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Local and Global Measure of Dissimilarity between Two Segmentations

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Abstract— the implementation of a segmentation method in a system requires knowledge of the performance of the method in a given situation. Hence, it is highly desirable to have a criterion for measuring the quality of the result obtained by a segmentation algorithm. This study focuses on two measures of dissimilarity between two segmentations, by means of a mapping. The local measure proposed is based on the map of local dissimilarities that capture the differences between two images. This allows a simple way to quantify the local dissimilarities and to determine their spatial distribution. Thus, we are building a global measure based on local measurements. Both measures local and global are successfully tested on synthetic and medical images.

Index Terms— k-means, Region Growing, Hausdorff distance, distance transformation, local dissimilarity, global dissimilarity.

I. INTRODUCTION

The multiplicity of segmentation algorithms makes it necessary to search for a method of evaluation of several algorithm performance in order to find the most adequate algorithm and consequently improve the segmentation result. This objective implies the existence of a method for measuring the quality of a segmentation result in a given situation. We propose a method based on the map of local dissimilarities between the segmented images. We deduce all local and spatial distributions taken form different areas of the images. Thus global measure of dissimilarity is calculated from the map to estimate the overall quality between the two segmentations. After a review on Hausdorff and modified Hausdorff distance, we present a method to compute the dissimilarity between two segmentations. We then give some experimental results obtained on synthetic and medical images.

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II. DISSIMILARITY MEASURES

Among dissimilarity measures between images, there is Hausdorff distance. This distance has often been used in the field of searching for images by content. It has been successfully applied to the matching of objects [2] or to face recognition [3]. For sets of finite points, Hausdorff distance can be defined as:

A. Definition of Hausdorff distance

Given two sets of non-empty dots
A = (a1; …...; an) *and* B = (b1; …….. ; bn) *of* R^2,
Hausdorff distance *is given by:*

$$HD(A;B) = max(h(A;B), h(B;A)) \quad (1)$$

With

$$h(A;B) = max_{a \in A}(min_{b \in B}(d(a;b))) \quad (2)$$

h(A;B) is called a directed Hausdorff distance and d is the underlying distance. The classic Hausdorff distance has good properties but it takes account of points, which were introduced into sets A and B by error or points that have been contaminated by noise in previous treatments. Hausdorff distance is therefore it is sensitive to noise [4]. Several changes have been proposed in order to modify Hausdorff distance for the purpose to improve it, including the modified Hausdorff distance [5].

B. Definition of the modified Hausdorff distance

The direct modified Hausdorff distance is defined in [5] by:

$$h_{MHD}(A;B) = \frac{1}{n*n}\sum_{i=1}^{n}\sum_{j=1}^{n} d(a_{ij};B) \quad (3)$$

With $$d(a,B) = min_{b \in B}(d(a;b)) \quad (4)$$

$$MHD = \max(h_{DHM}(A;B), h_{DHM}(B;A)) \quad (5)$$

The modified Hausdorff distance has a better behavior for real applications.

C. The map of local dissimilarities in Hausdorff distance

An algorithm to calculate the map of local dissimilarities is proposed in this paragraph [1]. It consists in making the window size grow from a minimum size in order to find the optimal radius of the window for the local measurement of the Hausdorff distance.

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Algorithm 1: Computing the Map of Local Dissimilarities by Hausdorff distance

```
compute HD(A;B)
For pixel p Do
      n := 1
      While HDw(p;n)(A,B) = n & n <HD(A;B) Do
            n := n + 1
      End While
      LDMap(p) = HDw(p,n-1)(A;B) = n -1
End For.
```

This algorithm shows (in the while loop) how the window is adapted to the local dissimilarity.

However, this algorithm is computationally expensive as a matter of fact, the computational complexity is O (n^4) for two images of respective size n * n pixels.

The following paragraph provides a formula for computing the map of local dissimilarities that is much more quick. The computation is fast. The interpretation in terms of local dissimilarity measure is derived from algorithm 1.

D. Map of local dissimilarities in distance transform

$$MLD(p) = |A(p) - B(p)| \max(Td_A(p); Td_B(p)) \quad (6)$$

Equation (6) gives a value for each pixel, which depends on the distance transform Td_A and Td_B of images A and B respectively. Fast algorithms have been developed for the calculation of the distance transformation, their complexity is O(n^2) for the image of size n * n pixels. So the complexity of the map of local dissimilarities using equation (6) is O (n^2). However, there are several ways to calculate the distance transform of an image. Equation (6) can be simplified, for binary images [6]:

$$MLD(p) = B(p)Td_A(p) + A(p)Td_B(p) \quad (7)$$

The distance transform associates to each zero pixel of an image, the distance to the nearest non-zero pixel. It can be calculated quickly by the use of the chamfer distance, which is a good approximation of the Euclidean distance. It also allows calculating the distance transform, by twice scanning the image by a structuring element [7] [8].

III. SEGMENTATION

The segmentation is an important step in image processing. It consists in partitioning an image into homogeneous regions and according to a given criterion, for analysis and interpretation by a higher-level process. Image segmentation is important in an image analysis system; we present in the following paragraph some segmentation methods.

A. Region growing algorithm

The algorithm regions growing was originally developed by Muerle [9] The principle of this algorithm is to grow a region by gathering neighboring pixels. pixels are selected to maintain the homogeneity of the region, a uniformity indicator should then be defined. Neighboring pixels are added to the region if the uniformity indicator is true, a pixel is aggregated to a region if difference between the gray level and the average gray level of the region is low. Growth stops when you can not add more pixels without breaking the homogenety criterion [10] [11].

B. Region growing evolutionary approach

The Evolutionists growth regions algorithm consists of selecting from all possible segmentations, the optimal segmentation that minimizes a criterion for validating the image segmentation [12].

C. K-means algorithm

The k-means algorithm is the best known method of metric automatic classification. It is the most applied because of its simplicity of implementation. The approach assumes that the number of classes is known a priori. The segmentation obtained strongly depends on the initialization of this algorithm [13] [14].

IV. EXPERIMENTATION AN TESTS

To evaluate the performance of the method for measuring the quality of segmentation by measuring the proposed local and global dissimilarity indices, we considered three images in grayscale, a synthetic image and two real medical images.

A. Local dissimilarities measures

Three segmentation methods are compared: regions growing (RG), evolutionary regions growing (ERG) and Kmeans (KM) with a segmentation test used as a reference.

The method computes the dissimilarity map between the segmented image and its reference. The three maps of local dissimilarities are presented in fig1, fig2, fig3. Shifts appear bright and dark areas dissimilar.

The extent of local dissimilarities of a synthetic image in fig1 provides the most accurate information as distortions of object contours are well detected. This example is a good illustration of the effectiveness of the map of local dissimilarity as a measure of quality of segmentation between a segmented image and its reference.

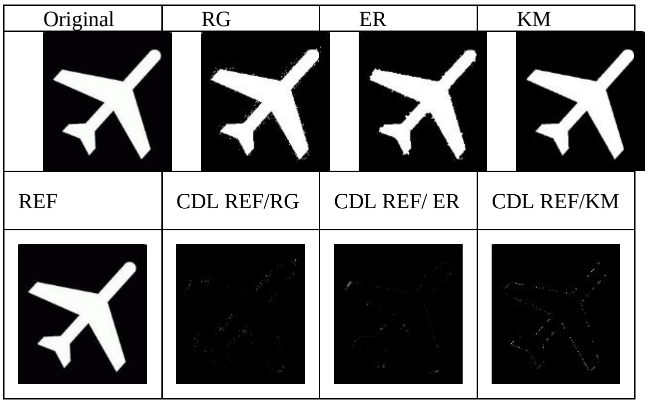
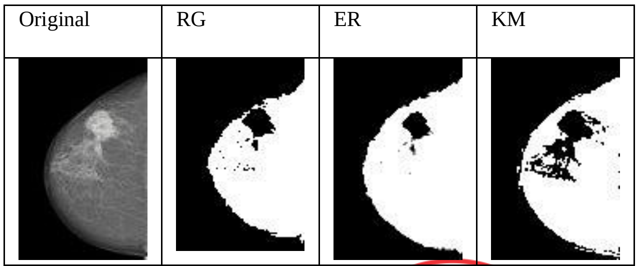


Fig. 1: The three maps of local dissimilarities between two segmentations of Test 1



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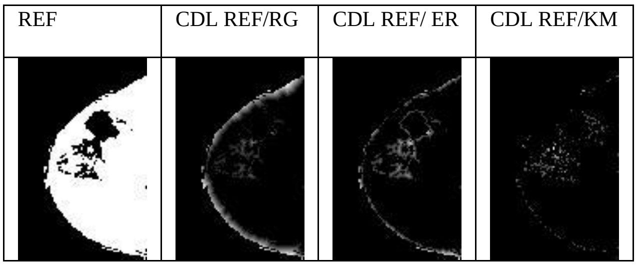

Fig. 2: The three maps of local dissimilarities between two segmentations of Test 2

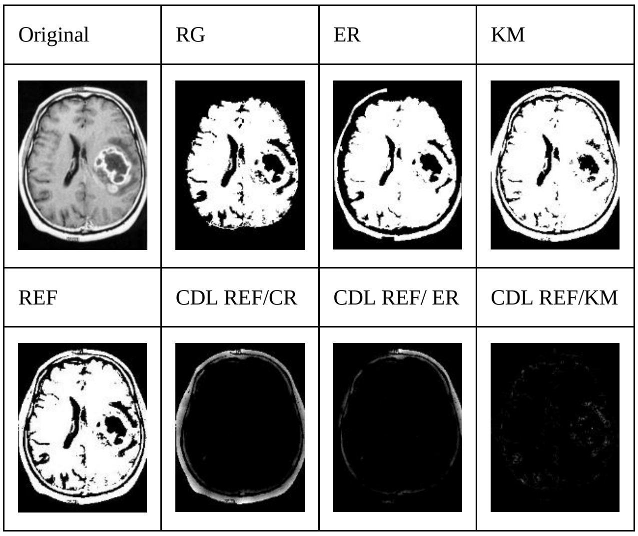

Fig. 3: The three maps of local dissimilarities between two segmentations of Test 3

The difference in behavior of the three methods is illustrated in Fig 1, Fig 2 and Fig 3. The three maps are easy to read, the differences between the three methods are clearly highlighted.

B. Global dissimilarity measure

We propose to compute a scalar from all local measurements by using the map of local dissimilarities. For a global measurement of quality between two segmentations, a simple sum could be used but Borgefors [15] showed that a quadratic sum was more discriminating. The measure of global dissimilarity (MGD) is then proposed:

$$MGD = \sqrt{\sum_{i=1}^{n}\sum_{j=1}^{m}(MLD(i,j))^2} \qquad (8)$$

For all the images of the test database, the Hausdrff Distance (HD), the Modified Hausdorff Distance (MHD) and the MDG are calculated between the reference and a range of segmented versions of this reference; three unsupervised segmentation algorithms are then compared: growing region, evolutionary region growing and kmeans.

TAB 1: Three quality measures between segmented synthetic image and its reference

	HD	MHD	MGD
REF/RG	2,8284	1,1750	55,0809
REF /ER	3,1623	1,0262	31,8434
REF /KM	1,7321	0,4917	12,2066

TAB 2: Three quality measures between segmented medical image 1 and its reference

	HD	MHD	MGD
REF/RG	3,7417	1,2842	82,1827
REF /ER	3,8730	1,2117	34,4674
REF /KM	2,8284	0,7899	16,6433

TAB 3: Three quality measures between segmented medical image 2 and its reference

	HD	MHD	MGD
REF/RG	7,4162	4,3886	964,0628
REF /ER	6,7072	4,1278	416,4181
REF /KM	5,5678	2,9929	72,4914

Subjectively, we tend to favor the k-means method over the evolutionary regions growing and to favor evolutionary regions growing over regions growing. This result is confirmed by MGD in all cases. Alternatively, Hausdorff distance favors regions growing over evolutionary regions growing which is show in Tab 1. This is because Hausdorff distance is sensitive to noise.

V. CONCLUSIONS

We propose a measure of the local dissimilarities and their spatial distribution between two segmentations. We calculate a global measure of dissimilarity from all the local measurements. Good local behavior results in good global behavior. This technique takes into account the geometry of the regions because it is interested in the locality of poorly grouped pixels. The disadvantage of this technique is that it is expensive in computation time. Nevertheless, in the case of characterizing the performance of a segmentation algorithm, the computation time does not interest us because we are checking the results quality, which indicate what the is best segmentation algorithm to use; we assign a degree of confidence in the algorithm once it is implemented.

REFERENCES

1. E. Baudrier, F. Nicolier, G. Million and S. Ruan, " Binary image comparison with local-dissimilarity quantification", Pattern Recognition, vol. 41, n. 5, pp. 1461–1478, jan. 2008.
2. D.P. Huttenlocher and W.J. Rucklidge, "Comparing images using the hausdorff distance", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 15, n. 9, pp. 850–863, 1993.
3. B. Takacs, “Comparing faces using the modified Hausdorff distance”, Pattern Recognition, vol. 31, no 12, 1998, pp. 1873-1881.
4. J.Paumard, “Robust comparison of binary images”, Pattern Recognition Letters, vol. 18, no 10, 1997,pp. 1057-1063.
5. M. Dubuisson and A. Jain, “A modified Hausdorff distance for object matching,” Proc. 12th IAPR International Conference on Pattern Recognition, Oct 1994, pp. 566-568.
6. F. MORAIN-NICOLIER, J. LANDRE and S. Ruan, " Détection d'objet par mesure de dissimilarités locales ", XXIIe Colloque GRETSI, Dijon, september 2009.
7. G. Borgefors, "Distance transformations in digital images", Computer Vision graphics and Image processing, vol. 34 n. 3, pp. 344-371, 1986.
8. A. Rosenfeld and J. Pfaltz,”Distance functions in digital pictures”, pattern Recognition, vol. 1, pp 33-61, 1968.
9. J. Muerle and D. Allen, “Experimental evaluation of techniques for automatic segmentation of objects in a complex scene”, Pictorial Pattern Recognition, Thompson, Washingthon DC, pp. 3-13, 1968.
10. S.W. Zucker, “Regiong growing: childhood and adolescence”, Computer Graphics and Image Processing, Vol. 5, pp. 382-399, 1976.
11. J.Fan, D.K.Y. Yau, Elmagarmid and W.G. Aref, “Automatic image segmentation by integrating color-based and seeded region growing”, IEEE Transaction on Image processing, Vol. 26, n 10, pp. 1454-1466, 2001.

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12. A. Elallaoui and all, "Threshold optimization by genetic algorithm for segmentation of medical images by region growing", International journal of emerging trends an technology in computer science, Vol. 1, n. 2 pp. 161-166, 2012.
13. D.E. Goldberg, K. Deb and J.H. Clark, "Genetic algorithms noise, and the sizing of populations", Complex Systems, Vol. 6, pp. 333-362, 1992
14. J.C. Bezdek and R.J. Hathaway, "Optimization of fuzzy clustrtring criteria using genetic algorithms", Proceedings, First IEEE Conference on Evolutionnary Computation, Piscataway, NJ: IEEE Press, Vol. 2, pp. 3-52, 1994.
15. G. Borgefors, "Hierarchical chamfer matching : a parametric edge matching Algorithm", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 10, n. 6, pp. 849–865, 1988.G. O. Young, "Synthetic structure of industrial plastics (Book style with paper title and editor)," in *Plastics*, 2nd ed. vol. 3, J. Peters, Ed. New York: McGraw-Hill, 1964, pp. 15–64.

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