Generation of virtual anatomical models
from the multimodal medical image data

Michał Chlebiej[a], Zdzisław Król[b], Paweł Mikołajczak[a]

[a]*Faculty of Mathematics, Physics and Computer Science, Maria Curie-Skłodowska University,
pl. M.Curie-Skłodowskiej 1, 20-030 Lublin, Poland*
[b]*Modelling Group, Research Center Caesar, Ludwig-Erhard-Allee 2, 53175 Bonn, Germany*

Abstract

In this work we present and discuss some methodological issues associated with the generation of the computer based anatomical models. The importance of the virtual patient models is becoming increasingly recognized in modern medicine. The advantages of using such biomedical virtual models are analogous to those of real system behavior simulation in the engineering or material sciences. Particularly significant is its role in the simulation of various pathogenic physiological processes and therapeutical procedures. Such models enable as well the optimization of many diagnostic and therapeutical subroutines. Segmentation, registration, measurement, interaction and visualization modules constitute actually the main pool of the software engineering tools, which enables the surgeon to create a virtual patient-specific anatomical model of the region of interest. Based on this model the physician can simulate and plan different treatment approaches as well as carry out quantitative measurements to identify the optimal therapeutical procedure.

1. Introduction

There are presently many different medical imaging devices providing high-resolution complementary diagnostic information. Three-dimensional tomographic datasets acquired daily in hospitals worldwide yield information counted in terabytes. Sophisticated image processing methods for 3D medical images are of considerable importance to the effective use and understanding of medical imagery in many applications, particularly in those requiring accurate representation of anatomical structures like diagnosis, therapy planning and simulation. A large number of algorithmic techniques for reconstruction, segmentation, registration, visualization and other image processing methods have been reported in literature [1]. One of the most exciting challenges in this area of research is how to integrate diverse forms of raw and processed information towards a common information framework. Tomographic images of different modalities, and outcomes of the above mentioned image processing methods provide structural input to such framework called in literature as the

virtual patient-specific anatomical model. Such models provide many advantages for diagnostics and treatment planning, particularly in the radiation therapy or for complex surgical procedures. The virtual patient-specific anatomical models enable enhanced perception of the region of interest as well as simulation of the surgical or radiation treatment and the evaluation of its potential scenarios. Segmentation procedures let identify in the acquired tomographic datasets the anatomical structures and lesions. The registration approach plays an important role in the generation of the virtual anatomical model for the patients undergoing two or more imaging studies. Because the acquisition of the data is procedurally and technologically independent, the complementary information provided by different imaging modalities has to be correlated by means of numerical methods. The usability of the complex virtual patient models depends strongly on efficient visualization methods that enable exploration of such huge amount of data. This paper is organized into two main sections. In the first part the methodological issues associated with the registration and segmentation methods are presented and discussed. The second part is devoted to generation and exploration of the virtual anatomical model. The related results and problems will be discussed at the end of this paper.

2. Integration of the multimodal information

Clinically relevant integration of the high-resolution complementary diagnostic information from the acquired data requires a sophisticated registration paradigm, efficient and reliable numerical methods and their robust software implementation. The registration along with the segmentation task belong to the major efforts in the process of generation the patient-specific virtual anatomical model. The registration problem induced by the fact that two datasets of the same patient taken in one modality at different times or in more than one modality differ with respect to resolution, acquisition plane, or parameter measured. Before they can be used in conjunction with each other, at first it is necessary to register or correlate geometrically these two or more sets of data (see Fig. 1). Because of the above differences the process of spatial alignment is not trivial. To solve this problem using numerical methods we have to define a geometrical transformation relating the two data sets as well as a criterion for the goodness of a given transformation. We treat the registration problem as a non-linear optimization task aimed at the minimization of the dissimilarity measure.

2.1. Formal statement of the registration problem

Given a pair of volumetric datasets (let us call them *model* and *object*) we can define the similarity measure C as the objective function, which has to quantify how well both datasets match with each other. The transformation mapping T is

defined as a geometric transformation that takes an *object* volume point p_0 and gives the corresponding *model* point p_M. The majority of registration methods share a common optimization framework, where the goal is to estimate numerically the optimal transformation $\mathbf{T}_v$, which establishes the anatomically optimal spatial correspondence between the *model* and the *object*. In the case of rigid body transformation (six degrees of freedom) a six-component vector $v = \left[r_x r_y r_z t_x t_y t_z \right]$ has to be estimated. Many different registration approaches to spatially aligning volumetric data have been proposed in literature [2]. The work presented here describes two distinct methods based on different definitions of the similarity measure. The first one is the surface similarity measure:

$$C(v) = \sum_{i=1}^{N} d^2(\mathbf{T}_v(p_i)), \tag{1}$$

where $d(p)$ is the Euclidean distance in $\mathfrak{R}^3$ between any transformed *object* point $p = \mathbf{T}_v(p_o)$ and some closest to *p model* data point p_m. N is the number of the segmented *object* points. The second similarity function is the mutual information measure:

$$C(v) = -\sum_{g_i \in G_O} \sum_{g_j \in G_M} P(g_i, g_j) \log \frac{P(g_i, g_j)}{P(g_i)P(g_j)}, \tag{2}$$

where $P(g_i, g_j)$ is a probability distribution of the scatter-plot histogram [2], and the $P(g_i)$, $P(g_j)$ are the probabilities for each *object* and *model* voxel value in the intersection volume. G_M and G_0 are the voxel value sets of the *model* and *object* volumes. Both similarity measures represent different approaches to quantify the similarity between two datasets. Both similarity measures represent different approaches to quantify the similarity between two datasets. The first one is taking into account features identified at the preprocessing stage in a non-automatic segmentation step. The second one uses the entire voxel value information from both datasets and does not need any preprocessing stage. In the surface similarity approach, the similarity assessment takes place in the Euclidean space. The mutual information measure works in a different mathematical space and estimates the distance between the probability distribution of the scatter-plot histogram $P(g_i, g_j)$ and distribution $P(g_i)P(g_j)$ of two independent signals.
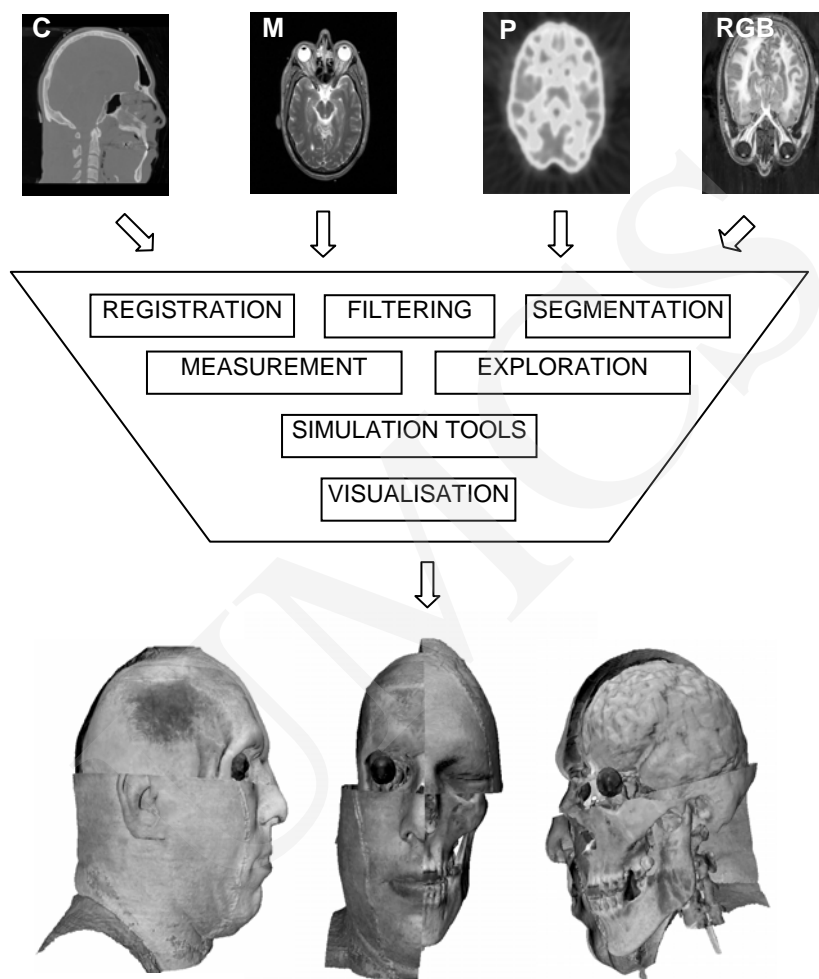
Fig 1. Generation of the virtual patient-specific anatomical model. Top line (left to right): individual CT, MR, PET and RGB slices from the acquired volumetric datasets. Software engineering tools required at the generation stage (middle). Bottom: virtual patient-specific anatomical model generated from the multimodal datasets

Thus, the assessment of the matching quality takes place in the probability distribution space. The crucial role in the registration problem is played by the optimization. The estimation of the best alignment requires in the majority of matching problems an iterative numerical approach. There are plenty of different numerical optimization methods [3]. To choose the most adequate one for a specific class of registration problems, one has to consider a few important factors. Assessing the match quality for the volumetric medical data in the continuous Euclidean or probabilistic spaces determines the continuous nature of the

registration problem. The nonlinear nature of the matching functions and the existence of local minima have been described in literature [2]. Because of the huge size of the datasets, computation of the objective function value or its derivatives is a very time consuming part of the whole optimization process. The existence of local minima requires applying global non-deterministic optimization methods [3]. But in this class of methods a high number of objective function calculations is often necessary to satisfy convergence criteria, which is impractical in the case of medical data registration. On the contrary, there exists a wide group of much less time consuming, deterministic algorithms. Depending on the kind of objective function we can use different deterministic optimization techniques. If we are only able to compute the value of the function for a given set of variable parameters and we cannot even estimate its gradient we can use Powell's method [3]. In the cases when we are able to compute something more than just a function value we can choose a few numerical techniques that follow the simple nonlinear optimization solution. The simplest method, gradient descent (or ascent) just follows the gradient of the objective function until it hits a local minimum and then stops [3]. Some more recent methods for solving optimization problems methods like Davidon-Fletcher-Powell [3] or Levenberg-Marquardt [4] try to estimate or compute second derivatives of the objective functions. With this information, local areas of the objective function can be approximated quadratically for the better convergence properties. With deterministic methods for highly nonlinear optimization problems, the absolute best solution is not always guaranteed unless we start close to it. In this work two deterministic methods have been chosen: the Levenberg-Marquardt optimization scheme for the surface similarity measure and the Powell's method for the optimization of the mutual information based objective function.

3. Segmentation for virtual anatomical models

Segmentation plays a crucial role in the patient-specific anatomical model generation process. The quality and the usefulness of the created virtual anatomical model depend strongly on the quality of the applied segmentation procedures. There are many alternative ways that enable the quality improvement of the segmentation process. In this work, we present a novel segmentation approach based on the registration paradigm. This method can be applied if there are available volumetric datasets of the same patient acquired in different modalities. Usually, such multi-modality datasets have different resolutions and they differ in the degree of diagnostic significance. We classify the data into quality classes according to the resolution and the contents of the relevant diagnostic information. Lower quality datasets are used in the early stage of the proposed method and the highest quality datasets in the final segmentation step. The method consists of three main steps (see Fig. 2).
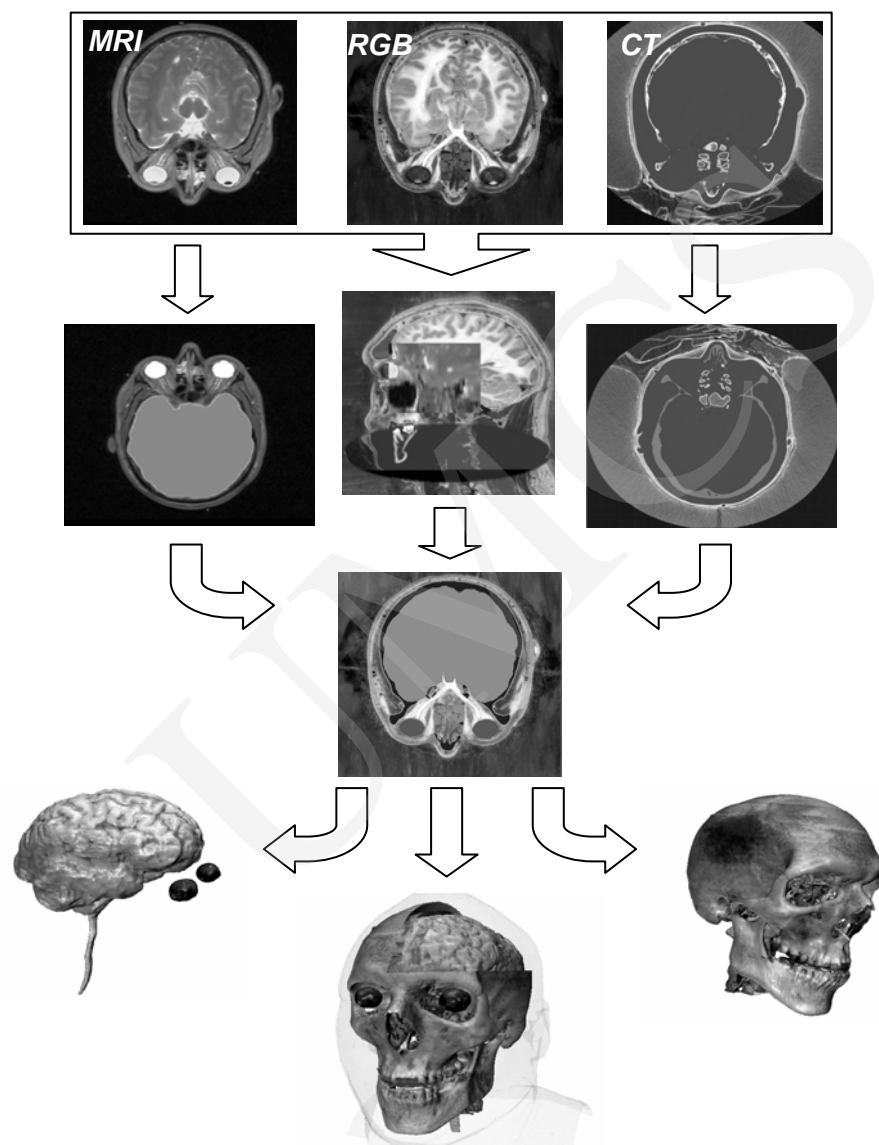
Fig 2. Registration based segmentation process. The acquired multimodal datasets (top) are registered and segmented (second row). The segmented masks from the segmentation step in the lower quality datasets (MR and CT) are used as constraints for the segmentation algorithms in the higher quality dataset (RGB). The final segmentation stage yields a high-quality patient-specific virtual anatomical model (bottom)

In the first step we perform the registration of all acquired datasets. In this and the next registration stages we use the affine matching transformation, the normalized mutual information as the similarity criterion and the Powell's method as the optimization algorithm. The second step is the preliminary

segmentation of the low quality datasets. Its main goal is to create binary masks corresponding to anatomical structures in these datasets (in our case MRI and CT). Various segmentation methods can be used in this step, depending on the data modality. Threshold based segmentation, region growing and scan line algorithms together with morphological operations can be successfully applied in this stage. The segmentation accuracy in this step is not the main goal, the most important is the creation of the mask that fully covers the segmented structures. Such masks are going to be used in the next stage. The third and the final step is the segmentation of the dataset with the highest spatial resolution and the most relevant diagnostic information. In our case (data originated from the Visual Human Project [5,6]) the best dataset available is that one, which consists of a large stack of high-resolution RGB photographs. Such photographs, in contrast to the data obtained from CT or MRI scanners, reveal the anatomical details with a superior resolution. The standard segmentation algorithms applied to the RGB data would fail to delineate these structures properly, because the colors corresponding to adjacent anatomical structures are much more tough to distinguish than the gray-values in the CT and MRI datasets. To make this segmentation process possible we use masks that come from the previous step. These masks have to be transformed by the optimal transformation parameters estimated in the first step. The transformed masks from the lower quality datasets (MR and CT) are used now as constraints for the segmentation algorithms applied to the higher quality dataset (RGB) and allow the delineation of the structures of interest only. The region-growing algorithm with different decision criteria can be used for obtaining the most satisfying results. For example, the border of the mask can be used as a sharp stopping criterion, or we can define some probability distribution function that enables more accurate classification of the voxels situated near the border of the mask (the closer to the boundary, the lower probability of the voxel association with the structure of interest). This final segmentation stage yields high quality masks that can be used to create a high quality patient-specific virtual anatomical model. The same procedure can be applied as well to segment different soft tissue types in the MR data based on the segmented (with reduced quality) corresponding or complementary regions in the CT data.

4. Results

For analysis of the registration and segmentation methods in the anatomical model generation process all above described registration and segmentation methods have been implemented and tested on the Visible Human Project male dataset [5,6]. Multiple test series with different registration and segmentation approaches have been conducted. For each registration trial a 2D-misregistration graph with the convergence track has been generated and the matching results visually inspected. The registration procedures described in this article have

been performed on a PC system (Athlon XP 3200+ 2.2 GHz, 512 MB RAM). The matching process of the MRI and RGB datasets using the mutual information measure and the Powell's optimization method took 20 minutes 41 seconds (two-step rigid and affine multi-resolution approach) and required 2531 evaluations of the mutual information objective function. In the second case (CT and RGB datasets) the total running time took 4 hours 50 minutes 4 seconds (two step multi-resolution approach) and the mutual information function has been evaluated 1735 times.

Fig. 3. Three-dimensional visualization techniques: (from left) surface rendering, combination of volume and surface rendering, 3D-slices combined with surface rendering

The presented above registration approaches together with the novel segmentation techniques enable creation of highly detailed virtual patient-specific anatomical models (see Figs 1, 2 and 3), which provide the most efficient diagnostic assistance and can significantly improve many surgical or radiation therapy planning procedures. Variety of visualization methods enables different problem-oriented views of the whole model or the region of interest only. In Fig. 3 different views of the same virtual model have been presented. Depending on the medical indications the virtual anatomical models can be visualized using 2D slice views or as 3D reconstructions. Effective exploration of the correlated datasets for diagnostic purposes can be achieved using inspection window or adjustable alpha-blending technique. For surgery or radiation therapy planning the surface rendering and volume rendering techniques (or both mixed with the 3D slice views) can be applied for an effective visualization of the spatial relationships and to reveal some anatomical information that is not optimally visible in 2D. The most advanced approach to explore and interact with the virtual models offers the virtual reality environment, where the physician is fully or partially immersed in the virtual representation of the anatomical model. The virtual patient-specific anatomical models coupled with the intraoperative navigation systems facilitate substantially the interventional medicine and are capable of helping physicians improve the accuracy and security of treatment.

5. Conclusions

In this work different issues related to methodological and numerical approaches in the generation of virtual patient-specific anatomical models have been presented and discussed. Various approaches to solve the registration and segmentation problem have been presented and analyzed. The two deterministic optimization methods applied to different similarity measures reveal various convergence behavior and computational costs, but from the medical point of view both approaches result in the anatomically correct alignment. The correlated volumetric datasets found the base for the construction of the virtual patient-specific anatomical model. The novel segmentation method presented in this paper is one of the simplest approaches taking into account the registered multimodal datasets. More advanced approaches can be developed. They can use two or more dimensional histograms created from all registered datasets available. In the near future we plan to investigate this class of segmentation algorithms. After the segmentation step the presented variety of visualization methods enables efficient exploration and utilization of the virtual patient model. In addition to the currently implemented optimization methods in the future work we plan to include also non-deterministic optimization methods like e.g. genetic algorithms or hybrid methods e.g. deterministic simulated annealing. Furthermore, we work on the improvement of the rendering and model manipulation tools to achieve more intuitive and user-friendly interaction within the virtual scene. Future work foresees also the development of physically based deformable models for surgery simulation and treatment planning.

Acknowledgments

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