computer-aided surgery planning, segmentation, pelvic reconstruction, statistical shape model, pelvic tumours, pelvic osteotomy

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USING OF STATISTICAL SHAPE MODELS FOR PELVIS RECONSTRUCTION IN THE ONCOLOGIC SURGERY

The reconstruction of the osseous structures in the pelvic region after bone tumour resection is highly complex and challenging. Up to now the reconstruction of the pelvis defects by autologous or allogenous grafts (for instance the fibula transplants) are highly unsatisfied because of large shape differences. Therefore there is a huge demand for patient-specific and anatomically shaped implants. Our pelvis reconstruction planning approach is based on the statistical shape model. For generation of the statistical pelvis shape model a large data pool of CT datasets has been collected. The following CT data segmentation and surface processing methods delivered the required pelvis geometries. Via Procrustes analysis of the collected pelvis surfaces the parameterized pelvis shape mean model has been calculated and the principal component analysis (PCA) [3] applied for estimating the anatomically optimal graft or implant geometry. We will demonstrate on the clinical pelvis reconstruction case that the using of statistical shape models in the oncologic surgery planning is robust and very promising method.

1. INTRODUCTION

Bone tumour is an abnormal growth of cells within the bone. That may be benign (noncancerous) or malignant (cancerous). Benign bone tumours are more common than malignant ones. However, benign tumours do not spread and are rarely life-threatening. Cancer that arises in the bone (primary bone cancer) are rare. Metastatic cancers that spread to the bone from another part of the body (secondary bone cancer), such as the breasts, lungs, kidney, thyroid and prostate), are the most frequent malignant tumours found in bone. The most common type of bone cancer is osteosarcoma, which develops in new tissue in growing bones. Another type of cancer, chondrosarcoma, arises in cartilage. Evidence suggests that Ewing's sarcoma, another form of bone cancer, begins in immature nerve tissue in bone marrow. Osteosarcoma and Ewing's sarcoma tend to occur more frequently in children and adolescents, while chondrosarcoma occurs more often in adults. The pelvis oncologic surgery is beside the radiotherapy the most common treatment of malignant bone tumours. Pelvis is one of the principal elements of the human locomotor system therefore the reconstruction of the pelvis after resection of malignant pelvic tumours presents a highly complex and challenging problem. One of the main problems is the shape definition of artificial implants or autologous transplants for anatomically optimal reconstruction of the resected osseous part. The analysis of the anatomical shape and statistical shape modelling is a wide area of investigation. In the past many authors have developed statistical shape models for different anatomical structures (see for instance [4]). The purpose of this paper is to investigate the use of statistical shape models in the preoperative surgery planning for pelvis reconstruction.

2. METHODS

There are different planning approaches for reconstruction of the resected part of the pelvis. A standard computer-aided surgery planning procedure in the reconstructive surgery is the mirroring method. It is based on the preoperatively acquired computed tomography (CT) dataset of the patient. After segmentation of the unaffected side a mirrored surface is aligned with the defected region. It enables fast generation of an anatomically similar model of the target region. The drawbacks of this method are the natural asymmetry in human anatomy and the fact that the existing osseous structures on the unaffected side are often malformed due to increase of load on the healthy side. The additional limitation is that this method can be applied to unilateral defects. The bilateral defects still remain a challenging problem in the reconstructive pelvic surgery planning.

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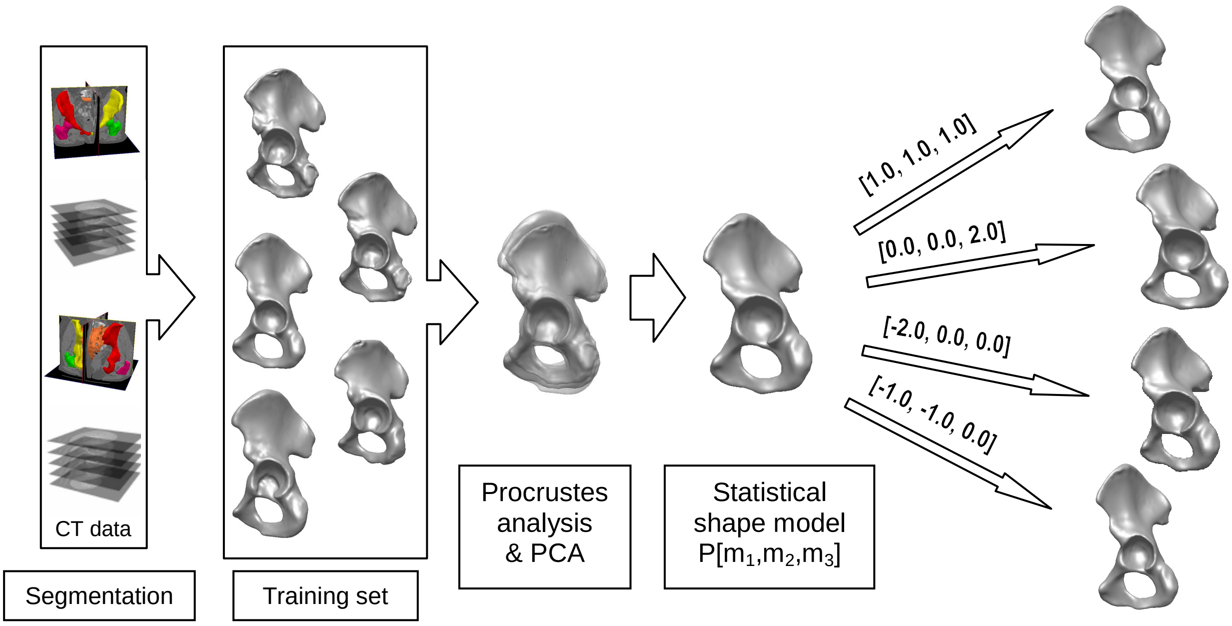


Fig. 1. Different stages of the data processing pipeline for generation of the statistical pelvis shape model.

Our new planning approach is based not only on the patient single CT dataset for the fitting the designed implant shape to the existing osseous structures but uses the statistical pelvis shape model for the optimal reconstruction of the morphological region of interest (ROI). For generating the statistical pelvis shape model one need a large data pool of pelvis CT datasets. The required pelvis geometries (called training set) are obtained via segmentation and surface processing methods. Different stages of the data processing pipeline for generation of the statistical pelvis shape model are presented in Figure 1.

In this section we present a brief overview of the statistical shape model generation process. The main stages of the method: segmentation, surface mesh processing, data alignment and the principal component analysis are explained and illustrated.

The training set for the pelvis statistical shape model has been generated using a CT data pool (n = 12) collected at our hospitals. In our approach the pelvis shapes are described by triangular mesh surfaces. The generation of the training set is done via segmentation of the CT data. Various segmentation methods implemented in our self developed segmentation, visualization and modelling system SeVisMo [6] has been used for generation of the training set. The region growing segmentation methods: connected threshold, neighbourhood connected, confidence connected, isolated connected; flood fill methods, mask operations as well as the manual segmentation tools were required to identify and separate all bones in the pelvis region (right pelvis, left pelvis, sacrum, right femur and left femur) for all CT datasets (see Figure 2). In Figure 3 are presented five left pelvis bones segmented using the mentioned above methods and belonging to our pelvis shape training set.

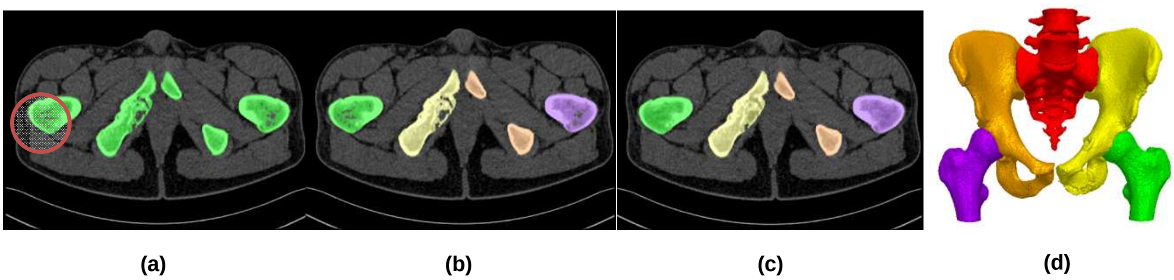


Fig. 2. CT data segmentation of the patient with a tumorous lesion at the left ischiopubic ramus (red circle):
(a) oseous structures (green) segmented using the connected threshold method,
(b) manually separated bones,
(c) masks with filled internal structure of bones, final stage of the segmentation process,
(d) surface mesh representation of the segmented bones, generated by the marching cubes algorithm [9].

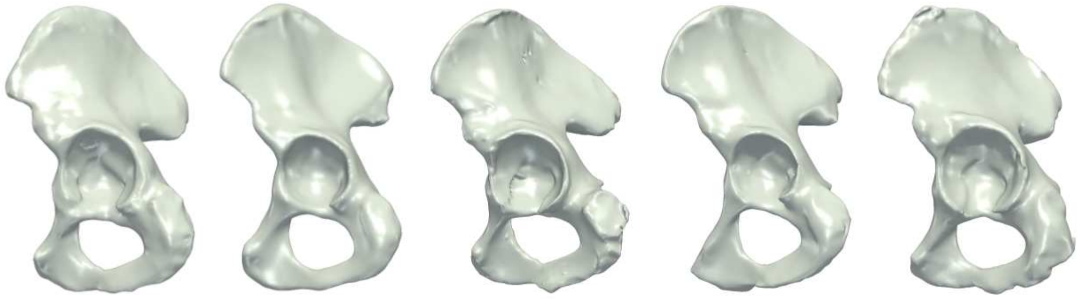
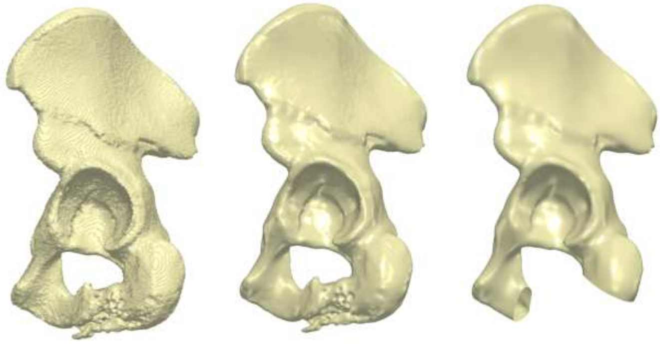


Fig. 3. Five triangular mesh surfaces of the left part of pelvis bone segmented from our pelvis CT datasets and belonging to our training set. One can observe for instance different shapes and sizes of the acetabulum.

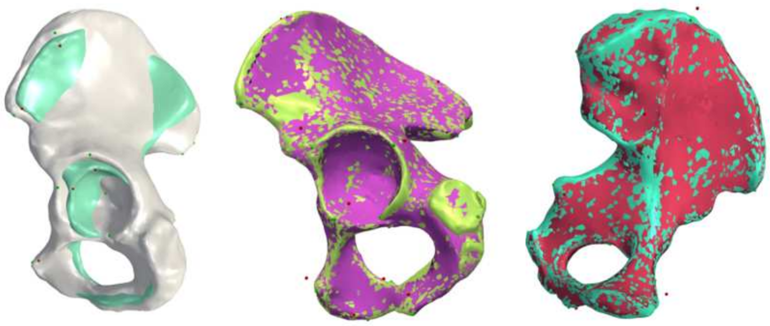
After the segmentation stage and before the incorporation into the training set the triangular mesh surfaces are undergone special processing and optimization. The surface mesh representation of the segmented bones is generated by the marching cubes algorithm [9]. Because the CT data sets are noisy and could contain different imaging artefacts the following surface mesh processing methods are required: cleaning, smoothing, remeshing and decimating. In Figure 4 is presented the original left pelvis surface generated by the marching cubes algorithm (a) and optimized using the above mentioned methods (b), the virtual tumor resection on the surface mesh data is showed in Figure 4c.



(a) (b) (c)

Fig. 4. Left part of the pelvis surface (a), the same surface after cleaning, smoothing, remeshing, decimating (b), virtual pelvic tumour resection (c).

At the next stage our data processing pipeline the establishing of correspondence between different pelvis shapes for statistical analysis has to be done. First, the same number of nodes in all anatomically corresponding meshes of the training set must be achieved. We perform it using the thin plate spline transformation [1]. We choose from the training set the surface mesh which is the best anatomical representation of the pelvis. This base surface mesh is then elastically matched with each of the pelvis surfaces from the training set. In this way we obtain approximated copies of the original pelvis surfaces but with the same number of nodes. In Figure 5 below are presented the effects of the thin plate spline transformation applied to one of the surfaces from the training set.



(a) **(b)** **(c)**

Fig. 5. Two instances of the left pelvis bone from the training set before alignment (a), the corresponding landmarks for both surfaces are coloured red and green, the green bone surface is the target surface. The aligned surfaces after applying the thin plate spline transformation to the grey surface (b and c).

Once the correspondence between different shapes from the training set has been established, a Procrustes analysis and the PCA [2], 3] method are performed, resulting in a mean pelvis shape model and in the most dominant modes of variation. The pelvis statistical shape model P can be defined as follows

$$P = P_0 + \sum_{k=1}^{n} \lambda_k D_k \qquad (1)$$

where P_0 is the mean pelvis shape model representation and λ_k is the eigenvector matrix characterizing the prior information. Changing the deformation parameters D_k, allows us to get a model instance, which is a deformed version of the mean model P_0.

We have built a statistical hemi-pelvis model from the twelve training pelvis mesh surfaces. In Figure 6 the shape changes corresponding to the first three principal modes of variation are presented. The generated pelvis statistical shape model allows estimating the optimal morphological target geometry for arbitrary region of interest to be reconstructed.

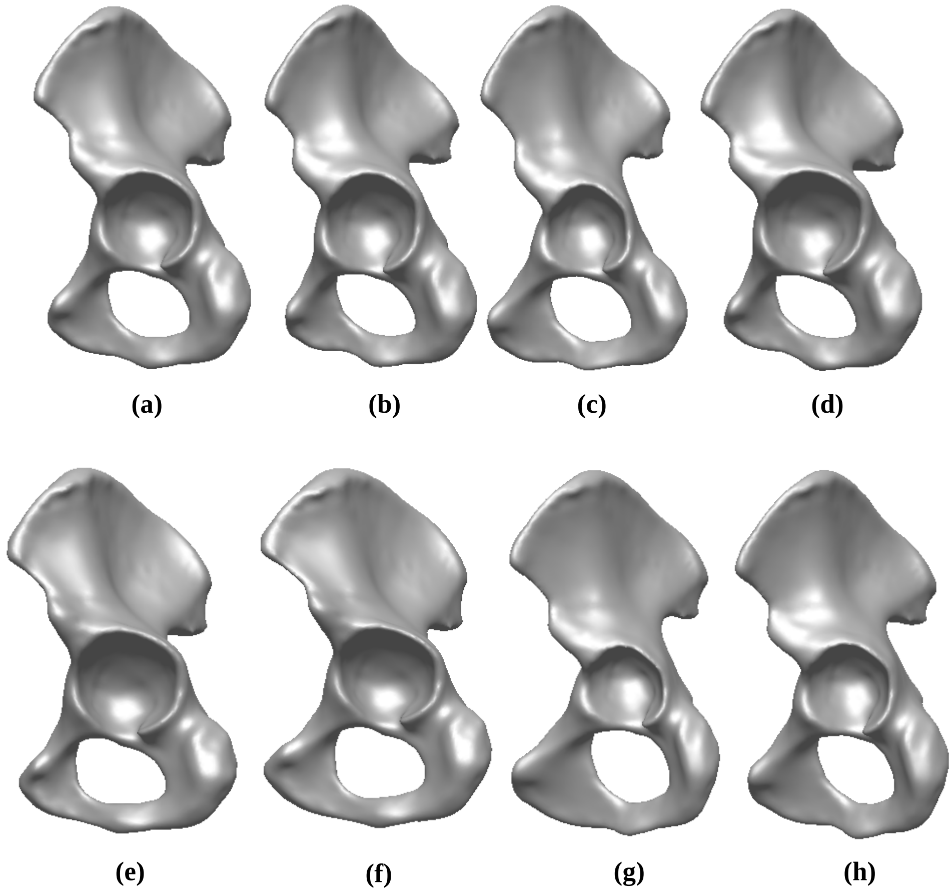


Fig. 6. Demonstration of the shape changes corresponding to the first three principal modes of variation
The left pelvis bone generated using our pelvis statistical shape model for different values of variation modes:
0.0, 0.0, 0.0 (a), -1.0, -1.0, 0.0 (b), -2.0, 0.0, 0.0 (c), 0.0, -1.0, 0.0 (d), 0.0, 0.0, 2.0 (e), 1.0, 1.0, 1.0 (f), 0.0, 1.0, -2.0 (g), 0.0, 0.0, -2.0 (h).

The implementation of the described approach in the SeVisMo [6] is based in part on the Vtk library. For the establishing of the correspondence between different instances of the pelvis in the training set two Vtk classes has been used: *vtkIterativeClosestPointTransform* and *vtkThinPlateSplineTransform*. Vtk also includes classes dedicated for generation of the statistical shape model. *vtkProcrustesAlignmentFilter* and *vtkPCAAnalysisFilter* are filters making possible the application of PCA to 3D surface meshes. These two methods have been implemented in our application too.

3. RESULTS AND DISCUSSION

The explained above surgery planning approach based on the statistical shape model has been applied to find the anatomically optimal bone shape for reconstruction of the pelvis after tumour resection (see the clinical case in Figure 4). The value setting of the variation modes has been done in an interactive way with the visual inspection of the matching quality.

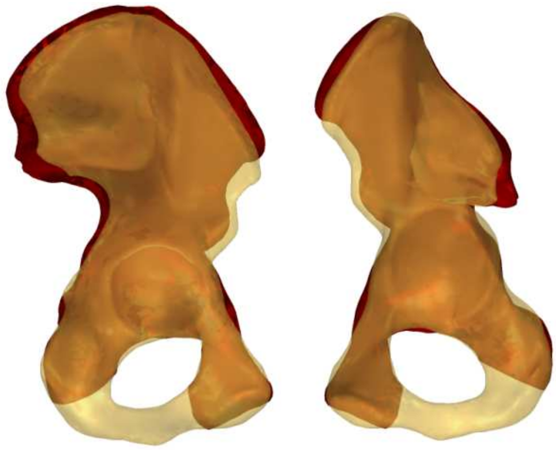


Fig. 7. Application of the planning approach for the clinical data.
Statistical shape model matched with the patient pelvis model (after virtual resection of the bone tumour), front and back view.

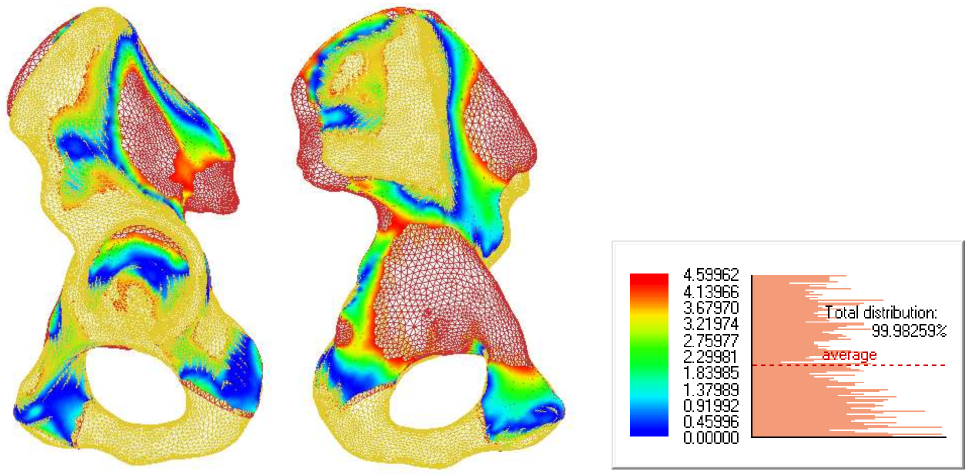


Fig. 8. Distance deviation between the original patient pelvis model and the pelvis surface generated by using of the statistical shape model approach. We can observe the optimal alignment on the boundary of the region of interest. The deviation of both surfaces is on average 2 mm and on the boundary of the ROI less than 1.5 mm.

The demonstrated application of the surgery planning method based on the statistical shape model shows that the reconstruction of the resected pelvis bone is successful and strongly correlates with the anatomical shape of the region of interest. The presented in Figure 6 pelvis models also demonstrate the robustness of the statistical shape model approach in generation of huge spectrum of pelvis shapes, which can be in an easy way aligned with an arbitrary clinical pelvis data. It is a valuable tool for the reconstructive surgery planning. It has been shown that even few datasets in the training set can be enough to create a clinically applicable statistical shape model and give satisfactory results.

4. CONCLUSIONS AND FUTURE WORK

In this paper a framework for pelvis reconstruction planning approach based on the statistical shape model has been presented. For generation of the statistical pelvis shape model a CT data pool consisting of twelve pelvis CT datasets has been collected. The data segmentation and surface processing methods delivered the required pelvis geometries. Via Procrustes analysis of the collected pelvis surfaces the parameterized pelvis shape mean model has been calculated and the principal component analysis method applied for estimating the anatomically optimal graft or implant geometry. As demonstrated the generated pelvis statistical shape model allows estimating the optimal morphological target geometry for arbitrary region of interest in the pelvis reconstructive surgery.

In the future we are planning to improve the presented surgery planning method by increasing its level of automation. At present the deformation of the model for aligning with the bone part to be reconstructed is realized by manual methods and controlled by visual inspection. We aim for application of numerical optimization methods for determination of anatomically optimal transplant or implant shapes in the reconstructed region. In the ongoing work, we intend to extend the training set to 40 different pelvis geometries.

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