# Correction Tool for Active Shape Model Based Lumbar Muscle Segmentation*

Waldo Valenzuela[1], Stephen J. Ferguson[2], Dominika Ignasiak[2], Gaëlle Diserens[3], Peter Vermathen[3], Chris Boesch[3] and Mauricio Reyes[1]

***Abstract*— In the clinical environment, accuracy and speed of the image segmentation process plays a key role in the analysis of pathological regions. Despite advances in anatomic image segmentation, time-effective correction tools are commonly needed to improve segmentation results. Therefore, these tools must provide faster corrections with a low number of interactions, and a user-independent solution.**

**In this work we present a new interactive correction method for correcting the image segmentation. Given an initial segmentation and the original image, our tool provides a 2D/3D environment, that enables 3D shape correction through simple 2D interactions. Our scheme is based on direct manipulation (DM) of free form deformation (FFD) adapted to a 2D environment. This approach enables an intuitive and natural correction of 3D segmentation results. The developed method has been implemented into a software tool and has been evaluated for the task of lumbar muscle segmentation from Magnetic Resonance (MR) Images. Experimental results show that full segmentation correction could be performed within an average correction time of 6±4 minutes and an average of 68±37 number of interactions, while maintaining the quality of the final segmentation result within an average Dice coefficient of 0.92±0.03.**

## I. INTRODUCTION

Medical image segmentation is still an on-going research topic. The wide variability of imaging protocols with combinations of scanning parameters makes it difficult to have a unique solution for image segmentation [18], [3]. Moreover, the performance of segmentation methods is also impaired by the presence of pathologies. For example, MR images produced with sequences such as DIXON or IDEAL [4], [12], are used to study fat infiltration in the musculoskeletal system. However, the quality on the muscle segmentation is reduced by the presence of fat in the muscle and low contrast of edges describing their interfaces.

From the early 1980s, the problem of segmentation has been addressed from a variety of directions [2], [11], [13]. Pattern recognition, image processing, and computer vision fields have assembled a wide spectrum of segmentation algorithms. Nevertheless, the performance of these algorithms is still application-specific. As a result, the segmentation task has become a process where a post-correction and checking has to be performed to achieve an optimal solution. The most popular correction method used in the clinics is the so-called *Brushing Tool*. Clinicians (typically a radiologist) spend several hours checking slice by slice and correcting segmentation results using these tools. For instance, the correction procedure of lumbar muscle segmentation takes between 60±20 minutes. In this regard, the key issue is to reduce the correction time and the number of user interactions, while maintaining the quality of the segmentation results.

Several correction methods have been proposed in the literature to handle errors produced by intensity based and shape based segmentation techniques. Firstly, for intensity based segmentation correction, Heckel et al. [6] used a 2D live-wire extrapolation to edit the segmentation contours, Grady et al. [5] used a graph based approach to edit the initial segmentation, and Kronman et al. [10] used a combination of min-cut segmentation and laplacian deformation for the correction. In the case of shape based segmentation correction, Timinger et al. [17] proposed a modified active shape model-based segmentation that introduces user interactions into a user-defined deformation energy term. Schwarz et al. [15] proposed the used of contour-dragging interactions and a Gaussian kernel in order to weigh the local influence of 3D shape deformations. The problem with these approaches is that the correction depends on the number of modeled shapes, which is a main problem of shape-based segmentations [7].

We propose a new correction method that produces a real-time 3D shape correction through 2D contour manipulation. We combined and adapted the DM approach presented by Hsu et al. [8] with FFD of Sederberg et al. [16] to create an intuitive and fast correction tool.

## II. METHODS

From the point of view of the clinical environment, a 3D image correction tool has to provide an intuitive 2D environment. We developed a 2D slice-wise interface, where the clinician can explore and correct the 3D segmentation result (see Fig. 5). Additionally, we selected a deformation algorithm that reduces the number of interactions, and enables real-time 3D deformation through 2D interactions. The correction pipeline (Fig. 1) start with a medical image and its initial segmentation. Three views (sagittal, coronal and axial) with the contour of the 3D segmented shape are displayed. These contours represent the intersections between the 3D segmentation result and the image planes.

*This work have been supported by AOSpine International and SNF projects 320030-138150/31003A-132935.

[1]Institute for Surgical Technology and Biomechanics, University of Bern, Switzerland waldo.valenzuela@istb.unibe.ch

[2]Institute for Biomechanics, ETH Zurich, Switzerland

[3]Department of Clinical Research / AMSM, University of Bern, Switzerland

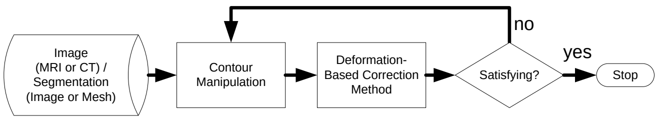



Fig. 1: Correction Pipeline. The process received as a input a medical image (e.g. MRI or CT) and the segmentation result (labeled image or mesh). After, the user performs the contour manipulation in a 2D environment, the deformation method and the contours shape are computed.

The correction process is performed through *Contour Manipulation*, which means that the user can drag and drop any point of the contour, Fig. 4. Upon contour manipulation, the deformation method computes the new shape based on the current position. The time difference between the events is less than a second, which enables a fluent correction process.

### A. Deformation-based correction method

To create a fast and intuitive interactive correction framework, we propose a FFD [16] based model to generate 3D deformations from 2D user interactions. In particular, the shape is represented by a tensor product of trivariate Bezier polynomial. The new shape of the geometrical model $\mathbf{X}$ can be computed as

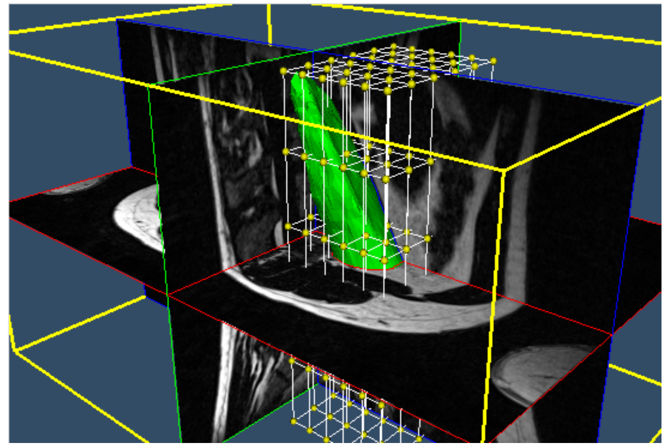
$$x_{ffd} = \sum_{i=0}^{l} \binom{l}{i} \left[ (1-s)^{l-i} s^i \left[ \sum_{j=0}^{m} \binom{m}{j} (1-t)^{m-j} t^j \left[ \sum_{k=0}^{n} \binom{n}{k} (1-u)^{n-k} u^k \mathbf{P}_{ijk} \right] \right] \right], \quad (1)$$

where $x_{ffd}$ is the deformed position of the point $x$, $\mathbf{P}$ is a vector containing the cartesian coordinates of the control points (yellow spheres in Fig. 2a) created on the parallelepiped region of $\mathbf{X}$, and ($s$, $t$, $u$) are the local coordinates of the point $x$.

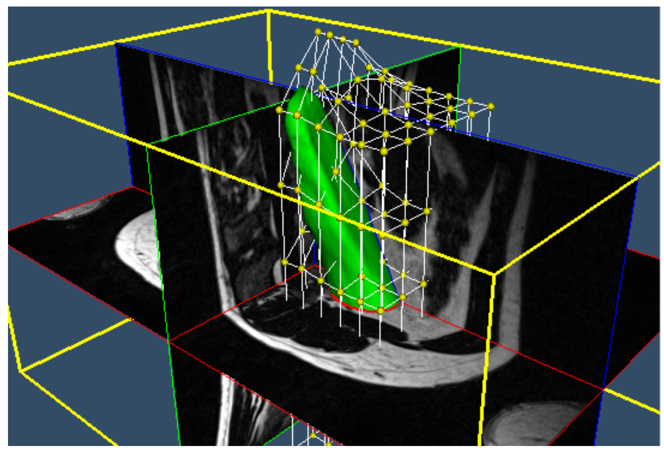
The essential idea behind (1) is that the deformation of the shape can be achieved through 3D control point manipulation, (Fig. 2a). However, the direction of the motion of the control points is not directly related with the desired deformation and it is difficult to find the correct position of the control points yielding a specific deformation. The solution to this was proposed by Hsu et al. [8], where the user defines a desired deformation through 3D vertex manipulation. The position of the control points that produces the deformation is computed by solving an "inverse" FFD. In this way the deformation becomes more intuitive. However, 3D-based manipulation techniques requires a training on a 3D environment. To tackle this, we modified the method to work directly on 2D, while keeping 3D deformations as explained in the next section.

### B. Correction Pipeline

The correction pipeline starts with a 2D visualisation of the 3D medical image and 3D segmented shape (Fig. 3). Initially, three 2D viewers (axial, sagittal and coronal views located at the center of the image) are shown to the user. The position and orientation of these slices can be defined by the user (arbitrary re-slicing). The correction process starts when the user drags the contour to a new position (red arrow, Fig. 4a). This gives the initial and end-points of the 2D displacement, which are transformed to the 3D



(a) Before deformation



(b) After deformation

Fig. 2: 3D deformation using FFD. (2a) A grid of control points (yellow spheres) equally space on each direction is placed on the shape. (2b) Ones the user has moved the 2D contour the new position of the control points are computed to create the 3D deformation of the shape. Note: the grid of control points is not presented to the user during the correction process.

coordinate system. The resulting 3D displacement is passed to the Direct Manipulation of Free Form Deformation (DM-FFD) algorithm [8], which computes the position of each control point. Then, using the computed control points, the FFD algorithm updates the new shape. Finally, the contours of the 2D viewers are updated (see Fig. 4b). Note that the complete pipeline is executed in real-time, which gives a smooth correction process.

## III. RESULTS

To test the performance of the proposed correction methodology, we developed a [1]software tool and evaluated it on ASM-based lumbar muscle segmentation. Our focus was in measuring the correction time, number of interactions, and how different are the correction result from users with different backgrounds.

[1]the tool is available on http://www.istb.unibe.ch/content/research/medical_image_analysis/software

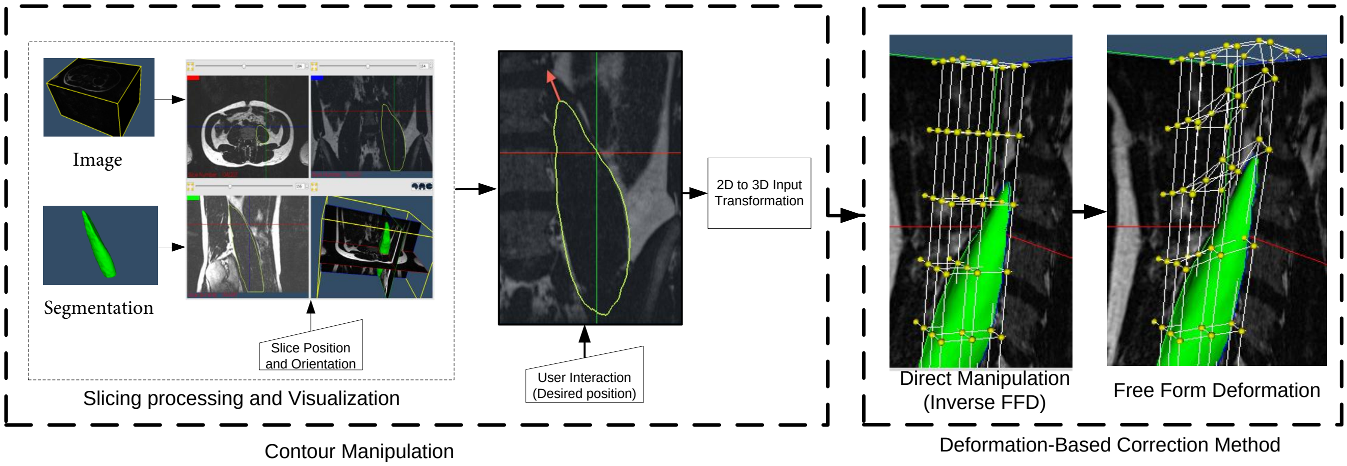
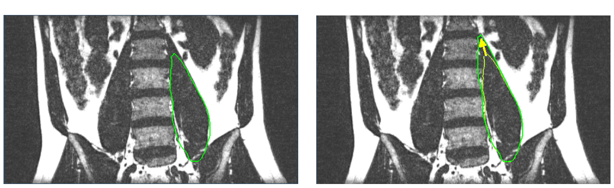



Fig. 3: Detailed Correction Pipeline. Left: shows the GUI and a 2D vector (red arrow) that represents interactions on 2D contour deformation. Right: shows the position of the control points before and after the deformation. Note: The grid of control points is shown only for illustrative purposes. It is not shown to the user in practice.

### A. Evaluation Database and Initial Segmentions

Scans from 20 volunteers were used to create the testing database. MR images of the lumbar section between vertebrae L1 and S1 acquired with a Dixon sequence, providing fat and water images, were used as input images (Fig. 4). To create the initial segmentations we implemented Active Shape Model-based (ASM) segmentation proposed by Cootes et al. [1]. We used a multi-resolution scheme to speed up the segmentation and a statistical model of the intensity profile for the fitting part. As initialization, we performed manual alignment of the mean shape to each patient image. The tool and the ASM was implemented in C++, with the Insight Toolkit for Segmentation and Registration (ITK) [9], and the visualization Toolkit (VTK) [14] and Qt (http://qt-project.org/) for visualization and GUI, respectively. To create the statistical shape model for muscle segmentation, we randomly selected six manually segmented cases from the muscle database and used the remaining 14 for the ASM-based segmentation. The average Dice coefficient of the ASM-based segmentation was 0.82±0.04. Fig. 7 (left) summarizes the results for the ASM-based segmentation.



(a) Before deformation (b) After deformation

Fig. 4: 2D deformation using FFD. Left: shows the segmented 2D contour before deformation. Right: shows the 2D contour before and after the deformation, the yellow arrow indicates the direction of the 2D interaction.

### B. Correction Protocols

To test the correction method, two different users (a clinician "**User B**", expert in the anatomy and corrections, and a software engineer "**User A**", expert in the tool, but not expert in the anatomy) were asked to perform the corrections

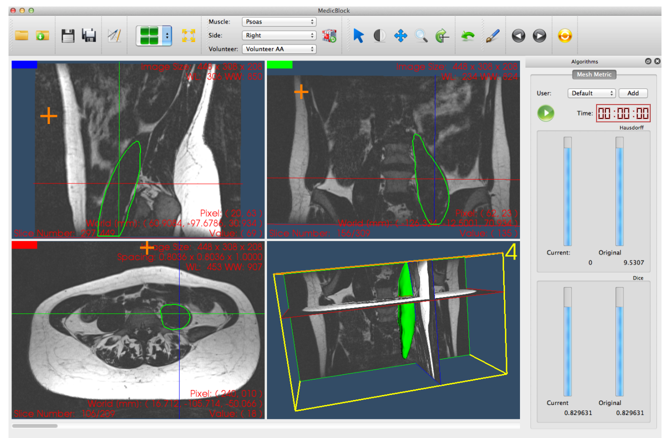
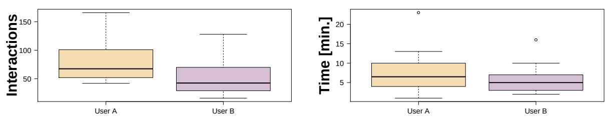


Fig. 5: Correction software. The figure shows the graphical user interface (GUI) of the software developed for the test.

on fourteen randomly selected subjects from the database. The users followed a correction protocol consisting of three steps: First, to start the corrections, the user had to select one subject from database (we did not specify any selection). After the selection, the MR image, contours of the initial segmentation and initial Dice coefficient (blue status bars) are displayed, Fig. 5. The Dice coefficient could be computed at any time during the correction and does not interfere with the rest of the process. Second, for the correction, the user could explore the image using any 2D viewer. Once the error is located, the user have to drag the segmented contour and drop it to its correct position, which produces a 3D correction over the overall segmentation. A global internal counter stores the number of interactions performed on all the slices. Third, once the user is satisfied with the result the internal chronometer had to be stopped. Number of corrections, and correction times were saved automatically. Furthermore, no additional information about the correction using the tool was provided to the user. To perform the corrections, the users should only rely on their expertise of the anatomy and the provided visualizations.




(a) Number of Interactions (b) Interaction Time

Fig. 6: Comparison between users. The yellow boxplot represent the result of the User A and the purple represent the result of the User B.

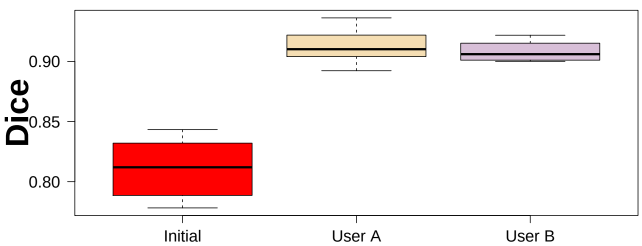



Fig. 7: Dice coefficient after the muscle correction. The figure shows the initial Dice coefficient (red box) and the final Dice coefficient per user after correction.

### C. Correction results

For an increase in Dice coefficient from 0.82±0.04 to 0.92±0.03 (see Fig. 7), our numerical evaluations on the correction time and the number of interactions showed no significant difference between the users (see Fig. 6). For both users, and independently of their different level of expertise, the correction tool provides a fast correction process using a lower number of interactions. The speed up of the correction is due to the fact that one interaction on the contour produces a full 3D deformation, which automatically covers sections that are close to the slice where the user is working. This reduces the slice-wise corrections on the image.

## IV. CONCLUSIONS

The variety of MR image protocols and the quality of these images, has shown to produce errors in the result of segmentation algorithms. Therefore, correction on the segmentations is critical for clinical analysis, where the correction time and its quality plays a key role.

In this paper we presented a new correction method for medical image segmentation. Our approach combines the direct manipulation of free form deformation algorithm within a 2D environment used in clinics, which enables 3D shape deformations through 2D interactions. This approach produces an intuitive and time-effective correction method, providing a natural user-interface for correction of 3D medical image segmentations.

The major limitation of the proposed method lies on the complexity of the segmented shape, where the performance of the FFD component lies on the number of control points needed to model local correction. An increase on the number of control points, increase the computation time of the deformation method, affecting directly on the real-time response of the tool. Nevertheless, in our experiments the number of control points allowed us to keep real-time response. As a consequence, this method cannot be used for correcting intricate structures such as brain, without further acceleration schemes.

The future work will focus on solving the mentioned limitation through adaptive control points, where the complexity of the shape in the region is measured and used as a decision parameter to decrease or increase the number of control points of the FFD component.

## ACKNOWLEDGMENT

We would like to thanks Dr. Med. Atif Aksekli and Dr. Stefan Bauer for the work performed during segmentation and testing of our correction tool.

## REFERENCES

[1] Tim Cootes. An introduction to active shape models. *Image Processing and Analysis*, pages 223–248, 2000.

[2] JS Duncan and et al. Medical image analysis: Progress over two decades and the challenges ahead. *IEEE-TPAMI*, 22(1):85–106, 2000.

[3] AS El-Baz, R Acharya, AF Laine, and JS Suri. *Multi modality state-of-the-art medical image segmentation and registration methodologies*. 2011.

[4] Michael A Fischer, Daniel Nanz, Ann Shimakawa, and Gustav Andreisek. Quantification of Muscle Fat in Patients with low Back Pain : Comparison of Multi-Echo MR Imaging with Single-Voxel. *Raiology*, 266(2):555–563, 2013.

[5] Leo Grady and Gareth Funka-Lea. An energy minimization approach to the data driven editing of presegmented images/volumes. *MICCAI*, 9(Pt 2):888–95, January 2006.

[6] F Heckel and et al. Sketch-based Image-independent Editing of 3D Tumor Segmentations using Variational Interpolation. *EWVCBM*, pages 73 – 80, 2012.

[7] Tobias Heimann and Hans-Peter Meinzer. Statistical shape models for 3D medical image segmentation: a review. *Medical image analysis*, 13(4):543–63, August 2009.

[8] WM Hsu, JF Hughes, and Henry Kaufman. Direct manipulation of free-form deformations. *ACM Siggraph Computer Graphics*, 2(July):177–184, 1992.

[9] L Ibanez, W Schroeder, L Ng, and J Cates. *The ITK Software Guide*. 2003.

[10] Achia Kronman and Leo Joskowicz. Image Segmentation Error Correction by Mesh Segmentation and Deformation. *MICCAI*, pages 206–213, 2013.

[11] Zhen Ma, JMR da Silva Tavares, and RMNJ Jorge. A review on the current segmentation algorithms for medical images. *1st International Conference on Imaging Theory and Applications (IMAGAPP)*, page 135.140, 2009.

[12] Robin L Marcus, Odessa Addison, Leland E Dibble, K Bo Foreman, Glen Morrell, and Paul Lastayo. Intramuscular adipose tissue, sarcopenia, and mobility function in older individuals. *Journal of aging research*, 2012:5, January 2012.

[13] DD Patil and SG Deore. Medical Image Segmentation: A Review. *International Journal of Computer Science and Mobile Computing*, 2(January):22–27, 2013.

[14] Will Schroeder, KM Martin, and WE Lorensen. *The Visualization Toolkit, Third Edition*. 2006.

[15] Tobias Schwarz and et al. Interactive Surface Correction for 3D Shape Based Segmentation. *Proceedings of SPIE*, 6914:69143O–69143O–8, March 2008.

[16] TW Sederberg and SR Parry. Free-Form Deformation of Solid Geometric Models. *ACM Siggraph Computer Graphics*, 20(4):151–160, 1986.

[17] H Timinger, V Pekar, and J von Berg. Integration of Interactive Corrections to Model-Based Segmentation Algorithms. pages 171 – 175, 2003.

[18] Habib Zaidi. *Quantitative Analysis in Nuclear Medicine Imaging*. Springer US, Boston, MA, 2006.