, complex semantic classes such as parking lots (car parkings, ports, truck parkings or airports) comprise aligned groups of transport vehicles. Therefore, the identification of aligned groups of transport vehicles can be useful for the recognition of such classes.

The detection of groups of aligned points in digital images has been widely studied as low level processing in computer vision [2, 3]. These methods can be extended to the groups of objects with aligned barycenters [2]. However, when the groups are composed of objects of different sizes, it is not possible to detect the alignment by observing just their barycenters (see Fig. 1). In this work we present a novel method to detect alignments of objects of different sizes.

2. ALIGNMENT DETECTION

To determine whether a group of points is aligned, there are two possible strategies. The first one, used in [2], is to search a thin strip where all the points fall into. The second one deals with searching an angle θ such that every point of the group is approximately located at a direction θ or $\theta + \pi$ from the other points of the group. If we try to extend the first strategy to groups of objects, we face the problem of defining the width of the strip when objects have different sizes. The difficulty of extending the second strategy relies in measuring the angle between the objects. We propose in this work to use measures of relative direction used in spatial reasoning to determine the orientation (or angle) between two objects with respect to the horizontal axis.

Because of the ambiguity related to determining when an object is located approximately at a direction θ from another object, the alignment relation is also ambiguous. Therefore we use fuzzy set theory to model it. Before going into the definition of alignment we introduce a measure of the orientation between two objects.

Throughout this paper we use the following notation. Points in the image are denoted by p_x, p_y, objects represented by regions in the image are denoted by lower case letters $a, b, c, \ldots$, groups of objects by upper case letters $A, B, \ldots$, and $\wedge$ denotes a t-norm (fuzzy conjunction) and $\vee$ a t-conorm (fuzzy disjunction) [4].

2.1. Measuring the orientation between two objects

The relative orientation between two objects a and b is represented through an orientation histogram $O(a, b) : [0, \pi) \to [0, 1]$ which can be seen as a fuzzy number with membership function:

$$O(a, b)(\theta) = \frac{|h(a, b, \theta)|}{\max_{\phi \in [0,\pi)} |h(a, b, \phi)|}, \qquad (1)$$

*This work was done within the Center Of Competence on Information Extraction and Image Understanding for Earth Observation of CNES-DLR-Telecom ParisTech .

a) Segmented objects b) Barycenters of objects

Fig. 1. Example of an aligned group of objects with non-aligned barycenters

where

$$h(a,b,\theta) = \{(p_a, p_b) : p_a \in a, p_b \in b, \quad \mod\left(\angle\left(p_a, p_b\right), \pi\right) = \theta\}$$

and $\angle\left(p_a, p_b\right)$ denotes the angle between the segment joining p_a and p_b and the horizontal axis. An orientation histogram is simply a normalized angle histogram [5] where the angles are computed modulus π and its support has a length equal to π.

To evaluate the degree to which two orientation histograms are approximately the same, we have to consider the imprecision linked to comparing whether two angles are the same. We introduce this imprecision by performing a fuzzy morphological dilation [6] of each histogram by a structuring element ν_0, which is designed such that it represents the imprecision attached to the angle comparison. In our experiments we modeled ν_0 by a trapezoid function. The dilated orientation histogram, $D_{\nu_0}(O(x,y))$ can be also considered as a fuzzy number. To compare the dilated histograms we can use any similarity criterion between two functions or between fuzzy numbers. We decided to use the maximum of the intersection of the dilated histograms [7], therefore we define the degree of similarity between n orientation histograms $\{O(a_i,b_i)\}_{i=0}^{n}$ by:

$$sim(\{O(a_i,b_i)\}_{i=0}^{n}) = \max_{\phi\in[0,\pi[} \bigwedge_{i=0}^{n} D_{\nu_0}(O(a_i,b_i))(\phi), \quad (2)$$

where $D_{\nu_0}(O(x,y))$ is the fuzzy morphological dilation of $O(x,y)$ by a structuring element ν_0 [8].

2.2. Alignment Definition

In order to extract the groups of aligned objects of an image, we introduce two definitions of alignment; *global* and *local* alignment. For the extraction we first identify the *local* alignments, and use these alignments as candidates for *global* alignments. The *globally* aligned groups of objects correspond to the alignments mentioned in Sec. 2

Both *locally* and *globally* aligned groups should be connected by a neighborhood relation. By neighborhood relation we mean a spatial neighborhood, for instance a Voronoi neighborhood or a neighborhood defined by a fixed distance around an object. Then, we say that a group is connected by a neighborhood relation if for every pair of objects a and b in the group, there exist $c_0, \ldots, c_n$ objects in the group, such that $c_0 = a$ and $c_n = b$ and for every $i = 0, \ldots, n-1$ the objects c_i and c_{i+1} are neighbors. The *locally* and *globally* aligned groups should be connected by the neighborhood relation to ensure that the members of the groups are close together.

We say that a group is *globally* aligned if it is connected by a neighborhood relation and there exists an angle θ such that for every member a of the group, all the other members of the group are located at an orientation "approximately" θ from a.

Definition 2.1. Given a group of objects $S = \{a_0, \ldots, a_N\}$, with $N \geq 3$, we define a degree of *global* alignment as:

$$\mu_{ALIG}(S) = sim\left(O(a_0, S\setminus\{a_0\}), \ldots, O(a_N, S\setminus\{a_N\})\right). \quad (3)$$

We say that a group of objects is *locally* aligned if it is connected by a neighborhood relation, and if for every object a in S and every pair of objects b, c in the neighborhood of a the orientation histograms $O(a,b)$ and $O(a,c)$ are similar.

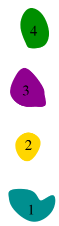
Definition 2.2. The degree of *local* alignment is defined by:

$$\mu_{LA}(S) = \min_{a,b,c:Neigh(a,b)\wedge Neigh(b,c)} sim(O(a,b), O(b,c)), \quad (4)$$

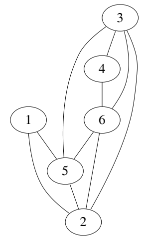
where $Neigh(a,b)$ is a binary relation that is equal to 1 when a and b are neighbors and 0 otherwise.

2.3. Method for extracting *local* and *global* aligned groups of objects

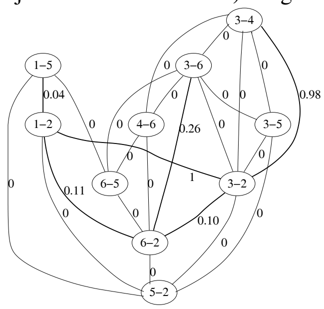
Given a group of objects $A = \{a_1, \ldots a_n\}$, we first determine the possible subsets of *locally* aligned groups of objects. To do this, we construct a neighborhood graph $G_N = \{V, E\}$, where the vertices represent the objects of the group, and there is an edge between two vertices if and only if the corresponding objects are neighbors. Using the neighborhood graph we construct its dual graph. The dual graph is denoted by $\tilde{G}_N = \{\tilde{V}, \tilde{E}\}$ where each vertex $\tilde{V}_i$ represents an edge in the graph G_N. An edge exists between two vertices $\tilde{v}_i$ and $\tilde{v}_j$ of $\tilde{G}_N$ if the two corresponding edges of the graph G_N have a common vertex. Each edge $\tilde{e}_{ij}$ is attributed with the similarity value s_{ij} between the orientation histograms corresponding to the nodes represented by $\tilde{v}_i$ and $\tilde{v}_j$. The dual graph allows us to compare directly the orientation between the pairs of objects which have one object in common. Figure 2 shows an example of neighborhood graph and its dual graph. Notice that the edges of $\tilde{G}_N$ with a high value represent two pairs of objects with a similar orientation histogram, which share a common object. For instance, in the dual graph the edge between the nodes (1 - 2) and (2 - 3) has a similarity value of 1, this edge corresponds to the objects labeled 1, 2 and 3 of Fig. 2(a). In a similar way, edges with a low value represent objects which are not aligned, for example in the dual graph the edge between the nodes (1 - 2) and (6 - 2)



a) Labeled objects



b) Neighborhood graph of a)

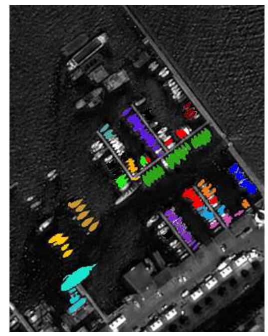


c) Dual graph of b)

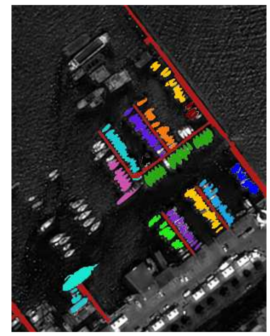
Fig. 2. Neighborhood graph and dual graph of a group of objects

a)

b)



c)



d)

Fig. 3. a) Original Image. b) Segmented boats. c) Sets of *globally* aligned boats with a degree greater than or equal to 0.8. d) Groups of *globally* aligned groups which are parallel and near to the decks (in red).

has a similarity value of 0.11 and corresponds to the objects labeled 1, 2 and 6, which do not form an alignment.

Following the approach proposed here, a connected subset $\tilde{A} \subseteq \tilde{V}$ for which all the edges connecting its vertices have a value superior to α, where α is a user defined tolerance, corresponds to the edges joining a locally aligned group A in G.

The locally aligned groups are the possible candidates for aligned groups. To determine if a *locally* aligned group A forms a *globally* aligned group we measure its *global* degree of alignment (Eq. 4). If the *global* degree is inferior to the user specified value α, then we eliminate the vertex $\tilde{v}$, from the corresponding subset $\tilde{A}$ on the dual graph, which has the lower average edge value over all the edges connected to it. This vertex represents the pair of objects in A which have an orientation less similar to those of their neighbors. We repeat this elimination process until the group has a *globally* aligned degree greater than or equal to α, or until it has less than three elements, and in that case it is not considered as *globally* aligned.

3. RESULTS

The algorithm was applied to the objects of Figs. 1(a), 2(a), 3(a) and 4(b). For Fig. 1(b) the whole group is successfully obtained with a degree of *global* alignment of 0.88. For the case of Fig. 2 the group containing the objects 1, 2, 3 and 4 is found and has a degree of *global* alignment of 1.0.

Fig. 3(c) shows some of the *globally* aligned subsets of boats with a degree greater than or equal to 0.8 obtained from the set of segmented boats of Fig. 3(b). In this experiment, boats were obtained by manually selecting the objects belonging to boats after performing a mean shift segmentation [9]. In Fig.3(c) we can observe that the algorithm obtains the most distinctive groups of the image (purple, blue, yellow and green sets), which can be used for identification of a harbour. However, not all the obtained groups are meaningful for the description of the scene (pink and orange sets), since these are subsets which are aligned but they do not give any information about the arrangement of the boats. To interpret the image it is necessary to consider only the meaningful groups of aligned objects (those which give us some information about the objects arrangements). In the case of Fig. 3 the meaningful groups of aligned objects correspond to the groups that are "parallel to" and "close to" a linear object. The spatial relation "parallel to" and "close to" are modeled in the same way as in [10] and [11], respectively. Fig. 3(d) shows the groups satisfying of *globally* aligned boats which are parallel to a linear object and the linear objects. By using the spatial relations of alignment and parallelism it is possible to extract the structural arrangement of the scene.

Fig. 4(c) shows some of the aligned subsets of houses obtained from the set of segmented houses of Fig. 4(b). It is not possible to show all the aligned groups found by the algo-

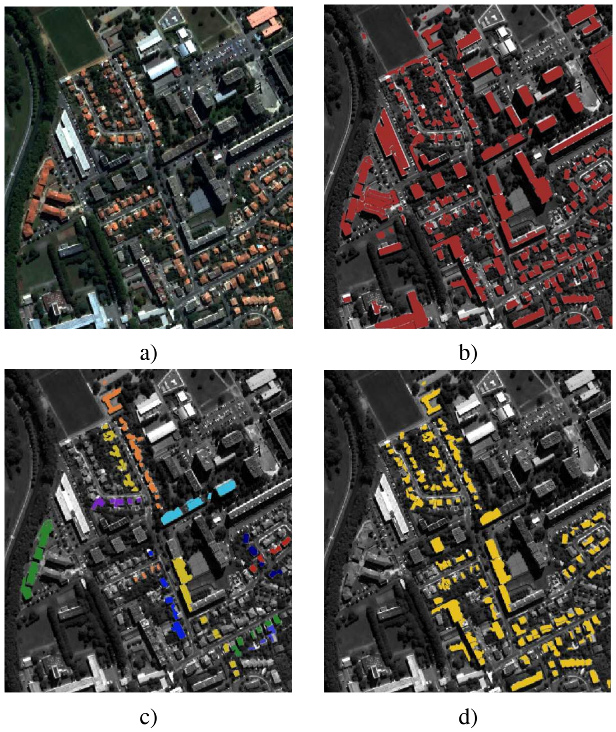


Fig. 4. a) Original Image. b) Segmented buildings. c) Some sets of *globally* aligned buildings. d) Clusters of buildings belonging to *globally* aligned groups which are parallel and near to other groups.

rithm since there are objects which belong to more than one group. In this experiment, buildings were obtained by using the method described in [12]. For the extraction we used an $\alpha = 0.85$ and a Voronoi neighborhood constrained by a distance of 30 pixels equivalent to approximately 21 m. Notice that the method obtains groups of *globally* aligned objects of different sizes which do not have aligned barycenters. From the obtained *globally* aligned groups of houses we extracted the groups which are "parallel" and "close to" another group. The spatial relation "parallel to" and "close to" are modeled as in the previous example. The groups of houses satisfying the previous conditions are shown in Fig. 4(d). These houses correspond to the regions containing organized groups of houses, which are characteristic of residential areas.

4. CONCLUSIONS

In this work, we presented an original method to determine aligned groups of objects in high resolution remote sensing images. The proposed method extracts the *local* alignments by considering the relative directional position between the objects. Once the *local* alignments have been detected, these are used as candidates for *global* alignments, then objects in the group are eliminated until the group satisfies the desired degree of *global* alignment. The relation was illustrated in real images showing its interest for high level image interpretation.

Future work aims at further investigation of image interpretation tasks by combining alignments with other types of structural information.

5. REFERENCES

[1] S. Steiniger and R. Weibel, "Relations among map objects in cartographic generalization," *Cartography and Geographic Information Science*, vol. 34, no. 3, pp. 175–197, 2007.

[2] A. Desolneux, L. Moisan, and J.M. Morel, "A grouping principle and four applications," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 4, pp. 508–513, 2003.

[3] R.O. Duda and P.E. Hart, "Use of the Hough transformation to detect lines and curves in pictures," *Communications of the ACM*, vol. 15, no. 1, pp. 11–15, 1972.

[4] D. Dubois and H.M. Prade, *Fuzzy sets and systems: theory and applications*, vol. 144 of *Mathematics in Science and Engineering*, Academic Press, 1980.

[5] K. Miyajima and A. Ralescu, "Spatial organization in 2D segmented images: Representation and recognition of primitive spatial relations," *Fuzzy Sets and Systems*, vol. 65, pp. 225–236, 1994.

[6] I. Bloch, C. Pellot, F. Sureda, and A. Herment, "Fuzzy Modelling and Fuzzy Mathematical Morphology applied to 3D Reconstruction of Blood Vessels by Multi-Modality Data Fusion," in *Fuzzy Set Methods in Information Engineering: A Guided Tour of Applications*, D. Dubois R. Yager and H. Prade, Eds., chapter 5, pp. 93–110. John Wiley and Sons, New-York, 1996.

[7] R. Zwick, E. Carlstein, and D. V. Budescu, "Measures of similarity among fuzzy concepts: A comparative analysis," *International Journal of Approximate Reasoning*, vol. 1, pp. 221–242, 1987.

[8] I. Bloch and H. Maître, "Fuzzy Mathematical Morphologies: A Comparative Study," *Pattern Recognition*, vol. 28, no. 9, pp. 1341–1387, 1995.

[9] D. Comaniciu and P. Meer, "Mean shift analysis and applications," in *Proceedings of the 7th IEEE International Conference on Computer Vision (ICCV-99)*, Los Alamitos, CA, Sept. 20–27 1999, vol. II, pp. 1197–1203, IEEE.

[10] M.-C. Vanegas, I. Bloch, H. Maître, and J. Inglada, "Approximate Parallelism Between Fuzzy Objects: Some Definitions," in *International Workshop on Fuzzy Logic and Applications WILF*, Palermo, June 2009, vol. 5571, pp. 12–19.

[11] C. Hudelot, J. Atif, and I. Bloch, "Fuzzy spatial relation ontology for image interpretation," *Fuzzy Sets Systems*, vol. 159, no. 15, pp. 1929–1951, 2008.

[12] V. Poulain, J. Inglada, M. Spigai, J-Y. Tourneret, and P. Marthon, "Fusion of high resolution optical and SAR images with vector data bases for change detection," in *IEEE International Geoscience and Remote Sensing Symposium, IGARSS 2009*, juillet 2009.