A study of the suitability of evolutionary computation in 3D modeling of forensic remains

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Abstract. Image registration is a fundamental task in image processing. Over the last decades, it has been applied to a broad range of situations from remote sensing to medical imaging, artificial vision, and CAD systems. Different techniques have been independently studied resulting in a large body of research. In the last few years, there is an increasing interest on the application of the evolutionary computation paradigm to this task in order to solve the ever recurrent drawbacks of traditional image registration methods. In this work, we will perform an experimental study on the performance of the most relevant evolutionary image registration methods proposed to date. This study will be carried out facing a challenging problem named 3D model reconstruction. In particular, we will consider image acquisition technology based on laser range scanners. Specifically, we will make use of image datasets of human skulls provided by the Physical Anthropology Lab of the University of Granada, Spain.

Keywords: Image registration, evolutionary computation, 3D modeling, forensics

1 Introduction

Image registration (IR) [20], is a crucial task in image processing systems. It is used to finding either a spatial *transformation* (e.g, rotation, translation, etc.) or a correspondence (matching of similar image entities) among two (or more) images taken under different conditions (at different times, using different sensors, from different viewpoints, or a combination of them), with the aim of overlaying such images into a common one. Over the years, IR has been applied to a broad

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range of situations from remote sensing to medical imaging, artificial vision, and CAD systems. Different techniques have been independently studied resulting in a large body of research. In particular, the range image registration (RIR) problem is focused on the registration of images, named range images, acquired by laser range scanners [7].

IR is the process of finding the optimal spatial transformation (e.g, rigid, similarity, affine, etc.) achieving the best overlay between two (or more) different images. They both are related with the latter transformation, measured by a *Similarity metric* function. Such transformation estimation is interpreted into an iterative optimization procedure in order to properly explore the search space. Two search approaches have been considered in the IR literature: *matching-based*, where the optimization problem is intended to look for a set of correspondences of pairs of those more similar image entities in both the scene and the model images, from which the registration transformation is derived; and the *parameter-based*, where the strategy is to try to directly explore inside each range of the transformation parameters.

Aspects such as the presence of noise in images, image discretizations, orders of magnitude in the scale of the IR transformation parameters, the magnitude of the transformation to be estimated, etc., cause difficulties for traditional IR algorithms as the well-known *iterative closest point* (ICP) [2] algorithm, thus they become prone to get trapped in local minima.

In the last few years, the adoption of the *evolutionary computation (EC) [1]* paradignm has introduced an outstanding interest in the IR community in order to solve those problems due to their global optimization techniques nature. In particular, evolutionary algorithms (EAs) have been successfuly applied for tackling the IR optimization process. The first attempts to solve IR using EC can be found in the early eighties [9]. Since then, several EC-based IR methods have been proposed to solve the IR problem.

In this work we introduce a practical study on the applicability of the EC paradignm for solving the IR problem. To do so, we consider some of the most relevant IR proposals making use of EC. Likewise, we will carry out an experimental study of the performance of these methods facing a real-world application of the IR problem named 3D object reconstruction using laser range scanners. In particular, we considered reconstructions of human skulls by using 3D images provided by the Physical Anthropology lab at the University of Granada (Spain).

The structure of this paper is as follows. First, Section 2 describes the IR problem and its specific application in the 3D model reconstruction of forensic objects using RIR methods. Next, Section 3 is devoted to introduce some of the most relevant IR methods using EC. Section 4 performs an experimental study by considering the previous introduced EC-based IR methods facing the real-world application of 3D model reconstruction of human skulls. Finally, Section 5 shows some conclusions of this work.

2 Preliminaries

2.1 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 [20]. However, IR methods usually require the following four components (see Figure 1): two input **Images** named as Scene $I_s = \{\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_n\}$ and Model $I_m = \{\boldsymbol{p}_1{}', \boldsymbol{p}_2{}', \ldots, \boldsymbol{p}_m{}'\}$, with $\boldsymbol{p}_i$ and $\boldsymbol{p}_j{}'$ being image points; a **Registration transformation** f, being a parametric function relating the two images; a **Similarity metric function** 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** that looks for the optimal transformation f inside the defined solution search space.

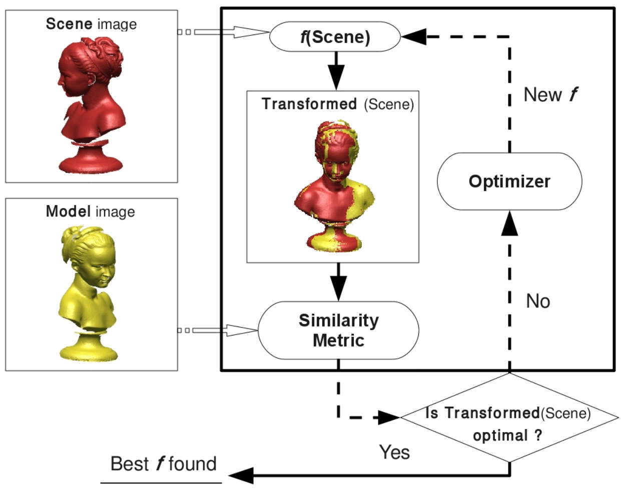

Fig. 1. The IR optimization process.

Likewise, an iterative process is often followed until convergence, for instance, within a tolerance threshold of the concerned similarity metric. This is the case of the well-known ICP IR method [2], that has been extensively cited in the literature. However, the original ICP proposal has one main drawback: it is strongly dependent on the initial estimation (transformation), then it usually gets trapped in local optima. As we will demonstrate later, the application of EAs to the IR optimization process has caused an outstanding interest in the last few decades. Thanks to their global optimization nature, EAs aim to solve the drawbacks, not satisfactorily tackled by traditional IR methods as the ICP algorithm.

2.2 3D model reconstruction based on range image registration

Range scanner devices are able to capture 3D images, named range images, from different viewpoints of the sensed object. Every range image partially recovers the complete geometry of the scanned object, then placing each of them in a different coordinate system. Thus, it is mandatory to consider a reconstruction technique to perform the accurate integration of the images in order to achieve a complete and reliable model of the physical object. This framework is usually called 3D model reconstruction and it is based on applying RIR techniques [17]. There are two RIR approaches to integrate multiple range images. The *accumulative* approach accomplishes succesive applications of a pair-wise RIR method[1]. Once an accumulative RIR process is accomplished the *multiview* approach takes into account all the range images at the same time to perform a final global RIR step. Figure 2 depictes the steps of the 3D model reconstruction procedure when 3D models of human skulls are acquired.

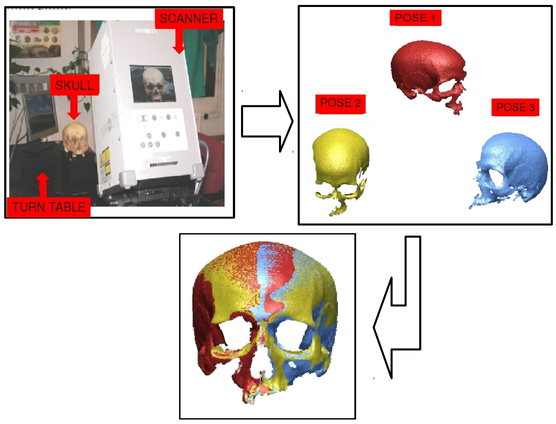

Fig. 2. 3D model reconstruction procedure.

As depicted in Figure 2, the 3D model reconstruction procedure carries out several pair-wise alignments of two adjacent range images in order to obtain the final 3D model of the physical object. Therefore, every pair-wise RIR method tries to find the Euclidean motion that brings the *scene* view (I_s) into the best possible alignment with the *model* view (I_m). We have considered an Euclidean motion based on a 3D rigid transformation (f) determined by seven real-coded parameters, that is: a rotation $R = (\theta,\ Axis_x, Axis_y, Axis_z)$ and a translation $\boldsymbol{t} = (t_x, t_y, t_z)$, with θ and $\boldsymbol{Axis}$ being the angle and axis of rotation, respectively. Then, the transformed points of the *Scene* view are denoted by

[1] The use of the term *pair-wise* is commonly accepted to refer to the registration of pairs of adjacent range images.

$$f(\boldsymbol{p}_i) = R(\boldsymbol{p}_i - \boldsymbol{C}_{I_s}) + \boldsymbol{C}_{I_s} + \boldsymbol{t}, \quad i = 1 \cdots N_{I_s} \tag{1}$$

where $\boldsymbol{C}_{I_s}$ is the center of mass of I_s. We define the distance from a transformed I_s point $f(\boldsymbol{p}_i)$ to the *Model* view I_m as the squared Euclidean distance to the closest point $\boldsymbol{q}_{cl}$ of I_m, $d_i^2 = \|f(\boldsymbol{p}_i) - \boldsymbol{q}_{cl}\|^2$.

Hence, the RIR task can be formulated as an optimization problem developed to search for the Euclidean transformation f^* achieving the best overlapping of both images according to the considered *Similarity metric* F:

$$f^* = \arg\min_{f} \; F(I_s, I_m; f) \;\; s.t.: \;\; f^*(I_s) \cong I_m \tag{2}$$

Particularly, we used the median square error (MedSE) for tackling the RIR problem:

$$F(I_s, I_m; f) = MedSE(d_i^2), \quad \forall i \in \{1, \ldots, N_{I_s}\} \tag{3}$$

where $MedSE()$ corresponds to the computation of the median d_i^2 value of the $N_{I_s}^{th}$ scene points. We have used the grid closest point (GCP) scheme ([19]) to speed up the computation of the closest point q_{cl} of I_m.

Finally, we have considered the feature-based RIR approach [20] in the subsequent experimental section. We used a 3D image processing algorithm in order to extract the most relevant features of the range images. These synthetized 3D images are used by the RIR method under study. we have followed the feature extraction procedure used in [17] to extract *crest lines* as salient features.

3 Evolutionary image registration

In the last few years, a new family of approximate algorithms is being extensively used by the IR community. They are named metaheuristics [10] and 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 scape from local optima. That is one of the most relevant pitfalls of traditional IR methods (see Section 2.1).

As said, EC [1] 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. [9] proposed such approach using genetic algorithms (GAs) [11, 13] 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 [17, 19, 12, 3, 6, 5].

We have found the following evolutionary IR methods contributed in the last few years. Yamany *et al.* [19] used a GA based on the original binary representation of solutions proposed by Holland [11, 13] facing the IR of 3D dental images;

He and Narayana [12] tackled the IR of magnetic resonance images (MRIs) applying the explorative capabilities of the latter method by using more apropriated genetic operators together with a real-coded representation of solutions; Chow *et al.* [3] contributed with a new design of GA also using real-coded solutions and with the main novelty based on the inclusion of a restart mechanism named *dynamic boundary* in order to speed up the convergence of the algorithm tackling a RIR problem; Wachowiak et al. [18] contributed with a broad study on the performance of particle swarm optimization (PSO) [4, 14] algorithms for solving the IR problem in biomedical applications, specifically registering single slices (2D images) of 3D volumes to whole 3D volumes of medical images; Cordón *et al's.* [6] proposal adapts the original binary scheme of the CHC [8] EA to a real-coded one and making use of characteristic information extracted from 3D MRIs; recently, Santamaría *et al.* [5] contributed with an enhanced extension of their previous proposal based on the scatter search (SS) [15] applied to RIR problems [17].

4 Computational experiments

4.1 Experimental design

The Physical Anthropology Lab of the University of Granada provided us three adjacent range images, I_1, I_2, and I_3, of a human skull. The size (number of points) of every image is 76794, 68751, and 91590, respectively. Next, in order to follow the said feature-based RIR approach, we extracted crest lines features from each of these images, thus obtaining a reduced version of their original ones with 1181, 986, and 1322 number of points, respectively. Figure 3 shows the input 3D range images together with the result of applying the 3D crest line detector to every image

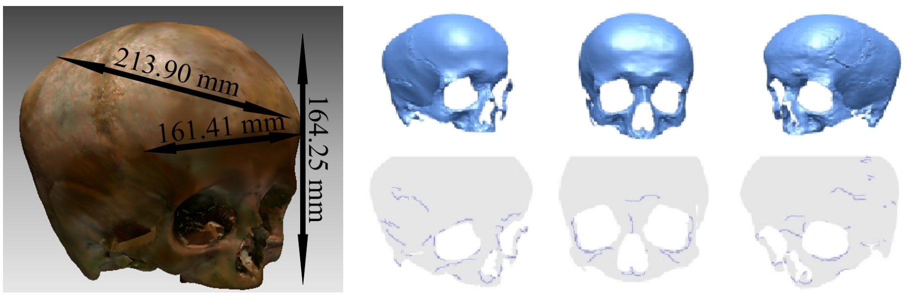

Fig. 3. From left to right: reconstructed 3D model and the three selected I_1, I_2, and I_3 range images acquired by a laser range scanner. Below the latter three is shown the resultant images after the application of the crest line detector.

Finally, we configured two different RIR scenarios in order to accomplish the reconstruction of the 3D model: RIR(I_1,I_2) and RIR(I_3,I_2). Notice that the scene images I_1 and I_3 are aligned to the same model image, I_2, that is condiered as the anchor image.

4.2 Parameter settings

All the methods presented in Section 3 have been run thirty different times. A different random rigid transformation is considered in every of the thirty runs. Thus, (2×30)=60 different RIR problem instances have been configured. We used a 2.6 GHz Intel Pentium IV CPU with 2GB RAM. We maintained the original parameter values of every IR method. On the other hand, we also used a recent enhanced version of the ICP algorithm [16] as a traditional (non metaheuristic-based) IR algorithm (see Section 2.1) for comparison purposes.

4.3 Analysis of results

We used a turn table device (see Figure 2) with the aim to validate the reconstruction results estimated by the considered RIR methods. A ground-truth 3D model of the physical object is obtained using the latter mechanism. We considered the mean square error (MSE) metric in order to measure the quality of the RIR results:

$$MSE = \sum_{i=1}^{r} ||f(\boldsymbol{x}_i) - \boldsymbol{x}_i{}'||^2/r \tag{4}$$

where $f(\boldsymbol{x}_i)$ refers to the i^{th} transformed point of image scene using the estimated rigid transformation f, r is the image size of the latter one (before the application of the crest line detector), and $\boldsymbol{x}_i{}'$ corresponds to the same i^{th} scene point in the ground-truth location.

Table 1 presents the statistical results of the considered RIR scenarios. We notice that how the traditional ICP-based Liu-ICP algorithm is absolutely unsuitable to address the challenging RIR scenarios considered. Moreover, all the evolutionary RIR methods outperform the results achieved by Liu-ICP according to both the best (minimum) and the mean MSE values. On the other hand, we highlight the low averaged performance (according to mean MSE value) of the binary-coded GA (Yamany-GA) against the remaining of evolutionary proposals that make use of more advanced evolutionary designs as a real-coded representation of solutions. Among them, Santamaria-SS becomes the evolutionary RIR method achieving the most accurate and robust outcomes due to its more suitable explorative strategies facing the RIR problem.

Some of the estimated 3D model reconstruction results are presented in Figure 4. On the other hand, the best outcome of Liu-ICP corresponds to a local optimum. On the other hand, Santamaria-SS is able to provide the refinement algorithm[2] (Liu-ICP) with an initial solution that converges to a near optimal RIR solution. Figure 5 shows these results in more detail.

[2] Due to the evolutionary RIR approach usually obtains coarser results, a final refinement stage using ICP-based RIR algorithms is applied in order to obtain accurate outcomes.

Table 1. Statistics (from thirty different runs of every RIR method) of the considered RIR scenarios. In bold font are marked the best results according to minimum and mean values of MSE.

	RIR(I_1,I_2)			RIR(I_3,I_2)		
	Min.	*Mean*	*Std. dev.*	*Min.*	*Mean*	*Std. dev.*
Liu-ICP	159	9538	10185	2391	11334	8747
Yamany-GA	13	1884	4044	153	2691	4182
He-GA	**9**	93	73	75	872	1220
Chow-GA	43	1009	1013	117	2710	2130
Wachowiak-PSO	20	596	645	9	1608	4128
Cordón-CHC	18	248	780	131	1411	1495
Santamaría-SS	11	**74**	41	**66**	**389**	366

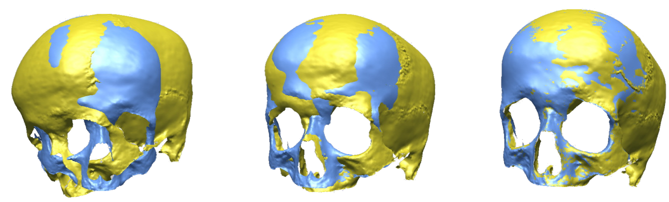

Fig. 4. RIR(I_3,I_2) scenario. From left to right: the first figure reffers to the best estimation of Liu-ICP and the next two show the results provided by Santamaria-SS and its refined outcome by using Liu-ICP, respectively.

5 Concluding remarks

In the last few decades, the adoption of EC approches have become a promising solution due to their bahevior as global optimization techniques. They own a capability to perform robust search in complex and ill-defined problems as IR.

In the last few years, EC has been adopted in IR community to face some of the most challenging drawbacks of traditional methods. Evolutionary IR methods have demonstrated their good behavior facing the latter pitfalls. The main difficulty to be tackled is to find a reliable/robust manner to escape from locally optimal registration solutions. Several works reviewing the state of the art on IR/RIR methods have been contributed in the last years ([20]), but none of them addresses those IR contributions adopting an EA as optimization component. With the aim of bridging this gap, in this work we have introduced a preliminar study on, in our modest opinion, the most relevant state of the art evolutionary IR methods to date.

From the results obtained, we highlight the high performance and accurate results offered by the evolutionary RIR methods against those achieved by the traditional ones, when facing the 3D model reconstruction of human skulls. Nevertheless, the results presented in this contribution correspond to a preliminar study. Thus, we plan to extend this initial work considering a larger number of case studies together with including other state of the art evolutionary RIR methods.

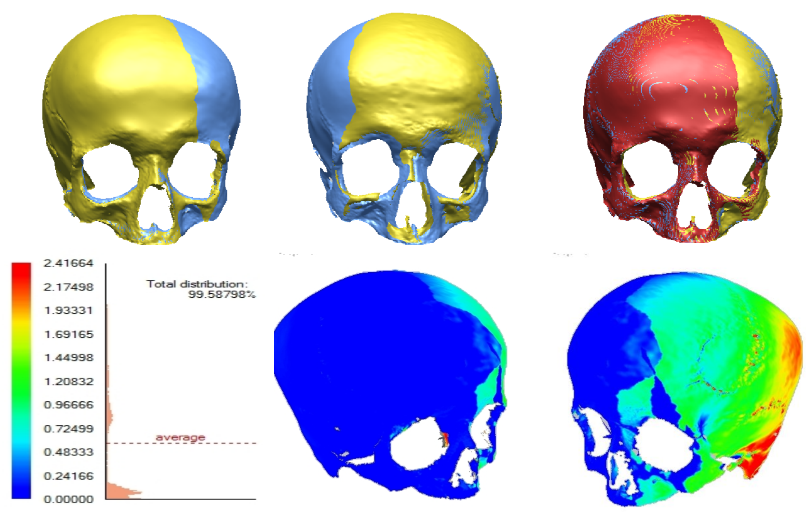

Fig. 5. From left to right: the top row shows the best two (pair-wise) prealignment IR results obtained by Wachowiak-*PSO* and the reconstruction result (combining the previous two prealignments) of the forensic dataset after refinement. The bottom row depicts the distance deviation histogram comparing the latter reconstruction result and the ground-truth 3D model (see Figure 3).

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