Evaluation of Various Evolutionary Methods for Medical Image Registration

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***Abstract*—In the last few decades, image registration (IR) has been established as a very active research area in computer vision. Over the years, it has been applied to a broad range of real-world problems ranging from remote sensing to medical imaging, artificial vision, and computer-aided design. IR has been usually tackled by iterative approaches considering numerical optimization methods which are likely to get stuck in local optima. Recently, a large number of IR methods based on the use of metaheuristics and evolutionary computation paradigms has been proposed providing outstanding results. In this contribution, we aim to develop a preliminary experimental study on some of the most recognized feature-based IR methods considering evolutionary algorithms. To do so, the IR framework is first presented and a brief description of some prominent evolutionary-based IR proposals are reviewed. Finally, a selection of some of the most representative methods are benchmarked facing challenging 3D medical image registration problem instances.**

I. Introduction

Image registration [1]–[3] is an important research field in digital image processing [4]. It is used to align two or more images acquired under different conditions: at different times, using different sensors, from different viewpoints, or a combination of some of the latter situations. In IR, the input and output images are available, but the specific transformation that produced the output image from the input one is usually unknown. IR aims to estimate the best geometric transformation leading to the best possible overlapping transforming those independent images into a common one.

Medical IR is a mature research field with theoretical support and two decades of practical experience [5]. A wide variety of applications have been proposed [6] and there are excellent review works that provide an up-to-date progress in the application of classical optimization techniques to the medical IR field [5], [7]–[9]. Recently, IR approaches based on *evolutionary computation (EC)* [10] and other *metaheuristics (MHs)* [11] have demonstrated to be a promising solution for facing some of the most challenging drawbacks of the latters, specifically for escaping from local optima solutions [12]–[17].

The aim of the current contribution is two-fold. On the one hand, we aim to provide a brief review of those, in our modest opinion, most relevant evolutionary-based IR methods in the state of the art. On the other hand, we aim to develop an experimental study on the performance of some of the previous contributions in order to achieve a better comprehension of this family of methods. To do so, we have considered a feature-based IR approach [3] in which a preprocessing step, previous to the application of IR, is performed in order to extract a concise subset of salient features of the medical 3D images. In particular, the considered image dataset comes from the well-known BrainWeb repository at McGill University [18]. We will deal with complex scenarios by facing non-rigid IR problem instances considering similarity transformations, which are constituted by a rotation, a translation, and a uniform scaling. Thus, the conducted experiments will provide us with actual information about the degree of suitability of evolutionary-based IR methods to solve IR problems in medical imaging environments.

The structure of this contribution is as follows. Section II describes the IR problem analyzing the principal components of a generic IR method. Next, Section III introduces the EC paradigm. Section IV develops a review of the state of the art in IR methods based on EC and their most relevant pros and cons. Section V presents a broad experimental study facing a realistic medical application of IR datasets in which several of the reviewed methods have been tested. Finally, some conclusions are drawn in Section VI.

II. Image Registration

There is not a universal design for a hypothetical IR method that could be applicable to all registration tasks, since various considerations on the particular application must be taken into account. Nevertheless, IR methods usually require the four following components (see Figure 1): two input **Images** named scene $I_s = \{\vec{p}_1, \vec{p}_2, \ldots, \vec{p}_n\}$ and model $I_m = \{\vec{p}_1{}', \vec{p}_2{}', \ldots, \vec{p}_m{}'\}$, with $\vec{p}_i$ and $\vec{p}_j{}'$ being image points; a **Registration transformation** f, being a parametric function relating the two images; a **Similarity metric** F, in order to measure a qualitative value of closeness or degree of fitting between the transformed scene image, noted $f'(I_s)$, and the model image; and an **Optimizer** which looks for the optimal transformation f inside the defined solution search space.

In order to avoid many of the drawbacks related to classical voxel-based IR methods, the feature-based IR approach is based on the extraction of prominent geometric primitives/features from the images [3]. The proper comparison of feature sets will be possible using a reliable feature detector that accomplishes the accurate extraction of invariant features.

978-1-61284-336-0/11/$26.00

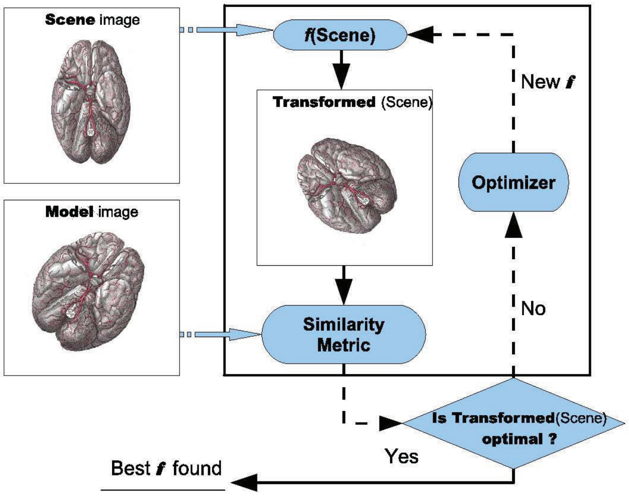

Fig. 1. The IR optimization process

Those are features which are not affected by changes in the geometry of the images, radiometric conditions, and appearance of noise. There are many different kinds of features that can be considered, e.g., *region features*, *line features*, and *point features*. Hence we have decided to follow the feature-based approach in the later experimental study developed in this contribution.

The registration transformation considered will depend on the application addressed and the nature of the images involved. The first category of transformations includes *affine* transformations, which preserve the operations of vector addition and scalar multiplication, being a combination of translation, rotation, scaling, and shear components. Among the most common IR transformations we found rigid, similarity, affine, projective, and curved [2]. Linear transformations are global in nature, thus not being able to model local deformations. The second category of transformation includes *"elastic"* or *"non-rigid"* transformations which allow local warping of image features, thus allowing local deformations [8]. In particular, we use similarity transformations in the experiments of this contribution.

One of the most important components of any IR method is the similarity metric [19]. It is considered as a function F that measures the goodness of IR problem solution given by a registration transformation f. The final performance of any IR method will depend on the accurate estimation of F. Each solution is evaluated by F as follows. First, f is usually applied to the scene image ($f(I_s)$). Next, the fitting degree between the transformed scene and the model images is determined.

As said, the key idea of the IR process is focused on determining the unknown parametric *transformation* that relates two images. According to the search strategy component, we can distinguish two different IR approaches in the literature to determine that parametric transformation:

- *Matching*-based approach: it performs a search in the space of feature correspondences (typically, correspondences of image points). Once the matching of scene and model features is accomplished, the registration transformation is derived (see the top picture in Figure 2).
- *Transformation parameters*-based approach: a direct search in the space of the f parameters is done (see the bottom picture in Figure 2).

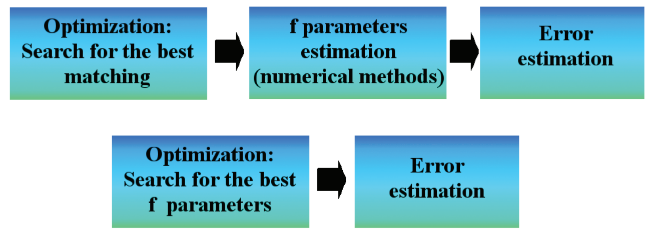

Fig. 2. From top to bottom, the matching-based and transformation parameters-based IR approaches

In both approaches, IR arises as a *non-linear optimization problem* that cannot be solved by a direct method (e.g. resolution of a simple system of linear equations) because of the uncertainty underlying the estimation of f. On the contrary, it must be tackled by means of an iterative procedure searching for the *optimal estimation* of *f*, following one of the said approaches. Classical numerical optimizers can be used. However they usually get trapped in a local minima solution.

III. Evolutionary Computation

Metaheuristics (MHs) [11] are among the most prominent and successful approximate or *heuristic* techniques to solve a large amount of complex and computationally hard combinatorial and numerical optimization problems arising in human activities, such as economics (e.g., portfolio selection), industry (e.g., scheduling or logistics), or engineering (e.g., routing), among many others. MHs can be seen as general algorithmic frameworks that require relatively few modifications to be adapted to tackle a specific problem. They are a diverse family of optimization algorithms including methods as simulated annealing (SA), tabu search (TS), multi-start methods, iterated local search (ILS), variable neighborhood search (VNS), greedy randomized adaptive search procedures (GRASP), and ant colony optimization (ACO).

Similarly to MHs, evolutionary computation (EC) [10] makes use of computational models of evolutionary processes for evolving populations of solutions as key elements in the design and implementation of computer-based problem solving systems. EC approaches constitute a very interesting choice since they are able to achieve good quality outcomes when, for instance, global solutions of hard problems cannot be found with a reasonable amount of computational effort.

There is a variety of EC models that have been proposed and studied, which are referred as evolutionary algorithms (EAs) [10], [20]. Among them we refer to four well-defined EAs which have served as the basis for much of the activity in the field: genetic algorithms (GAs), evolution strategies (ES), genetic programming (GP), and evolutionary programming (EP). In particular, GAs are probably the most used EAs in the literature to face real-world optimization problems. Some other EAs have been proposed in the last few years improving the state of the art in this field by adopting more suitable optimization strategies: the CHC algorithm[1] and differential evolution (DE).

In the last decade, it has been increased the interest on the application of EC principles to the IR optimization problem due to their more suitable and improved global optimization behavior. Thus, next section is devoted to introduce a short revision of some of those, in our modest opinion, most relevant EC-based IR methods proposed to date.

IV. Evolutionary Image Registration

A. Previous Work

In the last few years, approximate optimization approaches based on both MH and EC are being extensively used by the IR community. As stated, they are based on the extension of basic heuristics by considering their inclusion in an iterative process of improvement. One of the main advantage of these optimization alternatives is their capability to escape from local optima. That is one of the most relevant pitfalls of traditional IR methods.

As said, EC [10] is one of the most addressed approaches within metaheuristics. EC involves those strategies using computational models inspired on evolutive procedures of nature as key elements in designing and developing of problem solving systems based on computers. In particular, the first attempts facing the IR problem using EC can be found in the eighties. Fitzpatrick et al. [23] proposed such approach using genetic algorithms (GAs) [24], [25] to register 2D angiographic images in 1984. Since then, evolutionary IR has become a very active area and several well-known EAs have been considered to tackle the IR optimization process, causing an outstanding interest [13]–[15], [17], [26], [27].

1) He and Narayana's GA-based Proposal: This IR method [14] is a slight improvement of the previously reviewed Yamany et al.'s approach [13]. It considers a real coding scheme that makes use of arithmetic crossover and uniform mutation operators within an elitist generational model including a restart mechanism. This evolutionary IR method deals with rigid transformations following a two-step technique. First, a coarse parameter estimation is faced using a real-coded GA. Then, the obtained preliminary solution is refined by means of a local search procedure based on the dividing rectangle method. In the coarse resolution, the ranges of the parameters were set to: ± 20 voxels along x and y directions, and ± 40 voxels along z direction for the translation, and rotations of $\pm 10°$ around x and y axes, and $\pm 20°$ around z axis. However, the setting of the parameters range and the use of a simple rigid transformation may be a weak point when applying this method to some real-world environments.

[1]The CHC acronym stands for Cross generational elitist selection, Heterogeneous recombination, Cataclysmic mutation [21], [22].

2) Chow et al.'s GA-based Proposal: The authors proposed in [26] the same generational and proportionate-fitness models for population reproduction than the method by He and Narayana [14]. However, Chow et al. introduced the use of a crossover operator that randomly selects the number of genes to be swapped. The value to be accumulated for a mutated gene is generated randomly within a constant range for the rotation genes and dynamically computed for the translation ones according to the fitness value of the chromosome. They also make use of a GA with more suitable components to the current EC framework such as a real coding scheme and a sophisticated restart mechanism (named "dynamic boundary"). In spite of these improvements, there are some drawbacks in terms of accuracy, due to the fact that the authors work with a smaller, randomly selected data set from scene images with a huge amount of data. Besides, although the algorithm aims to get a quick registration estimation with the latter procedure, the efficiency could be reduced since it needs to perform a sort operation for each evaluation of the fitness function. As many of the mentioned proposals, it also has the limitation of only considering a rigid transformation (translation and rotation). The restart scheme assumes that, prior to its application, the population will fall in a search space region that is near to the global optimum, which could be not always the case.

3) Cordón et al.'s CHC-based Proposal: This contribution used the sophisticated CHC EA [21], [22] that shows a very good intensification/diversification trade-off for the IR of MRIs [27]. Authors introduced two different variants of the method. First, they used binary-coded solutions and the HUX crossover [28], based on the original CHC structure. The second variant of the CHC-based IR method extends the latter structure to work in a real-coded fashion by considering a real to binary coding translation mechanism as well as using different specific real-coded genetic operators as the blend crossover operator (BLX-α) [29]. Authors considered similarity transformations, thus eight-dimensional real coded solutions are considered to encode the transformation (four parameters for rotation, three for translation, and one for uniform scaling). They proposed the following objective function in order to tackle these particular scenarios:

$$F'(f', I_s, I_m) = \omega_1 \cdot \left(\frac{1}{1 + \sum_{i=1}^{N} \parallel (sR\vec{p}_i + \vec{t}\ ) - \vec{p}_j\,' \parallel^2} \right) + \omega_2 \cdot \left(\frac{1}{1 + |\rho_c^s - \rho^m|} \right) \quad (1)$$

where I_s and I_m are the scene and model images; f is the transformation encoded in the evaluated solution; $\vec{p}_i$ is the i^{th} 3D point from the scene and $\vec{p}_j\,'$ is its corresponding closest point in the model obtained with the GCP data structure [13]; ω_1 and ω_2 ($\omega_1 + \omega_2 = 1$) weight the importance of each function term; ρ_c^s is the radius of the sphere wrapping up the scene image transformed with the current f; and ρ^m is the radius of the sphere wrapping up the model image. As the first term of F reveals, the modeled error corresponds to the MSE. Note that F maximizes up to 1.0 for a rarely perfect fit.

4) De Falco et al.'s DE-based Proposal: Authors proposed a new IR method based on the DE EA [30]. DE is a parallel direct search method that has proved to be a promising candidate to solve real-valued optimization problems [31], [32]. DE combines simple arithmetic operators with the classical crossover, mutation, and selection genetic operators within an easy to implement scheme. It shows the advantage of considering few control parameters, named mutation factor (F) and recombination rate (CR). The fundamental idea of DE is a new scheme for generating trial solutions by adding the weighted differenced vector between two population members to a third one. The proposed method is applied to two 2D IR problems: mosaicking and changes in time of satellite images. Registration is carried out from the transformation parameters-based approach searching for the most suitable affine transformation (given by eleven real-coded parameters) in terms of maximization of the MI similarity metric.

B. Pros & Cons

There are different advantages and drawbacks that have been stated either to justify or to avoid the use of these methods when tackling complex optimization problems like IR. Some advantages follow:

- In contrast to classical gradient-based methods, those based on EC do not depend on the starting solution[2], thus being more robust approaches. Moreover, they provide specific strategies to escape from local optima. In particular, they can cope with multimodal functions to tackle IR [33].
- They are conceptually simple and easy to implement.
- They can handle arbitrary kinds of constraints and objectives easily. The latter can be considered weighted components of the fitness function. Thus, it is easier the adaptation of the optimization scheduler to the particular requirements of a wide range of possible objectives. They can also be integrated in a multi-objective scheme for solving the IR problem [16].
- Unlike other numerical IR techniques (e.g. gradient-based) that are only applicable for continuous functions or other constrained sets, their performance is independent of the solution representation.

The most important shortcomings related to the use of EC are:

- The EC-based IR methods need an initial tuning of control parameters following a manual expert-based procedure. In the last few years, advanced strategies are arising in order to provide new optimization algorithms with an adaptive behavior of control parameters [34].
- The estimation of the appropriate stop criterion is not easy and it is closely related to the fair comparison of the different methods under study. Moreover, it is problem dependent. Either the CPU time or the number of function evaluations are typical criteria. The former should be preferred tackling methods with heterogenous designs.

[2]Despite stochastic approaches, the success of EC methods does not fully rely on providing a near-optimal starting solution.

V. Experimental Study

In this section we aim to develop a comparative study of the performance of some of the state-of-the-art evolutionary-based IR contributions previously presented in Section IV facing a medical application. Moreover, we aim to extend the analysis of performance focusing our attention not only on the best individual results but also on the robustness of the methods.

A. Experimental Design

We considered the following evolutionary-based IR methods introduced in Section IV:

- He-GA [14] (EV1)
- Chow-GA [26] (EV2)
- Cordón-CHC [27] (EV3)
- DeFalco-DE [30] (EV4)

All of these methods are based on the transformation parameters IR approach, which has been the most adopted one in the last years due to the successfull results. Moreover, we included an improved variant [35] of the well-known iterative closest point (ICP) algorithm [36] in order to compare with a classical non-evolutionary IR method. All these IR methods have been implemented in C++ and compiled with GNU/g++. We used a computer with an Intel Pentium IV 2.6 MHz processor and 2GB RAM.

We considered the parameter values originally proposed by the authors in every contribution. Nevertheless, we have adapted the majority of the methods by using the same objective function (i.e. Eq.(1)) and coding scheme for representation of solutions in order to carry out a fair comparison. In particular, the solutions are based in a real-valued vector coding the similarity transformation as: a rotation $R = (\theta,\ Axis_x, Axis_y, Axis_z)$, a translation $\vec{t} = (t_x, t_y, t_z)$, and an uniform scaling s, with θ and $\vec{Axis}$ being the angle and axis of rotation, respectively.

A feature-based IR approach [1], [3], [37] has been considered for our medical application. It aims to reduce the huge amount of data of the original images in order to speed up and guide the optimization procedure. Feature extraction is considered as a preprocessing step, previous to the application of the IR method. It is based on the selection of a small subset of truly representative characteristics of the images to be registered. We used a 3D crest lines algorithm [38], [39] to obtain feature points from medical images. These preprocessed images are the ones that will be used by every IR method to estimate the registration transformation. Once the IR method has finished, the raw images are considered to measure the quality of the final results.

As stated, we designed several IR problem instances using similarity transformations, thus coping with the specific characteristics of the application domain of medical applications. For each problem instance tackled by the five IR methods, thirty different runs are performed. Each run considers a different (randomly generated) similarity transformation. In order to perform a fair comparison among the methods included in this study, we considered CPU time as the stop criterion. After a preliminary study, we noticed that twenty seconds was a suitable stopping criterion to let all the algorithms converge properly.

The way a particular run is performed is as follows: a random (similarity) transformation is applied to the ground-truth image and then the IR method estimates the unknown inverse transformation. Thus, ground-truth registration is available for the addressed medical application. In particular, similarity transformations are randomly generated following a uniform probability distribution as follows: each of the three rotation axis parameters will be in the range $[-1, 1]$; the rotation angle will range in $[0°, 360°]$; the three translation parameters in $[-40mm, 40mm]$; and the uniform scaling ranges in $[0.5, 2.0]$. The mean square error (MSE) function is used for IR evaluation, thus the quality of the final IR result is evaluated using the image estimated by the IR method and its counterpart ground-truth (both images in their original/raw versions, i.e. previous the application of the feature extraction) as follows:

$$MSE = \frac{\sum_{i=1}^{r} ||f(\vec{x}_i) - \vec{x}_i{}'||^2}{r} \quad (2)$$

where $f(\vec{x}_i)$ refers to the scene image's i^{th} point transformed by the estimated similarity transformation f, r is the scene image size, and $\vec{x}_i{}'$ is the latter $\vec{x}_i$ scene point considering in its ground-truth coordinates. It is clear that this procedure cannot be used in those situations where ground-truth is not available. It is only a mean to accomplish an accurate evaluation of the performance of the IR methods considered.

B. Medical Image Dataset

We use a dataset from the BrainWeb public repository[3] of the McConnell Brain Imaging Centre [18]. The BrainWeb repository is a Simulated Brain Database (SBD) providing synthetic MRI data computationaly generated. Such MRIs have been extensively used by the neuroimaging community to evaluate the performance of different methods [40]–[43]. In particular, Wachowiak et al. [43] generated a T1 MRI volume of a normal brain with the BrainWeb system in order to register single 2D-slices with respect to the whole 3D volume. The SBD provides MRI data based on two anatomical models: normal and multiple sclerosis (MS). Full 3D data volumes have been simulated for both models using three sequences (T1-, T2-, or proton-density- (PD) weighted) and a variety of slice thickness, noise levels, and levels of intensity non-uniformity (RF).

We extracted the isosurface and select crest-lines points with relevant curvature information from the original images using a 3D crest-line edge detector [38], [39]. The resulting datasets comprise around five hundred points (see Figure 3). Table I details the nature of each of the three MRIs considered for testing the IR algorithms.

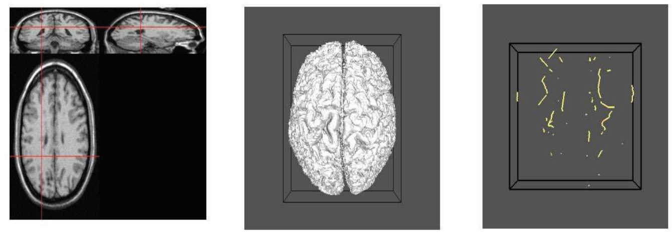

Fig. 3. From left to right: the original medical image, the corresponding extracted isosurface, and the crest-lines extracted from the isosurface of one of the three BrainWeb's MRIs.

TABLE I
DETAILED DESCRIPTION OF THE BRAINWEB DATASET

	Lesion	Noise	Crest-line points
BW(1)	-	-	583
BW(2)	MS	1%	348
BW(3)	MS	5%	284

C. Results

Our results correspond to a number of medical IR problem instances for the 3D medical images presented in Table I. The three IR scenarios we consider are: BW(1)-BW(2), BW(1)-BW(3), and BW(2)-BW(3), each one considering a randomly generated similarity transformation in every of the thirty runs performed. Thus ninety different IR problem instances are addressed by every IR method.

Since we are performing thirty runs per IR problem and method, we can analyze the distribution of the registration error during the said runs. Table II shows statistical results computed from the MSE (Eq. 2) of the five IR methods included in our study. Every entry of the table refers to the minimum, mean, and standard deviation (in brackets) MSE values in the thirty runs. The best minimum and mean MSE values in each IR problem are highlighted using bold font. The code included in the first column of the table will be used to refer to every method from now on. The unit length of the data in this table is squared millimeters.

Figure 4 is a boxplot[4] derived from the MSE values of the thirty different runs. Every boxplot includes 5 boxes corresponding to each IR method considered. In each box, the minimum and maximum MSE values are the lowest and highest lines, the upper and lower ends of the box are the upper and lower quartiles, and a thick line within the box shows the median. In data with no dispersion, all the quartiles are grouped together and the box turns into a single line. Outliers are represented by circles.

[3]Available at http://www2.bic.mni.mcgill.ca

[4]The bottom and top part of the box correspond to the $25th$ and the $75th$ percentiles, respectively. The horizontal line inside the box is the $50th$ percentile, i.e. the median value.

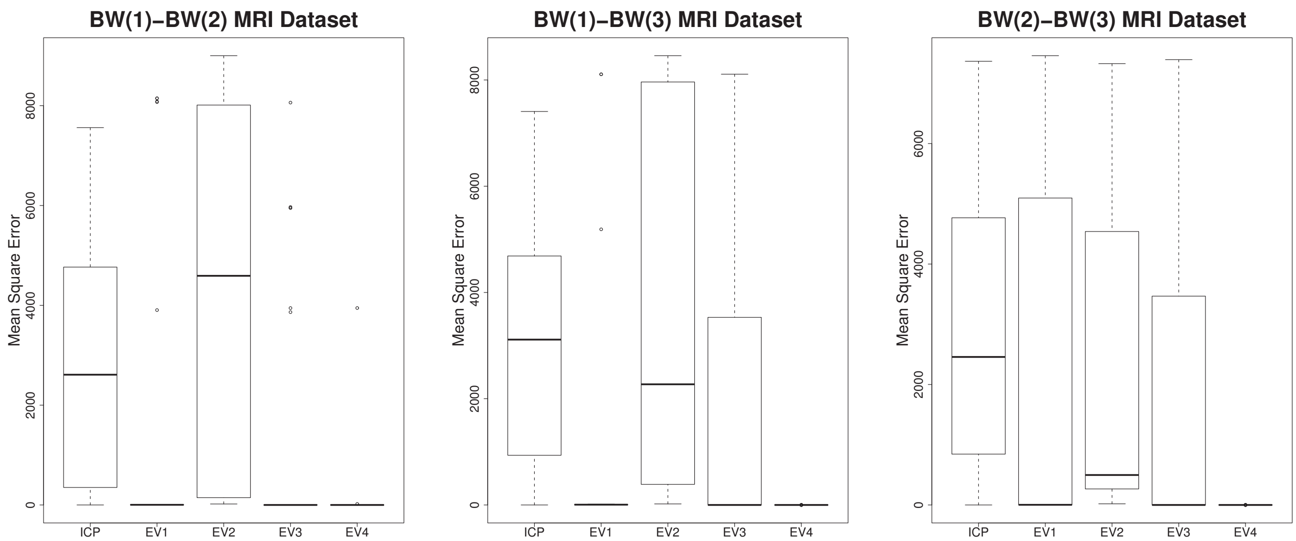

Fig. 4. Boxplots highlighting the MSE distribution during the thirty runs of all the IR methods in every medical IR problem

TABLE II
MEDICAL IR RESULTS. EACH ENTRY CORRESPONDS TO THE MINIMUM (TOP), MEAN (BOTTOM), AND STANDARD DEVIATION (IN BRACKETS) MSE VALUES OBTAINED FROM THE THIRTY DIFFERENT RUNS. THE BEST MINIMUM AND MEAN MSE VALUES ARE IN BOLD.

Code	**BW(1)-BW(2)**	**BW(1)-BW(3)**	**BW(2)-BW(3)**
	0.279	0.046	0.042
ICP	2788 (±2364)	3009 (±2279)	2929 (±2094)
Evolutionary-based IR methods			
	0.466	1	0.342
EV1	1214 (±2794)	718 (±2182)	2014 (±3158)
	19	19	18
EV2	4261 (±3417)	3604 (±3351)	2398 (±2667)
	0.001	0.007	**0.008**
EV3	1124 (±2338)	1910 (±3283)	1865 (±2998)
	0.001	**0.006**	0.024
EV4	**132** (±708)	**0.013** (±0.002)	**0.026** (±0.001)

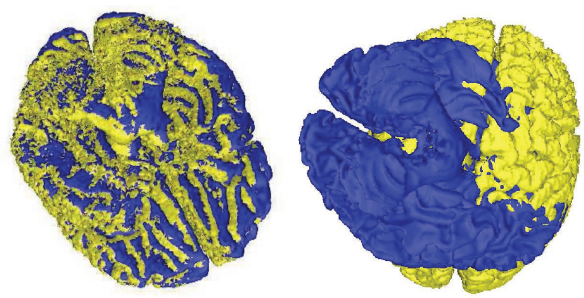

Fig. 5. From left two right: two indepent runs of EV4 and EV2 showing high and low quality IR results, respectively.

D. Discussion

From the obtained results in Table II, we can see how the evolutionary-based IR methods achieve the best performance compared to the classical ICP-based method. Specifically, both EV3 and EV4 obtains the best acurate results (according to minimum value of MSE), and EV4 the most robust proposal (according to mean value of MSE). The low performance of EV2 is due to the "dynamic boundary" scheme proposed by the authors which is more suited for tackling IR scenarios with a width search space of solutions. Figure 4 shows how robust are each of the compared algorithms and Figure 5 depicts the most relevant visual results.

VI. CONCLUSION

Unlike traditional methods, IR methods based on EC have demonstrated their good behavior handling this ill-conditioned problem in the last few years. The main difficulty to be tackled is to find a reliable/robust manner to escape from locally optimal registration solutions. In this work we have introduced a preliminary experimental revision of some of, in our modest opinion, the most relevant IR methods of the state-of-the-art following the said optimization approaches.

In order to establish a better comprehension of this family of methods, experiments considering IR case studies tackling a realistic medical application have been carried out. In particular, we adopted a feature-based IR approach and we considered a similarity transformation in order to better face the specific characteristics of the medical application. From the results obtained we remark the high performance and accurate results offered by several of the reviewed IR methods against those achieved by a recent version of the classical ICP algorithm. We aim to corroborate the similarity of evolutionary approaches for tackling the medical IR problem with a broader experimental study including both new case studies and other methods based on evolutionary and other metaheuristics.

ACKNOWLEDGMENT

This work is supported by the Spanish Ministerio de Educación y Ciencia (Ref. TIN2009-07727) including EDRF

fundings.

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