Block Matching Monomodal Image Registration using Robust Similarity Measure and a combination of optimization and interpolation

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Abstract. In this paper we present a Block Matching approach to registration of medical 2D images IRM/IRM. The registered images are assumed to be rigidly aligned before starting this procedure. The sum of absolute differences (SAD), sum of squared differences (SSD), mutual information (MI) and correlation coefficient (CC) are used as measures of similarity to determine the similarity between images as well as to evaluate the degree of robustness of registration. In order to provide the best value of a measure of similarity, process of optimization and interpolation are introduced. The duration of the algorithm's execution is dependent on the block's size. The objective of this article is to choose the best suitable measure of similarity and to test the effect of subdivision of blocks on the duration of execution which is for the benefit of medicine. This approach was tested and leads to interesting results.

Keywords: Block Matching, registration, measures of similarity, optimization, interpolation.

1 Introduction

Image registration is the process of determining the correspondence between all points in two images of the same scene [8]. It is possible to align the images manually, but that requires too much time and it is irreproducible. It is consequently desirable to automatic means of registration of the entire images.

The automatic algorithms of registration of the images were the subject of many publications, but in the field of medicine, software of registration of images isn't yet used. However, the important demand for hybrid equipment, there necessities a true need for precise methods of registration.

This contradiction can be due to the fact that in this field, the doctors are less familiarized with the various aspects of registration: choosing the criteria that allow the choice of the method of the most suitable registration and solving the practical

problems during the application of the algorithms constitute the major issues of registration to be treated [15].
Image registration methods can be categorized into intensity-based [7] and feature-based method [10]-[13]. The feature-based method involves extracting corresponding features. Intensity-based registration [7] creates a cost function from voxel intensity space directly and iteratively optimizing this function among different transformation parameters. Various intensity-based methods have been successfully devised for rigid registration of medical images.
For the monomodal as well as the multimodal case, the general approach consists in assuming a global relationship between the intensities of the images to register and then deriving and maximizing a suitable similarity measure sum of absolute differences (SAD), sum of squared differences (SSD), mutual information (MI) and correlation coefficient (CC) [18].
In this paper, we deal with these similarity measures while using a block matching strategy interleaved with a robust transformation estimator. Block matching techniques have already been used in non-rigid medical image registration but rarely in rigid registration.
When block matching is used in rigid registration the displacements to be found are much larger than in non rigid registration [17]. To overcome this major difficulty, the blocks have to be moved in wider neigh broods which may cause the resulting displacement field to contain some severe outliers. The outliers may affect the estimation of the rigid transformation and for that reason; the robustness of the transformation estimator is a key issue.
Section 2 describes our implementation of block matching in rigid mode. Section 3 and 4 deal with optimization and interpolation which aim at ameliorating the parameters of transformation and therefore the accuracy of the registered image. Finally section 5 presents our experiments and results obtained.

2 Description of the method

The algorithms of registration can be decomposed into three elements: a measurement of similarity, which quantifies the degree of alignment of the two images, a model of transformation, which specifies the type of transformation applicable to the target image so that it is added to the image of reference and an algorithm of optimization, which varies the parameters of the transformation to maximize the measurement of similarity. Indeed the algorithm takes two images as input: a reference image I and a floating image J. the output will be the transformation T and the image $J' = JoT^{-1}$, which is aligned with I. The whole process is a two step procedure. It follows in iterative scheme through a block matching strategy. At each step, two successive tasks consist computing a displacement field between I and the current floating image J'.

The second consists in gathering these displacements to determine a rigid transformation S according to $T \leftarrow SoT$ and we resample only once the image J in terms of the new T to get the new floating image J'. In this section, we have chosen to describe the 2D implementation of the method [2].

2.1 Computation of correspondence by a block matching strategy

We consider two 2D images. These images, put in correspondence, are of the same size 256*256. We note (x,y) the positions on the grid of voxels of the images. For that we cut out the reference image into a set of under-images which we will call blocks.
These blocks will be noted B in the reference image I and B' in the targets image J. These blocks have identical size N*N [1]. Initially, they are 32*32, in second place 16*16, then 8*8 and finally 4*4 [2]-[3].
Then we seek the best correspondents in the image target of a set of blocks B of the reference image, for a criterion of similarity given. Each couple of blocks will be stored by the position of its center because of the required movement of the block (translationnel movement). Moreover we announce the point of the center is that for which the local relation between the blocks is statically just. It is this set of couples of points which will define a field of vectors between our two images.
The principle of the algorithm selected is to put in correspondence a reference image area with a target image area. We can carry out this research on all the image or of course on a zone around the position of reference the image area.
That is to say for a block B of I, we thus seek in a vicinity Ω which is defined by 2*rayon block B, J the best corresponding B'. At the time of the phase of pairing, we take into account that the step between two consecutive blocks in the given vicinity of the target image is Δ, which can of course be anisotropic along the axes. In the traditional strategy of pairing of areas, we brought ourselves to carry out a complete research in this vicinity. That is to say that we explore all the positions in whole coordinates in Ω. By making the assumption that, in given vicinity, the criterion of similarity which we optimize is convex, then we can carry out an almost complete research (Fig. 1) [3]-[4].
Indeed, by using this property of convexity, we can for example explore a position on two, and consider the found solution as the nearest position to the real solution (complete research).

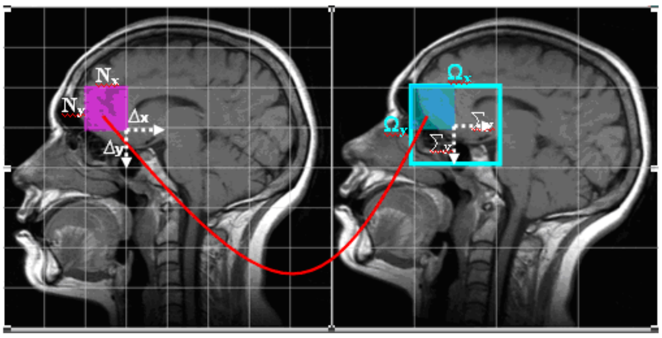

Fig. 1. Illustration of the pairing of areas on a cut IRM [4].

For a given direction, N is the size of the block Ω, is the size of the zone of research, $\sum$ is the resolution of the field of vectors, Δ is the density of the field of vectors. On this figure, the center of the block B is noted m_i and that of the B' block is noted $m_{i'}$.

2.2 Similarity measures

Block Matching involves comparison of corresponding images to be registered and identification of the similarity between two blocks. The accuracy of block matching process depends on the accuracy of the metric used to determine the similarity between two blocks. The more accurate this metric, the more accurate the block matching process. The cost of the block matching procedure is strongly dependent on the time required to evaluate the similarity measure between two blocks.
Various metrics or similarity measures have been applied. There isn’t a single similarity measure that’s assumed to produce the best result in all situations. Depending on the types of images provided, one similarity measure may work better than another in block matching [6].
In the following, we will evaluate existing similarity measures.

a. Sum of absolute differences (SAD)

Displayed Sum of absolute differences is the Minkowski metricnof order one and is defined by (1):

$$SAD = \sum_{m=1}^{M-1}\sum_{n=0}^{N-1}\left(I_1(m,n) - I_2(m,n)\right). \qquad (\mathbf{1})$$

Where $I_1$and I_2 are the intensity functions in each of the two images and M is the width of image in pixels, N is the height of the image in pixels, m and n represent the coordinates of a point of the image on the reference mark [9]. The closer this sum is to zore, the more similar the images are.

b. Sum of squared differences (SSD)

The Sum of squared differences seeks to munimize the sum of differences of the intensities of the pixels $I_1$and I_2 [9]. It’s calculated according to the following formula (2):

$$SSD = \sum_{m=1}^{M-1}\sum_{n=0}^{N-1}\left(I_1(m,n) - I_2(m,n)\right)^2 . \qquad (\mathbf{2})$$

Where $I_1$and I_2 are the intensity functions in each of the two images and M is the width of image in pixels, N is the height of the image in pixels, m and n represent the coordinates of a point of the image on the reference mark.

c. Mutual information (MI)

Mutual information is the quantity of information of an image contrained in another image [14]. The MI between two imahes I and J is given by (3):

$$I(I,J)=\sum_{I_1 I_2} P_{IJ}(I_1,I_2)\log(\frac{P_{IJ}(I_1,I_2)}{P_I(I_1)P_J(I_2)} . \quad (3)$$

Where $P_{IJ}(I_1,I_2)$ is the joint possibility distribution of intensity value pairs (I_1, I_2) in two images I and J; $P_I(I_1)$ and $P_J(I_2)$ are marginal possibility distributions. The mutual information of I and J measures the degree of dependence of I and J as the distance between the joint distribution $P_{IJ}(I_1,I_2)$ and the distribution associated to the case of complete independence $P_I(I_1)P_J(I_2)$. The assumption is that the maximal dependence is achieved between intensity values of the images when they are aligned [19].

d. Correlation coefficient (cc)

Correlation coefficient is defined by (4):

$$. \ CC(I,J)=\frac{\sum_{I_1}\sum_{I_2} I_1 I_2 P_{I_1 I_2} - \mu_{I_1}\mu_{I_2}}{\delta_{I_1}\delta_{I_2}} \quad (4)$$

According to this formula we will treat the cases of the value of correlation is defined. The nearest the value of the coefficient is to 1 the more similar the two images are that's they are very strongly correlated. That more different the two images are, the more the coefficient will have a value near to 0. That means that there isn't any correlation between the two images and that the variations of the first image don't influence on the variations of the second image. The negative values of this coefficient between 0 and -1 indicate an apposite similarty between the images [19].
Once the type of the transformation and the measurement of similarity are appropriate, the algorithms of optimization are responsible to vary the parameters which determine the transformation in order to maximize the measurement of similarity. The method used by these algorithms is often iterative and each iteration uses the corresponding estimate of the transformation to calculate the measurement of similarity. The algorithm continue optimization until the iterations do not improve

any more the values of measurement of similarity. Various measurements of similarity can bring the algorithms of optimization to the solution by the variation of the parameters.

3 Optimization

Image registration algorithms must follow a process of optimization to obtain the parameters of the transformation which will provide the best value of a measure of similarity. These algorithms must be fast and sufficiently robust in order not to remain blocked on the local minima of the measurement of similarity, which are not the optimal values. Some of these local minima can be made farther from the optimal solution and can be caused by the artefact of interpolation.
These local minima can be eliminated by smoothing the images before registration. In fact, we generally use a hierarchical procedure in which we register first of all the images with low resolution, then we uses the result as starting estimate for registration with more high-resolution.
However, that does not eliminate completely the local minima in space from the parameters. To mitigate this problem, we can start from several initial estimates of the parameters and choose the solution which corresponds to the smallest value of the measurement of similarity. This approach functions well with algorithms of superposition of surfaces but, for the algorithms using the measurements of similarity based on the intensity of the voxels, the desired minimum isn't always the total minimum. For example, in the case of a registration by joint entropy or mutual information, the solution which uses the optimal value of the measurement of similarity can only superpose the zones of the images representing of the air.
To prevent that the procedure of optimization remains blocked on a minimum, the solution is to start from an initial estimate of the parameters which is included in the fork of capture of this maximum. The fork of capture associated with a minimum is the whole of initial estimates of the parameters which make that solution of the algorithm is minimum.
In theory, the forks of capture are unknown, but we can suppose that if the initial estimate is sufficiently close to the solution, it will be included in the fork of capture. So it is advised in the majority of the cases to carry out a manual registration of images before proceeding to registration by automatic algorithm. A visual monitoring is often enough to determine if the algorithm arrived to an incorrect solution. In this fact, it is necessary to repeat the procedure on the basis of a more exact manual alignment.

4 Interpolation

When transforming points from one image to another, interpolation is usually required to estimate the gray value of the resulting point [11]. Much of registration algorithms transform by iteration a target image compared to an image of reference, by optimizing a measurement of similarity which depends on the intensity of the

voxels. Each iteration generates an estimate of the transformation T including an interpolation which makes it possible to evaluate the target image at the points corresponding to the sampling of the image of reference.
During the registration process interpolation, necessitates a tradeoff between accuracy and speed. In addition, interpolation is required to yield a final, registered image. Since this task is performed only once, speed is less of an issue and a different choice of interpolation method may be more appropriate.
The most popular technique of interpolation is linear interpolation, which defines the intensity of a point as the weighted combination of the intensities of its neighbors. The weights are linearly dependent on the distance between the point and its neighbors [11], as shown in the 2-D example in Fig. 2.

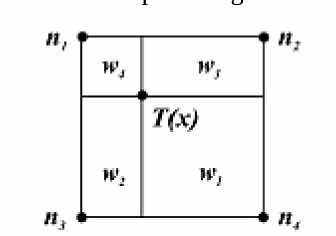

Fig. 2. Interpolation weights; the areas for 2-D linear interpolation.

In this work, we have applied the later type of interpolation. This is shown in Fig.3 where (a) represents the registered image before interpolation while (b) represents the later after interpolation.

Fig. 3. Registered image before and after interpolation.

However, the algorithms of interpolation are prone to errors and blacken the image. If the process is iterative, the interpolation errors accumulate and the target image darker at each time. A serious problem with interpolation is that it can cause patterns of artefacts in the registration function. When the grids of two images can be aligned for certain transformations, no interpolation is required for such transformations. Because interpolation influences the value of the registration measure, the absence of interpolation at grid-aligning transformations can cause a sudden change in the value of the measure, resulting in a pattern of local extrema. The occurrence of such patterns has been noted in several publications [11]. In [12], the different patterns created by linear and partial volume interpolation are extensively studied.

5 Experiments and results

In order to evaluate the performance of our algorithm as well as of similarity measures, we used at this stage the database vanderbilt and we limited our experiments only to IRM images 2D intra-subjects and particularly to the four first series. It is announced that the images are of gray level and of size 256x256 (16 bits/pixels).
N is the size of the block Ω and is the size of the zone of research, $\sum$ is the resolution of the field of vectors and Δ is the density of the field of vectors.

5.1 Choice of similarity measure

We have implemented various similarity measures SSD, SAD, MI and CC on four series of IRM images 2D monomodal intra-subjects according to the variation of these three parameters where N=32, $\sum$=8 and Δ=31 (table 1).

TABLE 1. Values of measures of similarity before and after registration using the LTS

Image\ Method	Reference image \ Floating image	Reference image \ Register image
SSD	7.6415	1.6366
SAD	1492777	639513
MI	4.1733	4.1731
CC	0.72	0.94

The choice of similarity measure constitutes the problem of intensity based registration MI, SAD, SSD and CC for monomodality registration have been widely used. In practice, SAD and MI are better adapted to multimodal registration than to monomodal [20].
Whereas the CC and SSD are well suited for monomodal registration registration. This view concides with that of Christopharos Nikou [5]. First the value of SAD after registration is superior to that before registration. Also the values of MI after registration are inferior to that before registration. This constitutes inconvenient to there basic principals and implies the dissimilarity of images.
Whereas the values of CC and SSD after registration bring more efficient and logical results. Another important result to bear in mind is that the CC is the best equivalent measure to monomodal registration. This coincides with the view of lemieux [16]. These comparative performances lead us to these said previously following observations.

5.2. Robustness

To achieve a perfect block matching procedure, and a grat degree of similarity betwwen two blocks we cut the blocks into different blocks while taking into account the parameters Δ which is the density of the field of vectors and Σ which is the resolution of the field of vectors. The duration of calcul is also token into our consideration as robustness constitutes an important criterion to achieve a perfect matching. This is well reflected in table 2.

TABLE 2. Variation of execution duration according to the size of the block

Size of block	Δ	Σ	CC	Duration of execution (ms)
32	31	8	0.94	1780
16	15	7	0.87	3125
8	7	*3*	0.96	10763
4	1	1	0.98	27592

Another observation is that the size of block is execution unproportionnal to the duration. In fact whenever the size of the block is high, the duration of execution is low. This is well illustrated in Fig4.

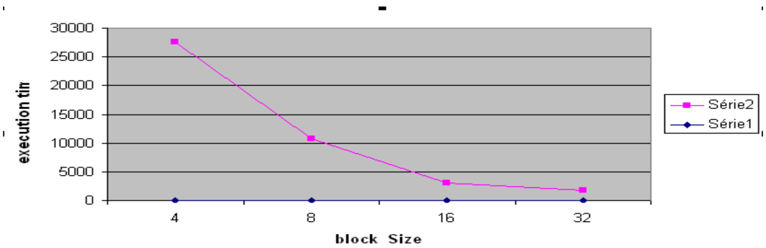

Fig. 4. Variation of execution duration according to the size of the block

Our obtained results are considered logical compared particularly with Christophoros Nikou [5] and generally with those of other groups adapted on the web of the project: http://cswww.vuse.vanderbilt.edu/"image/registration.

6. Conclusion

In this paper we have presented a general strategy for the regid registration of 2D monomodal medical images IRM/IRM which is based on a combination of block matching technique with a robust transformation estimator. The importance of the implementation of this method shouldn't be underestimated since implementation and decisions have a large influence on the registration results.

The main choices involve optimization and interpolation. The variations of the values of similarity before and after registration by using the least trimmed squarres estimator (LTS) are high lighted [9].
Also we have presented variation of the duration of execution according to the size of the block.
Our results suggest that the best measure of similarity and the degree of robustness of the registration are dependent on the size of the block.
Further analysis is needed in order to better demonstrate its interest in other monomodal registration issues.

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