Segmentation of Shoulder MRI Data for Musculoskeletal Model Adaptation

Tomáš Ryba and Zdeněk Krňoul

Department of Cybernetics, University of West Bohemia, Univerzitni 8, Pilsen, Czech Republic

Keywords: Image Segmentation, MRI, Medical Imaging, Deltoid Muscle, Humerus, Clavicle, Scapula.

Abstract: Applying image processing techniques to medical images has already brought many useful applications. This work is focused on using these methods in the process of adapting a musculoskeletal model of the shoulder joint. Comparing the model of healthy individuals and the patient with joint damage leads to a subject-specific convalescence treatment. This work describes the procedure for segmentation of magnetic resonance imaging (MRI) of the shoulder joint. Firstly three bones inside the shoulder area: humerus, clavicle, scapula are identified and thereby it provides initial reference objects. A major step is the segmentation of the deltoid muscle needed for the subsequent adaptation of the musculoskeletal model. This step is challenging in terms of image processing due to the closeness of soft tissues, which are almost identical in intensity and the boundaries between them are often barely visible. The approach to resolving this problem is described and possible improvements and future work are described.

1 INTRODUCTION

Automated segmentation of medical image data is still an unresolved task. There are computed tomography (CT) data that are characteristic of their high image quality. At work (Kodym and Španěl, 2018), the authors deal with a semi-automatic segmentation method for general use. However, existing applications or algorithms for segmentation of magnetic resonance imaging (MRI) data are always semi-automatic and require some user intervention to set initial parameter values that are often specific to the task only. Therefore, for MRI data, we can find Vascular modeling toolkits (2016) or voice tract segmentation capturing the articulation of healthy subjects (Engwall and Badin, 1999), (Ojalammi and Malinen, 2017), etc.

There are also applications for MRI segmentation usable for general task but require very time-consuming user inputs to define initial configurations. These parameter values are often different for different anatomies, can not always be derived directly from the data, and the user usually has to proceed based on an attempt of error. Recently, there are very successful general segmentation methods of the supervised machine learning based on convolutional neural networks (Xue et al., 2018), (Liu et al., 2018). This solution, however, leads to an enormous amount of manual work during the preparation of the large training data needed as reference for their learning. On the other hand, in (Ojalammi and Malinen, 2017), the aim is to process extensive MRI data sets of upper respiratory and oral routes with minimal user interference.

The examination of MRI is useful to improve the current understanding of the human body's relationships. The MRI imaging technique is an attractive alternative to CT because it has no-ionizing radiation. This aspect is particularly important for the processing of healthy subjects. We are considering the healthy subjects for an identification of the musculoskelatal model ((Havelková et al., 2017)). On the other hand, the disadvantage of MRI against CT, is the worse spatial resolution given by the low raw voxel data quality. This is caused by the imaging principle including motion artifacts due to a scanning time, which can exceed 10 seconds for one high resolution stationary 3D image.

The aim of this work is segmentation and subsequent 3D reconstruction of the deltoid muscle of the shoulder complex from MRI volume data. The task is to separate the muscle from the background. The background consist of other muscles and bones, moreover some of them anatomically attached to the segmented muscle. The 3D reconstruction transforms segmented deltoid muscule to 3D surface model that

Ryba, T. and Krňoul, Z.
Segmentation of Shoulder MRI Data for Musculoskeletal Model Adaptation.
DOI: 10.5220/0007580701550160
In *Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2019)*, pages 155-160
ISBN: 978-989-758-353-7

is the input to musculoskeletal simulation of the shoulder complex.

We try to perform the segmentation with minimal user interference. Our work is directed to subsequent research needing processing of extensive data of both healthy individuals and patients with a shoulder complex disorder. Therefore the application is not specifically designed for doctors to examine the patient, nor is it an alternative to the software and user interface provided by the MRI scanner manufacturer.

2 RELATED WORK

The hard tissue segmentation is a well-managed technique in terms of their good visibility, in both computed tomography (CT) and magnetic resonance imaging (MRI). It is often used for diagnostic purposes, such as assistance in preoperative planning or initiation of downstream segmentation techniques of other non-hard tissues. Precise and, at the same time, fully automatic segmentation of hard tissue is achieved when the patient's anatomy does not deviate significantly from the standard. The results are currently also used for example for 3D implant printing (Tetsworth et al., 2017) or teaching aids (Jiřík et al., 2014).

The different non-hard tissues have low contrast borders with each other in both CT and MRI data and make its automatic segmentation very difficult also due to anatomical variability or various pathologies. In this case, the semi-automatic approaches are currently successful. The user searches for specific algorithm parameter values to achieve the required segmentation result accuracy. Although some applications do not require very anatomically precise surface models, for the precise segmentation, it must to be done by clinical professionals processing volumetric data one slice after another. This is very challenging due to tedious processing of a large number of slices in volume data.

The segmentation of the hard tissue is sufficient by adaptive thresholding techniques (Rathnayaka et al., 2011) or area growth algorithm (Xi et al., 2014). The segmentation failure is where the boundaries of an object pass through areas of the low contrast. To deal with this problem, there are approaches based on models of active contours, (Pinheiro and Alves, 2015), optimizing the smoothness and a continuity criteria.

Moreover, the methods of active or statistical shapes (He et al., 2016) and (Yokota et al., 2013) assume prior shape of a segmented object. However, this must be obtained by learning from previous (often manual) ideal segmentation of all potentially possible shapes. This can be a problem with unpredictable anatomical pathologies. On the other hand, the user input during their application degrades only on the pre-positioning of the model in reference pose as near as possible to the location (Virzì et al., 2017) or, in the case of a fully automated method, this step is completely eliminated (Antong et al., 2010).

As another form of segmentation, the image registration can be considered (Hajnal and Hill, 2001). This is not the pure segmentation technique because needs a reference image in addition. It determines the geometric relationship between each point of the reference image and the processed image as a cost-optimization function. However there are unregulated registration algorithms for comparing deform-able organs such as the brain, liver or lung (Rohlfing and Maurer, 2003), (Ino et al., 2005). The failure of registration caused by dropping search algorithm into local optima is prevented through generating a large training set for the deep-learning image registration (Ito and Ino, 2018).

More recently, graph-based methods provide binary segmentation as the search for a global optima separating object from the background. These methods are reliable if the user again provides a sufficient amount of accurate user inputs. For MRI or CT, it has a form of seeds labeled in many slices of volumetric images. Furthermore automation reducing amount of manual inputs benefits from a combination of graph-cut techniques with prior information provided by some edge detection method (Keustermans et al., 2012), (Krčah et al., 2011) or a classification technique based e.g. on random decision forests (RDF) (Kodym and Španěl, 2018). The last mentioned method searches for optimal binary segmentation of volumetric data with respect to the probability field obtained from RDF classifiers online trained on only a few expertly annotated sections.

In general, the convolutional networks are machine powerful learning techniques and are currently a successful segmentation technique for the medical imaging data (Ghosal and Ray, 2017), (Prasoon et al., 2013). They overcome previously popular segmentation techniques based on RDF classification (Loh, 2011), which uses random subsets of available training data to build a set of binary decision trees. In the context, these data-driven and supervised techniques need training data that is very varied due to a wide range of imaging techniques used in medicine. There are methods increasing accuracy and robustness by generating thousands of synthetic training data from only a few input original images (Ito and Ino, 2018) and-or often combining with an augmentation method (Milletari et al., 2016), (Ronneberger et al., 2015).

3 METHODS

3.1 Image Preprocessing

A common problem in image processing is the image noise. In order to deal with it, several options may be used. The commonly used method is the Gaussian filtering. Unfortunately, an obvious disadvantage of this approach is blurring of image edges. As already stated main goal of this work is to segment one certain muscle in the shoulder complex. The boundary between this muscle and background is barely visible. Therefore, it's not a reasonable approach to blur them even more.

To reduce the image noise and leave the edges untouched at the same time an edge preserving filter must be used. In this work the bilateral filter (Tomasi and Manduchi, 1998) is used. The weights in this filter correspond not only to distance as in the Gaussian filter but to the intensity difference of pixels as well. This way, only pixels that are geometrically close and have similar intensity are taken into account during filtering. And because edges are defined as pixels with high intensity gradient, they're usually filtered very slightly.

Comparison of the Gaussian filter and the bilateral filter is shown in Figure 1.

3.2 Image Segmentation

For the purpose of image segmentation, a semiautomatic tool was developed. It works on an established system of placing seed points representing the object of interest and another group of points representing the background. For the algorithm processing the data with defined seed points, we tested three commonly used methods - Graph Cut (GC) (Boykov and Jolly, 2000), Random Walker (RW) (Grady, 2006) and Watershed (WS) (Dobrin et al., 1994).

The GC method is based on creating intensity models for each object. These models are calculated from given seed points. Using the GC often leads to overtrained models. This is due to very similar object densities when segmenting one specific muscle. In this case, points with similar density are marked as two different objects. Moreover, to mark the background object properly the corresponding model needs to describe image parts that significantly differ in intensity. The resulting model is not descriptive enough and the algorithm gets confused.

Given the set of seed points, the RW algorithm finds the closest path to one of the seed point for each unlabeled pixel. There are no direct connections to an intensity model like in the GC algorithm. Therefore, the closest path depends strongly on the seed position, which often yields to a significantly higher amount of needed seed points that spreads on all parts of the object. The needed interactivity was overwhelming especially when segmenting the muscle.

Using the simple WS algorithm provides us with the best results regarding the precision of segmentation and the amount of needed interaction. Another important advantage of this approach is its efficiency and computation speed. Using the WS algorithm makes the whole segmentation process faster and more fluent.

To help the operator with orientation it's possible to switch between different views - coronal, sagittal and axial. This way, it is possible to change the views during the segmentation process to define the seed points more accurately.

3.2.1 Extracting the Bones

For easier orientation and further data processing, three bones are segmented: humerus, scapula, and clavicle. The Humerus is a long bone of the arm that forms the shoulder joint on the one end and the elbow joint on the second end. The Scapula or shoulder blade is a triangular bone that lies on the upper back. The Clavicle is an anterior bone of the shoulder. Its main function is to support the shulder.

In the MRI the bones are well separated due to their high intensity. The contrast between a bone and near soft tissues is significant. Therefore, the needed amount of interactivity is much lower comparing to the muscle segmentation.

Nevertheless, to use a fully autonomous approach, e.g. thresholding, is not recommended. Despite the bones, the're different objects with the similar intensity that would be segmented as well. Using such an approach often yields to results where for example the clavicle and the skin are connected into one big object.

On the other hand, the WS algorithm is perfectly suited for this task. The final segmentation of the humerus is shown in the second image in Figure 2.

3.2.2 Extracting the Deltoid

Segmentation of one specific muscle is a much more challenging task. The reason for this is the intensity similarity of the soft tissues and an unclear boundary between individual muscles. The risk of overtraining a segmentation algorithm based on intensity models is

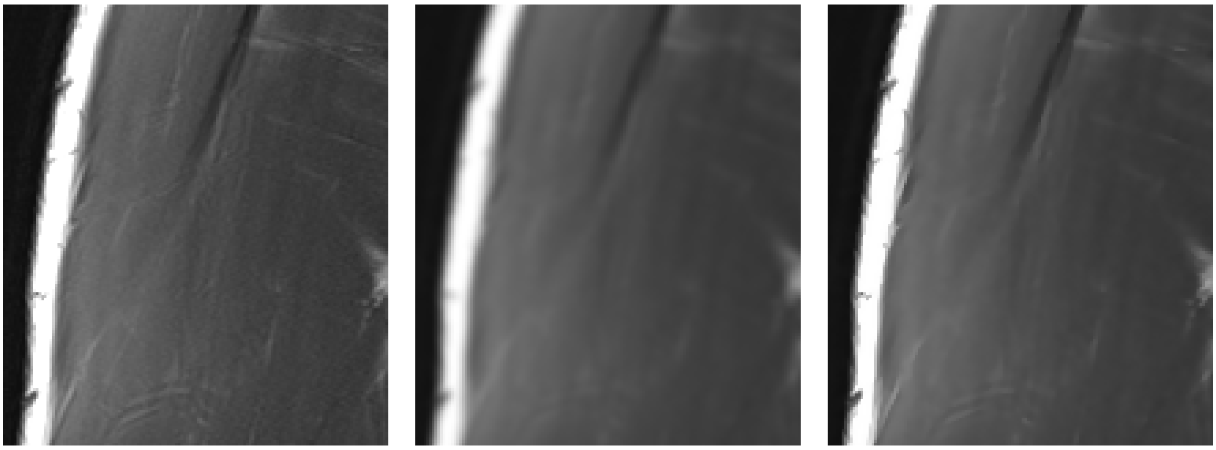

Figure 1: Input image (left) filtered by Gaussian (middle) and by a bilateral filter (right).

significantly higher than in the bones extraction case and the amount of interactivity increases.

Moreover, this task is much more focus demanding than the bone segmentation. A certain amount of anatomy knowledge is also needed, especially in parts with an unclear boundary between individual muscles. Segmentation of bones prior to the muscle segmentation is recommended for a better orientation.

The WS algorithm meets its limits here but still provides reasonable results. Therefore, the segmentation refinement that is described in the next section is very important in these cases.

3.3 Segmentation Refinement

The segmentation obtained by the WS algorithm is sometimes very coarse and inaccurate. The reason for that is the algorithm's sensitivity to the noise and unclear object boundaries. Despite the preprocessing and proper noise filtration, the filtered data are still not perfect. Is it, therefore, appropriate to use a segmentation method that will start at the coarse segmentation and will refine the result to better match the reality.

An information that could be used in this step is that most of the objects in the human body tend to be compact with no sudden changes in shape. A perfect approach that respects such an information is the active contours approach (Pinheiro and Alves, 2015).

Methods based on active contours need to be initialized by an initial curve. This initial curve should be as close to the desired result as possible, which minimizes the possibility of getting stuck in a local energy minimum. In this work, this initial curve corresponds to the boundary of the coarse segmentation achieved from the image segmentation. During the iterative process the curve evolves and due to the calculation tends to be smooth and compact.

The last step in the postprocessing procedure is the morphological filtering. This way the boundary of the segmentation is smoothed even more, which yields more reliable results.

4 RESULTS

In this work, we used the MRI of a 30 years old healthy male subject. The final segmentation of the humerus and the deltoid muscle is shown in Figure 2.

The main result of this work is the software for MRI processing. The developed software is used for segmentation of specific bones and soft tissues in the shoulder.

The segmentation is done with an interactive version of the watershed algorithm. Using this approach yields to fast responses of the algorithm as the user draws seed points over the input data. This coarse segmentation is then refined using an active contours method.

As more data are processed the software will learn and the future processing should be faster.

5 CONCLUSIONS AND FUTURE WORK

To develop a fully autonomous segmentation process is a very challenging task especially regarding muscle segmentation. We faced this challenge using an interactive method based on the watershed algorithm. Probably the biggest disadvantage of this approach is the amount of needed interactivity in some cases. This interactivity could be reduced using several ways.

For example, a thresholding algorithm could be used for segmentation of the bones. As already men-

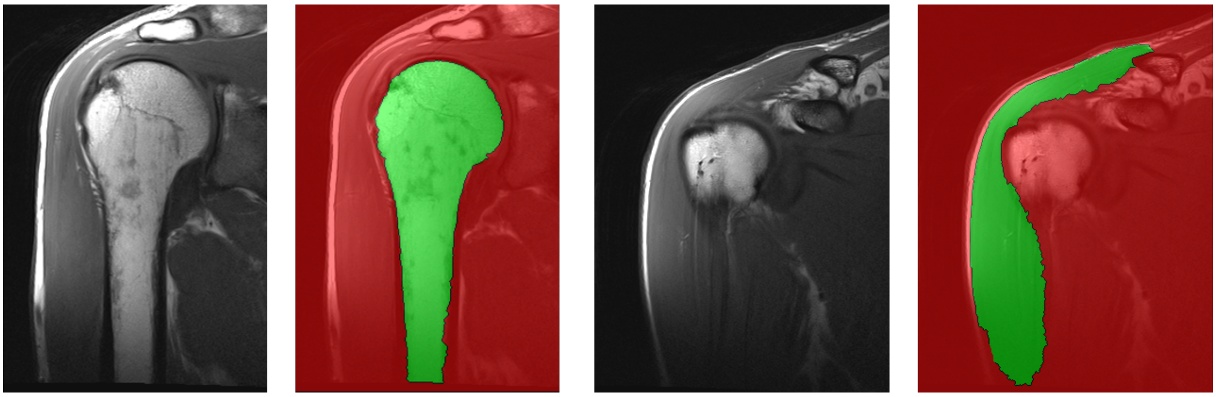

Figure 2: Segmentation of bones (the humerus on the first two images) and segmentation of soft tissues (deltoid muscle on the last two images).

tioned, using such an approach could yield to a big object consisting of a bone and other objects. We believe that with a proper postprocessing this problem could be solved. Therefore, at least some steps could be automized in the future work.

At this moment, the segmentation process is calculated over the whole image. To improve the processing speed defining a region of interest could be implemented.

Another goal of our work is to create a statistical representation of the position of the deltoid muscle. This means that for each point we would like to calculate a probability that this point belongs to the deltoid muscle. Segmented humerus, scapula, and clavicle will be taken as the reference objects. Creating such an atlas could autonomously propose seed points defining the deltoid thus decreasing the needed amount if interactivity.

The problem of this approach is the uniqueness and difference between subjects - factors such as height, weight, musculature, sex etc. plays a significant role regarding the position and shape of the corresponding deltoid muscle. Having a large number of data containing all of these factors, it could be possible to create more statistical atlases and then use the one that best fits the given subject.

ACKNOWLEDGEMENTS

This research was supported by the project ”38 Virtual human body model for prevention, therapy and rehabilitation of shoulder diseases” realized within the frame of the Program INTERREG V-A: Cross-border Cooperation between the Czech Republic and the Federal State of Germany Bavaria, Aim European Cross-border Cooperation 2014 - 2020. The realization is supported by financial means of the European Regional Development Fund and the state budget of the Czech Republic.

REFERENCES

Antong, C., Deeley, M. A., Niermann, K. J., Moretti, L., Dawant, B. M., Department of Radiation Oncology, Vanderbilt-Ingram Cancer Center, . n. A. S. N. T. ., of Electrical Engineering, D., and Computer Science, Vanderbilt University, N.-T. . (2010). Combining registration and active shape models for the automatic segmentation of the lymph node regions in head and neck CT images. *Medical Physics*, 37(12).

Boykov, Y. and Jolly, M.-P. (2000). Interactive organ segmentation using graph cuts. In *International conference on medical image computing and computer-assisted intervention*, pages 276–286. Springer.

Dobrin, B. P., Viero, T. J., and Gabbouj, M. (1994). Fast watershed algorithms: analysis and extensions. In *Nonlinear Image Processing V*, volume 2180, pages 209–221. International Society for Optics and Photonics.

Engwall, O. and Badin, P. (1999). Collecting and analysing two- and three-dimensional MRI data for swedish. *Quarterly Progress and Status Report - Royal Institute of Technology, Department of Speech, Music and Hearing*, 3.

Ghosal, S. and Ray, N. (2017). Deep deformable registration: Enhancing accuracy by fully convolutional neural net. *Pattern Recognition Letters*, 94:81 – 86.

Grady, L. (2006). Random walks for image segmentation. *IEEE transactions on pattern analysis and machine intelligence*, 28(11):1768–1783.

Hajnal, J. and Hill, D. (2001). *Medical Image Registration*. Biomedical Engineering. Taylor & Francis.

Havelková, L., Špička, J., and Hynčík, L. (2017). The new torus obstacle method used for musculoskeletal modeling. In *23st CONGRESS OF EUROPEAN SOCIETY OF BIOMECHANICS*.

He, B., Huang, C., Zhou, S., Hu, Q., and Jia, F. (2016). Fast automatic 3D liver segmentation based on a three-level adaboost-guided active shape model. *Medical Physics*, 43(5).

Ino, F., Ooyama, K., and Hagihara, K. (2005). A data distributed parallel algorithm for nonrigid image registration. *Parallel Computing*, 31:19–43.

Ito, M. and Ino, F. (2018). An automated method for generating training sets for deep learning based image registration. In *Proceedings of the 11th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2018) - Volume 2: BIOIMAGING, Funchal, Madeira, Portugal, January 19-21, 2018.*, pages 140–147.

Jiřík, M., Ryba, T., Svobodová, M., Mírka, H., and Liška, V. (2014). LISA - liver surgery analyzer software development. In *Proceedings of the 11th World Congress on Computational Mechanics (WCCM 2014), Barcelona*.

Keustermans, J., Vandermeulen, D., and Suetens, P. (2012). Integrating statistical shape models into a graph cut framework for tooth segmentation. In Wang, F., Shen, D., Yan, P., and Suzuki, K., editors, *Machine Learning in Medical Imaging*, pages 242–249, Berlin, Heidelberg. Springer Berlin Heidelberg.

Kodym, O. and Španěl, M. (2018). Semi-automatic CT image segmentation using random forests learned from partial annotations. In *Proceedings of the 11th International Joint Conference on Biomedical Engineering Systems and Technologies - Volume 2: BIOIMAGING,*, pages 124–131. INSTICC, SciTePress.

Krčah, M., Székely, G., and Blanc, R. (2011). Fully automatic and fast segmentation of the femur bone from 3D-CT images with no shape prior. In *2011 IEEE International Symposium on Biomedical Imaging: From Nano to Macro*, pages 2087–2090.

Liu, F., Zhou, Z., Jang, H., Samsonov, A., Zhao, G., and Kijowski, R. (2018). Deep convolutional neural network and 3d deformable approach for tissue segmentation in musculoskeletal magnetic resonance imaging. *Magnetic resonance in medicine*, 79(4):2379–2391.

Loh, W.-Y. (2011). Classification and regression trees. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 1(1):14–23.

Milletari, F., Navab, N., and Ahmadi, S.-A. (2016). V-net: Fully convolutional neural networks for volumetric medical image segmentation. *2016 Fourth International Conference on 3D Vision (3DV)*, pages 565–571.

Ojalammi, A. and Malinen, J. (2017). Automated segmentation of upper airways from MRI: Vocal tract geometry extraction. In *Proceedings of the 10th International Joint Conference on Biomedical Engineering Systems and Technologies*, volume 2, pages 77–84. SciTePress.

Pinheiro, M. and Alves, J. L. (2015). A new level-set-based protocol for accurate bone segmentation from CT imaging. *IEEE Access*, 3:1894–1906.

Prasoon, A., Petersen, K., Igel, C., Lauze, F., Dam, E., and Nielsen, M. (2013). Deep feature learning for knee cartilage segmentation using a triplanar convolutional neural network. In *International conference on medical image computing and computer-assisted intervention*, pages 246–253. Springer.

Rathnayaka, K., Sahama, T., Schuetz, M. A., and Schmutz, B. (2011). Effects of CT image segmentation methods on the accuracy of long bone 3D reconstructions. *Medical engineering & physics*, 33(2):226–233.

Rohlfing, T. and Maurer, C. R. (2003). Nonrigid image registration in shared-memory multiprocessor environments with application to brains, breasts, and bees. *IEEE Transactions on Information Technology in Biomedicine*, 7(1):16–25.

Ronneberger, O., Fischer, P., and Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *International Conference on Medical image computing and computer-assisted intervention*, pages 234–241. Springer.

Tetsworth, K. D., Block, S., and Glatt, V. (2017). Putting 3D modelling and 3D printing into practice: virtual surgery and preoperative planning to reconstruct complex post-traumatic skeletal deformities and defects. In *SICOT-J*.

Tomasi, C. and Manduchi, R. (1998). Bilateral filtering for gray and color images. In *Computer Vision, 1998. Sixth International Conference on*, pages 839–846. IEEE.

Virzì, A., Marret, J. ., Muller, C. O., Berteloot, L., Boddaert, N., Sarnacki, S., and Bloch, I. (2017). A new method based on template registration and deformable models for pelvic bones semi-automatic segmentation in pediatric MRI. In *2017 IEEE 14th International Symposium on Biomedical Imaging (ISBI 2017)*, pages 323–326.

Xi, T., Schreurs, R., Heerink, W. J., Bergé, S. J., and Maal, T. J. J. (2014). A novel region-growing based semi-automatic segmentation protocol for three-dimensional condylar reconstruction using cone beam computed tomography (CBCT). In *PloS one*.

Xue, Y., Xu, T., Zhang, H., Long, L. R., and Huang, X. (2018). Segan: Adversarial network with multi-scale l 1 loss for medical image segmentation. *Neuroinformatics*, pages 1–10.

Yokota, F., Okada, T., Takao, M., Sugano, N., Tada, Y., Tomiyama, N., and Sato, Y. (2013). Automated CT segmentation of diseased hip using hierarchical and conditional statistical shape models. In Mori, K., Sakuma, I., Sato, Y., Barillot, C., and Navab, N., editors, *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2013*, pages 190–197, Berlin, Heidelberg. Springer Berlin Heidelberg.