A local technique based on vectorized surfaces for craniofacial reconstruction

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1. Introduction

Facial reconstruction is justified by the fact that the craniofacial substrate may, to a certain extent, be considered as a matrix supporting soft facial tissue. All facial reconstruction techniques are based on the relationship between the soft tissue morphology and the underlying skull substrate. The aim of facial reconstruction is to obtain an approximate representation of the real face to suggest a resemblance to a missing person [13,2].

Traditionally, facial reconstruction uses techniques such as drawing or sculpture. Sculpture is usually realized after one or several preprocessing steps such as (i) evaluation of the thickness of soft tissues at reference landmarks on the craniofacial block, (ii) positioning of morphological characteristics such as muscular attachments [14,19], and (iii) use of geometrical rules for localization of the eyebrows or of the tip of the nose (see [28] and references within). Facial reconstruction has evolved greatly due to the development of computer science and medical imaging (see the surveys in [6,8–10,38] and references therein). Today, the computerized reconstructions range from practitioner-led methods, which only facilitate the sculpture, to fully automated reconstructions which aim at reducing operator-related subjectivity.

We can distinguish two kinds of fully automated approaches. The first one uses a data analysis framework where each individual is represented by a same set of variables, either (landmark approach:) skull anatomical points and associated soft-tissue thicknesses [7,36], or (head model approach:) generic meshes describing the skull and face surfaces [3,17,32]. In this setting, people learn from the database the statistical relation between skull variables and soft-tissue variables so as to predict soft-tissue variables associated to a new dry skull. The second type of approaches aims at using a continuous representation of the skull and face surfaces. In this setting, the skull surfaces within the database are mapped onto a new dry skull so as to estimate the unknown face surface. This estimate is obtained applying on the faces the deformation learned on the skulls. The deformations used for mapping surfaces can be parametric (e.g. B-splines) [18,35], implicit using variational methods [23,24], or volumetric [27,26]. In landmark and head model approaches the computation of statistics like means or the data mining analysis (e.g. Principal Component Analysis) are straightforward as the data can be summarized in a table. This is unfortunately not the case for continuous surfaces as these objects are not embedded in a vectorial space.

All these approaches are global, since they consider the whole head as the object of interest. Consequently, one needs to describe...
either the generic meshes or the deformations by a large number of parameters in order to capture properly the complexity of the object to be estimated. But, statistically, it is well known that, in order to control the estimation quality, one should obtain a good trade-off between bias measuring the accuracy of the estimator and variance related to the number of estimated parameters [37]. Hence, the global approaches cannot achieve a good estimation quality, as the number of estimated parameters is too large. This is especially true as the size of the learning database is usually small. Besides, in all these approaches, the soft-tissue is recovered using an average computed over the population of a whole database (either mean soft tissue depths or mean surfaces). As a result, these non-adaptive reconstructions tend to enhance coarse and global similarities between individuals and to disregard the local variability of the facial morphology.

In this paper, we present an original technique of facial reconstruction which departs from the previous ones according to several aspects. First of all, the technique is not based on the use of a parametric approach, neither landmark nor head model. Instead, it relies on a continuous representation of the individual surfaces which makes it possible to capture their natural complexity. Second, the technique is local and thus, needs only few parameters for the reconstruction. It consists in estimating the soft-tissue surface over well-defined areas called "patches". These patches are delimited by surface geodesics linking a few predefined anatomical points in a same neighborhood of the skull. The estimation is done using the same patches available in our large database composed of whole head CT scans, extracted skull and face surfaces, and some useful anatomical and geometric information [31]. Furthermore, our estimator is constructed in a non-linear way to ensure its statistical adaptivity to individual and local disparities.

Our reconstruction technique is based on a representation of surfaces, as introduced in [33,34] using the mathematical notion of currents. This representation, which has since proved effective in many other medical applications [1,12], considers surfaces as vector fields defined on the whole space. It provides several features which are essential for the design of our facial reconstruction technique. Geometrically, the mathematical framework of currents is particularly well adapted for defining and computing distances between surfaces. The mathematical objects associated to surfaces belong to a scalar number. Thus, statistically, the average of surfaces can be defined and computed, which is fundamental for the facial reconstruction. Another major advantage of currents is that it does not require any parameterization of the surface: the surface is only represented by a cloud of points (the number of which may vary between surfaces) associated to a set of normal vectors. Mathematically, this flexibility of currents permits local manipulation of surfaces, and in the context of facial reconstruction, enables to envisage a local approach to soft tissue estimation based on dense meshes representing bone and skin surfaces.

The paper is organized as follows. The materials and the methods are presented in Section 2: the mathematical representation of the surface is introduced in Section 2.2, the construction and the registration of patches are respectively described in Sections 2.3 and 2.4. Our statistical estimation is presented in Sections 2.5 and 2.6. Section 2.7 summarizes the reconstruction technique. Section 3 is devoted to the presentation of the reconstruction results on two patches corresponding to chin and nasal regions. These results are discussed in Section 4.

2. Materials and methods

2.1. Materials

The study was carried out on a database of 47 whole head CT scans performed on European voluntary female patients, aged 20–40 years. Mathematical and computational processes were performed on the scanned images to extract the skin and bone surfaces. We also manually located about 30 anatomical points on each CT scan. This database, and the processes performed on it, are described in detail in [31].

2.2. Extended normal vector field

Here we briefly describe the mathematical model which underlies our approach. This section directly takes up ideas presented in [33] while presenting them in a somewhat more intuitive manner. We start from a given arbitrary surface \( S \), and associate to it the set of unit and oriented normal vectors to the surface. For points \( x \in S \), we will denote \( \tilde{S}(x) \) the corresponding normal vector. The map \( x \mapsto \tilde{S}(x) \) is the intrinsic normal vector field of the surface. This vector field defined on the surface \( S \) is then transformed into a vector field defined on the whole space called extended normal vector field (ENVF), as follows. Consider the tridimensional Gaussian kernel

\[
 k_r(r) = \frac{1}{(\sqrt{2\pi})^3} e^{-(r^2/2\sigma^2)},
\]

associated to the density of the centered Gaussian distribution with standard deviation \( \sigma \) in \( \mathbb{R}^3 \). This choice of kernel was favored because of its intuitive interpretation. We construct a so-called ENVF \( \tilde{S} \) which is defined for every point \( x \) in space by

\[
 \tilde{S}^x(x) = \int \frac{1}{k_r(|y-x|)} \tilde{S}(y) \, 
\]

where

- \( |y-x| \) represents the Euclidean norm of vector \( y-x \),
- the integral \( \int \) is taken on the whole surface \( S \),
- \( dS(x) \) represents the infinitesimal element of surface at point \( y \).

Fig. 1. Localization on the skull of the anatomical landmarks available in the database [31], and the two patches (in blue), delimited by geodesics between the selected sets of landmarks, corresponding to the chin and nasal regions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)
Intuitively, this extension allows us to give the surface a “thickness” in space by applying a dispersion blur (here Gaussian) at each point on the surface $S$.

In practice, the integral over the whole surface is not computable and we used a discretized version based on the knowledge of the mesh defining the skin surface. If the surface $S$ is represented by a triangulated mesh, for a triangle $t$ of the mesh, we denote $(a_t, b_t, c_t)$ its vertices, and $O_t = (a_t + b_t + c_t)/3$ its barycenter. We compute the (non-unitary) normal vector with the formula

$$n_t = \frac{1}{3} (b_t - a_t) \wedge (c_t - a_t),$$

where $\wedge$ denotes the cross-product of two vectors in space. This vector is orthogonal to the triangle and has its Euclidean norm equal to its area. We denote the surface $\mathbb{S}$ discretized version based on the knowledge of the mesh defining the skin surface. If $n_t$ the (non-unitary) normal vector with the formula

$$n_t = \frac{1}{3} (b_t - a_t) \wedge (c_t - a_t),$$

where the sum is taken over all triangles of the mesh.

2.2.1. Operations and distances between ENVFs

The introduction of ENVF enables to define

- the addition of two ENVF $S^x$ and $T^x$ as the vector field defined at each point $x$ in space by $S^x(x) + T^x(x)$,
- the multiplication of ENVF $S^x$ by a scalar $r$ as the vector field defined at each point $x$ in space by $rS^x(x)$.

In other words, the set of ENVFs has a vector space structure, on which one can define averages. This vector space can be equipped with a Hilbert structure associated to the scalar product defined by:

$$\left\langle (S^x, T^y) \right\rangle_o = \int \int k_o(y - x) \langle S(y), T(y) \rangle dS(x) dT(y),$$

where $(u,v)$ denotes the usual Euclidean inner product in $\mathbb{R}^3$. Using meshes to describe the surfaces $S$ and $T$, this formula is approximated by

$$\left\langle (S^x, T^y) \right\rangle_o \approx \sum_{t \in T} \sum_{i \in S} k_o(y - x) \langle (O_t - O_s), (n_t, n_i) \rangle,$$

where the first sum (respectively the second) is taken over all triangles indexed by $s$ (respectively by $t$) of the mesh describing $S$ (resp. $T$). Based on this scalar product, it is then possible to define a distance $d$ between surfaces as follows:

$$d_o(S^x, T^y) = \left\langle (S^x, S^x) \right\rangle_o + \left\langle (T^y, T^y) \right\rangle_o - 2 \left\langle (S^x, T^y) \right\rangle_o.$$

This distance is expressed in terms of the kernel $k_o$, and surfaces $S$ and $T$.

2.3. Patches

In order to localize the problem of estimation, we focus on sub-areas of the skull and skin surfaces. For this purpose we define a patch as an ordered sequence of anatomical points (see Fig. 1). We will name bone-patch the corresponding surface delimited on the skull of an individual and skin-patch the corresponding surface delimited on the cutaneous tissue. These notions of bone-patch and skin-patch are observable individual notions, thus practicable from a statistical point of view.

2.3.1. Bone-patch extraction

To specify a bone-patch, we have at our disposal, on the one hand, some anatomical points located on the skull mesh as vertices and, on the other hand, geodesics linking these points. The bone-patch is extracted by selecting the closed portion of surface delimited by the geodesics between the anatomical points.

2.3.2. Skin-patch extraction

For a given individual, we want to extract a part of the skin surface which will be defined as skin-patch. For each anatomical points located on the bone (see Section 2.3.1), we find the closest point on the skin surface, called projected anatomical points. Using a similar approach as in Section 2.3.1 we define the skin-patch as the interior of the surface defined by the geodesic of these projected anatomical points.

Let us emphasize that the main area of interest is that inside the patch distant from its boundaries. Using our method, the possible undesired effects due to the boundary do not influence the estimation on the central part of the patch. Typically, in the case of the nose, we want to estimate the soft tissues over the nasal orifice with greater precision. This area is located in the center of the patch and is consequently well covered.

This method of determination of a skin-patch can be applied to simply-connected bone-patches (without any hole) as well as to not simply-connected bone-patches such as those surrounding the nasal orifice.

![Fig. 2. Nose reconstruction of one individual in our database. From left to right: bone surface of the individual to be reconstructed; the three closest neighbors to the previous surface in the database; their associated skin surfaces; the estimated skin surface, obtained by averaging the skin surfaces in the database with weights defined by (3); true skin surface of the individual. N.B. The selected individual was removed from the database for the reconstruction.](image-url)
2.4. Semi-rigid registration of patches

We performed a semi-rigid registration of the bone-patch $B_i$ on a reference patch $B_0$ on the basis of positions of the anatomical points delimiting the patches. This registration is obtained by determining the semi-rigid transformation $\phi_{0i}$ (composition of rotations, translations and scalings) which minimizes the distance $d_o$ (introduced in Section 2.2.1) between the ENVF corresponding to the surface mesh $B_i$ and the surface mesh $B_0$, aligned and rescaled by the transformation. In other words, we determine the semi-rigid transformation $\phi_{0i}$ which minimizes, over all semi-rigid transformations $\phi$, the quantity

$$j(\phi) = d_o(\phi(B_i)^\tau, B_0^\tau),$$

where $\phi(B_i)$ is the surface obtained by moving $B_i$ through the deformation $\phi$. From a practical point of view, this corresponds to moving all vertices of $B_i$ through the transformation $\phi$. This method is directly derived from the registration method described in [33], but here we limit ourselves to semi-rigid transformations.

This provides the registered surface $\phi_{0i}(B_i)$. Applying the same transformation $\phi_{0i}$ (computed on bone surfaces) to the skin surface $S_i$, we obtain the registered skin-patch $\phi_{0i}(S_i)$.

Let us remark that in this construction, the ENVF of a registered surface coincides with the registered ENVF of the same surface $i.e.$ $\phi(B_i)^\tau = \phi(B_0^\tau)$.

2.5. Estimation of the skin surface

The problem of estimating the skin surface given a dry skull may be statistically understood as a semi-parametric regression problem with random design. In this setting, we observe a sample of an unknown distribution of warped “heads” (association of skull and skin) and, given a new warped skull, one wants to estimate its most probable associated skin, which is the conditional expectation of the skin under the unknown distribution, given the sample and the knowledge of the new skull.

Mathematically, one can only define a distribution and hence a conditional expectation on the Hilbert space of the ENVF following the construction described in [5]. In this space, we observe warped couples of ENVF

$$(B_{0i}^\tau, S_0^\tau) = (\phi_{0i}(B_i), \phi_{0i}(S_i)), \ i = 1, \ldots, n$$

where $(B_{0i}^\tau, S_0^\tau)$, $i = 1, \ldots, n$ are independent couple of random variables drawn from an unknown distribution $\pi$ defined on the Hilbert space of the ENVF and where the $\phi_0$’s are individual unknown parametrical transformations of the space $\mathbb{R}^3$.

Given a new $B_0^\tau = \phi_0(B_0^\tau)$, we aim at estimating its unknown associated $S_0^\tau = \phi_0(S_0^\tau)$. In a statistical learning framework, and up to the parameters $\phi_0$’s, we face a non-parametric prediction problem for which the solution is the conditional expectation $\bar{S}(\pi, \phi(B_0^\tau), i = 1, \ldots, n, B_{0i}^\tau)$ with respect to the unknown distribution $\pi$ and knowing the warped and extended couples $(B_{0i}^\tau, S_0^\tau), i = 1, \ldots, n$ of our database and the warped and extended surface $B_{0i}^\tau$ of the dry skull.

This problem is related to the work in [21,15]. In their setting, $B_i$ is known and fixed and it is the time interval corresponding to one day (fixed design regression); $S_i$ is the traffic intensity over a road at a precise location $i$ and the parameter $\phi_i$ is a shift in time.

In our random design context, if the $\phi_0$’s were known and invertible, a classical estimate of the conditional expectation would be a generalization of the Nadaraya-Watson kernel estimator [25] defined by

$$\bar{S} = \frac{\sum_{i=1}^{n} (\phi_{0i}^{-1}(S_0^\tau)) K((d_o(B_{0i}^\tau, \phi_{0i}(B_0^\tau))) / h))}{\sum_{i=1}^{n} K((d_o(B_{0i}^\tau, \phi_{0i}(B_0^\tau))) / h))},$$

where $K$ is a positive kernel and $h$ (the bandwidth) is a smoothing parameter. In this expression, $\phi_{0i} \sim \phi_0^{-1}$ clearly appears as the transport of the information.
we set at 4 the value of the window size.

We computed the evaluation error through leave-one-out cross-validation (see Section 2.7. Summary of the method).

Average weight; (2) above an adaptive distance (c) is minimal. Then, using the technique described in [33], we perform a non-rigid registration ψ to ensure that the transported ENVF ψφo(Si) matches with the average ENVF S.

Finally, our estimate of the unknown surface Si is ψφo(S).

2.6. Choice of weights \( w_{0} \)

We now specify the choice of weights \( w_{0} \) which appear in Eq. (2) that we have used in our applications. Intuitively, smaller values of \( d_{s}(B_{0}, \phi_{0}(B_{i})) \) indicate bone surfaces which are similar in shape. Assuming that this similarity in shape between bone-patches corresponds to the similarity in shape between skin-patches, we decided to give a weight \( w_{0} \) inversely related to the distance \( d_{s}(B_{0}, \phi_{0}(B_{i})) \). More precisely, we defined

\[
w_{0} = \begin{cases} 
0 & \text{if } d_{s}(B_{0}, \phi_{0}(B_{i})) > c \min_{i \neq 0} d_{s}(B_{0}, \phi_{0}(B_{i})) \\
1/d_{s}(B_{0}, \phi_{0}(B_{i})) & \text{otherwise.}
\end{cases}
\]

where \( c \geq 1 \) is a constant to be chosen by the user. This choice of adaptive weights solves two problems: (1) the closer the individual \( i \) is to individual 0, the greater her average weight; (2) above an adaptive distance \( c \) times the minimal distance, one individual is no longer part of the evaluation of the mean.

We tried several values of the constant \( c \) in the range \([1, +\infty)\). For each value of \( c \), we computed the evaluation error through leave-one-out cross-validation (see Section 3.3). After these experiments, we chose the value 1.4. After several experiments, we set at 4 the value of the window size \( \sigma \) appearing in the expression of the kernel to compute ENVFs. This value is about the same as the thickness approximation error [31].

2.7. Summary of the method

Our estimation method can be summarized in three points:

1. Definition and extraction of the skin \( S_{i} \) and bone \( B_{i} \) patches on all subjects. This step is described in Section 2.3.
2. Rigid registration of the patches. For each subject \( i \), a rigid transformation \( \phi_{i} \) which best matches surfaces \( B_{i} \) and \( B_{0} \) is computed and applied to surfaces \( B_{i} \) and \( S_{i} \). This puts all surfaces into the neighborhood of subject 0. This step is described in Section 2.4.
3. Estimation of the unknown skin surface \( S_{0} \). This estimation of the unknown skin surface is obtained by computing a weighted average of the registered skin surface ENVF: This step is described in Section 2.5.
4. Choice of the weights \( w_{0} \). Choice of weights correspond to the choice of kernel \( K \) and bandwidth \( h \) appearing in (1). The precise choice of weights is described in Section 2.6.

3. Results

3.1. Application to chin and nasal regions

We chose to conduct this study first on nasal and chin areas. The chin bone-patch is determined from the right mental, gnathion, left mental and infradental points. The nose bone-patch is determined from the right infraorbital, prosthion, infraorbital and nasion points.

Fig. 2 shows one typical reconstruction. One individual has been taken out from the database in order to test our facial reconstruction method on the bone patch of the nasal region. The three closest nasal bone patches (which have highest weights for the reconstruction) of our database are presented, together with their associated skin patches. The estimated skin using the weights given by formula (3) is shown with the true skin, which was considered as unknown.

For these areas, we present here an evaluation by leave-one-out cross-validation of the mean reconstruction error and a visual comparison of real and estimated soft tissue morphologies.

![Fig. 4. Comparison between true (rows 1 and 3) and estimated (rows 2 and 4) nose patches for two individuals of the database. From left to right, three orientations are chosen: front, oblique, profile. The color plot shows the distribution of estimation errors \((d(v, \pi_{i}(v)), see section 3.3)\) in mm over the estimated patch. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)](image)
3.2. “leave-one-out” validation

We studied 47 individuals for whom we had whole head CT scans from which we extracted bone-surfaces and skin-surfaces meshes. This set of couples (bone-mesh, skin-mesh) formed our learning database, denoted \( \mathcal{D} \) in the following. To evaluate our reconstruction methods, on a given patch, we used the “leave-one-out” cross-validation method. For each individual \( i \) of the learning base, we considered the sub-family \( \mathcal{D}_{i,i} \) made up of all the individuals except individual \( i \). For the individuals of the sub-family \( \mathcal{D}_{i,i} \), we had full information (bone-mesh, skin-mesh). For the individual \( i \), only the “bone-mesh” information was considered to be known. The soft tissue estimation for individual \( i \) given the chosen patch, was computed from the sub-family \( \mathcal{D}_{i,i} \) and is denoted \( \hat{S}_i \) in the following.

3.3. Estimation error over the selected patch

The supplementary “skin-mesh” information of the individual \( i \) was used to calculate an estimation error over the selected patch, referred to as \( e_i \). This estimation error is defined as the surface-average over the estimated skin-patch \( \hat{S}_i \) of the distances from every vertex of \( \hat{S}_i \) to the full real skin triangulated surface \( S_i \) of individual \( i \). More precisely, we computed

\[
e_i = \frac{\sum_{v \in \hat{S}_i} \hat{A}(v)d(v, \hat{P}_F(v))}{\sum_{v \in \hat{S}_i} \hat{A}(v)}
\]

where \( \hat{P}_F(v) \) denotes the projection (closest point) of \( v \) on true surface \( F_i \); \( d(\cdot, \cdot) \) is the euclidean distance in \( \mathbb{R}^3 \); \( \hat{A}(v) \) is the local area of surface \( \hat{S}_i \) around vertex \( v \), defined as one third of the sum of areas of triangles connecting \( v \).

Figs. 3 and 4 show two visual outputs of our reconstruction method with their associated error maps, for the chin and the nasal regions. More examples of reconstruction for the nasal region are provided in Fig. 5 which shows 12 individuals, selected for their visual quality of reconstruction, with their associated error maps, providing a comparison between visual quality and error measurements; Fig. 6 shows superimpositions of true and estimated surfaces for the 47 individuals of the database.

The error calculated by “leave-one-out” cross-validation was defined as the empirical mean of \( e_i \) when \( i \) ranged from 1 to 47. For both chin region and nasal region, the mean reconstruction error was 0.99 mm. The individual errors \( e_i \) range from 0.58 mm to 1.83 mm for the nasal region, and from 0.21 mm to 2.41 mm for the chin region. This upper bound of 2.41 mm is mainly due to artifacts in the mesh generation and could be improved. The histograms of the \( e_i \)’s for both patches are presented in Fig. 7.

Fig. 8 shows the cumulative empirical distributions of the errors at each vertex for both regions.

4. Discussion

Facial reconstruction can be regarded as the estimation of the face by a surface. This surface is the result of a “sculpture” realized after the application of markers representing the thickness of soft tissues at reference landmarks on the craniofacial block. In order to improve the facial reconstruction, one can either multiply the number of landmarks/thickness pairs or use morphological characteristics such as muscular attachments and muscle representations. Both techniques aim at providing a better description of the external surface of the tissue. Unfortunately, on one hand, proper landmarks miss the skull and, on the other hand, muscle description is difficult to estimate and to handle automatically. To avoid these problems, we propose to work directly with surfaces defined in between a small number of landmarks located on the skull and also on the face for the examples of our learning database. The skull/face surface pairs generalize in a continuous way the landmark/thickness pairs. Our approach allows to take into account long range characteristics in between landmarks. Using a mathematical representation of surfaces as flows of vector fields, and based on a statistical learning approach, the external tissue surface is directly estimated without the need of actual sculpture.

In the learning approach, it is assumed that the size of database is large in order to achieve good estimation. Here, because of the small size of our database, we are not expecting to achieve good (visual or mathematical) results for all cases. We only expect that few cases may be properly reconstructed, in order to show the feasibility of our approach. Since the estimated tissue is built as an average of known surfaces of the database, we cannot expect to reconstruct features which are uniquely found in the unknown subject.

Our local technique was motivated by the statistical need to control the number of parameters involved in the reconstruction (e.g. the parameters of the registrations) and to develop a piecewise reconstruction locally adaptive with respect to the choice of the neighbors. We applied this technique to two regions of interest, the chin and the nose, on a homogeneous database of CT-scans of female caucasian subjects with age 20–40.
Fig. 6. Cumulative empirical distributions of the errors ($- \| v; \Pi_1 \| v \|$), see section 3.3) in mm computed at each vertex $v$, for each of the 47 estimated individual (thin lines), and for the whole set of vertices (bold line). Left: chin region, right: nasal region.

Fig. 7. Nasal region reconstruction of 12 individuals of our database, selected for their visual quality. Each line presents two individuals. For each individual, true (left), estimate (middle) and error color maps (right) are represented. Errors ($- \| v; \Pi_1 \| v \|$, see section 3.3) are in mm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)
The soft-tissue of the chin mainly can be assumed to be strongly related to the underlying bone support. However, a certain amount of variability between soft tissue and bone in this area has been reported [20]. It is mainly due to the variability in skin elasticity and to the presence of different amount of adipose tissues. Moreover, the chin is part of the buccal mandibular complex. Certain particularities of chin morphology are related to possible skeletal imbalance and to occlusion, but others cannot be identified from observing the bone. As mentioned in [2], the soft tissue of the skin may mask or accentuate an anomaly of the skeletal profile. For the chin region, our algorithm performs well: the error estimated by cross-validation on the whole database is below 1 mm, the lowest mean individual error being 0.21 mm.

Nasal reconstruction from a simple bone support raises a certain number of issues and is known to be one of the most difficult goals to reach. Indeed, the bone support of the nasal region is not simply connected. Moreover, the nose consists of a bone area, a cartilaginous area and a tip that is practically free. Only the upper...
region of the nose has a bone support. When bones are found, usually the cartilaginous area is missing and often the nasal bones and the anterior nasal spine are fractured. These are the only elements which are likely to bring any information concerning the morphology of the nasal crest and the base of the nose. The positioning of the tip of the nose is also problematic and the slope of the anterior nasal spine greatly impacts the position of the nasal tip [16,11]. For certain authors [22], the morphology of the nasal tip may present numerous variations that cannot be predicted from observing bone morphology. Despite all these difficulties concerning the nasal region, our algorithm has the same performance for this region as for the chin: the error estimated by cross-validation on the whole database is also below 1 mm. The mean individual error ranges from 0.58 mm to 1.83 mm.

From a local reconstruction point of view on a quantitative basis made from mm deviations, the deviations obtained on the nose outperform the deviations obtained in [39,29]. We obtain a mean absolute deviation less than 1 mm. This is to compare with the deviations found in [39] which are 2.5 mm on average and above 3 mm in the nasal area. These results have to be put into perspective, considering the small size of the databases.

Next we compared our results to those of [35]. Among global reconstruction approaches, their technique is the closest to ours as it uses a continuous representation of surfaces. Their study was conducted on a database of 20 CT scans which is more than twice smaller than the one we use. Moreover, their database is constructed without any selection on the basis of age, sex or origin. In their study, the reconstruction error integrated over the complete face is on average 1.9 mm with a standard deviation of 1.7 mm. The greatest reconstruction errors occurs at the nostril and masseter regions. From the figures of [35], we deduced that the reconstruction error on the nasal regions is about 2.5 mm on average, with a standard deviation of 1.5 mm, and on the chin region, between 2 and 2.5 mm on average, with a standard deviation around 1.75 mm. Let us point out that these results are similar or even better than usual results obtained with global techniques. The computation of errors are averaged over surfaces and hence normalized by surface area. Thus, it is possible to compare directly our local reconstruction error with the global ones. Our technique significantly outperforms the global results.

The surfaces that we use for reconstruction are defined by anatomical landmarks and provide information on the geometrical properties like tangents, geodesics, etc. Hence, our approach generalizes classical methods based on landmarks [19], and geometrical characteristics [28]. Our specific mathematical formulation of vectorized surfaces allow to use these complex objects for statistical regression and prediction based on nearest neighbor. Our statistical estimate uses the database instead of the knowledge of a practitioner. Due to statistical properties (like the law of large numbers, concentration, etc.) we can expect this estimate to mimic properly an expert practitioner when the size of the database becomes large.

5. Conclusion

In this paper, we presented an original technique of local facial reconstruction which satisfies the paradigm of non-parametric statistics and is adaptive to individual and local variations. This technique relies on a continuous representation of the individual surfaces embedded in the vectorial space of extended normal vector fields. This allows to compute deformations and averages of surfaces. It consists in estimating the soft-tissue surface over patches delimited by surface geodesics between anatomical points of the skull. Using a homogeneous database described in [31], we obtained encouraging results which outperform those of the global reconstruction techniques found in the literature.

This study has been conducted on caucasian female subjects within a same age range. It would be of interest to extend this study to other populations in order to quantify the influence of factors (age, gender, origin) on facial reconstruction.

Our results would benefit from the use of a larger database. Since our technique is local, it allows the exploitation of incomplete CT-scans which are commonly acquired during medical exams (e.g. sinus or dental) and which could be automatically added to our database.

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References


