Automatic 3D Skull Reconstruction using Invariant Features

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ABSTRACT

In this work we propose a new method to segment range images. It automatically extracts invariant features directly from point clouds. Points belonging to such features are used as the input to improve an evolutionary approach to 3D range image registration in forensic anthropology. We use such features in the automatic reconstruction of an accurate 3D model of the skull. Our reconstruction method includes a pre-alignment stage, that uses a subset of feature points, and a refinement stage. Results are presented over a set of instances of real problems.

Categories and Subject Descriptors
I.4.6 [Image Processing and Computer Vision]: Segmentation

General Terms
Algorithms, Experimentation

Keywords
Invariant features, range image registration, 3D skull reconstruction, evolutionary algorithms

1. INTRODUCTION

The aim of our study is to assist the forensic experts in one of their main tasks: the cranio-facial identification of a disappeared person. In outstanding approaches, this is usually done by the superimposition of the 3D model of the skull on a facial photograph of the missing person [4]. This crucial task is considered as a last chance for identification. The first stage of this process is the accurate construction of a 3D model of the skull. There is a need to use a range scanner to develop a computerized study of the skull. This device is not able to cover the whole surface of the 3D object in just one scan. Hence multiple scans from different views are required to supply the information needed to construct the 3D model. Range image registration (RIR) 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. Software tools for the automation of this work are a real need. In previous works we have proposed a method based on evolutionary algorithms (EAs) for the alignment of several range images acquired from skulls [7]. The method consists of a multi-stage approach: in the first stage, the Scatter Search (SS) EA [5] is used for pre-alignment; in the second stage a local optimizer is used for refinement. Typically, in the pre-alignment step only a subset of points is used, while the refinement step is applied to the whole images. In [6], we evaluated two point selection approaches: a semiautomatic and an automatic one. The semiautomatic outperformed the automatic one, but it required the expertise of human intervention. On the other hand, the automatic approach required more computation time in order to achieve a suitable accuracy.

In this work we propose an automatic method for the extraction of points belonging to representative and invariant features meaningful in our scenario, and we compare results with the two previous approaches in [6]. The paper structure is as follows. In Section 2 we review our method for the skull 3D model building. Section 3 introduces the automatic procedure for point selection. The suitability of the method is tested in Section 4 over different scenarios of skull modeling. Finally, in Section 5 we present some conclusions and future works.

2. RANGE IMAGE REGISTRATION

We follow a feature-based approach to the RIR problem. The aim is finding a near-optimal geometric transformation that aligns every adjacent pair of views acquired by the range scanner. The general approach to this pair-wise RIR problem consists of two steps: pre-alignment and refinement. To do so, we use an efficient stochastic optimization tech-
where the objective function introduced in our previous proposal [6].

problem of classical Euler matrices representation that suffers from the resonably. 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 [8]. In this contribution, we used the objective function introduced in our previous proposal [6]. It considers the Median Square Error to deal with the small overlapping between adjacent views:

\[ F(f, I_{v1}, I_{v2}) = \text{median}(\| f(\tilde{p}_i) - \tilde{p}_j \|^2), \quad \forall \tilde{p}_i \in I_{v1} \]  

where \( f \) is the transformation we are searching for, \( I_{v1} \) and \( I_{v2} \) are the two views, \( f(\tilde{p}_i) \) is the point after the transformation is applied to the point \( \tilde{p}_i \) of the first view, and \( \tilde{p}_j \) is the point of the second view closest to \( f(\tilde{p}_i) \).

2.1 Pre-alignment

2.1.1 Basis of scatter search.

SS fundamentals were originally proposed by Fred Glover in [3] and have been later developed in works [5]. The main idea of this technique is based on a systematic combination between solutions taken from a considerably reduced evolved pool of solutions named reference set. This way, an efficient and accurate search process is encouraged thanks to the latter and to other innovative components. The general SS approach is graphically shown in Fig. 1. 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 implementation.

2.1.2 Coding scheme and objective function.

As coding scheme, the 3D rigid transformation \( f \) is determined by fixing seven parameters: translation \( f = (t_x, t_y, t_z) \) and rotation \( R = (\theta, \text{Axis}_x, \text{Axis}_y, \text{Axis}_z) \), where \( \theta \) and \( \text{Axis} \) 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 [8]. In this contribution, we used the objective function introduced in our previous proposal [6]. It considers the Median Square Error to deal with the small overlapping between adjacent views:

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2.2 Refinement

Once we have a rough approximation to the global solution, we will apply a local optimizer to refine the result from the first stage. One of the most known feature-based algorithms for the refinement stage of RIR is the Iterative Closest Point (ICP), proposed by Besl and McKay [1]. After pre-alignment, we will assume the motion between the two adjacent views is small. This is a precondition of ICP to get reasonable results, and it holds when the pre-alignment achieves near-optimal results.

3. Feature Extraction

In [6], we evaluated two point selection approaches: a semi-automatic and an automatic one. Both approaches try to reduce the large set of points involved in the registration. For the semi-automatic approach, the crest lines are extracted from the curvature information of the surface [10]. The crest lines provide a useful subset of data, because they have a very strong anatomical meaning (as pointed out by Subsol et al. [9], they emphasize the mandible, the orbits, the cheekbones or the temples). However, their extraction requires the expertise of human intervention. The latter drawback is an important obstacle for the forensic anthropologists, because they have neither the knowledge nor the time to extract them. On the other hand, an uniform random sampling of the input images is used in the automatic approach. Although a larger number of points needs to be selected in order to achieve a suitable accuracy, it is a fully automatic and really helpful solution for the forensic anthropologists. However, we observed that choosing points in a complete random way over the range images can produce non-representative samples that reside in areas having few geometric features and therefore this makes hard the identification of the corresponding points in the second image.

Hence, we aim to propose a method that can choose points belonging to meaningful features in our scenario. These features should be: (1) representative of the skull object we will deal with, (2) invariant to rigid transformation between views, and (3) composed by the smallest number of points.

The features having such properties provide a subset of data really useful for the registration task.

Since range images are taken from different views, the shape descriptor should be view independent to be useful for registration. An invariant is a quantity that does not change under some linear transformation. In other words, \( i(x) \) is an absolute invariant with respect to a linear transformation \( f \) if \( i(x) = i(f(x)) \) for all \( x \). We are most interested in Euclidean invariants, quantities that are invariant to 3D rigid motion.

As said, we want the features to be representative of the object, i.e. the skull. We focus our attention on some regions corresponding to significant anatomical parts: orbits, nasal cavity and cheekbones. These regions appear surrounding holes in the surface. Let us formally characterize these regions. At each point \( P = (p_x, p_y, p_z) \) of those surfaces, we can define a spherical neighborhood \( N_P \) whose points \( Q = (q_x, q_y, q_z) \) satisfy the condition:

\[ \sqrt{(p_x - q_x)^2 + (p_y - q_y)^2 + (p_z - q_z)^2} \leq r \]  

where \( r \) is the radius of the neighborhood.

If we consider the skull object, the intersection between the sphere and the surface is different in distinct regions. The area of this intersection is smaller when the sphere is located in boundary regions, i.e. in our regions of interest. Hence, we will be able to identify different regions by measuring the size of the intersection area.

We can define a weighted density at each point \( P \) of the surface of the skull:

\[ d_i = \frac{\sum_{j=1}^{N} \| P_j - M_j \|}{4\pi r^3/3} \]  

get reasonable results, and it holds when the pre-alignment achieves near-optimal results.
where $M = \{M_1, \ldots , M_n\}$ is the set of points of the skull that are inside the sphere centered in $P_i$ with radius $r$. Notice that the volume of the sphere in Eq. 3 is a constant value. Hence it can be neglected without affecting the results.

Assuming a roughly uniform sampling of the surface, $d_i$ is directly related to the area of the intersection between the surface and the spherical neighborhood. Thus, $d_i$ will be higher in regions where the intersection area is larger. On the contrary, boundary regions interesting for us will correspond to lower values of $d_i$. However, the uniform sampling assumption cannot be always guaranteed. In some cases we observed that boundary regions are more crowded than the rest. That is problematic because the $d_i$ values will then be higher in these regions that will be considered as not relevant. To avoid this situation we applied a power-law transformation to $d_i$ to increase the contribution of the farther points while decreasing the contribution of the closer ones:

$$u_i = \sum_{j=1}^{n} ||P_i - M_j||^{\alpha}$$ (4)

Hence, we are characterizing every point based on the local neighborhood. Recalling that our regions of interest have smaller intersection area, and consequently contain points having small values of $u_i$, a suitable threshold on this quantity can identify different areas and therefore segment our surface in two different regions. Points having values of $u_i$ less than the threshold belong to our regions of interest.

In other words, the subset of relevant features can be defined as:

$$I_{p'} = \{p_i \in I_p \mid u_i \leq \alpha \cdot u_{\text{max}}\}$$ (5)

where $u_{\text{max}}$ is the $u_i$ maximum value and $\alpha \in [0, 1]$ is a threshold to identify the relevant regions. The coefficient $\alpha$ can be chosen analyzing the distribution of the $u_i$ values. The number of points should be enough to represent the important features while being as small as possible.

The proposed method for the extraction of invariant features can be summarized as follow. Given a point sampled surface $I_p = \{\bar{p}_i\}$, for each point $\bar{p}_i$ calculate the value $u_i$ using Eq. 4. Threshold these values to obtain a subset of points $I_{p'}$ representing the searched features.

Our algorithm is somehow similar to the boundary detection algorithm presented by Dey et al. [2]. However, that algorithm finds the exact boundary samples. In our case, we prefer to identify boundary regions. Indeed, exact boundary samples may change between two views (due to noise generated during the acquisition process) while boundary regions, that comprise higher number of samples, make easier to find corresponding points between adjacent views.

Our algorithm can also be seen as a segmentation algorithm. Indeed, it performs a partition of the input image into two regions: one contains the feature points and the other contains the remaining points.

### 4. EXPERIMENTAL STUDY

In this section we aim to analyze how our proposed approach for automatic feature extraction can improve the evolutionary approach to generate 3D skull models. As commented on the beginning of this paper, this reconstruction stage is the first step of the whole photographic supra-projection process. It plays a crucial role as the more accurate the reconstructed skull model is, the more reliable the identification decision will be. Moreover a fully automatic method, as the present one, is really helpful for the anthropologist.

We will tackle the different problems the forensic expert has to deal with during the reconstruction stage. Next, Section 4.1 describes the considered dataset. Sections 4.2 details the experimental design and the parameter settings. Finally, Section 4.3 is devoted to the analysis of results.

#### 4.1 Input range images

The Physical Anthropology Lab at the University of Granada, Spain, provided us with a number of datasets of human skulls acquired by a Konica-Minolta® 3D Lasserscanner VI-910. It should be highlighted that the three forensic objects considered for this experimental study were chosen by the experts according to several forensic criteria to guarantee a maximal differentiation regarding to skull features. The acquisition process includes noise removal and the use of smoothing filters.

To ease the forensics’ work, we have taken into account important factors regarding to the scanning process like time and storage demand. Indeed, we consider a scan every 45° that is a reasonable trade-off between number of views and overlapping regions. Hence, we deal with a sequence of only eight different views: 0° – 45° – 90° – 135° – 180° – 225° – 270° – 315°, which supposes a great reduction both in the scanning time and storage requirements. The datasets we will use in our experiments are limited to five of the eight views: 270° – 315° – 0° – 45° – 90°. The reason is that our aim is to achieve a 3D model of the most interesting parts of the skull for the final objective of our research project, the cranio-facial identification of a missing person, i.e. the frontal part of the skull. These five views of every forensic object will provide us fifteen different problems to test the performance of our proposal.

#### 4.2 Experimental setup

We focus our attention on the impact of the invariant feature selection on the RIR performance. We compared it to the two previous approaches used in [6]: automatic and semi-automatic. We tested all the methods on a set of problem instances that simulate an unsupervised scanning process, i.e. not oriented by any device.

For the semiautomatic approach, Yoshizawa et al.’s proposal [10] was considered to extract the crest lines. In the purely random automatic approach, we have followed an uniform random sampling of the input images. We fixed a 15% of the original dataset as a suitable value for the time and accuracy trade-off. In the present approach, the invariant features are extracted using the method described in Section 3. Based on the skull dimension and its anatomical knowledge, the size of the neighborhood has been fixed to $r = 5$mm. The coefficient $\alpha = 0.475$, chosen as described earlier, proved to be appropriate for our objects and their feature shapes. Random sampling with uniform spatial probability density is then performed on the extracted features. We fixed a 50% of the derived dataset. The present approach is also fully automatic. Indeed the values of $r$ and $\alpha$ do not need to be tuned by the anthropologists.

Table 1 (top) summarizes the size (number of surface points) of the forensic range images of the considered skulls. The original size and the size after the application of our extraction procedure are reported. Table 1 (bottom) reports...
the number of point of the three datasets that will be used by the RIR method. The lower number of points resulting in Skull1 are due both to the pathological alterations of this case and its irregular sampling already noted. Therefore these view datasets are used as it by the RIR method, without the 50% random sampling. However, the good performance of the method also in this case confirm its robustness. Figure 2 shows two partial views of one of the skull and their corresponding extracted features.

On the one hand, the experimental design addresses four different pair-wise RIR problems for each skull: $I_{270}^0 - I_{315}^0$, $I_{315}^0 - I_{270}^0$, $I_{245}^0 - I_{295}^0$, and $I_{295}^0 - I_{245}^0$; leading to a global set of twelve problems. On the other hand, the RIR instances are designed from a rigid transformation, noted $f_i$, which is applied to one of the two images of every pair-wise RIR problem. For instance, $f_i(I_{245}^- - I_{295}^0)$ represents a certain RIR instance to be tackled by the RIR method, where the rigid transformation $f_i$ is applied to the $I_{245}^-$ image to be placed in some other location different from its correct original one. The RIR method aims to recover the original dataset location (the inverse transformation $f_i^{-1}$) achieving a minimum distance (or maximum overlapping) criterion between the couple of images. We will consider different rigid transformations $f_i$ in every run of the RIR method. These transformations will significantly change the object location, as described in details in [7].

In order to avoid execution dependence, the RIR method will tackle thirty different runs for each pair-wise considered RIR problem instances. The initial diverse set $P$ comprises $P_{size} = 30$ solutions and the RefSet is composed of the $b = 8$ best ones of them. BLX-$\alpha$ is applied with $\alpha = 0.3$, while the Improvement Method is selectively applied during 25 evaluations each time. We performed experiments with execution time ranging from 20 to 200 seconds for all the RIR problem instances. In order to have a fair comparison between the methods we will report only results obtained with 20/50/100 seconds for the semiautomatic approach using crest lines, the new automatic approach based on invariant features and the random approach, respectively. These values are proportional to the number of points of the problem instance considered (see Table 1). On the other hand, we observed no improvement in the previous approaches using longer time. Instead the present approach shows some improvement. The stop criterion for ICP refinement stage is a maximum number of 10 iterations.

### 4.3 Analysis of results

We have used the rotary stage as a positional device to actually validate the results of the registration for every problem instance. Since a high quality pre-alignment is provided from the scanner’s software, when this device is available and a very experienced user performs the scanning, a 3D model is also available and it can be considered as the ground truth for the problem. Therefore, we know the global optimum location of every point in advance by using this 3D model. We use the usual Mean Square Error (MSE) to measure the quality of the process, i.e. how good was the transformation estimation $f$ achieved by the RIR method. MSE is given by:

$$MSE = \frac{1}{r} \sum_{i=1}^{r} ||f(\vec{x}_i) - \vec{x}_i^0||^2$$

where $f(\vec{x}_i)$ corresponds to the i-th scene point transformed by $f$ (which is the result of our RIR method), $r$ is the number of points in the scene image, and $\vec{x}_i^0$ is the same scene point but now using the optimal transformation $f^*$ obtained by the positional device. Therefore, both $\vec{x}_i$ and $\vec{x}_i^*$ are the same point but its location can differ if $f \neq f^*$. The availability of an a priori optimum model lets us to use this MSE definition to study the behavior of the RIR method in real world situations. Indeed, this evaluation is not applicable in real environments where no optimum model is available. MSE is evaluated after the pre-alignment stage and at the end of the whole process.

<table>
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<th>295</th>
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Figure 2: Partial views of a skull acquired at 0° and 45°, respectively. From top to bottom: original images (88732 and 111834 points), crest lines (2408 and 2341 points) and invariant features (8318 and 12265 points)
Figure 3: MSE values represented by means of box-plots for the 3 datasets and the different problem instances. From top to bottom: skull1, skull2, skull3. From left to right: random, invariant features and crest lines.

The new automatic approach, based on invariant features, is compared with our two previous approaches: the automatic and semiautomatic one, applied to subsets of points randomly chosen and after crest lines extraction, respectively. Figure 3 offers a graphical information of our results. Each graph refers to one method and one skull. Each graph contains four box-plots representing the MSE distribution, measured at the end of the RIR process in the four pair-wise problem instances. In each box, the minimum and maximum values are the lowest and highest lines, the lower and upper ends of the box depict the first and third quartiles respectively. A thick line within the box shows the median (second quartile).

The first conclusion is an improved performance. The method that uses invariant features clearly outperforms the previous automatic method. Moreover it reduces the mean error over the crest lines based method in ten of twelve problem instance. The minimum values are lower in the previous approaches. However, the new method always finds a higher number of good solutions. It is worth to remind that in the new method the extraction of invariant features is fully automatic, while the crest lines require the human intervention for their localization, and therefore a preprocessing time definitively much higher.

We should also observe that, using the new method, most of the MSE values measured at the end of the pre-alignment step are reduced by the refinement step (see Figure 4). This confirms the validity of the feature selection approach. Indeed many solutions found by the random approach are local minima (not near-optimal results) and can not be improved by the ICP algorithm. The use of invariant features strongly reduces such cases. Thus, the pre-alignment provides near-optimal results, that are good initial states to the ICP.

In other words, the problem of the local minima can be described by observing the shape of our objects. The presence of large flat areas increases the chance for the RIR of being trapped in local minima. Indeed, by observing the registered images we noted that in the images obtained by the random RIR, the large flat areas match, while sharper areas containing meaningful anatomical characteristics are wrongly paired. This is because using the random sampling, the large amount of points in such not significant areas have larger influence on the fitness of the RIR than other points, despite the fact they are not properly matched with their corresponding one. On the other hand, focusing on significant areas like the invariant features here proposed, can provide subset of points whose match properly guides the RIR toward the optimal solution.

In Figure 4 we can observe how error values measured at the end of the pre-alignment step are reduced by the refinement step. Each graph contains eight box-plots representing a zoom of the lower part of the MSE distribution, measured at the end of the two stages (pre-alignment and refinement), in the four pair-wise problem instances. Because of lack of space we only present results of invariant features and crest lines. Finally, Figure 5 aims to show some of our reconstructed 3D models.

5. CONCLUDING REMARKS

We have presented a new approach for feature extraction from range images, represented as point clouds. These fea-
features are: representative of the object, invariant between the different views of the object and composed by the smallest number of points. These properties make our approach an excellent preprocessing step for the registration algorithm. Indeed, the present method clearly outperforms our previous automatic approach, while being still fully automatic. It is also comparable, and in many cases slightly better than the semiautomatic method based on the extraction of crest lines. The proposed approach overcomes the trade-off between having a fully automatic method and a low number of points located on meaningful features.

The proposed method can detect regions close to boundaries, and also localize small and sharp features where usually undersampling happens. The values of the parameters needed by the method ($r$ and $\alpha$) have been selected empirically in our experiments and do not need to be tuned by the forensic anthropologists. The proposed method is fully automatic, easy to implement and fast from the computational point of view. Our method does not need any mesh information. Moreover, it does not require calculation of curvature values, unlike the crest line extraction. Hence it is faster and simpler. Besides, it is accurate enough for our scope, as we demonstrated.

We are planning to extend this study by including an automatic preprocessing stage (smoothing filter and noise removal) and a more general design of the invariant feature selection. Actually, our primary goal in developing the feature extraction method was to find some invariant features to improve our skull registration. Hence, our features are skull-oriented. However, the method can be easily extended for general purpose and applied to other objects.

Finally we aim at tackling the rest of the craniofacial identification problem, by the 3D skull model-2D face photo superimposition, and by designing procedures to assist the forensic expert in the whole identification process.

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7. REFERENCES


