Soft Comput (2007) 11:819–828
DOI 10.1007/s00500-006-0132-0

ORIGINAL PAPER

A scatter search-based technique for pair-wise 3D range image registration in forensic anthropology

J. Santamaría · O. Cordón · S. Damas · I. Aleman · M. Botella

Published online: 5 September 2006

Abstract Different tasks in forensic anthropology require the use of three-dimensional models of forensic objects (skulls, bones, corpses, etc) captured by 3D range scanners. Since a whole object cannot be completely scanned with a single image, multiple scans from different views are needed to supply the information to construct the 3D model. Range image registration methods study the accurate integration of the different views acquired by range scanners, with pair-wise approaches progressively processing every adjacent pair of scanned views until reconstructing the whole 3D model of the object. Our proposal is based on the adaptation of our previous work (Cordon et al, IEEE Conference on Evolutionary Computation, pp 2738–2744, 2005 in Pattern Recognit Lett 27(11); 1191–1200, 2006) in order to apply the scatter search evolutionary algorithm to pair-wise image registration in forensic anthropology applications. To measure the performance of this adaptation, we design an experimental setup considering some of the most recent and accurate evolutionary techniques for the problem, as well as one skull from our Physical Anthropology Lab. Two additional volumes, commonly used in other pair-wise range IR contributions, have also been considered to complement the comparison of results among the proposals.

This work was supported by the Ministerio de Ciencia y Tecnología of Spain under project TIC2003-00877 (including FEDER fundings).

J. Santamaría (✉)
Department of Software Engineering, University of Cádiz, 11002 Cádiz, Spain

O. Cordón · S. Damas
European Centre for Soft Computing, 33600 Mieres, Spain
e-mail: oscar.cordon@softcomputing.es

O. Cordón
Department of Computer Science and A.I., University of Granada, 18071 Granada, Spain

S. Damas
Department of Software Engineering, University of Granada, 18071 Granada, Spain

I. Aleman · M. Botella
Physical Anthropology Lab, University of Granada, 18071 Granada, Spain

1 Introduction

Forensic anthropology is best conceptualized more broadly as a field of forensic assessment of human skeletonized remains and their environments (Iscan 1981a,b). This assessment includes both the identification of the victims' physical characteristics and cause and manner of death from the skeleton (Krogman and Iscan 1986). This way, the most important application of forensic anthropology is the identification of human beings from their skeletal remains.

The most relevant information to be obtained for the identification task is the "virtual model" of the physical object itself, so that it is an accurate model of the real object we are trying to represent. Since a whole object cannot be completely scanned with a single image, multiple scans from different views are required to supply the information needed to construct the 3D model (Fig. 1). Therefore, the more accurate the alignment of the views the better the reconstruction of the object.

When dealing with forensic anthropology objects, anthropologists do not usually know how to calibrate the scanner or put into correspondence the different views

Fig. 1 Arrangement of objects on a Konica-Minolta© rotary stage by the team of the Physical Anthropology Lab

of the acquired object. An automatic model-building method would be really helpful for them.

Image registration (IR) is the task that aims at finding the optimal point/surface correspondence/overlapping between two (or more) images, captured in a local coordinate system by a specific acquisition procedure, i.e. from different points of views (multiple views), at different times, and by different sensors. Thus, the key idea of the IR process is focused on achieving the transformation (rotation, translation, etc.), noted as *f*, that places different images in a common coordinate system bringing the points as close together as possible by minimizing the error of a given metric of resemblance.

In *Pair-wise* range IR, the process starts by firstly registering two different views of the object, goes on with the next pair, and so on until reconstructing the whole 3D model of the object. The most important issue is to minimize the number of views to reduce error accumulation in the 3D model and because data acquisition is expensive (Ikeuchi and Sato 2001). Therefore, it is fundamental to adopt a proper and robust technique to align the views in a common coordinate frame, to avoid model distortion in a subsequent surface reconstruction stage (Silva et al. 2005), assuring a minimum overlaying between adjacent views.

In this work, we try to adapt the **scatter search** (SS) (Laguna and Martí 2003) evolutionary algorithm (EA) to solve the 3D pair-wise IR problem related to the 3D volume reconstruction in forensic anthropology applications. Unlike classical genetic algorithms (GAs) (Michalewicz 1996), SS components are designed considering a deterministic non-randomized scenario, encouraging a tradeoff between search intensification and diversification. Hence, our intention is not only to adapt SS to a specific scenario but also to provide a more robust and more accurate technique than those in the IR literature (Chow et al. 2004, Lomonosov et al. 2006). A practical application of a complex 3D model reconstruction of a skull from our Physical Anthropology Lab will reveal its success. We will also consider two other objects commonly used in the area in order to complement the comparison of results among the different proposals, although the complexity introduced by the skull is significantly much higher than the rest of objects as we will describe in Sect. 4.1.

The paper structure is as follows. In Sect. 2 we give some pair-wise IR basics. Section 3 describes our SS proposal and its adaptation to tackle pair-wise IR for 3D model reconstruction in forensic applications, which is tested in Section 4 over different objects, confronted with some of the most accurate and recent evolutionary proposals in the pair-wise IR literature (Chow et al. 2004, Lomonosov et al. 2006). Finally, in Sect. 5 we present some conclusions and new open lines for future works.

2 3D modeling by pair-wise IR methods

This section is devoted to expose different concepts on 3D modeling using pair-wise IR methods. Once we have introduced 3D modeling basics in Sect. 2.1, we will describe the pair-wise range IR modality in Sect. 2.2.

2.1 3D modeling basics

Recently, the computer vision community has a growing interest in techniques to build 3D models of real-world objects and scenes without requiring humans to manually produce these models using laborious and error-prone CAD-based approaches, having a deep interest in many practical applications, such as visual inspection, reverse engineering, forensic identification, etc.

In range IR, several difficulties arise due to: (1) the object shape acquisition regarding the illuminance conditions (recovering noisy shapes); (2) the presence of occlusion (region of the scanned object shape only present in one of the two consecutive scanned images); (3) the fact that the object to be scanned has either a globally symmetric shape or the symmetry appears along the shape of two consecutive views; and (4) the absence of an *a priori* known transformation or, at least, an approximated motion between consecutive scanned images (mainly when the scanner's rotary stage is not present or cannot be used). In many cases when these drawbacks arise, the reconstruction procedure is forced to be performed by a manual and time consuming range IR process without ensuring the best possible outcomes.

Due to the latter, several approaches for the automatic registration of the scanned views have been proposed in the last few years. In *pair-wise* range IR, the object modeling process starts by firstly registering two adjacent views, goes on with the next pair, and so on, building a partially reconstructed shape each time. Its main drawback is that it iteratively accumulates a residual error along the registration process, however it does not need all scans to be done to operate [as *multi-view* range IR approaches (Blais and Levine 1995). Thus, there is an increasing interest on new proposals improving pair-wise methods in the last few years.

2.2 Pair-wise IR

After acquiring a set of range images (scans), a *pre-alignment* transformation or coarse alignment (a good approximation of the real one) is generally known. Such information is achieved either from some type of positional sensors (i.e. a rotary stage) or, if it is not possible, via an IR algorithm as a global search method. Then, as a fine-tuning step, a final refinement is applied, by means of a local search process, typically by using the commonly known *Iterative Closest Point* (ICP) algorithm (Besl and McKay 1992). Many variants of this method proposing a better performance (Fusiello et al. 2002) have been presented (Liu 2004, Masuda and Yokoya 1995, Okatani and Deguchi 2002, Zhang 1994).

Unfortunately, every of these fine-tuning registration methods still assume the starting from an initial near-optimal transformation and concentrate on improving it. However, as said, this is not always the case. There have been many proposals that can provide a good starting point without requiring an initial guess, known as pre-alignment IR algorithms and based on global search-based methods. To do so, two different approaches to the IR problem can be adopted (Cordón et al. 2005b, Cordón and Damas 2006, Cordón et al. 2006a). On the one hand, the *search in the matching space* approach guides the process seeking the best correspondences of common features previously extracted from the images to be registered. On the other hand, when the search is guided by the registration transformation parameters (i.e. *search in the transformation parameters space*), the best tuning of the parameters defining the transformation relating the images is wanted.

Among the matching space pre-alignment proposals, Chen et al. (1998) proposed the *RANSAC* method based on finding the best three point correspondences between two range images in order to obtain an estimation of the transformation parameters (three points are the minimum required pairs in order to compute the rigid motion between both views). This point-matching search is iterated for several three points in the scene view in order to obtain different trial transformations, until a stop criterion is reached and the best overall solution is returned. The outcomes of the method are of good quality and, theoretically, the precision of the results increase with the resolution of the image. A quite different approach has been proposed in Jonhson and Hebert (1999) that makes use of *spin images*, 2D images characterizing a point using the information of the surface near to it. That is, for a given point, a normal vector is computed approximating the points of the local surface with a plane. Then, two distances are computed in order to determine the spin image and they are used to construct a table where each cell contains the number of points that belong to this region. When point correspondences from spin images are found, false matchings are removed using the mean and the variance of the errors. The IR problem is solved by using the best correspondences found.

Another matching-based approach to solve the IR problem was proposed by us in Cordón and Damas (2006), considering the use of the iterated local search metaheuristic (Lourenço et al. 2003). To do so, IR is first re-defined as a combinatorial optimization problem, then the use of image-specific information to guide the search in the form of an heuristic function is considered, and finally an iterated local search procedure for the feature matching problem is introduced.

The main problem of the previous IR methods is the high computational cost to find correspondences, when significant image data must be handled, and particularly when features are extracted to be matched. To solve this limitation, other pre-alignment IR algorithms focused on the *transformation search space* approach have been proposed. Specifically, the application of several emerging EAs to the IR optimization process has caused an outstanding interest in order to solve the latter problems thanks to their global optimization techniques nature (Chow et al. 2004, Cordón et al. 2006b, Garai and Chaudhuri 2002, Han et al. 2001, He and Narayana 2002, Lomonosov et al. 2006, Yamany et al. 1999).

In this work, we focus our attention to the evolutionary proposals devoted to pair-wise IR. Lomonosov et al. (2006) the authors proposed an integer-coded GA where each registration transformation parameter has to be mapped by normalization onto a real-valued range for evaluating the fitness function. Simple one-point crossover and both shift and replacement mutation operators were considered. The tournament-based selection together with an elitist scheme was used. In order to improve the efficiency of the algorithm, the proposal makes a pre-processing step (before registration) by randomly resampling both input images, maintaining 100 and 1,000 image points, respectively. Meanwhile, the use of GAs with more suitable components to the current EC framework is considered in Chow et al. (2004), such as a real coding scheme and a sophisticated restart mechanism ("dynamic boundary"). In spite of these improvements, there are some drawbacks in terms of accuracy, since the authors work with a smaller, randomly selected data set from images with a huge amount of data. Besides, although the algorithm aims at getting a quick registration estimation with the latter procedure, the efficiency could be reduced since it needs to perform a sort operation for each fitness function evaluation.

Hence, in this paper we will study the robustness of the mentioned EC-based pre-alignment IR contributions, as well as our SS-based IR proposal adapted to range images, by evaluating the quality of their outcomes as proper initial estimations for the subsequent refinement step. Their performance for the final 3D modeling procedure will be evaluated in a complex forensic anthropology scenario, as well as in two objects classically used in pair-wise IR contributions such as (Lomonosov et al. 2006, Silva et al. 2005).

3 Scatter search for 3D pair-wise range IR

The aim of our proposal is finding a near-optimal geometric transformation, competitive enough considering both robustness and accuracy criteria, when comparing to state-of-the-art methods. To do so, we will use an efficient EA named SS (Laguna and Martí 2003) to first achieve a coarse pair-wise IR estimation. In particular, if the scanning device calibration is not known, this coarse pre-alignment is mandatory. Then, we will carry out a refinement step by using a local search I-ICP (Liu 2004) algorithm.

In this section, we start by introducing the pair-wise IR framework where our SS-based proposal is located (Sect. 3.1). Fundamentals of SS are described in Sect. 3.2. The SS coding scheme and objective function are introduced in Sect. 3.3. Finally, the composition of the five methods related to any SS design is detailed in Sect. 3.4.

3.1 SS-based pair-wise IR

The pair-wise IR framework requires the four following components: two adjacent **Views** of the 3D object, $V_1 = \{\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_N\}$ and $V_2 = \{\mathbf{p}_1', \mathbf{p}_2', \ldots, \mathbf{p}_M'\}$, with $\mathbf{p}_i, \mathbf{p}_j{}'$ being the points from every view; a **Registration Transformation** f, which is a parametric function relating both views; a **Similarity metric function** F, in order to measure a qualitative value of *closeness* between the views; and an **Optimizer** which looks for the optimal transformation within the definition interval of each f parameter.

Likewise, IR is the process of finding the optimal spatial transformation achieving the best fitting (measured using F) between the points in every view, $F(f(\mathbf{p}_i), \mathbf{p}_j{}')$, where $(f(\mathbf{p}_i), \mathbf{p}_j{}')$ is a point matching. Such a transformation estimation is interpreted into an iterative optimization process in order to properly explore the search space (Fig. 2).

Note that, as we mentioned in Sect. 2.2, this is just a pre-alignment process inside the whole pair-wise IR framework. In order to perform a fine-tuning of the SS results, we will apply a final step involving a local search using I-ICP (Liu 2004) to achieve the final f estimation (Fig. 3).

We can sort the different kinds of transformations f according to the maintenance (or not) of an established relation among the points before and after applying it, i.e., if f is a *rigid transformation*, as the ones considered in this paper, every edge is preserved after it is applied. Hence, a rigid transformation can be split in two ones: translation and rotation. Other examples of f transformations are the similarity, affine, projective, and elastic ones (Brown 1992).

3.2 Basis of scatter search

Scalter search fundamentals were originally proposed by Fred Glover in Glover (1977) and have been later developed in some texts like (Laguna and Martí 2003). The main idea of this technique is based on a *systematic* combination between solutions (instead of a randomized one like that usually done in GAs) taken from a considerably reduced evolved pool of solutions named **Reference set** (between five and ten times lower than usual GA population sizes). This way, an efficient and accurate search process is encouraged thanks to the

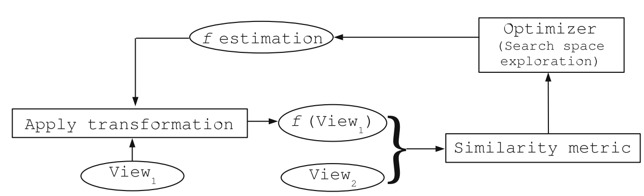

Fig. 2 Image registration framework

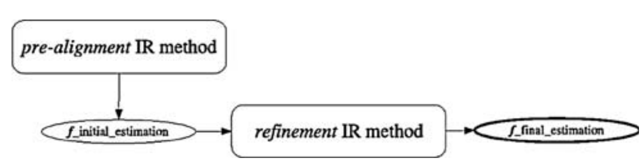

Fig. 3 Pair-wise image registration framework

latter and to other innovative components that we will describe later. The general SS approach is graphically shown in Fig. 4.

3.3 Coding scheme and objective function

As coding scheme, the 3D rigid transformation f is determined fixing seven real-coded parameters which will be the ones we will look for. That is: a rotation $R = (\theta, \ \text{Axis}_x, \ \text{Axis}_y, \ \text{Axis}_z)$ and a translation $\mathbf{t} = (t_x, t_y, t_z)$, where θ and **Axis** define the 3D rotation given by an angle and an axis, respectively. Moreover, for a more suitable rotation representation, we consider quaternions instead of the three classical Euler matrices representation that suffers from the problem of *gimbal lock* (Shoemake 1985).

In this contribution, we consider the usual Similarity metric found in the IR literature (Chow et al. 2004, Lomonosov et al. 2006), i.e., the objective function (noted as F) corresponds to a minimization problem, as shown as follows:

$$F(f, I_{v_1}, I_{v_2}) = \frac{\sum_{i=1}^{N} \parallel (R\mathbf{p}_i + \mathbf{t}) - \mathbf{p}'_j \parallel^2}{N} \tag{1}$$

where I_{v_1} and I_{v_2} are two adjacent views of the 3D object; f is the transformation encoded in the evaluated solution; $\mathbf{p}_i$ is the i^{th} 3D point from I_{v_1} and $\mathbf{p}_j{}'$ is its corresponding closest point in I_{v_2}, and N is the number of points in view I_{v_1}.

3.4 SS-based pair-wise IR implementation

The fact that the mechanisms within SS are not restricted to a single uniform design allows the exploration of strategic possibilities that may prove effective in a particular

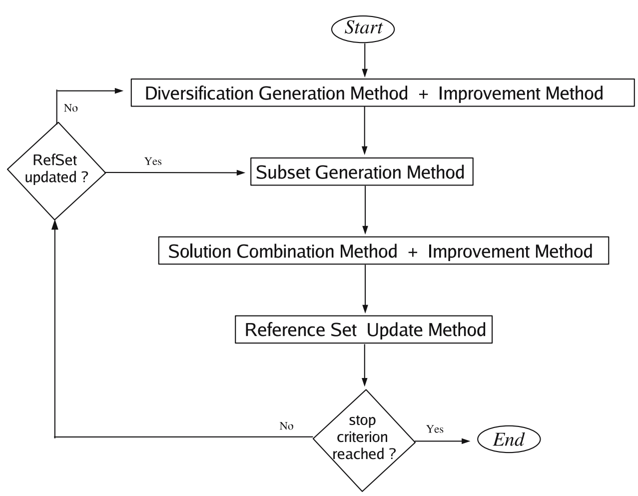

Fig. 4 The control diagram of SS

implementation. Of the five methods in the SS methodology, only four are strictly required. The *Improvement Method* is usually needed if high quality outcomes are desired, but a SS procedure can be implemented without it. Next, we will briefly describe the specific design of each component of our SS-based pair-wise IR pre-alignment method outlined in Fig. 5, where P denotes the initial set of solutions generated with the *Diversification Generation Method* (with *Psize* being the size of P), the reference set is noted as *RefSet* (with b being its size, usually significantly lower than *Psize*), and *Pool* is the set of trial solutions constructed with the *Combination* and *Improvement Methods* each iteration.

Diversification generation method: This method makes use of a controlled randomization based on frequency memory to generate an initial set P of *Psize* diverse solutions (Glover et al. 2003). We carry out this by dividing the range of each variable (in our case, each one of the seven rigid transformation parameters) into four sub-ranges of equal size. A solution will be constructed in two steps. First, a sub-range is randomly selected for each variable, where the probability of choosing a sub-range is inversely proportional to its frequency count. Initially, the frequency count for each variable subrange is set to one and the number of times a sub-range j has been chosen to generate a value for variable i in a solution is accumulated in *frequency_count*(i, j). Then, as second step, a value is randomly generated within the selected sub-range. Finally, the *Improvement Method* is applied on the *Psize* solutions generated and the best b of them compose the initial *RefSet.*

Improvement method: The Improvement Method is based on Solis and Wets' optimization algorithm (Solis and Wets 1981), which has the advantage of not requiring to compute the gradient direction in order to operate. This classical local search algorithm uses fixed variances which are initially and uniformly one. These variances are used for probabilistically determining the change to be applied on a particular state variable. They are either doubled or halved during the run, depending on the number of consecutive failed or successful moves.

Subset generation method: This method generates a collection of solution subsets (noted as *Subsets* in Fig. 5) of the reference set as a basis for creating new combined solutions. In our implementation, the subsets are composed of all the possible pairs of solutions in *RefSet,* so $\frac{b \cdot (b-1)}{2}$ different subsets are generated.

Solution combination method: It is based on the use of the BLX-α crossover operator (Eshelman 1993), commonly used in real-coded GAs. This mechanism for combination obtains a trial solution, $x = (h_1, \ldots, h_k, \ldots, h_l)$ (with $l = 7$) being the number of parameters of the rigid transformation and h_k a given value for such k^{th}

```
P ← ∅
While (|P| < PSize) do
    Obtain a new solution x generated by the Diversification Generation Method
    Improve x with the Improvement Method generating the solution x'
    If x' ∉ P Then P ← P ∪ {x'}
Sort the solutions in P according to their objective function value (the best overall solution in P, that one with the highest F value, is the first in such list).
Add the first b solutions from P to RefSet

While (not reached the stop criterion) do
    NewElements ← True
    Pool ← ∅
    While (NewElements) and (not reached the stop condition) do
        Generate Subsets with the Subset Generation Method
        NewElements ← False
        While (Subsets ≠ ∅) do
            Select the next subset s from Subsets and delete it from Subsets
            Apply the Solution Combination Method on s to obtain a new solution x
              If (F(x) is higher than the F value of the median-solution ∈ RefSet)) Then
                Apply the Improvement Method to the solution x with a probability of 0.0625^a to obtain the solution x'
              Else x' ← x
              Add x' to Pool
        Apply the Reference Set Update Method selecting the best b solutions in RefSet ∪ Pool
        If (RefSet has at last one new solution) Then NewElements ← True
    If (not reached the stop criterion) Then
        Build a new set P using the Diversification Generation Method
        Replace the worst b − 1 solutions from RefSet with the best b − 1 solutions from P
```

[a] The use of such a probability value was justified in Hart(1994) and successfully applied in Lozano et al.(2004) in order to achieve a quick convergence to good solutions of the global SS procedure

Fig. 5 Pseudocode of the SS-based 3D IR optimizer

variable) from the two parent solutions $x^1 = (c_1^1, \dots, c_l^1)$ and $x^2 = (c_1^2, \dots, c_l^2)$, composing a given subset s (see Fig. 5), by uniformly generating a random value for each variable h_k in the interval $[c_{\min} - I \cdot \alpha\ ,\ c_{\max} + I \cdot \alpha]$, with $c_{\max} = \max(c_k^1, c_k^2)$, $c_{\min} = \min(c_k^1, c_k^2)$, and $I = c_{\max} - c_{\min}$. Hence, the parameter α allows us to make this crossover as disruptive as desired. Such combination method was successfully incorporated to SS in Herrera et al. (2006).

The solution obtained by the BLX-α is then selectively optimized by the *Improvement Method* and included in the *Pool*, as shown in Fig. 5.

Reference set update method: RefSet is updated to be composed of the b best solutions in *RefSet* ∪ *Pool* following a static strategy (first, the *Pool* set is built and then the updating is made) (Laguna and Martí 2003).

4 Experiments

We present a number of experiments to study the performance of our proposal. As a benchmark, the results obtained by our SS algorithm for the pair-wise IR problem will be compared against those obtained by two other evolutionary approaches: the fast real-coded dynamic GA (DGA) introduced by in Chow et al. (2004), and the proposal of Lomonosov et al. (2006) that considers the integration of a GA with the trimmed iterated closest point algorithm (GA–TrICP). The three algorithms maintain their original form and just for the refinement step the improved iterated closest point method (I-ICP) (Liu 2004)[1] is used in all of them in order to allow a fair comparison of results.

[1] I-ICP was improved by using a KD-tree data structure (Zhang 1994) in order to speed up the closest point computation.

4.1 Image registration problems considered

The most important problem tackled in this contribution is the one considering a skull object (named "Skull") scanned in our Physical Anthropology Lab by using a Konica-Minolta© 3D Lasserscanner VI-910 laser scanner. Such importance is related to both the topic of our proposal and the complexity of the problem. The difficulty relies on different reasons:

- **The high resolution of the scanner.** Three different views of the "Skull" volume have been considered: two lateral and a frontal one (see Fig. 6), composed of 40,886, 42,515 and 40,255 points, respectively. Considering around forty thousands points is a challenge in terms of speed and accuracy with respect to other pair-wise IR contributions. In particular, this is important because our SS-based pair-wise IR proposal does not discard any of these points. As said, DGA and GA–TrICP randomly select a certain (small) amount of points and discard the rest (Sect. 2.2).
- **The reduced number of views.** Following the indications in Ikeuchi and Sato (2001), Silva et al. (2005) (see Sect. 1), we are considering a few views of the object, in order to avoid error accumulation in the 3D model reconstruction process. Nevertheless, this leads us to tackle scenarios where the percentage of overlapping (considering both "$\text{Skull}_{\text{lateral}^1}$" vs. "$\text{Skull}_{\text{frontal}}$" and "$\text{Skull}_{\text{frontal}}$" vs. "$\text{Skull}_{\text{lateral}^2}$" IR problems) is minimum, thus raising the problem complexity.
- **The symmetry present in the scanned views.** The particular characteristics of the "Skull" object make

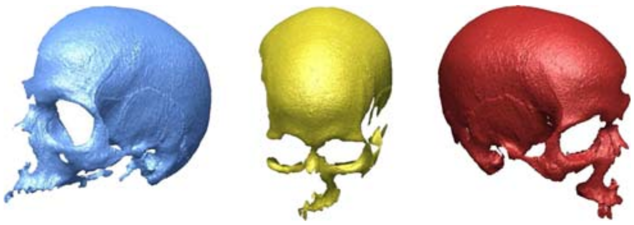

Fig. 6 From left to right: "$\text{Skull}_{\text{lateral}^1}$", "$\text{Skull}_{\text{frontal}}$" and "$\text{Skull}_{\text{lateral}^2}$" views of the "Skull" forensic object

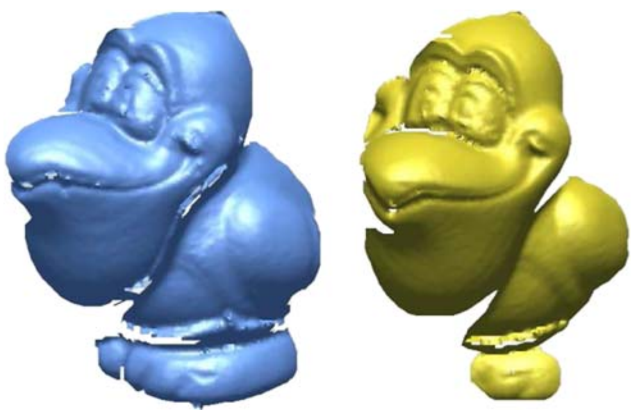

Fig. 7 Two views of the "Bird" object differing 20°, inputs to every pair-wise IR method

it a hard problem to face. The symmetry degree in every pair of adjacent views is really high and it causes that every pair-wise IR method tackling this object is prone to fall in search space local minima.

Two other 3D objects, named "Bird" and "Angel", have also been considered[2] in order to ease the comparison of our proposal since they are classically used in many contributions to the topic such as (Lomonosov et al. 2006, Silva et al. 2005). These objects have been acquired with another Konica-Minolta© 3D Lasserscanner VI-700 laser scanner. Specifically, two views of the "Bird" object differing 20° have been considered (Fig. 7), composed of 9,115 and 7,190 points, respectively. Meanwhile, two views of the "Angel" object have been used (differing 40°) (see Fig. 8), comprised by 14,812 and 10,632 points, respectively.

Therefore, every EA will tackle four different pair-wise IR problems: "$\text{Skull}_{\text{lateral}^1}$" versus "$\text{Skull}_{\text{frontal}}$", "$\text{Skull}_{\text{frontal}}$" versus "$\text{Skull}_{\text{lateral}^2}$", "Bird" versus "$\text{Bird}_{20^\circ}$", and "Angel" versus "$\text{Angel}_{40^\circ}$".

[2] These objects are free accesible at http://sampl.ece.ohio-state.edu/data/3DDB/RID/minolta/

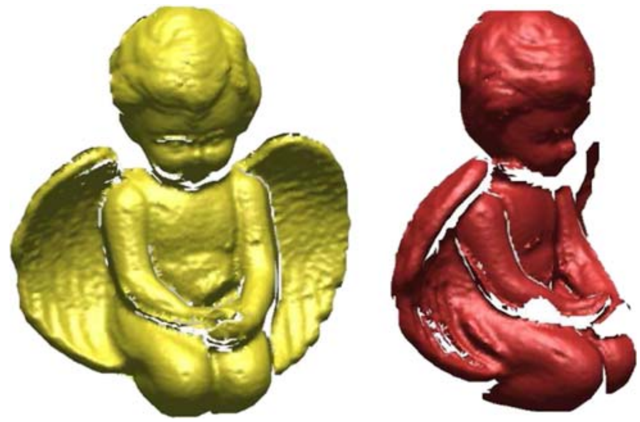

Fig. 8 Two views of the "Angel" object differing 40°, inputs to every pair-wise IR method

4.2 Parameter settings

All the methods are run on a PC with an Intel Pentium IV 2.6 MHz. processor. In order to avoid execution dependence, *one hundred different runs of each pair-wise IR algorithm have been performed.* Both DGA and GA–TrICP use three Euler angles for their rotation representation. Hence, every random rotation of DGA and GA–TrICP is initialized considering a range $[0°, 360°]$ for the *(X,Y,Z)* axes. Meanwhile, the rotation of our SS-based proposal is encoded using quaternions which store both the rotation axis and angle and they have demonstrated to be a more suitable rotation representation (Sect. 3.3). On the other hand, translation is initialized considering the range $[-10, 10]$, for all the methods. The I-ICP refinement step is applied with the parameter k set to 1.0.

For SS, the initial set P comprises Psize $= 20$ solutions and the RefSet is composed of the $b = 8$ best of them. BLX-α is applied with $\alpha = 0.3$, while the *Improvement Method* is selectively applied during 100 evaluations each time.

In order to perform the experiments as fairly as possible, every EA considers the same objective function (see Eq. 1), since we want to analyze the behavior of the proposals under the same conditions. When dealing with the "Bird" and "Angel" objects, the execution time for all the EAs is set to 30 s, while the I-ICP maximum number of iterations is 50. On the other hand, when considering the significantly more complex "Skull" forensic object, the execution time for all the EAs is set to 80 s, while the I-ICP maximum number of iterations is 150.

4.3 Analysis of results

All the statistics in this section are based on a typical error measure in the IR field, the *Mean Square Error (*MSE*),* given by:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N} \|f(\mathbf{p}_i) - \mathbf{p}_j{}'\|^2}{N}$$

where f is the estimated registration function, $\mathbf{p}_i$ are the $View_1$ points, and $\mathbf{p}_j{}'$ are the $View_2$ points matching the scene ones (the closest to the formers), and N is the number of points in view I_{v_1}.

Tables 1, 2 and 3 and Figs. 9, 10 and 11 show the performance of the different pair-wise IR algorithms applied, respect to the four pair-wise IR problems for the three test objects considered.

In view of the results obtained, we can see how our SS-based proposal achieves the most accurate results in the minimum, maximum, mean and standard deviation values. Although GA–TrICP and DGA obtain similar results as regards the minimum values for the "Bird" and "Angel" objects, as far as the problem complexity is much higher with the "Skull" object (see Sect. 4.1), SS outperforms them also with respect to the minimum results. Moreover, our approach is significantly better in terms of the really smaller mean values. The robustness of the SS algorithm is shown by the lowest standard deviation, which allows us to highlight its quick convergence to high quality solutions in all the one hundred runs performed.

When analyzing the reasons behind these good results, we have to highlight other improvements introduced in our proposal respect to the aforementioned methods apart from the clear differences in design. Since one of the most time consuming tasks in the IR process is the closest point computation (from every transformed point in the first view of the 3D object to its corresponding one in the second view) it is worth analyzing the way this task is performed. On the one hand, SS takes advantage of a distance map data structure to speed up the closest point computation (Yamany et al. 1999). Such data structure consists of superimposing a 3D fine grid on the 3D space such that the two views of the object lie inside the grid. Each cell holds an index of its closest point in the model set and they are filled in only once at the beginning of the registration process. Hence, for the N closest point computations to be performed corresponding to the N points in I_{v_1}, the worst-case search time is $O(N)$ since the time is constant for each individual closest point computation.

Meanwhile, both DGA and GA–TrICP use a slower KD-tree data structure (Zhang 1994), which is a generalization of bisection in one dimension to k dimensions. In our case, $k = 3$ and a 3-D tree is constructed. The worst-case search time to find a point in a binary tree is known to be $O(\log(N))$. Nevertheless, as demonstrated in Preparata and Shamos (1986) (pp. 77), the worst-case search time of every closest-point computation is $O(N^{2/3})$ for a 3-D tree. Therefore, for the N closest point computations to be carried out it becomes $O(N \cdot N^{2/3}) = O(N^{5/3})$.

Thus, our proposal outperforms the rest in terms of search time. However, this is not of course the only reason explaining our proposal best performance. Notice that, opposite to the other two approaches, SS uses all the points in every image, there is not a need of previously selecting a certain amount of points, taking advantage of the whole available information and avoiding the randomness introduced in the selection process applied by the other approaches. Hence, it is clear how the good choice of the evolutionary components of our SS-based pair-wise IR proposal is what allows us to process this large amount of information in so little time that it is possible to achieve high quality results.

Therefore, we are achieving one of the aims of our proposal, i.e. not only to adapt SS to a specific scenario but also to provide a more robust and more accurate technique than those in the literature (Sect. 1). Nevertheless, note that the mean value corresponding to our SS-based proposal is more than ten times higher when tackling the last pair-wise IR problem ("Skull$_{\mathrm{frontal}}$" vs. "Skull$_{\mathrm{lateral}^2}$"). This means that we are obtaining a really good approximation to the global optimum in certain runs, but there are still others where the MSE value is not so good.

Finally, in order to highlight the usefulness of our proposal in forensic anthropology, we present the reconstruction results of the "Skull" object in Fig. 12. We can

Table 1 MSE of the 100 runs corresponding to the "Bird" object

	"Bird"			
	Min.	Max.	Mean	SDev.
SS	0.186	11.359	0.302	1.111
GA–TrICP	0.186	11.455	0.441	1.455
DGA	0.186	11.572	0.715	2.262

Table 2 MSE of the 100 runs corresponding to the "Angel" object

	"Angel"			
	Min.	Max.	Mean	SDev.
SS	1.312	31.911	1.626	3.043
GA–TrICP	1.312	43.277	7.066	11.796
DGA	1.312	49.034	6.848	12.496

Table 3 MSE of the 100 runs corresponding to the “Skull” object

“Skull”	“Skull$_{V_1}$” vs. “Skull$_{V_2}$”				“Skull$_{V_3}$” vs. “Skull$_{V_2}$”			
	Min.	Max.	Mean	SDev.	Min.	Max.	Mean	SDev.
SS	5.671	428.567	99.218	146.526	60.799	1322.898	1217.931	251.333
GA–TrICP	199.322	3404.503	1195.494	647.260	184.379	8436.275	2305.035	1518.636
DGA	97.298	9246.161	1394.964	1405.463	300.572	8370.180	2564.305	1659.237

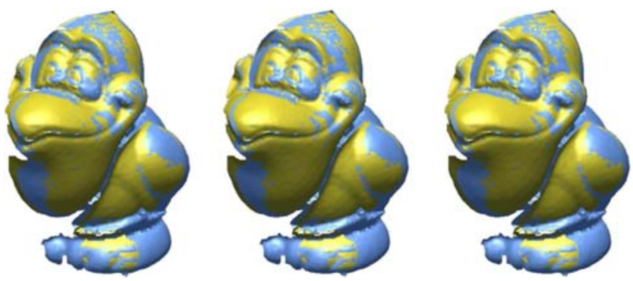

Fig. 9 From left to right: best alignment results of the “Bird” object achieved by SS, GA–TrICP and DGA

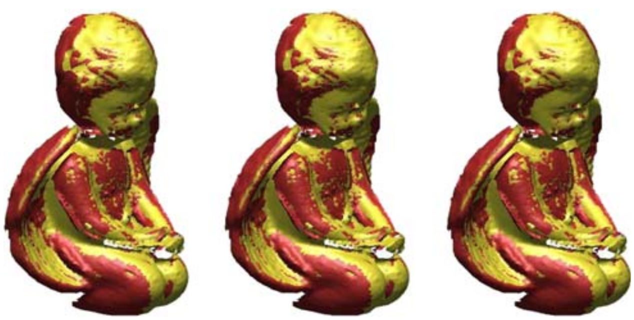

Fig. 10 From left to right: best alignment results of the “Angel” object achieved by SS, GA–TrICP and DGA

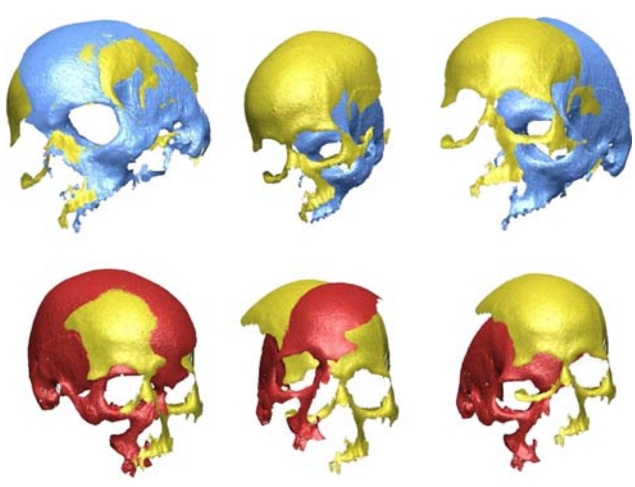

Fig. 11 From left to right: best alignment results of the “Skull” object achieved by SS, GA–TrICP and DGA. First row corresponds to the “Skull$_{lateral^1}$” vs. “Skull$_{frontal}$” first pair-wise problem. Second row corresponds to the “Skull$_{frontal}$” versus. “Skull$_{lateral^2}$” second pair-wise problem

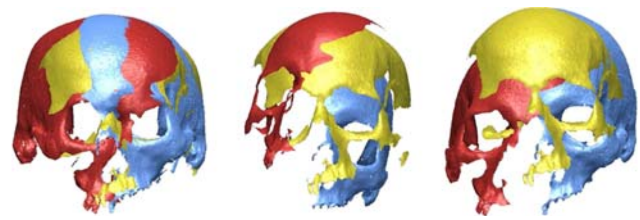

Fig. 12 From left to right: best reconstruction results of the “Skull” object from SS, GA–TrICP and DGA

see that SS clearly outperforms the latter evolutionary approaches, since the appearance of the 3D skull model obtained applying SS to the pair-wise IR reconstruction is more accurate than those from GA–TrICP and DGA. We find different reasons for such behavior:

– DGA and GA–TrICP are based on weak EA designs (Cordón et al. 2006a). If the overall EA framework is not the best, the results (specially in complex scenarios) may be not the most appropriate.
– As said, DGA and GA–TrICP are based on a random selection of points, which means that not all the data is been used. If the selected points correspond to a small region, local optima will be likely achieved.

5 Concluding remarks and future works

In this paper, we have adapted the use of a novel evolutionary framework, SS, to the pair-wise IR problem handling objects both from the literature and from forensic anthropology applications. Having in mind the interesting properties and the recent successful outcomes achieved by the former strategy in other IR problems (Cordón et al. 2005a, Cordón et al. 2006a), our aim was at adapting the methodology to the pair-wise IR framework. Beyond this basic objective, we provided a more robust and more accurate technique than those in the literature. To do so, state-of-the-art proposals (Chow et al. 2004, Lomonosov et al. 2006 were considered as a benchmark of ours which has demonstrated its accuracy and robustness in the different experiments performed. Such good global behavior for the 100 runs performed leads us to try to extend our approach to the IR problem in other real computational environments. Nevertheless, we realize there are still different shortcomings in the SS-based 3D model reconstruction. We aim at solving them if SS is able to take advantage of heuristic information previously extracted from the different views of the object (Cordón et al. 2005b). Other open lines are the improvement of the similarity metric to be used. In particular, it would be interesting to incorporate that from Silva et al. (2005) to our proposal.

References

Besl PJ, McKay ND (1992) A method for registration of 3-D shapes. IEEE Trans Pattern Anal Mach Intell 14:239–256

Blais G, Levine M (1995) Registering multiview range data to create 3D computer objects. IEEE Trans Pattern Anal Mach Intell 17(8):820–824

Brown LG (1992) A survey of image registration techniques. ACM Comput Surv 24(4):325–376

Chen CS, Hung YP, Cheng JB (1998) A fast automatic method for registration of partially overlapping range images. In: International conference on computer vision – ICCV 1998, pp 242–248

Chow CK, Tsui HT, Lee T (2004) Surface registration using a dynamic genetic algorithm. Pattern Recogn 37:105–117

Cordón O, Damas S, Santamaría J (2005a) A scatter search-based optimizer for the registration of 3D surfaces. In: IEEE conference on evolutionary computation – CEC 2005, pp 2738–2744

Cordón O, Damas S, Santamaría J, Martí R (2005b) 3D inter-subject medical image registration by scatter search. In: Second international workshop on hybrid metaheuristics (HM2005), Lecture Notes on Computer Science, vol. 3636, pp 90–103

Cordón O, Damas S (2006) Image registration with iterated local search. J Heurist 12(1–2):73–94

Cordón O, Damas S, Santamaría J (2006a) A fast and accurate approach for 3D image registration using the scatter search evolutionary algorithm. Pattern Recogn Lett 27(11):1191–1200

Cordón O, Damas S, Santamaría J (2006b) Feature-based image registration by means of the CHC evolutionary algorithm. Image Vis Comput 24(5):525–533

Eshelman LJ (1993) Real-coded genetic algorithms and interval schemata. In: Whitley LD (Ed) Foundations of genetic algorithms vol 2. Morgan Kaufmann San Francisco pp 187–202

Fusiello A, Castellani U, Ronchetti L, Murino V (2002) Model acquisition by registration of multiple acoustic range views. In: European conference on computer vision – ECCV 2002, pp 805–819

Garai G, Chaudhuri BB (2002) A cascaded genetic algorithm for efficient optimization and pattern matching. Image Vis Comput 20(4):265–277

Glover F (1977) Heuristic for integer programming using surrogate constraints. Decis Sci 8:156–166

Glover F, Laguna M, Martí R (2003) Scatter search. Theory and applications of evolutionary computation: recent trends. Ghosh A, Tsutsui S (eds). Springer, Berlin Heidelberg New York, pp 519–537

Han KP, Song KW, Chung EY, Cho SJ, Ha YH (2001) Stereo matching using genetic algorithm with adaptive chromosomes. Pattern Recogn 34(9):1729–1740

Hart WE (1994) Adaptive global optimization with local search. PhD Thesis, University of California, San Diego

He R, Narayana PA (2002) Global optimization of mutual information: application to three-dimensional retrospective registration of magnetic resonance images. Comput Med Imag and Graph 26:277–292

Herrera F, Lozano M, Molina D (2006) Continuous scatter search: an analysis of the integration of some combination methods and improvement strategies. Euro J Oper Res 169(2):450–476

Ikeuchi K, Sato Y (2001) (eds) Modeling from reality. Kluwer, Dordrecht

Iscan MY (1981a) Concepts in teaching forensic anthropology. Med Anthropol Newslett 13(1):10–12

Iscan MY (1981b) Integral forensic anthropology. Pract Anthropol 3(4):21–30

Jonhson AE, Hebert M (1999) Using spin images for efficient object recognition in cluttered 3D scenes. IEEE Trans Pattern Anal Mach Intell 21(5):433–449

Krogman WM, Iscan MY (1986) The human skeleton in forensic medicine. Springfield, Owerri)

Laguna M, Martí R (2003) Scatter search: methodology and implementations in C. Kluwer, Dordrecht

Liu Y (2004) Improving ICP with easy implementation for free form surface matching. Pattern Recogn 37(2):211–226

Lomonosov E, Chetverikov D, Ekart A (2006) Pre-registration of arbitrarily oriented 3D surfaces using a genetic algorithm. Pattn Recog Lett 27(11):1201–1208

Lourenço HR, Martin OC, Stützle T (2003) Iterated local search. In: Handbook of metaheuristics, Glover F, Kochenberger G (eds) Kluwer, Dordrecht pp 321–353

Lozano M, Herrera F, Krasnogor N, Molina D (2004) Real-coded memetic algorithms with crossover hill-climbing. Evolut Comput 12(3):273–302

Masuda T, Yokoya N (1995) A robust method for registration and segmentation of multiple range images. Comput Vis Image Understanding 61(3):295–307

Michalewicz Z (1996) Genetic algorithms + data structures = evolution programs. Springer, Berlin Heidelberg New York

Okatani IS, Deguchi K (2002) A method for fine registration of multiple view range images considering the measurement error properties. Compur Vis Image Understanding 87:66–77

Preparata F, Shamos M (1986) Computational geometry, an introduction. Springer, Berlin Heidelberg New York

Shoemake K (1985) Animating rotation with quaternion curves. ACM SIGGRAPH'85, pp 245–254

Silva L, Bellon ORP, Boyer KL (2005) Robust range image registration using genetic algorithms and the surface interpetenetration measure. World Scientific, Singpore

Solis FJ, Wets RJB (1981) Minimization by random search techniques. Math Oper Res 6:19–30

Yamany SM, Ahmed MN, Farag AA (1991) A new genetic-based technique for matching 3D curves and surfaces. Pattern Recogn 32:1817–1820

Zhang Z (1994) Iterative point matching for registration of free-form curves and surfaces. Int J Comput Vis 13(2):119–152