Reconstruction 3D régularisée à partir d'un faible nombre de projections en imagerie maxillo-faciale : faisabilité et premiers résultats expérimentaux

3D regularized reconstruction from a small number of projections in maxillo-facial imaging: feasibility and first experimental results

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Résumé

La reconstruction 3D à partir de projections est très répandue dans le domaine de l'imagerie médicale. Cependant, les contraintes particulières des acquisitions maxillo-faciales limitent la qualité des résultats. Nous montrons dans cet article que les méthodes de reconstruction algébriques régularisées sont bien adaptées à ce problème, et nous proposons une étude expérimentale pour l'optimisation des paramètres.

Introduction

3D reconstruction from radiographic projections is a widely addressed problem in the medical imaging literature. However, no application has been found so far in the mandibular reconstruction field. Dentists requirements are very specific and induce particular constraints:

- The information to be found is very specific: cortical bone and dental canal should be accurately reconstructed.
- 3D densities of the bone are important, which calls for a volumetric reconstruction, not only a surface one.
- The input data consist of very few radiographic projections (typically up to 8) and in very limited positions (due to anatomical constraints).

These constraints led us to develop an approach consisting of a reconstruction part and a regularization method (to constrain the reconstruction with some *a priori* information and to deal with the reduced number of projections).

The contribution of this paper is to show that regularized algebraic reconstruction is well adapted to this problem and to provide an experimental study for parameter optimization.

Algebraic reconstruction

The possibility of adding *a priori* information and adaptability to different geometries are absolutely necessary for our reconstruction problem. This is difficult to incorporate in analytical methods. On the other hand, statistical methods are often complex to implement [1].

Therefore, we have chosen algebraic methods. Among them, *ART (Algebraic Reconstruction Technique)* and *SIRT (Simultaneous Iterative Reconstruction Technique)* seem to be the more appropriate candidates.

Equation 1 expresses the problem to be inverted, where y represents the projection data, x is the objet to be reconstructed, H is the projection matrix and η represents data noise. The algebraic method principle is shown in the right term of the equation, where k is the iteration number and λ is a relaxation coefficient.

$$y = Hx + \eta \Rightarrow x^{k+1} = x^k + \lambda H^T(y - Hx^k) \quad (1)$$

Another advantage of these methods is that they can be implemented in a quite simple way. However, SIRT provides a better robustness against noise and is more stable than ART. That is why we preferred to use this method.

Regularization

The purpose of the regularization step is to limit the solution domain by introducing information about the object to reconstruct through the minimization of an energy function:

$$J = Q + \lambda \cdot \Psi$$

- The first term (Q) constrains the solution to have projections as close as possible to the original ones and is expressed as $||y - Hx||^2$.
- The second term (Ψ) models *a priori* knowledge about the object, as positivity of the values, homogeneity of the volume, contrast...

- λ is the parameter that controls the regularization weight compared to the projections information.

The second part is characterized by a *potential function* ϕ (that should be convex for convergence [2]). In our specific case, discontinuity preservation is needed. For this reason, we have chosen *Huber* (Eq. 2) and *Charbonnier* (or *minimal surfaces*) functions (applied on differences between neighbors) which are convex functions and which preserve discontinuities (see e.g. [2],[3]).

$$\phi(x) = \begin{cases} x^2 & \text{if } |x| \leq \alpha \\ 2 \cdot \alpha \cdot |x| - \alpha^2 & \text{if } |x| > \alpha \end{cases} \quad (2)$$

Experimental results

In order to perform experiments, a radiographic simulator has been developed. Thanks to it, we have taken several radiographic projections from real CT (*Computed Tomography*) scanner images.

It is obvious that the reconstruction quality depends directly on the number of projections we take, as we can see in Figure 2 comparing the reconstructed image with the original one.

The influence of the regularization parameters is as follows:

- When λ is higher, more noise is filtered.
- When α (see Equation 2) increases, then bigger differences between neighbors are smoothed [2].

So, we have to look for the best parameter combination (α and λ). See Figure 1.

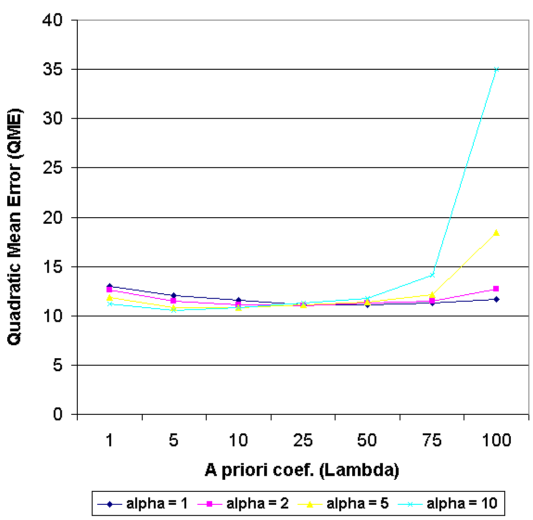

Figure 1: QME comparison for different combinations of λ and α with 8 projections

Figure 2 shows that regularization improves reconstruction results (cortical bone and dental canal are well reconstructed for an appropriate choice of the parameters).

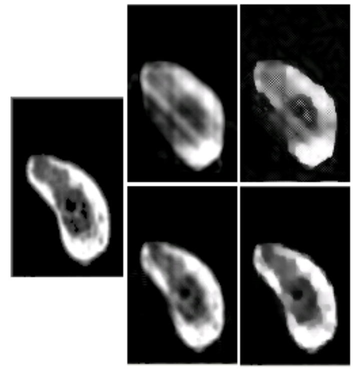

Figure 2: Original image (left) and from left to right and from top to bottom: SIRT with 4 projections, Regularized SIRT ($\lambda = 50$ and $\alpha = 5$) with 4 projections, SIRT with 8 projections, Regularized SIRT ($\lambda = 50$ and $\alpha = 5$) with 8 projections.

Conclusion

We can conclude that the optimal λ-α combination depends on the projection number. In our case, with 4 projections the optimal couple is $\lambda = 1$ and $\alpha = 2$. With 8 projections, the best combination is $\lambda = 5$ and $\alpha = 10$.

However, this combination is only applicable to similar images (same constrast levels, similar homogeneity properties, no noise) and with the same projection geometry (same number of projections, similar positions). This means that the optimal combination may depend on the patient (and the projection geometry) which calls for further investigation.

Future work aims at adding other *a priori* information obtained from statistical models of the mandibular bone densities, so that it will be easier to find visually in the reconstructed images the dental canal and the cortical bone of the jaw.

References

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