3D Medical Image Registration using Mutual Information and Scatter Search

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Abstract

Image Registration (IR) is a challenge that arises in many image processing applications when several images must be aligned. In particular, we treat the Medical Image Registration (MIR) case of different modalities. The big range of applications in medical imaging, goes from computer assisted diagnosis to computer aided therapy and surgery[2]. MIR is treated as an optimization problem with the goal of finding the spatial mapping that will bring a moving image into alignment with a fixed image. Deterministic algorithms are mainly used to solve it, together with some stochastic ones. A drawback of the latter is that many of them become stuck in local optima, especially in multimodal registration with several parameters [3], [4]. In this context, one of the most popular metric approaches is the Mutual Information based methods using deterministic optimization algorithms to compute the cost function with the mentioned problems. This work is aimed to overcome this disadvantage using the Scatter Search optimization algorithm[5] with the mutual information approach, proposed by Mattes et. al. [8]. The optimizer was tested and contrasted with Regular Step Descent Optimizer[9] and the 1+1 evolutionary algorithm[12]. Multimodal, rigid, 3D/3D, image registration of tomographic brain images was performed over a database available in RIRE[2] project. It was used the Insight Segmentation and Registration Toolkit (ITK)[3], which is a set of libraries in C++ designed for the development of registration methods [10]. Qualitative and quantitative validation of the results are satisfactory, the results proves the accuracy and applicability of the proposal method comparing with conventional methods, and not being stuck in local optima.

Keywords: Image Registration, Mutual Information, Scatter Search.

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[2]http://www.insight-journal.org/rire/

[3]http://www.itk.org

1. Introduction

Image registration (IR) is the process to establish a correspondence between two or more images of the same scene from different or similar sensors. The result of the IR process allows a comparison or integration of a set of images to enhance the overall evaluation, and for consideration in a higher context. Basically, IR process considers two images, an image A is fixed and is called reference image, and another image B which is movable and is called test. The process then is to find a transformation T to be applied to the test image B so that it stay aligned to the image A, as much as possible.

Moreover, various types of medical diagnostic studies are common whose results are images [1]. Some of them are computed tomography (CT), magnetic resonance (MR) and positron emission tomography (PET). With respect to RI processes in medical imaging can mention the RIRE project [4], has a database of images online, to be used as inputs in IR processes. In addition, to validate the effectiveness of the methods of registration, by checking the results with ground truth values.

In this paper, we propose the use of an optimizer based on the metaheuristic *Scatter Search* [6, 7]. The results are contrasted with respect to other proposals in the state-of-art, *Gradient Descent* [11] and *One Plus One* [12, 13]. As similarity metric is applied the so-called *Mattes Mutual Information* [8].

The following sections of this article, are organized as follows. Section 2 briefly describes the IR process. In section 3, the Mutual Information metric used in the implementation of the proposed approach is described. In section 4, algorithms Gradient Descent (GD) and One Plus One, which are considered as reference are presented. In section 5, explains in detail the proposed Scatter Search algorithm. In sections 6 and 7 the results and conclusions are presented respectively.

2. Image Registration

The Image Registration (IR) [14] is the process of determining a transformation, the best possible, which maps points of a B image, mobile or test called, with their counterparts points in an image A it called fixed or reference. Through IR seeks to unify, merge or supplement information from different types of images in order to improve their overall evaluation or consider the result in a higher context.

[4] http://www.insight-journal.org/rire/

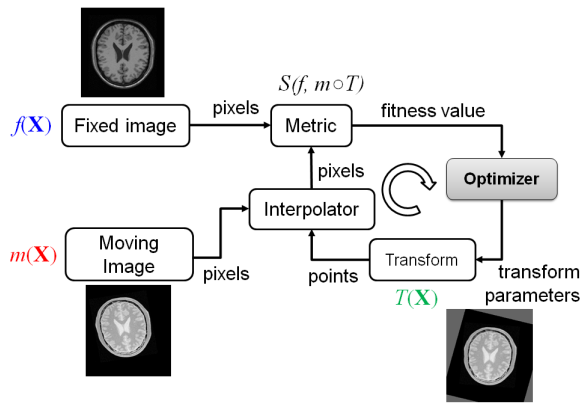


Figure 1: The basic components of the registration framework.

The IR can be treated as an optimization problem in which it has a cost function to be optimized. The cost function indicates the similarity between the image sets A and a version of the test image B to which has been applied a transformation T. This function then evaluates the transformation parameters applied to the image B.

A transformation model, applied to the image B could then be based on: Translation, altering the values for the axes x, y and z. Besides, rotation, using an inverter or rotation axis and a rotation angle [15].

Initially, the image B undergoing a process transformation $T(B)$ based on the model chosen. Then a Interpolator, maps the transformed $T(B)$, to the image space A, which allows to evaluate the similarity between the images through a particular metric model. According to the result, it can then be decided to submit the initial transformation parameters optimization process to improve the result. The idea discussed is illustrated in the Figure 1.

3. Mutual Information

In the context of information theory [18], Mutual Information (MI) [16, 17] is a measure of the amount of information that a random variable can offer about another random variable.

The MI can be applied as image similarity metric in IR implementations. Mainly because of its strength since the method is highly independent of the data and does not require pre-processing of the images as well as human intervention [16]. Currently some implementations of IR suggest as similarity

metric measure called *Mattes Mutual Information* [8, 19].

4. IR Optimizers

Optimizer is the component of the IR process that seeks to adjust the parameters of image transformation B in a way to maximize the similarity transformation $T(B)$ imagewise A. Currently there are different proposals [20, 21, 22, 23] of optimizers that can be classified both as deterministic, based on mathematical models, as well as stochastic, based metaheurticas.

4.1 Gradient Descent

Gradient Descent (GD) [11] is a deterministic optimization algorithm used to optimize convex functions [24]. Given the function $f(x)$ with $x \in R^n$, want to find the value of x that minimizes the same based on its gradient $\frac{\partial f(x)}{\partial x}$. The algorithm iteratively, takes the negative value of the gradient as step to minimize the function from an initial point x_0 to converge.

Several studies have demonstrated the applicability of GD as successful Optimizer in the IR process [20, 21, 22]. Also, you can see that this proposal is normally used as a preference implementations for optimization [22, 23] and is taken as a benchmark to measure the effectiveness of new proposals.

4.2 One Plus One Evolutionary

One Plus One Evolutionary (1+1) [12, 13] is an evolutionary strategy algorithm that generates random solutions around a current position in the search space. the position and search space is updated by a growth factor, a factor of decrease or reduction and isotropic probability function. 1+1 strategy can be applied as Optimize in IR processes [13].

5. Scatter Search

Scatter Search (SS) [6, 7] is a meta-heuristic technique based on the iterative evolution of a small set of elements called *ReferenceSet* . SS is based, unlike other evolutionary approaches, strategic and non-random selection of elements on a small set. Another important feature is generally also apply a local search approach. The best solutions found are stored in the reference set as the process progresses SS. It should also be noted that in SS, solutions not only remain within the reference set according to their quality, but also on the degree of diversity they bring.

5.1 Proposed algorithm

According to [25], for this work an optimization algorithm for IR based on SS presented in detail in the Algorithm 1 was applied.

Algorithm 1: Proposed scatter search

```
Data: pSize, bSize, b1Size, b2Size, maxIterations,
      maxAttemptsToImprove
diverseTrialSolutions ←
DiversificationGenerationMethod(pSize);
ImprovementMethod(diverseTrialSolutions,
maxAttemptsToImprove);
ReferenceSetConstruction(refSet, diverseTrialSolutions);
while maximum number of iterations unreached do
    subSets ← SubsetGenerationMethod(refSet);
    pool ← {};
    while subsets remain unevaluated do
        combinationsResults ←
        SolutionCombinationMethod(currentSubSet);
        ImprovementMethod(combinationsResults);
        while combinations remain unevaluated do
            if combination does not exist in the pool then
                add solution to the pool;
            end
        end
    end
    ReferenceSetUpdateMethod(refSet, pool);
end
return best resolution of the refSet
```

According to the notations proposed in the literature [25, 6], the proposed algorithm consists of the following methods:

- ***DiversificationGenerationMethod:*** can give rise to a set of random initial solutions (*diverseTrialSolutions*). So to preserve the diversity of this whole approach is implemented memory to not repeat initial solutions [26], and also a control to prevent similar solutions [25]. The latter control is carried out whenever necessary.

- ***ImprovementMethod:*** tries to improve each of the elements of the set of solutions that receives as a parameter. The improvement strategy is to iteratively combine a solution with another randomly chosen

from *diverseTrialSolutions*. If the resulting solution has better quality, then it replaces the current solution. The number of iterations is given by the initial parameter *maxAttemptsToImprove*.

- ***ReferenceSetConstruction:*** Initializes the reference set *RefSet* respect to the set *diverseTrialSolutions*. The *RefSet* consists of two subgroups of equal size (*b1Size* and *b2Size*). The first, called assembly quality, composed of the *b1Size* best solutions in a given instant. The second, called set of different solutions, containing the *b2Size* diverse solutions found so far.

- ***ReferenceSetUpdateMethod:*** Whereby, each solution is evaluated in the set *pool* generated after each iteration of the algorithm. If a solution of *pool* has better quality and greater diversity regarding any solution *RefSet*, the first replaces the second within the corresponding subgroup.

6. Experimental results

For this work, experiments were performed in processes of IR 3D/3D rigid, multi-modal and intrapatient [1, 14]. The images used in them come from the platform of the RIRE Project [27] and refer to actual tests computed tomography (CT) and magnetic resonance (MR) of 15 patients with brain disorders. Furthermore, in each case have three types of MR: *Magnetic Resonance Proton Density Weighted* (MR_PD), *Magnetic Resonance T1 relaxation time* (MR_T1) and *Magnetic Resonance T2 relaxation time* (MR_T2) and, for each patient were three independent IR processes: {CT - MR_PD}, {CT - MR_T1 } and {CT - MR_T2 }.

For validation of the results the evaluation module RIRE Project [27] was used. The metrics in this module are based on the difference in millimeters points called *Volumes of Interest (VOI)*. When the specific distances are smaller, the result can be considered superior. The locations of the VOI are not revealed so as to preserve the integrity of the assessment [27].

Insight Segmentation and Registration Toolkit (ITK) framework was used [29] and coding was done in C ++ language. For experiments, the SS algorithm proposed and adaptations necessary to GD based algorithms [28] and 1+1 [28] were implemented. In each of the 15 test cases, each implementation was executed a total of 30 times, given the random nature of the algorithms SS and 1+1.

In the proposed SS algorithm, the transformation parameters were limited as follows: (1) the range of translation to a maximum of 80 mm on

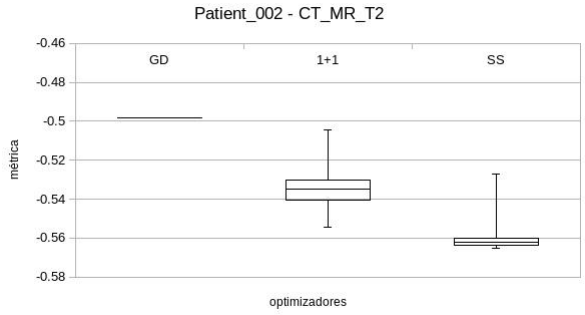


Figure 2: Boxes Plot - Patient_002 - CT _MR_T2.

each axis, (2) the angle of rotation up to 0.3 radians. In addition to the population size of different solutions *pSize* a value of 15 for the size of the reference set *RefSet* a value of 8 and the maximum number of attempts to improve an individual was selected *maxAttemptsToImprove* value was set at 5. These values were selected following exercises for adjusting them.

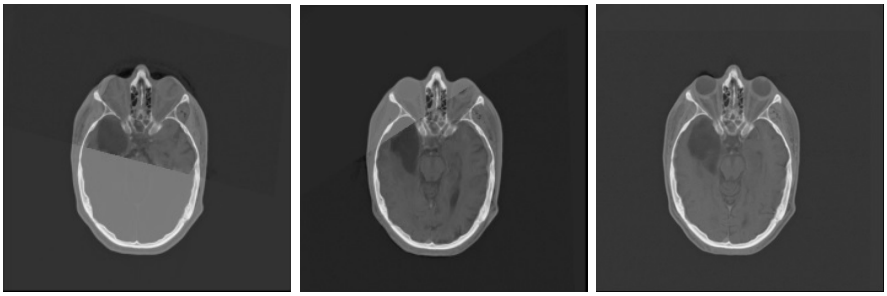
Regarding the results, it can be seen that the proposed algorithm SS was able to obtain better results than optimizers reference in several of the cases considered. As shown, then results for the *002* patient presented in the modality {CT - MR_T2}.

Table 1: Results RIRE in the modality CT - MR_T2

Optimizer	Mean Error	Max Error	Median Error
GD	7.178	65.456	2.448
1+1	3.618	13.596	3.139
SS	2.689	10.929	2.387

Thus, for the patient indicated in box plot Figure 2 illustrating the results of each algorithm are presented. They can be seen in a better average and maximum performance by the proposed algorithm based on SS.

Moreover, in figure 3 can see the differences between the images after having applied each of the algorithms considered. Thus, the same can notice the improved performance of the proposed algorithm SS respect others, especially regarding the algorithm based on GD. In this particular example, it is noted that the approaches used by GD optimizers and 1 + 1, have failed



(a) GD. (b) 1+1. (c) SS.

Figure 3: Diference after IR - Paciente 002 CT - MR_T2 de la Figura 2.

and using SS, was achieved the image registration.

7. Conclusions and Future Work

The results demonstrate the feasibility of the proposed algorithm SS as optimizer applicable to the problem of IR. It has been noted that in several cases evaluated based on the proposal presented better results SS. Moreover, in most cases where the SS based algorithm was passed, it has not been shown that this has been for significant margin.

Moreover, in table 1 as in all cases it has been observed that the proposed algorithm based on SS presented at lower average maximum error over other approaches considered, it can be considered the same as a robust alternative.

Finally, as future research could assess the feasibility of other metaheuristics, such as Particle Swarm Optimization (PSO). You might also consider experiments with other types of images, such as PET-SCAN. In addition, it may be significant to verify the feasibility of the proposed implementation process for Deformable IR.

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