

Seminar Presentation Summary

Extrapolation of Missing Craniofacial Skeletal Structure via Statistical Shape Models
Project 1, EN.600.646 Spring 2014

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1 Review

Our project is related to craniofacial transplant surgery. For this kind of surgery, the surgeon must decide whether to perform in 24 to 36 hours. It is a really short time period. There are several factors that the surgeon must concern. One important factor is whether the face of donor and patient are matched. Therefore, we want to use the statistical shape models of the face to extrapolate missing anatomical craniofacial skeletal structure. We hope it can assist the surgeon to make the decision more quickly. We choose two papers to discuss in this summary. One is about atlas creation. The other one is about surface estimation.

2 Atlas Creation

Paper: Statistical Atlases of Bone Anatomy Construction, Iterative Improvement and Validation, Gouthami Chintalapani, Lotta M. Ellingsen, Ofri Sadowsky, Jerry L. Prince, and Russell H. Taylor

This paper gives the pipeline of Atlas creation. Figure 1 shows three main steps for Atlas creation.

1. First of all, we have to choose how to represent our medical images. This representation must be easy to manipulate can reflect the information of anatomical structure such as shape and intensity. Triangular mesh and tetrahedron mesh are very popular representation for Atlas creation. In this paper, they use tetrahedron mesh.
2. This step is also known as "registration". The representation should be aligned first, since these medical image may be taken under different patient positions. This will impact on statistical analysis.

3. The statistical model is created after perform the statistical analysis.They use PCA to create the statistical model.

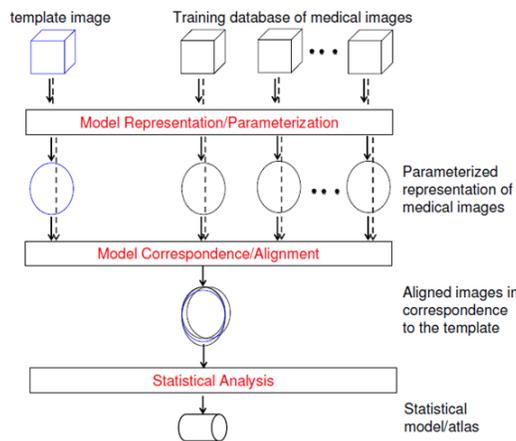


Figure 1: A high level overview of Atlas Creation.

Gouthami Chintalapann, Statistical Atlases of Bone Anatomy and Their Applications

Before computing the mesh, the image must be manually or semi-automatically segmented and labeled. It is a complicated and tedious work. The author use volumetric gray scale deformable registration method to avoid this time-consuming work. This method can give us dense deformation map. Dense deformation map is used to describe the transformation between two images. Suppose we have the mesh of one image and the deformation map which describes the transformation between this image and the other. We can compute the corresponding location for vertices of mesh in other image according the deformation map. Now, we not only get the mesh for the other image but also the correspondence of the vertex in different images.

The author modifies the first step of Atlas Creation. They pick one image as template, segment it and do the meshing algorithm. After that, we use the volumetric gray scale deformable registration to get dense deformation map between each training image and the template. Use this deformation map to deform the mesh of the template to get the mesh of each training data and the correspondences between the vertices of each mesh.

For second step, the author uses Procrustes Analysis method to align each mesh. This is used to remove the variation due to different patient pose. These variation includes global rotation, translation and scaling.

After having aligned meshes, $(S_1, S_2, S_3 \dots S_N)$, they can get mean shape of these meshes

by Eq(1)

$$M = \frac{1}{N} \sum_{n=1}^N S_n \quad (1)$$

and compute the the difference between mean shape and each mesh. Finally, they do the PCA on these difference to extract the shape variations. Now, we can describe any new shape S_{new}^{true} by Eq(2).

$$S_{new}^{est} = M + \sum_{k=1}^K \lambda_k U_k \quad (2)$$

U_k is the variation mode, and we use K variation mode. If we already aligned S_{new}^{true} with the mean shape, we can also compute the λ_k by Eq(3). U equals to $[U_1, U_2, \dots, U_K]$.

$$\lambda = U * (S_{new}^{true} - M) \quad (3)$$

The paper also provides an iterative framework to bootstrap the Atlas creation which can prevent the bias of template and result in stable and consistent Atlas. They use the mean shape and mean density polynomial from atlas to create a new image, consider as template, and do each step in the pipeline again. It will stop when the resulting Atlas does not change much.

They also do the leave-out validation test on their method. There are 110 healthy CT pelvis datasets for using . 90 datasets are used for Atlas creation. The remaining 20 datasets is used to perform leave-out validation test. The result is show in Figure 2.

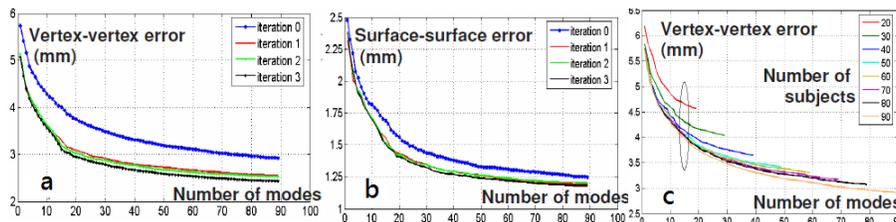


Figure 2: Error as a function of number of modes using(a) distance between estimated vertex to true vertex (b) closet distance between estimated vertex to true surface (c) Different number of dataset are used to create Atlas.

Gouthami Chintalapann, et al, Statistical Atlases of Bone: Construction, Iterative Improvement and Validation

We can see that the error in Fig(2a) and Fig(2b) become smaller when we do more iteration. In the beginning, the distance decreases significantly, and it converges after doing few iterations. The result in Fig(2c) shows that the more datasets that we can use for training, the less distance error we will get in estimation.

3 Surface Estimation

Paper: Statistical Atlas Based Extrapolation of CT Data, Gouthami Chintalapani, Ryan Murphy, Robert S. Armiger, Jyri Lepisto, Yoshito Otake, Nobuhiko Sugano, Russell H. Taylor and Mehran Armand

There couples of section in this paper, but we just discuss the section which is related to our project. In previous paper, it mentions how to create Atlas for anatomical structure. In this paper, it provides a method to deduce the missing anatomical information from partial of image and Atlas of full anatomical structure. As we can see in, S_j is what we observed, and the goal is try to infer S_i which is missing.

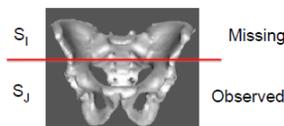


Figure 3: The illustration of the problem

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To deduce the missing part, we re-arrange the mean shape M and shape variations U in the beginning. Eq(4) is the form that we want to re-arrange.

$$M = \begin{bmatrix} M_I \\ M_J \end{bmatrix} U = \begin{bmatrix} U_I \\ U_J \end{bmatrix} \quad (4)$$

M_J and U_J are mean shape and corresponding mode vector of the observed data. M_I and M_J are mean shape and corresponding mode vector of the missing data. Then, they randomly sample m points, p^k $k = 1, 2, \dots, m$. We can register these sample points onto the Atlas by F which is the rigid transformation. Combining them together, we can get Eq(5)

$$F^t * p^k \approx M_J^k + \lambda^t * U_J^k \quad (5)$$

In this equation, F^t and λ^t are unknown. We can use iteratively method to solve these two unknown parameter. First, we fix F^t and solve for λ^t . Then, we fix λ^t and solve for F^t . We do these two steps until it converges.

After getting λ^t , we can use Eq(6) to estimate whole anatomical structure which includes missing region.

$$S^{est} = \begin{bmatrix} S_I^{est} \\ S_J^{est} \end{bmatrix} = \begin{bmatrix} M_I \\ M_J \end{bmatrix} + \lambda^t \begin{bmatrix} U_I \\ U_J \end{bmatrix} \quad (6)$$

S_J denotes observed data. It means we have the true information of S_J . Therefore, we replace S_J^{est} with S_{Jtrue} and we can get Eq(7). Finally, we can estimate the missing data

from prior Atlas and observed data.

$$S^{est} \begin{bmatrix} S_I^{est} \\ S_J^{true} \end{bmatrix} \quad (7)$$

This author also does the leave-n-out test to validate his method. There are 110 pelvis datasets. 104 datasets are used for Atlas creation. The remaining dataset are used for validation. The partial CT was simulated by keeping the slices which contain the hip joint region and removing others. The author uses the surface distance between true surface and estimated surface as residual error.

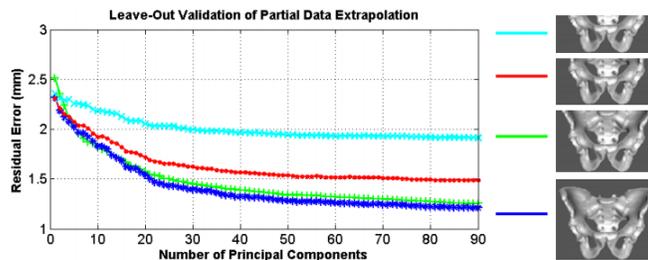


Figure 4: The result of leave-out test

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Fig(4) shows the residual error when observed different portion of the pelvis. We can see that the more data we observed the residual error are going to be smaller. As we can see if we observe the full data we can get the smallest error. If we just observe half of data the error will be largest in these four cases.

4 Analysis

In first paper, it provides the flowchart of Atlas creation for pelvis. For our project, we want to create the Atlas of ecraniofacial skeletal structure. Our problem is very similar to the problem they have. Therefore, we just need to slightly modify their method to solve our problem. There is no doubt that we change the subject from pelvis to skull. We use the triangular mesh in our case, since we just want the shape of the skull. Currently, we don't do bootstrapping in our method, since we don't have the information about mean density polynomial. However, we will try to modify this part and design a new bootstrapping algorithm which can use in our case. Then, we can get remove the template bias and get the more accurate Atlas.

The second paper talks about how to estimate the missing data according the observed

data and the Atlas. In our case, we can consider craniofacial skeletal structure with severe deformation as missing data and normal part as observed data. Now, we can estimate patient's appearance without abnormal pathology.