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Hausdorff Distance based 3D Quantification of Brain Tumor Evolution from MRI Images

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***Abstract*— This paper presents a quantification method which can be used to quantify the evolution of a brain tumor with time. From two segmented volumes, a Local Distance Volume (LDV) based on Hausdorff Distance is computed to show the true physical local distances between them. In the case of tracking a tumor volume during a therapeutic treatment, local variations can thus be shown by the LDV in particular where the tumor has regressed and where it has growed. This information can help radiologists to adapt the current treatment.**

I. INTRODUCTION

Accuracy in image segmentation is a nettlesome problem, especially in medical image analysis, where precision in segmentation is a prerequisite for a reliable interpretation of the results. Moreover, many current problems in the medical realm and diagnosis derive benefit from a precise brain segmentation. Multimodality image registration requires a good brain segmentation: indeed, surface matching techniques need to have a precise definition of the segmented volumes [4]. As a matter of fact, any image analysis technique has to be validated in an efficient way so as to legitimize its use in clinical day-to-day applications. A rigorous definition of image quality in terms of algorithm efficiency depends on the performance of some observer on some specific task; and the mathematical models for these observers have to be designed in order to allow task automation. In particular in the domain of brain tumor segmentation, important information is the evolution of the tumor with respect to a given treatment. Accessing the global variation of the tumoral volume is a first step but not necessarily sufficient. More precise information is the localization of the tumor variations volume. The paper is organized as follows. In the first part, we present the three-dimensional distance volume. This volume contains local Hausdorff distances between to references volumes. The obtained measures are robust to small registration error and are made of true physical distances. Thus it is possible localize big and small variations from one volume to the next one. The next part resumes the segmentation method used to extract the tumor. In the last section, we present the results of the local distance volume computed on these segmented volume slices. Local variations of the tumor are highlighted, in particular where it has regressed or progressed.

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II. 3D LOCAL DISTANCE VOLUME

A. Distance Measure: the Choice of the Hausdorff Distance

Among distance measures over binary images, the Hausdorff distance (HD) has often been used in the content-based retrieval domain and is known to have successful applications in object matching [5], [7] or in face recognition [11]. Let's have a brief review of the definition and of some properties related to the HD. Originally meant as a measure between two point collections, for finite sets of points, the HD can be defined as [5]:

Definition 1 (Hausdorff distance): Given two non-empty finite sets of points $A = (a_1, \dots, a_n)$ and $B = (b_1, \dots, b_m)$ of $\mathbb{R}^2$, and an underlying distance d, the HD is given by

$$D_H(A,B) = \max\left(h(A,B), h(B,A)\right) \quad (1)$$

$$\text{where } h(A,B) = \max_{a\in A}\left(\min_{b\in B} d(a,b)\right), \quad (2)$$

$h(A,B)$ is the so-called *directed Hausdorff distance*.

The interest of this measure comes firstly from its metric properties: non-negativity, identity, symmetry and triangle inequality. Moreover, the HD is a match methodology without point-to-point correspondence, so it is robust to local non-rigid distortions. For a small translation, the Hausdorff distance is small, which matches our expectation for a distance measure.

Some Modified Versions of the Hausdorff Distance: the classical HD has good properties but it measures the most mismatched points between A and B, and as a consequence it is sensitive to noise [9]. Indeed considering two volumes containing the same pattern and one point added to the first volume, far from the pattern, then the HD will measure the distance between the pattern and the point. Several modifications of the HD have been proposed to improve the classical HD [12]. However, these measures are global and cannot account for local distances. Indeed, the principle of HD is to be a "max min" distance and it means that the value of the HD between two volumes is reached for at least one couple of points. But it doesn't say if the value is reached in several parts or only for one pair,

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which corresponds to different degrees of distance. These remarks motivate us to design a local and parameter-free HD in the next section.

B. Local HD Measure

The notion of local distance is first discussed, then definition of a HD measure in a local window is presented. In all this section, A and B design two non-empty finite sets of points of $\mathbb{R}^2$, and W a convex closed subset of $\mathbb{R}^2$.

Producing locally a distance implies to compare the two volumes locally. It can be done thanks to a sliding window. The parts of both volumes viewed through this window are compared based on a distance measure. The sliding-window size plays an important role: it should fit the local distance so that the distance can give a local measure. Nevertheless, here is the general idea: if the pixels located in the sliding window belong to coarse features, the window should be big enough to grasp the feature's distances. Similarly, for fine features, a window "bigger" than the features will include unwanted information on distances. These requirements are important to obtain robust local measure. In particular it is important to be robust to registration error. Therefore, it is necessary to adapt the size of the window to obtain precise measures.

The local HD definition: the restriction of the HD to a window implies to modify its definition. It is indeed not available in the case that one of the sets is empty, which can happen in a window. Then the distance to the window border must be introduced (see [2]). With the new definition of the windowed HD, it is possible to define an algorithm which makes the window fit the local distance for each pixel (alg. 1). It consists of a sliding three-dimensional window whose radius is locally adapted to find the local optimal radius.

Algorithm 1 Computation of local HD

compute $D_H(F,G)$
for x a voxel **do**
  $n := 1$ {initialization of the window-size}
  while $HD_{B(x,n)}(F,G) = n$ and $n \leqslant HD(F,G)$ **do**
    $n := n+1$.
  end while
  $HD_{loc}(x) = HD_{B(x,n-1)}(F,G) = n-1$
end for

It is possible to express the local HD with the following formula to allow fast computations (for details, see [2]):

Definition 2 (local HD (fast version)): for x a voxel of the images,

$$HD_{loc}(x) = |B(x) - A(x)| \max(d(x,A), d(x,B)) \tag{3}$$

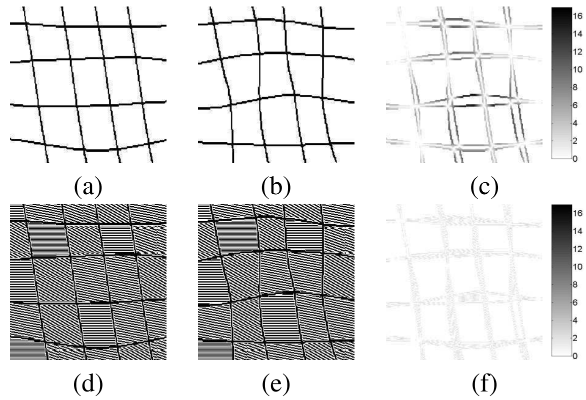

Fig. 1. Two images (a) and (b), their textured versions (d) and (e) and their LDMaps. The values of the LDMap (f) are low because of the large pattern pixel ratio in the textured images (d) and (e). The LdMap (c) between images (a) and (b) is representative (quantified and localized information) of their local differences.

The formula is faster to compute than the algorithm based on the windowed HD, but the obtained value interpretation comes from the local-distance window adaptation in the algorithm.

C. The Local Distance Volume

The local HD can be computed for all the points of the space, it results in the following definition:

Definition 3 (Local Distance Volume (LDV)): Let F and G design two non-empty finite sets of points of $\mathbb{R}^3$, the local distance volume LDV is defined by

$$\forall x \in \mathbb{R}^3, LDV(x) = \begin{cases} HD_{B(x,r_{max})}(F,G) & \text{if } \mathcal{R} \neq \emptyset \\ 0 & \text{if } \mathcal{R} = \emptyset. \end{cases} \tag{4}$$

The maximum value in the local distance map is the Hausdorff distance between the two input sets. For each pixel x, the formula gives a value that depends on the distance transform of the sets A and B. Fast algorithms have been developed for distance transformation. So the LDV complexity with the formula is a $O(m^3)$, which is linear in the pixel number.

Qualitative results: We present in this paragraph two kinds of images on which the a two-dimensional version of the LDV (named LDMap in this paragraph) is applied to evaluate their variation (see fig. 1). The given remarks applies equally on volumes. 1) The first images (a) and (b) are non textured grids. (b) is a locally deformed version of (a). The obtained information is quantified and localized. The values of the LDMap (up to 17) reflect the local distance between the images. Only where the grid-lines are different (between the two images) a non-zero distance is obtained. Morevover, the more important is the local distance, the more different the images are (locally). 2) For the second comparison (d) and (e), the images are textured and the pattern pixel ratio is large. The obtained

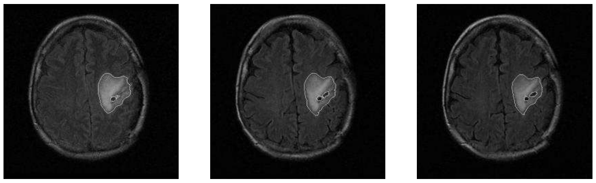

Fig. 2. Segmented MRI.

values in (f) do not reflect the similarity in this case. As a short conclusion, the LDMap is a useful tool for non-textured and well-defined images (or volumes). It is thus usable for segmented slices.

III. Results

A. Segmentation Method

MRI images are acquired on a 1.5T GE (General Electric Co.) machine using an axial 3D IR (Inversion Recuperation) T1-weighted sequence, an axial FSE (Fast Spin Echo) T2-weighted, an axial FSE PD-weighted sequence and an axial FLAIR. For one examination, we have 24 slices of the four signals with a voxel size of $0.47 \times 0.47 \times 5.5$ mm3. All the slices and all the examinations are registrated using SPM software.

We use the first examination for training SVM using RBF kernel [10]. The training set was obtained from one slice by using mouse to choose ten pixels into the tumour and ten outside. We perform the first segmentation of this volume by using the SVM model obtained. So, we build automatically about one hundred points into the tumour and outside from all the tumoral slices. We retraining a second SVM and use it for perform a second segmentation for improve the first result. With this last SVM model, we perform the segmentation of others examinations. At each segmentation of examination, we use this 2 steps process for improve the result. Fig 2 contains an example of the obtained segmentation. All the nine slices of two segmented volumes are given in figs 3 and 4.

B. Implementation Details

The computation of the LDV is done with a new mageJ plugin [6]. With a 2GHz opteron, the comparison of the two $512 \times 512 \times 9$ volumes is done in 39 seconds.

C. Results

The LDV is computed between volumes 1 and 2. The results are presented in fig 5. As the z-resolution is slightly greather than the $x-y$ resolutions (with a ratio of 11.7), the obtained distance depends only lightly on the z-axis information. Only when the obtained distance is greather than 11.7mm, the z-information has been taken into account. Fig 6 is a three-dimensional representation of the LDV.

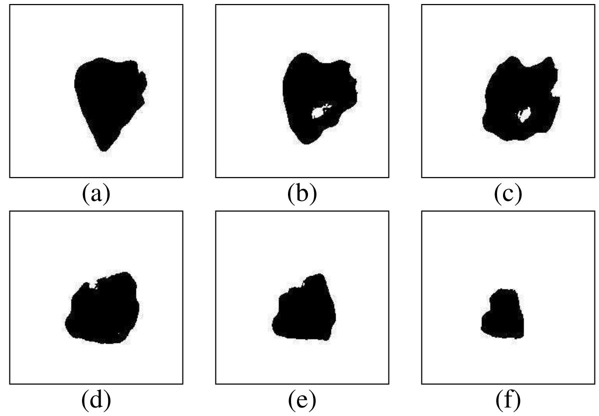

Fig. 3. Segmentation of the first volume (slices from 18 to 23, a-f) using SVM with RBF kernel.

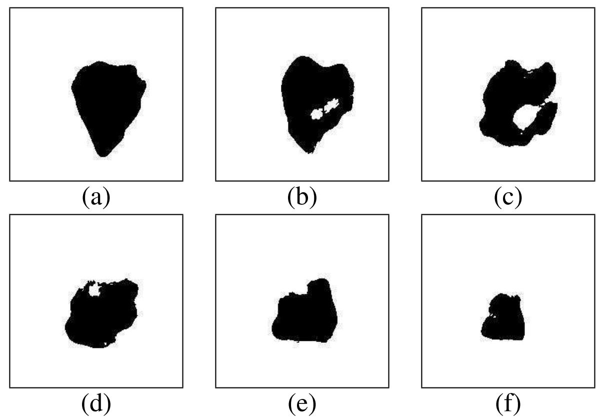

Fig. 4. Segmentation of the second volume (slices from 18 to 23, a-f) using SVM with RBF kernel.

As a true distance is used to compute the LDV, the given scalar are true physical distance in mm. The given distances histogram indicates there are much more low distances than high distances. This a coherent fact as non-zero LDV values are obtained in the intersection of the two volumes. The intersection is locally filled with increasing values, starting from zero up to the maximum local distance between the volumes. The maximum distance is 15.56mm. This represent the higher straight distance between the two volumes.

The proposed Local Distance Volume can be used to track more precisely the variations between two volumes. The Hausdorff Distance in a window (eq. (3)) is defined as the maximum of two directed distance. In the present case the directed distances carry useful information. $h_W(A, B)$ carry the information on voxels present in vol. 1 and not in vol. 2. Symmetrically $h_W(B, A)$ carry the information on voxels present in vol. 2 and not in vol. 1. So $h_W(A, B)$ indicates where the tumor has regressed and $h_W(B, A)$ where the tumor has progressed. This is illustrated in fig. 7 and fig. 8. The augmentation of the central occlusion is

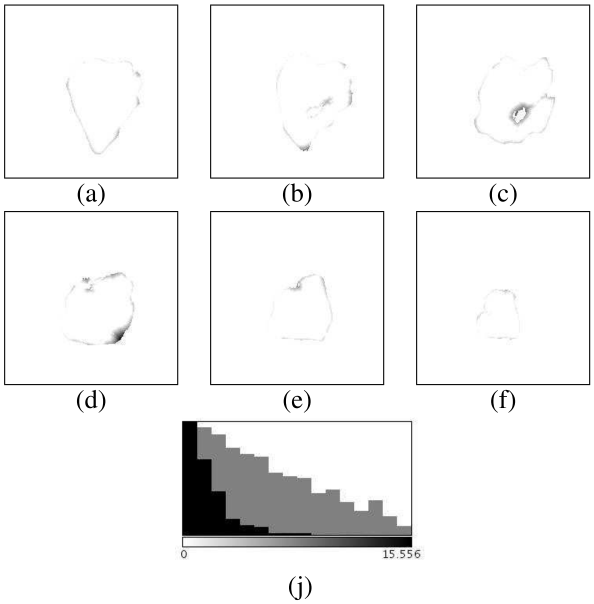

Fig. 5. Slices 18 to 23 (a-f) of the Local Distance Volume between volumes 1 (fig 3) and 2 (fig 4). The distances are absolute according to eq. (3). (j) is the distance histogram (logarithmic scale in gray) and the colormap of images (a-f).

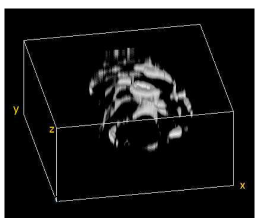

Fig. 6. A three-dimensional view of the LDV between volumes 1 and 2.

clearly seen (by high negative distances).

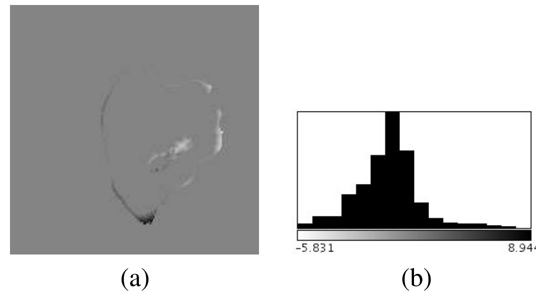

Fig. 7. Using the directed Hausdorff Distance to show where the tumor has regressed (in white with negative distances) and where is has progressed (in black with positive distances). (a) is the LDV with directed distances (only slice 5 is presented corresponding to (b) in 3 and 4). (b) is the histogram and the colormap of the directed LDV.

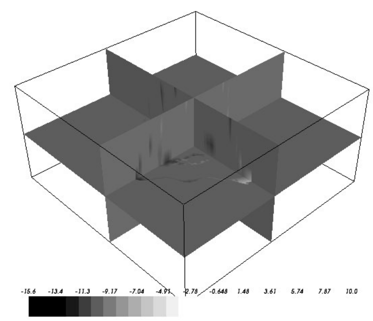

Fig. 8. Using the directed Hausdorff Distance to show where the tumor has regressed (in black with negative distances) and where is has progressed (in white with positive distances).

IV. CONCLUSION

A distance measure between volumes has been presented. Using local Hausdorff distances, the Local Distance Volume (LDV) is computed with adaptative size windows. This method allows to indicates where the volumes are similar. The LDV has been successfully applied on segmented MRI volumes containing a tumor. The evolution of the tumor between two acquisitions can be quantified by the obtention of true physical distances between volumes. Moreover, the method allow to track where the tumor has regressed and where it has progressed.

REFERENCES

[1] E. Baudrier, G. Millon, F. Nicolier, R. Seulin, S. Ruan, Hausdorff distance based multiresolution maps applied to an image similarity measure, *to appear in Imaging Science Journal*.

[2] E. Baudrier, G. Millon, F. Nicolier, S. Ruan, A fast binary-image comparison method with local-dissimilarity quantification, *International Conference on Pattern Recognition (ICPR'06)*, Hong Kong, vol. 3, 20-24 aug., 2006, pp 216-219.

[3] G. Borgefors, Distance transformations in digital images, *Comput. Vision Graph. Image Process*, vol. 34, no. 3, 1986, pp 344–371.

[4] J.C. De Munck et al., Registration of MR and SPECT without using external fiducial markers, *Phys. Med. Biol.*, vol. 43, no. 5, 1998, pp 1255-1269.

[5] D. P. Huttenlocher, W. J. Rucklidge, Comparing Images Using the Hausdorff Distance, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 15, no. 9, 1993, pp 850–863.

[6] ImageJ, Image Processing and Analysis in Java, *http://rsb.info.nih.gov/ij*.

[7] O.K. Kwon, D.G. Sim, R.H. Park, Robust hausdorff distance matching algorithms using pyramidal structures, *Pattern Recognition*, vol. 34, no. 10, 2001.

[8] Y. Lu, C. Tan, W. Huang, L. Fan, An approach to word image matching based on weighted Hausdorff distance, *Proc. 6th Internat. Conf. on Document Anal. Recogn.*, 2001, pp 921–925.

[9] J. Paumard, Robust comparison of binary images, *Pattern Recognition Letters*, vol. 18, no. 10, 1997, pp 1057–1063.

[10] S. Ruan, S. Lebonvallet, A. Merabet, J.M. Constans, Tumor Segmentation from a Multispectral MRI Images by Using Support Vector Machine Classification, **to appear in ISBI'07**, 2007, Washington (USA).

[11] B. Takacs, Comparing faces using the modified Hausdorff distance, *Pattern Recognition*, vol. 31, no. 12, 1998, pp 1873–1881.

[12] C. Zhao, W. Shi, Y. Deng, A new Hausdorff distance for image matching, *Pattern Recognition Letters*, vol. 26, 2004, pp 581–586.