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Visual Analytics for model-based medical image segmentation: Opportunities and challenges

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ABSTRACT

Segmentation of medical images is a prerequisite in clinical practice. Many segmentation algorithms use statistical shape models. Due to the lack of tools providing prior information on the data, standard models are frequently used. However, they do not necessarily describe the data in an optimal way. Model-based segmentation can be supported by Visual Analytics tools, which give the user a deeper insight into the correspondence between data and model result. Combining both approaches, better models for segmentation of organs in medical images are created.

In this work, we identify the main tasks and problems in model-based image segmentation. As a proof of concept, we show that already small visual-interactive extensions can be very beneficial. Based on these results, we present research challenges for Visual Analytics in this area.

1. Introduction

Segmentation of medical images serves as an indispensable basis in many medical treatments and diagnostic processes (Nahar, Imam, Tickle, & Chen, 2013; Stoean & Stoean, 2013). *Manual* segmentation is often very costly and time consuming as it needs to be performed by medical experts in a piecewise manner: each image slice is examined individually. Therefore, there is a strong need for *fast and automatic* (Engelke, Becker, Wuest, Keil, & Kuijper, 2013) segmentation algorithms. The goal of creating automatic algorithms is a segmentation without errors, as clinicians need to rely on the segmentation results. There are various segmentation methods (Preim & Bartz, 2007). We focus on techniques based on statistical shape models (SSMs), because they are robust and can cope with low contrast images. For SSM-based-modeling, there exist a large variety of algorithms, which can be steered by several parameters (Heimann & Meinzer, 2009). The algorithm results, however, still need to be significantly improved. Especially, there is *no* general rule determining which model to select for a given organ and image modality. Moreover, the selection is difficult as the modeling process consists of several steps. For each of them, several parameters have to be steered. This process is currently done in a "black-box manner" as modeling experts still lack tools providing deeper information on the data. Therefore, often standard models are chosen which do not describe the data in the best possible manner. We believe that Visual Analytics methods can provide valuable tools for optimization of model steps (incl. parameter choices), which would sizeably improve segmentation quality.

Visual Analytics is a research area dedicated to the development of tools that combine automated analysis techniques with interactive visualizations for an effective analysis of heterogeneous data sets (Keim, Mansmann, Schneidewind, Thomas, & Ziegler, 2008; von Landesberger, Bremm, Rezaei, & Schreck, 2009; von Landesberger, Görner, & Schreck, 2009). A large variety of methods for SSM-basedimage segmentation have been introduced. However, most of these methods are not practical for end users as their customization requires expert knowledge. Consequently, these existing methods need extensions to become more accessible for end users.

In this paper, we analyze the process of SSM-based medical image segmentation (also called model-based in the following) and identify the main tasks and problems that need to be addressed by Visual Analytics methods. We discuss new approaches which combine interactive data visualization and data analysis in all stages of this process. Owing to the large set of problems, we currently focus only on selected most-relevant issues in these stages as a proof of concept. The new tools already allow for creating better models for the segmentation of medical images. They thereby improve medical treatment planning and diagnosis. As the development of specific Visual Analytics tools for this area is still far from largely advanced, we state future challenges for this domain based on our experiences.

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This work is conducted as a close cooperation between two groups: Medical Computing and Visual Analytics. The collaboration ensures that real user problems are tackled and the new Visual Analytics approaches are directly evaluated in real modeling processes.

The paper is structured as follows: Section 2 reviews related work from Visual Analytics viewpoint. Section 3 describes a process in model-based image segmentation. Section 4 presents our approaches for Visual Analytics support of this modeling process. Section 5 reviews challenges for Visual Analytics research in this area and Section 6 concludes.

2. Related work

Visual Analytics is a relatively new research field, which develops visual-interactive methods combined with data analysis for support of efficient decision making (Keim et al., 2008). It covers a broad variety of research topics and application areas.

Visual Analytics techniques for medical imaging currently form only a small part of the wide portfolio of Visual Analytics methods. They apply automatic data analysis methods for highlighting interesting views on the data or for guiding the interaction with the visualization, or show additional data in linked views (e.g., Angelelli, Viola, Nylund, Gilja, & Hauser, 2010; Bruckner & Möller, 2010; Castellanos-Garzón, García, Novais, & Díaz, 2013; Preim & Bartz, 2007). They not only combine data analysis and interactive visualization, but also bridge information visualization and scientific visualization. However, this research field is still in a premature stage. Currently, there are few visual analytics methods for support of SSM-based medical image segmentation (e.g., Visualization of Shape Space (Busking, Botha, & Post, 2010)). Therefore, specific techniques for Visual Analytics support of modeling in this area need to be developed. As a basis, techniques from other Visual Analytics and Scientific Visualization areas can be extended or adapted to the specific needs.

2.1. Visual Analytics in the model-based image segmentation process

We review existing Visual Analytics techniques related to medical imaging process. The overview follows the modeling stages presented in Section 3.

Input data pre-processing: In the data pre-processing step, several data transformation algorithms are employed, which need the setting of many parameters. This is difficult and requires the analysis of the impacts of parameter changes on the output. With regard to modeling, an approach for visualization of impacts of parameter changes in the input space on the output values using scatterplots was presented by Berger, Piringer, Filzmoser, and Gröller (2011). They concentrate on low-dimensional spaces for analysis of engineering data. In image analysis, Pretorius, Bray, Carpenter, and Ruddle (2011) proposed an approach for assessment of results from various parameter settings on the output. They sample the input parameter space and show output images for selected parameter settings. The user then can tag the good results and continue the optimization. The method was used for analysis of biological cell images.

Model selection: The model selection step is difficult, as it requires the analysis of plausibility of model parameter choices with regard to the input data set. As part of this process, the input data set needs to be analyzed. The input data consist of several multi-dimensional vectors. For an exploration of multi-dimensional data space, several approaches have been proposed: multi-variate visualizations (e.g., parallel coordinates), matrices of low-dimensional data subsets, or projections of the data into low-dimensional space for visualization in scatter plots (Card, Mackinlay, & Shneiderman, 1999; Schreck, von Landesberger, & Bremm, 2010). Both parallel coordinate and scatterplot views have many extensions which overcome their limitations (Card et al., 1999).

Specifically for SSM-based image segmentation, Busking et al. (2010) developed a technique for visualization of the shape space. They present several visualizations for this purpose (PCA reduction, shape overlap, etc.). They, however, do not take the modeling aspect into account– they do not show the match of data distribution and the model assumptions.

Image segmentation: Usually, image segmentation is performed in a "black-box" manner, which does not allow the user to track the transformation from input to output. Depending on the choices in the initial analysis step, the results may emerge that do not comply with user preferences or the application context. In these cases, it is advantageous to allow the user to interactively oversee and control the calculation process. Such a technique has been introduced specifically for clustering of trajectories using self-organizing maps (Schreck, Bernard, von Landesberger, & Kohlhammer, 2009). It however, cannot be applied to this problem directly.

Segmentation evaluation: Evaluation encompasses assessment of the output quality. Output quality refers to the match between input data and model-based segmentation result. The visualization of output quality is tightly related to uncertainty visualization. The available uncertainty visualization techniques usually capture data quality or uncertainty by a quantitative or qualitative variable which is mapped to one or more graphical variables still free for use in the given visualization. These may be any typical visual variable including color, hue, saturation, size and position of visual element, and others. Also, the integration of additional graphical objects into the given data display, including uncertainty glyphs, labels, isosurfaces, or textures are possible. Extensive overviews of methods for visualizing data error, quality and uncertainty are presented in surveys (Griethe & Schumann, 2006).

In **summary**, Visual Analytics for model-based image segmentation is a new area. It needs to take care of specific needs of area experts. The development of new techniques is necessary. Current methods can serve as a starting point for the area of model-based medical image segmentation. They, however, need to be extended with new methods in order to cover the specific needs of this area.

3. Process for model-based image segmentation and its main problems

SSM-based medical image segmentation is a specific type of process in medical imaging (Kirschner & Wesarg, 2011; Kirschner, Becker, & Wesarg, 2011; Preim & Bartz, 2007) consisting of four main stages (see also Fig. 2):

1. *Input data pre-processing*: the input data consists of a small set of high-dimensional vectors extracted from the input images.
2. *Model selection*: the model consist of two parts: the shape model and the appearance model that both need to be specified.
3. *Image segmentation:* the selected models and input data are used for segmentation.
4. *Segmentation evaluation*: the segmentation is evaluated using ground truth data. In this way, the model quality is assessed.

It is important to note that each stage of the process may include several steps (algorithms), where each step requires a set of parameters. A good parameter choice in each step leads to high quality segmentations. The parameter setting and choice of the proper algorithm are difficult. As they are not supported by visual-analytical means, often default settings are used, which may not be optimal for the specific dataset.

In the following, we describe the stages from Visual Analytics perspective in more detail.

3.1. Input data pre-processing

The input data for modeling are tomographic scans of different anatomical regions of human patients and the corresponding expert segmentations of the organs of interest. The tomographic scans originate either from computer tomography (CT) or magnetic resonance imaging (MRI). Data resolution may vary with the particular data set. For model creation and evaluation, expert segmentations of the data are needed. As these are costly and time-consuming to obtain, often small data sets with only dozens of samples have to be used.

If not provided otherwise, input images and expert segmentations need to be pre-processed for their use in the modeling process. For example, the expert segmentations are smoothed before converting them to meshes in order to avoid staircase artifacts. In this way, they are more suitable for modeling than the raw data. From the expert segmentations a 3D landmark representation of the organs is generated, which is necessary for learning the shape model. Each shape is denoted as a high-dimensional vector, which is obtained by the concatenation of the so-called landmarks (see Fig. 3). Each landmark represents a specific anatomical region, which means that two landmarks which have the same index but belong to different shapes, correspond to each other. A single triangulation for all training shapes defines how the landmarks are connected with each other.

Moreover, in order to obtain training data for the appearance models at the organ boundary, vast amounts of image features (like intensity values or gradients) are extracted from the original images. (Kirschner & Wesarg, 2010).

3.2. Model selection

Statistical shape models (SSMs) represent the typical *shape* of an object class and likely shape variations by means of a probability distribution. The distribution is learned from a set of training shapes (Heimann & Meinzer, 2009). The variability of the data (i.e., the data model), is often captured by PCA analysis of the high-dimensional data (see Fig. 3 right). As a general assumption for PCA, standard Gaussian data distribution is assumed. However, this does not hold for all data sets (see Fig. 6). If a wrong data distribution is assumed, an incorrect model is selected, which may have a serious impact on segmentation quality (Kirschner et al., 2011). As users currently lack tools for inspection of input data topology, the standard model is often used.

In addition, SSM-based segmentation algorithms like the Active Shape Model also often employ an *appearance model*, which describes the texture around the organ boundary in input images. The appearance models are included either implicitly (e.g., using strongest edges), or are learned from training data. These models rely on the extracted image features. As the number of features that can be extracted is large, often the problem is to select the right features, which would describe the data well.

3.3. Image segmentation

After the models have been selected, they are used for segmentation. This phase is performed in expectation–maximization way, where the model is iteratively fit into the real data. Usually in medical imaging procedures, the calculation finishes when a pre-defined number of iterations is reached. Currently, this process is performed in a "black box" manner. The users do not see the results before the process terminated and cannot steer the process. Moreover, it is not possible for the users to analyze the development of the segmentation quality during iterations and therefore they cannot assess how the results were influenced by the algorithm parameters and the input data (Kuijper & Heise, 2008; Kuijper, 2004).

3.4. Segmentation evaluation

The assessment of segmentation quality plays a crucial role in SSM-based medical image segmentation. Segmentation quality also measures the quality of the model which formed the result.

There are two main ways of evaluation: algorithmic (i.e., quantitative) and visual.

1. In the quantitative evaluation, users compare the obtained segmentation results to manual expert segmentation using a small set of global metrics such as the Average Surface Distance and Maximum Surface Distance (Heimann, van Ginneken, & Styner, 2009). These global measures do not show whether a bad quality is caused by bad segmentation only in a certain area (locally bad quality) or is spread throughout the whole organ. For example, a liver segmentation system may effectively separate the liver from the heart, but not from the stomach.
2. Visual inspection of segmentation quality commonlyemploys standard visualization techniques as for example employed in ITK Snap (www.itksnap.org), see Fig. 4 for an example. It offers views on 2D slices of the real data overlaid with the resulting segmentation. The slice selection is done interactively by the user. Such visual inspection is subjective and time-consuming owing to a large amount of available views that have to be examined.

These methods look at each segmentation result individually, which prevents comparison of results across the test data set. This limits the assessment of the models as one model is applied to all input samples.

The construction of statistical shape models is difficult, it needs selecting the right shape model and appearance model. Afterwards the quality of the model has to be assessed. This process usually consists of several iterations. Visual Analytics methods can support this process.

4. Visual Analytics approach

Our Visual Analytics approach shown in Fig. 1 supports all stages of the above-mentioned modeling process: input data pre-processing, model selection, model-based segmentation, and model evaluation. It provides a set of techniques, which are useful for selected steps in the modeling pipeline, but they still have to be complemented by a variety of other methods to build up a general framework. The presented methods combine interactive visualization with data analysis. They offer insight into the segmentation process and its results. In this way, they can produce qualitatively better models, being our main goal. Note that our tools may also reduce time needed for model creation as well., ,

As a proof of concept, we apply our approach on real-world medical image data from 3D-IRCADb-01 database http://www.ircad.fr/softwares/3Dircadb/3Dircadb1/index.php. As a result, we could observe that application of the proposed Visual Analytics methods can lead to significant result improvements. In our case, all data was extracted from CT scans. The intraslice resolution ranges from 0.58×0.58 mm to 1×1 mm and the interslice resolution ranges from 0.7 to 5 mm.

4.1. Input data pre-processing

As a basis, the input data need to be pre-processed. In particular, meshes need to be extracted from the input images and artefacts need to be removed (see also Fig. 3). These meshes are then transformed into high-dimensional data for further

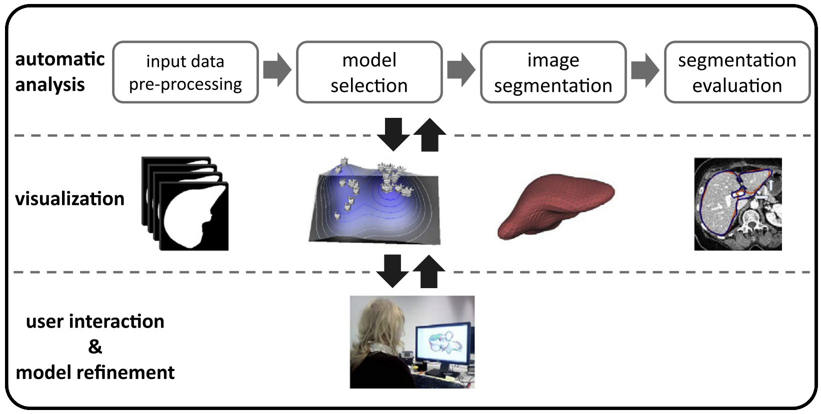


Fig. 1. The proposed approach to the process for model-based medical image segmentation. Each step of the process is supported with interactive visualization combined with data analysis. The process allows for feedback loops.

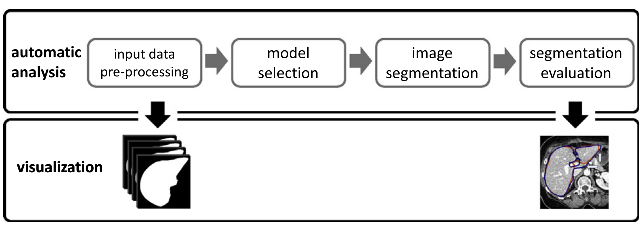


Fig. 2. Current SSM-based medical image segmentation process. Input data are pre-processed, then the model fitting this data well is selected. This model is used in the segmentation phase. Finally, the model-based segmentation result is evaluated.

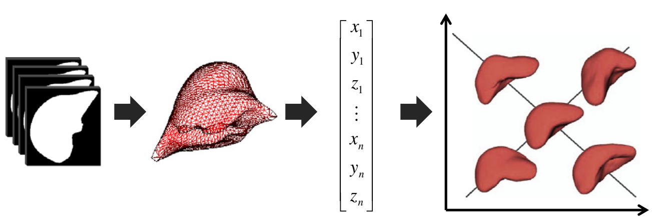


Fig. 3. Statistical Shape Model – from input data to the model. Input images of expert segmentations are transformed into 3D meshes and then into high-dimensional vectors, which are used as an input for model selection and segmentation (e.g., using PCA).

processing in the model selection phase by e.g., correspondence matching and data transformation.

The mesh extraction algorithm requires a set of input parameters (e.g., x-, y- and z-smoothing values). The quality of the resulting mesh is evaluated on the basis of quality metrics, e.g., the average distance of each vertex to its nearest voxel in the expert segmentation. By now, the users have used only default parameter settings as they could not visually inspect the impact of various parameter settings on the result. It is important to say that the result assessment requires both assessment of several quality indicators and visual inspection of the resulting mesh. Therefore, the extraction cannot be performed solely in an algorithmic way.

The proposed Visual Analytics approach offers interactive visualization that allows for selection of input parameters and assessment of the impact of input parameter changes on the resulting mesh quality. The approach has been inspired by the work by Berger et al. (2011). The display consists of two main views: parameter space view and mesh view (see Fig. 5(a) and (b)). Parameter space view shows all input parameters and all output quality measures for the selected points in the input data space in the parallel coordinates view on the bottom. As the input space is high dimensional and very large (R^m, m – number of input parameters), we restrict it to a user-defined subspace in the upper view. It shows detailed views for selected parameters and quality pairs as scatterplots.

The selected parameter space is formed by deviations of a selected center point (black-colored) over two selected parameter dimensions (see Fig. 5(a) top). The center point corresponds to the current default settings and the parameter space covers a set of values that allow to assess the impact of changing a parameter on the result quality. The correspondence between the input and output data is given by color-coding. For example, it can be seen that decreasing the X- and Y-smoothing values deteriorates the result quality. By selecting high quality results, the user can assess what parameters would improve the result. This is possible, for example, in the parallel coordinates view by restricting quality measures to good values (red intervals on the right).[1] The selected parameters are shown in brown color also in the view on the top. In this view, we can see that the brown parameters have high values of the Y-smoothing parameter for a given value of X-smoothing parameter. They show best quality values for the whole selected parameter space. This improvement can be seen also in the linked mesh visualization view (see Fig. 5(b)). It shows the extracted mesh with color-coded mesh quality metric (red means bad). We see that the default settings (on the left) have several regions with bad quality, while the improved settings lead to better quality over the whole mesh.

4.2. Model selection

The model selection stage is the most important part of the modeling process. In this stage, suitable shape and appearance models are selected for training. In our approach, we address the need to assess the correspondence of model assumptions with the inherent properties of the training data for selecting the proper shape model.

Currently, the data space (data distribution) is often not analyzed and therefore the default Gaussian data distribution is assumed. Using our proposed visualization technique, it could be easily shown that the organ variability changes for various organs (see Fig. 6 for an illustration). For example, Kirschner et al. (2011) visualized the vertebra data set finding out that Gaussian assumption does not hold and therefore Kernel PCA analysis instead of PCA analysis needed to be performed in the modeling process.

In our approach, we offer interactive exploration of the shape space with specific focus on match between the modeled and real

[1] For interpretation of color in Fig. 5, the reader is referred to the web version of this article.

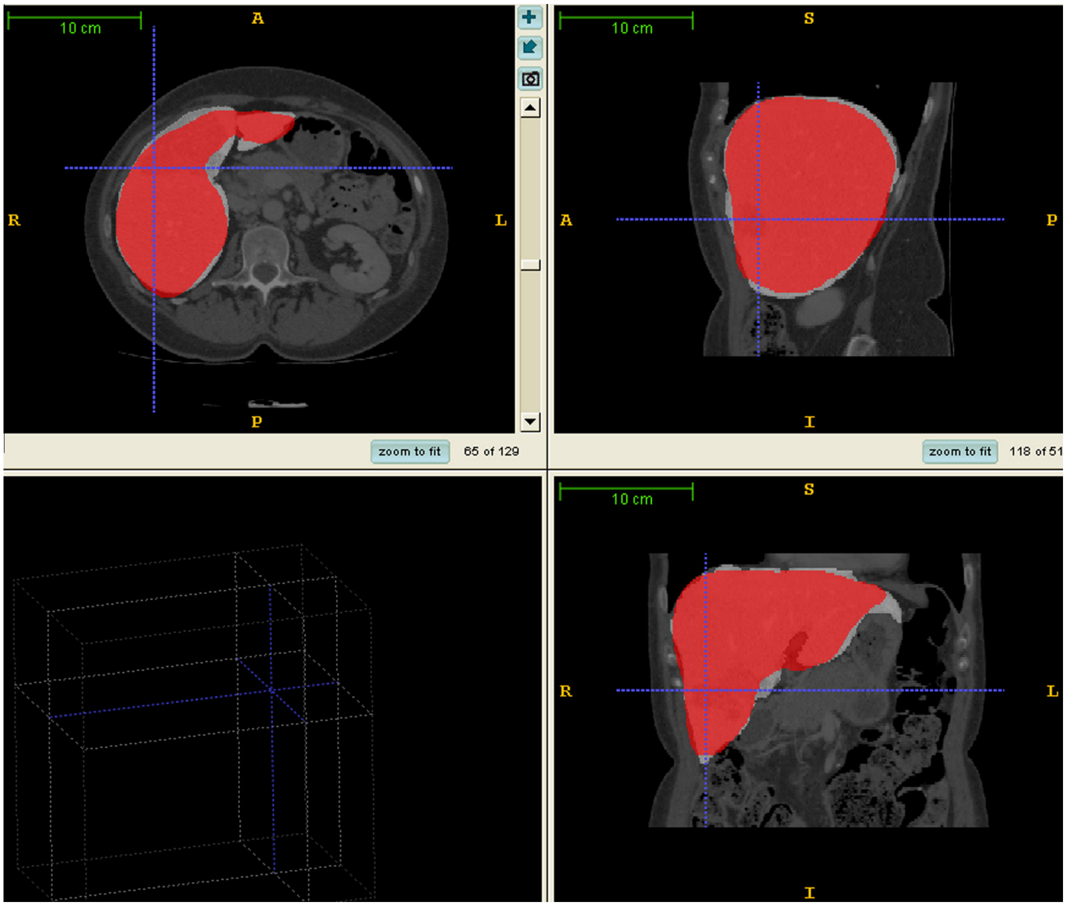


Fig. 4. Commonly employed view for assessment of segmentation quality using ITK Snap tool. Grey areas are expert segmentations and the red areas are model-based segmentations. It offers only 2D views on 3D data and requires cumbersome manual inspection of a large set of slices. Moreover, quantitative quality measures are missing. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

data distribution (see Fig. 6). The modeled data distribution is overlaid over the training data set. The training data set is positioned using principal component analysis (the two main axes are used). This corresponds to the standard models (Heimann & Meinzer, 2009) and therefore allows the comparison with them. The user can interactively change the assumptions about the distribution (e.g., Gaussian vs. Kernel density, or Kernel density estimation parameters). Note that other types of distributions can be easily extended in the implementation. After experiments and user feedback, we decided to visualize the distributions using both coloring and height field with isolines, thereby emphasizing the match between real and modeled data density. The height better shows the data density values, however suffers from occlusion is some views. The use of coloring solves the overlap problem however suffers from low discrimination of color differences in the display. Interactive changing of distribution parameters and the data views (e.g. rotation) allows the experts to analyze the model selections in various settings. The overlay with the true location of the data samples in the model enables the user to assess whether the chosen distribution parameters well match the data and thereby to choose the best data distribution parameters for the model. The final selected distribution is used as an input to the next step of the process - model-based segmentation.

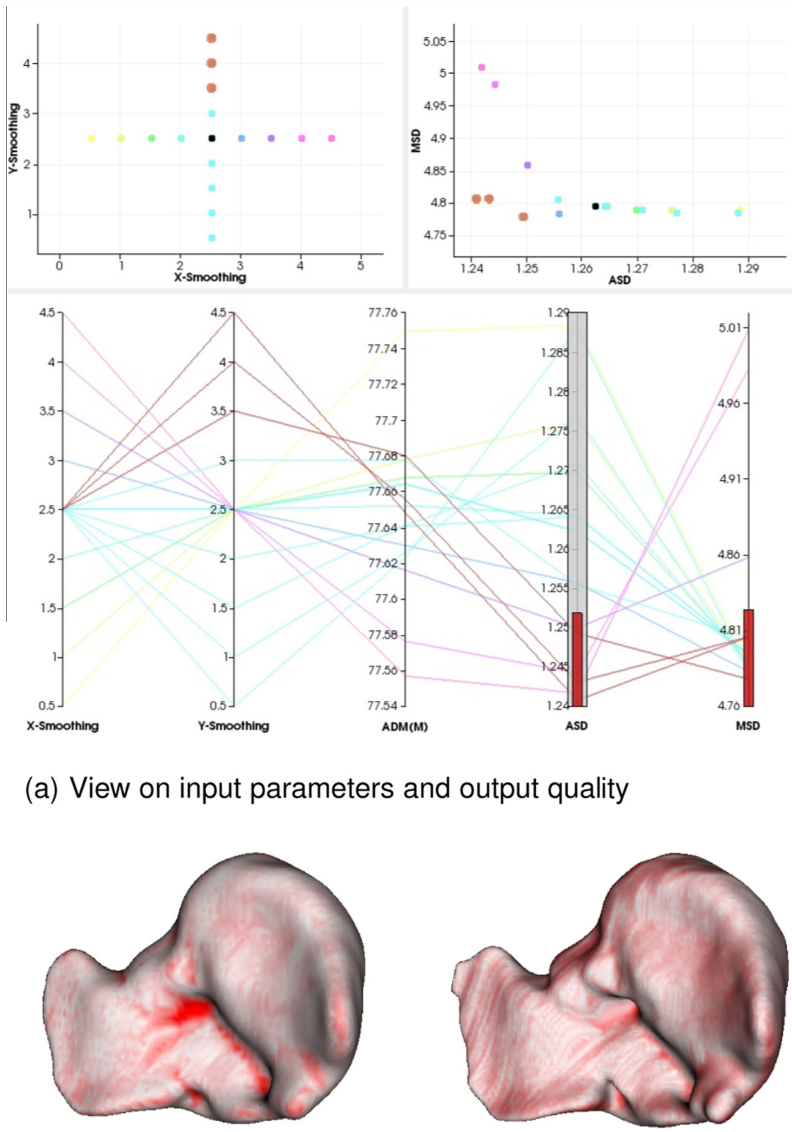
4.3. Image segmentation

We developed new methods for the analysis of the segmentation phase. The segmentation consists of a predefined number of expectation–maximization steps. By opening-up the black box of the segmentation calculation, the users can assess each step (i.e., iteration) with a set of quality metrics. This analysis offers the possibility to re-assess all stages of a finished segmentation process and to analyze problems in more detail. If needed, the users then can change settings and re-run the training with better parameters. For example, it can be reasonable to change the number of iterations. This is useful, when the pre-defined model parameters do not fit the data and therefore further iteration do not seem to progress to the desired quality or when the segmentation process reaches a turn-around point, causing some quality indicators to rise instead of their minimization (see Fig. 7 top right). In current modeling situations, such analysis is not possible.

Fig. 7 shows an interactive visualization of the segmentation calculation process. The left side shows the segmentation over the steps of the process (play/stop). The right side provides interactive visualization of selected quality metrics over all iterations. The user can see the general trend of the quality metrics and spot interesting time moments (red circles). In this data set, we can see a situation, where a lower number of iterations would improve the final result. After the red point on the top, this quality metric starts to worsen, while the second quality metric on the bottom stays stable.

4.4. Model-based segmentation evaluation

We offer users the possibility to assess model quality by comparing segmentation results for the whole data set. We thereby address the main drawback of state-of-the-art methods: individual assessment of the segmentations. Our approach consists of



(a) View on input parameters and output quality

(b) Resulting mesh with quality indication for two parameter settings. Red color means bad quality.

Fig. 5. Visual Analytics support for surface extraction from input images. Setting of the extraction parameters and their impact on output quality are interactively visualized.

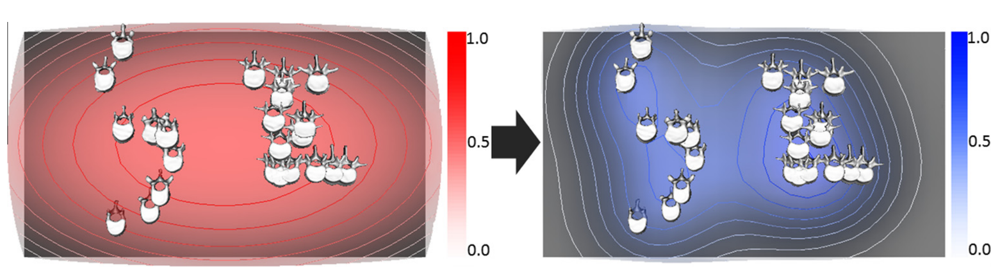


Fig. 6. Interactive distribution choice setting and by comparing two parameterizations. It shows the difference of a Gaussian vs. non-Gaussian distribution assumption for a vertebra data set.

linked-views showing the data at several levels of detail (see Fig. 8). The views show (1) distribution of global quality metrics across the test data set, (2) overall local quality (3) local quality for selected data objects. These views enable the users to see where

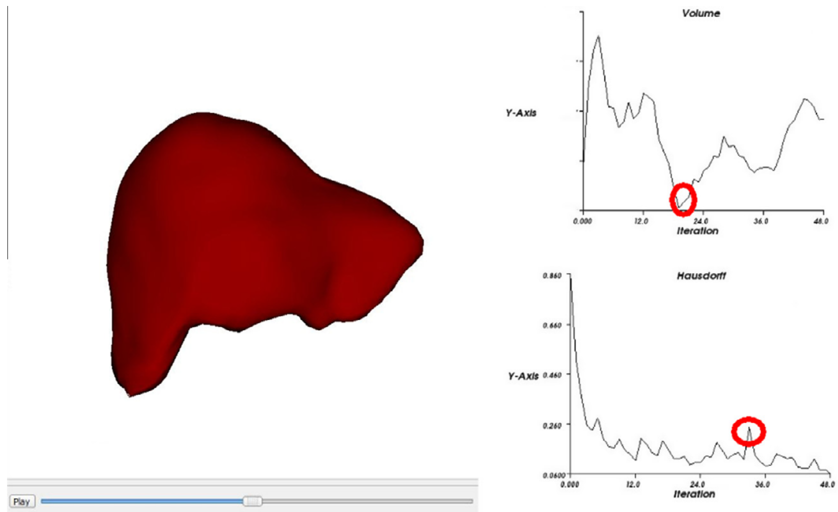


Fig. 7. Analysis of the segmentation process. Left: The interface for monitoring of the training with a view on the resulting model in the current iteration. Right: Visualization of quality metrics for all iterations. General trends and outliers (red circles) can be easily spotted. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

the model performs well and where it performs poorly. These insights can serve as a starting point for fine-tuning of model parameters (in particular for adapting the appearance model on local basis). (See Fig. 9).

(1) Histogram view shows the distribution of the values of global quality measures across the data set. We employ the measures proposed by Heimann et al. (2009) (e.g., volume difference, average distance, ...). They help to answer questions like: Are there many samples with good quality? or Are there objects with extraordinary bad quality? The interaction in histograms provides highlighting of samples in the detailed mesh view based on the quality distribution (see Fig. 8).
(2) Local quality view shows averages of a selected quality metric for each landmark of the mesh. We display the local quality as color in the resulting segmentation (see Fig. 8 top left, where red color means bad quality). We employ a selected quality metric (e.g., Euclidean distance between the expert and our segmentation) with local or global normalization. The displayed global normalization indicates that on average, our model performs very well (light colors), although the bottom regions are worse then the top. As averages provide only an indication of the quality, the comparison of data objects is needed (see Fig. 8 bottom).
(3) The detailed view shows selected objects with their local quality. The coloring is scaled globally across the whole data set. The objects are sorted according to the values of a selected global metric. In this view, the users can easily compare regions of low/high quality across the data set. For example, it can be seen that one region on the right poses major problems for a few samples.

5. Challenges

Based on the analysis of user tasks and identification of current problems in model-based medical image segmentation presented in Section 3 and the results of our approach discussed in Section 4, we state relevant challenges for Visual Analytics area. The modeling process is composed of several stages. In each stage, the input data, the respective parameter space and the result have to be analyzed. These steps should be integrated into one seamless process with the possibility of feedback loops. These feedback loops enable modeling with several iterations, creating the need for analyzing the whole process and comparing the iterations. Although these aspects are closely interrelated, we divide Visual Analytics challenges into three broad categories: input data, output evaluation and process analysis.

5.1. Data-related challenges

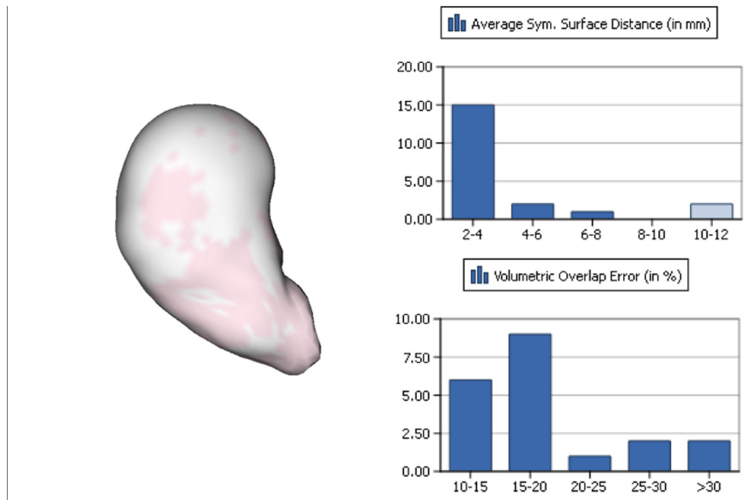
The analysis of the data and parameter space as well as data transformation are the main tasks performed throughout the process. The data complexity and the need for data space analysis methods are the main challenges in this area.

Data complexity: The input data in medical modeling have a specific form. They are based on expert segmentations. The creation of these segmentations is very costly and time consuming. Therefore, the modeling experts have to work with small data sets consisting only of tens to hundreds of input images (i.e., data objects). These segmentations are then transformed into meshes with thousands of points and further into high-dimensional data sets with thousands of dimensions. So there is *a mismatch between the high data dimensionality and small number of data samples*. This creates the main challenge in this area: Theneed to create models that are able to robustly segment any organ in human population on the basis of only a small number of training samples with high-dimensionality. This is a new challenge for Visual Analytics research.

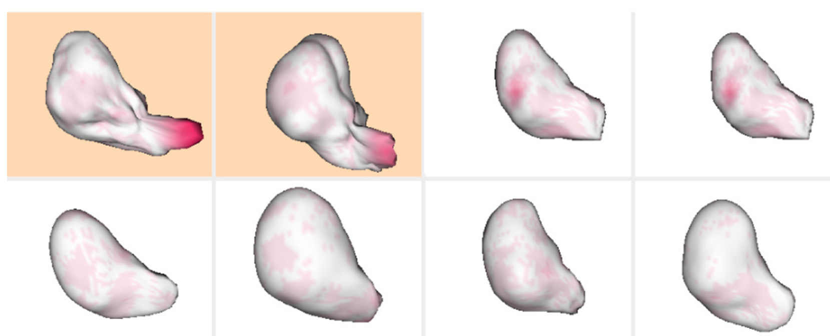
Data and parameter space analysis: Both the data pre-processing and model selection stage require the analysis of the data space. In the data pre-processing stage, data for both shape and appearance models are created. Only a high quality data can lead to very good models. So, the analysis of the data space and proper algorithm settings are necessary. We identify three main challenges in this respect.

5.1.1. The analysis of the data space in shape models

The shape model data consists of high-dimensional data vectors. The dimensions of these vectors, however are not independent, as theystem from spatial 3D meshes. Therefore, theyhave both an inherent spatial structure and are connected to each other. Although Visual Analysis of high-dimensional data is a core of the research area, the available methods cannot be applied directly to



(a) Global views



(b) Detailed view

Fig. 8. Visualization of model quality. Top: global views. Left: Mesh with average local quality metric. Right: Metrics distributions. Bottom: A selection of objects with local quality metrics. Red means bad quality. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

this problem as they deal with dimensions independently. There is a need for analysis of high-dimensional data with specific types of dimensional connections.

5.1.2. Feature extraction for appearance models

The input data for appearance models consist of a set of features that are extracted from input images on points at the boundary of the segmented organ. The choice of used features significantly influences the appearance model quality. Therefore, the main user questions are: Which features should be extracted and selected for use? Feature selection and dimensionality reduction is a problem addressed by several Visual Analytics methods. These methods, however, deal mainly with one-dimensional features and disregard the spatial organization of objects. Therefore, new tools need to be developed that allow for analysis of the feature space also in these conditions.

5.1.3. Parameter space analysis

The modeling process consists of a series of steps with algorithmic support. For many algorithms, a number of parameters need to be set so that they produce a high quality result. As an example, we discussed mesh extraction in the data pre-processing stage. The main task is the assessment of the impact of parameter choices on the output and the choice of the proper parameter setting. This task is challenging as both the input parameter space and the output quality space are high-dimensional and there is a large set of choices that can be made. Moreover, the output is 3D model, whose quality also needs to be visually inspected. Methods for assessment of parameter choices and analysis of parameter space still need to be developed in Visual Analytics. They can be based on approaches presented in Berger et al. (2011) and Pretorius et al. (2011).

5.2. Evaluation-related challenges

The evaluation of results at each stage is very important for modeling. The results need to be both visually inspected and quantitatively evaluated. Often, several results need to be compared in order to choose the best one. For example, this is important when choosing proper parameter settings in the pre-processing, or when comparing segmentation results using various models. Therefore, two main challenge areas arise: visualization of the model quality and comparison of multiple results.

Visual quality assessment: The methods for visual inspection of result quality need to cope with several issues. In particular, output quality is measured by several metrics. Therefore, methods for the choice of proper metrics and for visualization of multi-dimensional quality values has to be developed. Moreover, the user should be informed, how the quality changes with parameter choices, so the visualization should show uncertainty about final quality. We would like to encourage the development of new tools for quality assessment and uncertainty communication in Visual

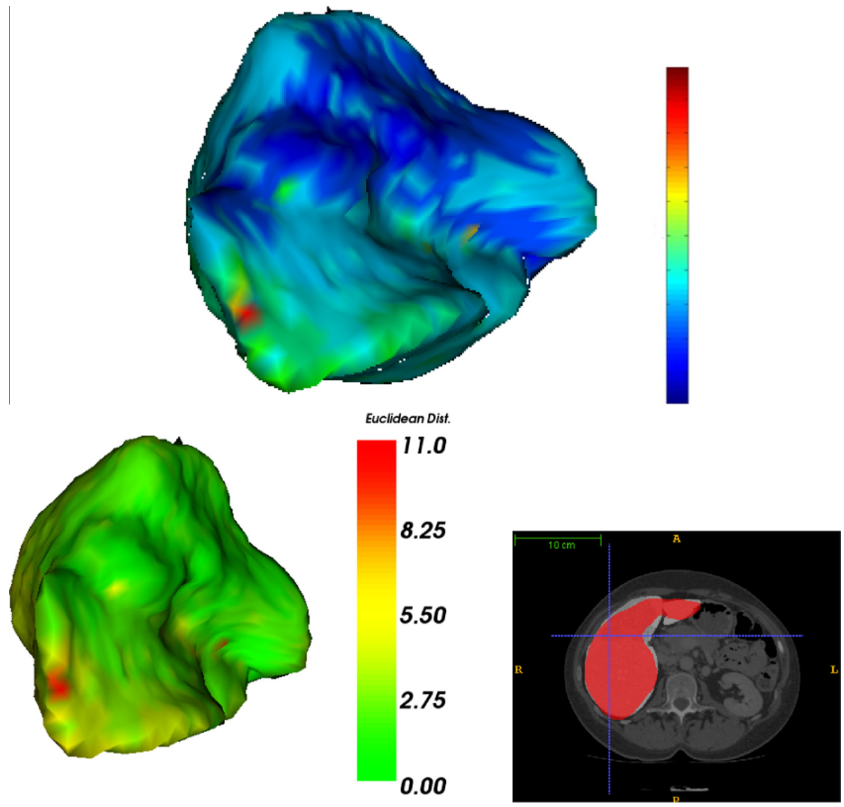


Fig. 9. View on local quality metrics. Difference view between real model and the correct segmentation based on Euclidean distance. The red area indicates part of the segmentation with bad quality and the green regions are well matched. (For interpretation of the references to colour in this figure caption, the reader is referred to the web version of this article.)

Analytics. First initiative in this respect was taken by the Workshop "Working with Uncertainty: Representation, Quantification, Propagation, Visualization, and Communication of Uncertainty" at VisWeek 2011 conference.

Comparative Visual Analytics: The comparison of algorithm and model results is a prerequisite for a proper assessment of results and choice of a high-quality model. This is difficult, because large number of results need to be compared. For example, each parameter setting produces different results. The comparison is needed both for quantitative values and for the output 3D models. In this respect, already the comparison of two results poses challenges (e.g., visual design, need for local quality measures, ...). However, the main challenge is in the comparison of several results simultaneously. Such methods are needed also in other application areas (e.g., biology for comparing phylogenetic trees, text analysis for comparing several document versions, etc.). Therefore, more focus needs to be put on comparative Visual Analytics.

5.3. Modeling process-related challenges

The creation of models fitting the data well is an iterative process. It consists of several refinements of the initial model, e.g., by changing models and their parameters. In an integrated modeling process, these refinements are supported by feedback loops.

As the users make a number of choices during the process, they need to get a support in selecting new parameter settings (which parameters have been already used and which parameters are potentially good candidates for the next iteration). Moreover, it is important for the user to know, why these parameter choices were made. These tasks should be supported by *insight provenance methods* from Visual Analytics area. However, current insight provenance systems are focused mainly on the analysis of user interaction in one process step (e.g., visual inspection of the data). Therefore, current research in the Visual Analytics community should be extended and adapted to the specific needs of medical modeling process.

A specific task in modeling process is the analysis of the *impact of model choices on the output*. A particular problem is the tight integration of two model types: shape model and appearance model. They both influence the segmentation output, but it is not clear to which extent: Does the bad segmentation quality stem from a bad shape, a bad appearance model, or their combination? Current Visual Analytics methods do not support these tasks. So new methods for analyzing the provenance of model output are needed.

6. Conclusions

In this paper, we addressed model-based medical image segmentation from the Visual Analytics perspective. The modeling of human organs is used for image segmentation widely applied in medical treatment and diagnosis. As expert segmentations are costly and time consuming, and current automatic segmentations are not precise enough, better segmentation algorithms are needed. They can be created with help of Visual Analytics tools.

We identified four stages of the modeling process and presented Visual Analytics methods for them. They improve the final result by better setting of the algorithm parameters, analysis of the input data set, and allowing visual assessment of output quality on local level.

Based on these first results, we discussed what we see as most relevant challenges for the community. Research in these directions will further improve the quality of image segmentation based on shape models.

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