EPiC Series in Health Sciences
Volume 6, 2024, Pages 75–81
Proceedings of The 22nd Annual Meeting of the International Society for Computer Assisted Orthopaedic Surgery

3D Reconstruction of Femur using Ultrasound - Hand Guided Evaluation and Autonomous Robotic Approach

Lovis Phlippen, Benjamin Hohlmann and Klaus Radermacher
Chair of Medical Engineering at
Helmholtz-Institute for Biomedical Engineering, RWTH Aachen University
phlippen@hia.rwth-aachen.de

Abstract

Total Knee Arthroplasty is a frequently performed surgery. Patient specific planning and implants may improve surgical outcome. For this purpose, 3D models of the bones are required, which are typically generated by using computed tomography. A radiation free and cheaper alternative could be ultrasound. However, bone segmentation and a competitive method of creating a complete bone model are a challenge.

In this work a fully-automatic bone reconstruction pipeline using ultrasound, which includes machine learning based image segmentation and an interpolation algorithm for missing areas using statistical shape models, is presented and evaluation results with free hand probe guidance are outlined. A mean surface distance error of 0.96 mm for femur bone reconstruction is achieved. Furthermore, a robotic scanning approach is presented to automate the entire process. Autonomous scanning of the anterior distal femur was successful for 4 out of 5 probands. On average, 54 % of the accessed bone surface could be reconstructed.

1 Introduction

Knee replacement surgeries are one of the most frequently conducted among all surgeries worldwide (OECD Library, 2019). For obtaining satisfactory rehabilitation results the size, shape and position of the implant are key factors (Asseln et al., 2021; Ritter et al., 2011). A first step in surgical planning is image acquisition of the knee. This becomes mandatory if patient specific implants or instruments are used. For this matter 3D planning has advantages in comparison to 2D planning, e.g. obtaining correct rotation of femoral components (Hirschmann et al., 2011; Pietrzak et al., 2018). Computed tomography (CT) is state of the art for acquiring 3D bone models, but it exposes the patient to radiation (Brenner & Hall, 2007; D'Amore et al., 2022; Ponzio & Lonner, 2015) and is an expensive procedure. Another imaging technique is ultrasound (US). It has no harmful effects (Moyano et al., 2022) and is cheap.

However, US images may be noisy due to diffuse deflections and bone surfaces may appear blurred (Hacihaliloglu, 2018; Karamalis, 2013). Therefore, one challenge in establishing a suitable alternative to CT is segmentation of bone surface in US images. State of the art in image segmentation are algorithms based on machine learning approaches (Pandey et al., 2020). Another challenge for 3D imaging with US is the full bone modelling. As common US probes are not covering the entire knee, images must be referenced to each other using a localization system for the probe (Hacihaliloglu, 2018). One approach is freehand 3D ultrasound, whereby an electromagnetic (Mahfouz et al., 2021) or optical localization system (B. Hohlmann & K. Radermacher, 2020) can be used. Furthermore, bone may be occluded using US, which requires interpolation based on statistical shape models.

Another extension that allows automation of the entire workflow is the use of a robot that guides the probe. For different applications focusing on soft tissue diagnosis several robotic ultrasound systems are described in literature, though no autonomous system is yet available on the market (Haxthausen et al., 2021; Li et al., 2021). For the application in this matter, 3D bone reconstruction, just a few groups have published their work (Kerr et al., 2017; Torres et al., 2012).

This work presents an in vivo study of knee reconstruction with a hand guided probe and introduces an approach for autonomous path planning and scanning of the knee using robotic ultrasound.

2 Hand Guided Scan

In this section a in vivo study of femur bone reconstruction using freehand 3D set up with a 2D ultrasound probe is presented. The reader is referred to a detailed report of the study (Hohlmann et al., 2023).

2.1 Material and Set Up

For data acquisition, a 2D probe with a flat array (L15HD, Clarius, Vancouver) and an optical tracking system (fusionTrack 500, Atracsys, Puidoux) was used. A rigid tracking body was attached to the probe and a dynamic reference base was fixated at the lower leg of the proband (Figure 1). Ten probands took part in the study with an age between 28 and 58. There were seven male and four female participants. Previously, they performed an MRI examination (approved by ethics committee) of their knee to generate ground truth data. Bone segmentation in MRI data was performed manually. For one subject a segmented bone model from a CT scan was available, which differed in average 0.86 mm from the MRI segmentation. For the ultrasound scan the probands were sitting with their scanned leg in 90° flexion, which moves the patella distally and minimizes occlusion of the femur. The leg was fixated in a mounted shoe to avoid movements during the scan procedure. A medical expert conducted the ultrasound scans on the frontal part of the femur for each proband.

2.2 3D Bone Reconstruction Method

The Clarius advanced programming interface (API) automatically adjusts the imaging parameters and transfers the images to our custom software where the images are matched to the tracking data, taking into account a time delay of 200 ms for the image processing pipeline Transformation between the rigid tracking body and the image is known from CAD data of the 3D printed mounting. Bone Segmentation in the 2D images is performed in real-time by a convolutional neural network. The Deeplabv3+ network was selected and trained on 4565 annotated images, which were spilt 10:1 for training and validation, respectively (Chen et al., 2018; Hohlmann et al., 2020). The segmented bone surface area is skeletonized to a line and transformed according to its tracked position. By this process, a 3D point set is computed.

After each data acquisition, the point set is registered to a statistical shape model (SSM) mean shape with a customized iterative closest point (ICP) algorithm of Matlab (R2022a, Mathworks, Natick). The SSM of the femur was built from CT data of 414 patient which underwent TKA (B. Hohlmann & K. Radermacher, 2020).

The SSM is used for the interpolation of the point sets to areas not covered by US. The algorithm conducts a direct optimization of pose and shape by minimizing an objective function on the average surface distance between the shape model and the incomplete point cloud. For this matter, a general-purpose optimizer ("fminsearch", Matlab) is used to minimize the objective function. In previous in-silico experiments, hyperparameter optimization was performed to optimally tune the algorithm.

2.3 Results

A masked shape of the distal femur covering the area relevant for TKA is used for computation of the metrics. The mean surface distance error for all ten reconstructed distal femurs is 0.96mm with a standard deviation of 0.31 mm.

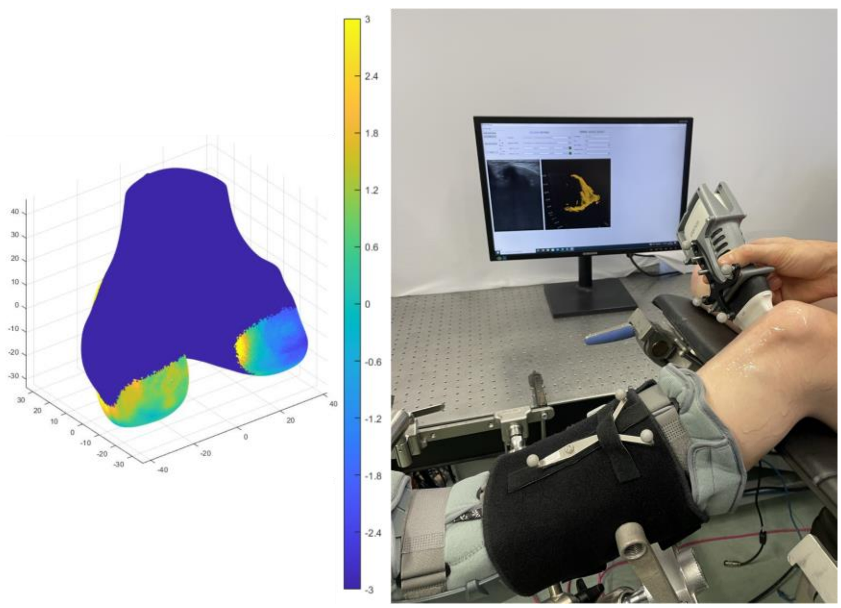

Figure 1: Heatmap visualization of the surface distance error (in mm) after reconstruction for an average performing scan (left). The freehand 3D ultrasound setup (right).

3 Autonomous Robotic Guided Scan

3.1 Material and Set Up

The setup consists of a lightweight robot with a moving mass of 12.8 kg and integrated collision detection (Panda, Franka Emika, Munich). The ultrasonic probe (L15HD, Clarius, Vancouver) and the depth camera (Intel Real Sense D415, Intel, Santa Clara) are attached to the robot end effector using a 3D printed mount (Figure 2). The software for control and data processing of the robot and depth camera is implemented in C++ in a ROS (ROS Noetic, Open Source Robotics Foundation) environment.

For an initial evaluation of autonomous path planning and scanning of the anterior side of the distal femur, 5 subjects were recruited. The leg was fixed in 90° flexion analogous to the description in paragraph 2.1.

3.2 Autonomous Scanning Method

For each record session, two images are initially acquired with the depth camera, one from a perspective on the left and one on the right of the knee. The robot moves for this purpose to predefined poses at a distance of about 30 cm from the knee. By geometric calibration and reading out the robot pose, both images can be transformed into a base coordinate system. A smoothing operation (PCL library, MovingLeastSquares) is then applied to the merged point cloud. The point cloud is transferred to Matlab (R2022a, Mathworks, Natick) where it is further processed by an algorithm for path planning. At first, the algorithm searches for the highest point on the skin surface corresponding to a point on the patella. Subsequently, an origin for the trajectory pattern is defined at a predetermined proximal distance of 3 cm on the skin surface. A planar trajectory pattern is then transformed to the defined origin and the path is unrolled onto the skin surface. The calculated trajectory consisting of points is then transmitted back to the robot controller. For the scan, the robot first moves to the starting point of the calculated trajectory using position control. Afterwards, torque control, which is overlaid by impedance control is used. Parameters were empirically defined to 450 N/m for translational stiffness and 85 Nm/rad for rotational stiffness. The robot is moved by continuously updating the equilibrium poses, which correspond to the path points shifted 10 mm along the surface normal towards the leg in order to maintain contact to the skin. Simultaneously, the framework for ultrasound reconstruction described in the last chapter is started. Instead of reading out the pose with the robot, optical tracking is used, since the accuracy of the optical tracking system is significantly better.

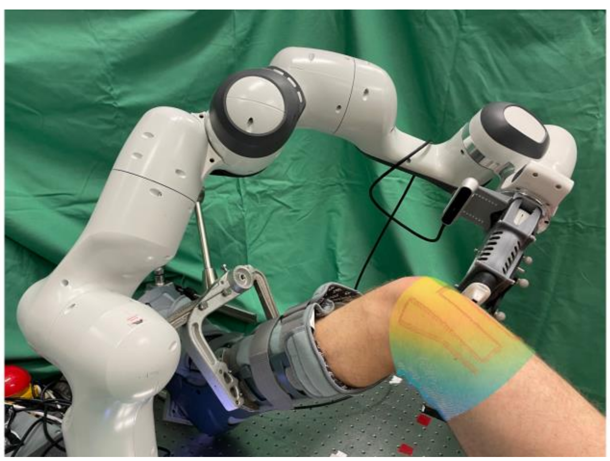

Figure 2: Set up for robotic ultrasound. The projection of the robot path onto the skin surface point cloud is overlayed.

3.3 Results

In total, 4 out of 5 trajectory generations and scans were successful. For the unsuccessful scan, the algorithm could not unroll the trajectory on the point cloud. The focus to evaluate the robotic approach laid on the correct probe orientation and contact to obtain segmentation data. For this purpose, the reconstruction was manually pre-aligned to each subject's ground truth data and then fine-positioned using an ICP algorithm. Hereafter, the ground truth data was cropped to the outer edges of the acquired reconstruction. Subsequently, areas of the bone not covered by the robotic scan were determined by calculating the mean distance error between the ground truth data and its corresponding reconstruction. If the distance error was greater than the point cloud resolution of 3 mm, the area was recognized to be not covered. An average of 54% of the scanned area was reconstructed. The best result among the 4 successfully scanned probands was 68 % and the worst 38 %.

4 Discussion

The in vivo evaluation study of 3D femur reconstruction using free hand ultrasound with the proposed pipeline shows promising results. The average mean distance error of the area relevant for TKA at the femur is slightly below 1 mm, despite the fact that only anterior ultrasound data was acquired for adapting the statistical shape model. However, maximum errors are up to 3 mm, which is critical for TKA planning. Accurate addition of posterior scanning data could increase accuracy especially related to the posterior condyles. Looking at the workflow, the line-of-sight issue must always be kept in mind, especially when scanning the posterior parts of the knee. To solve this issue, electromagnetic tracking (EMT) can be advantageous, which was used in an ex vivo study by another group which achieved reconstruction results of the femur with an accuracy of 1.07 mm (Mahfouz et al., 2021). However, robustness of EMT in clinical settings has to be further investigated regarding potential EM field distortions.

In order to fully automate the entire process, autonomous path planning was implemented on a robotic ultrasound system for imaging the distal femur and evaluated on 5 subjects. The authors are not aware of any other robotic ultrasound system described in literature that have implemented an in vivo autonomous bone reconstruction. Kerr et al and Torres et al. scanned and reconstructed bone in a water bath (Kerr et al., 2017; Torres et al., 2012). Other autonomous robotic ultrasound systems focus on soft tissue diagnostics (Haxthausen et al., 2021; Li et al., 2021).

The results presented show that, on average, 54 % of the scanned bone surface can be successfully segmented using the developed pipeline. The authors assume that the approach could be improved by adjusting the probe orientation relative to the bone surface instead of just to the skin surface. This is relevant for the contrast of bone in the ultrasound images. Further challenges are the robustness of the path planning algorithm and extension of the trajectory to cover more bone surface in the knee joint.

References

Asseln, M., Grothues, S. A. G. A., & Radermacher, K. (2021). Relationship between the form and function of implant design in total knee replacement. *Journal of Biomechanics*, *119*, 110296. https://doi.org/10.1016/j.jbiomech.2021.110296

B. Hohlmann, & K. Radermacher (2020). Augmented Active Shape Model Search – towards 3D Ultrasound-based Bone Surface Reconstruction. In *20th Annual Meeting of the International Society for Computer Assisted Orthopaedic Surgery*.

Brenner, D. J., & Hall, E. J. (2007). Computed tomography--an increasing source of radiation exposure. *The New England Journal of Medicine*, *357*(22), 2277–2284. https://doi.org/10.1056/NEJMra072149

Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. In *Proceedings of the European Conference on Computer Vision (ECCV)*.

https://openaccess.thecvf.com/content_ECCV_2018/html/Liang-Chieh_Chen_Encoder-Decoder_with_Atrous_ECCV_2018_paper.html

D'Amore, T., Klein, G., & Lonner, J. (2022). The Use of Computerized Tomography Scans in Elective Knee and Hip Arthroplasty-What Do They Tell Us and at What Risk? *Arthroplasty Today*, *15*, 132–138. https://doi.org/10.1016/j.artd.2022.03.008

Hacihaliloglu, I. (2018). 3d Ultrasound for Orthopedic Interventions. In G. Zheng, W. Tian, & X. Zhuang (Eds.), *Advances in experimental medicine and biology: Vol. 1093. Intelligent orthopaedics: Artificial intelligence and smart image-guided technology for orthopaedics* (pp. 113–129). Springer.

Haxthausen, F. von, Böttger, S., Wulff, D., Hagenah, J., García-Vázquez, V., & Ipsen, S. (2021). Medical Robotics for Ultrasound Imaging: Current Systems and Future Trends. *Current Robotics Reports*, *2*(1), 55–71. https://doi.org/10.1007/s43154-020-00037-y

Hirschmann, M. T., Konala, P., Amsler, F., Iranpour, F., Friederich, N. F., & Cobb, J. P. (2011). The position and orientation of total knee replacement components: A comparison of conventional radiographs, transverse 2D-CT slices and 3D-CT reconstruction. *The Journal of Bone and Joint Surgery. British Volume*, *93*(5), 629–633. https://doi.org/10.1302/0301-620X.93B5.25893

Hohlmann, B., Broessner, P., Phlippen, L., Rohde, T., & Radermacher, K. (2023). Knee Bone Models From Ultrasound. *IEEE Transactions on Ultrasonics, Ferroelectrics, and Frequency Control*, *70*(9), 1054–1063. https://doi.org/10.1109/TUFFC.2023.3286287

Hohlmann, B., Glanz, J., & Radermacher, K. (2020). *Segmentation of the distal femur in ultrasound images*. Universitätsbibliothek der RWTH Aachen. https://doi.org/10.18154/RWTH-2020-09601

Karamalis, A. (2013). *Ultrasound Confidence Maps and Applications in Medical Image Processing* [Dissertation]. Technische Universität München, München.

Kerr, W., Rowe, P., & Pierce, S. G. (2017). Accurate 3D reconstruction of bony surfaces using ultrasonic synthetic aperture techniques for robotic knee arthroplasty. *Computerized Medical Imaging and Graphics : The Official Journal of the Computerized Medical Imaging Society*, *58*, 23–32. https://doi.org/10.1016/j.compmedimag.2017.03.002

Li, K., Xu, Y., & Meng, M. Q.-H. (2021). An Overview of Systems and Techniques for Autonomous Robotic Ultrasound Acquisitions. *IEEE Transactions on Medical Robotics and Bionics*, *3*(2), 510–524. https://doi.org/10.1109/TMRB.2021.3072190

Mahfouz, M. R., Abdel Fatah, E. E., Johnson, J. M., & Komistek, R. D. (2021). A novel approach to 3D bone creation in minutes : 3d ultrasound. *The Bone & Joint Journal*, *103-B*(6 Supple A), 81–86. https://doi.org/10.1302/0301-620X.103B6.BJJ-2020-2455.R1

Moyano, D. B., Paraiso, D. A., & González-Lezcano, R. A. (2022). Possible Effects on Health of Ultrasound Exposure, Risk Factors in the Work Environment and Occupational Safety Review. *Healthcare (Basel, Switzerland)*, *10*(3). https://doi.org/10.3390/healthcare10030423

OECD Library. (2019). *Hip and knee replacement | Health at a Glance 2019 : OECD Indicators | OECD iLibrary*. https://www.oecd-ilibrary.org/sites/8b492d7a-en/index.html?itemId=/content/component/8b492d7a-en

Pandey, P. U., Quader, N., Guy, P., Garbi, R., & Hodgson, A. J. (2020). Ultrasound Bone Segmentation: A Scoping Review of Techniques and Validation Practices. *Ultrasound in Medicine & Biology*, *46*(4), 921–935.

Pietrzak, J. R. T., Rowan, F. E., Kayani, B., Donaldson, M. J., Huq, S. S., & Haddad, F. S. (2018). Preoperative CT-Based Three-Dimensional Templating in Robot-Assisted Total Knee Arthroplasty More Accurately Predicts Implant Sizes than Two-Dimensional Templating. *The Journal of Knee Surgery.* Advance online publication. https://doi.org/10.1055/s-0038-1666829

Ponzio, D. Y., & Lonner, J. H. (2015). Preoperative Mapping in Unicompartmental Knee Arthroplasty Using Computed Tomography Scans Is Associated with Radiation Exposure and Carries High Cost. *The Journal of Arthroplasty*, *30*(6), 964–967. https://doi.org/10.1016/j.arth.2014.10.039

Ritter, M. A., Davis, K. E., Meding, J. B., Pierson, J. L., Berend, M. E., & Malinzak, R. A. (2011). The effect of alignment and BMI on failure of total knee replacement. *The Journal of Bone and Joint Surgery. American Volume*, *93*(17), 1588–1596. https://doi.org/10.2106/JBJS.J.00772

Torres, P. M. B., Sanches, J. M., Goncalves, P. J. S., & Martins, J. M. M. (2012). 3D femur reconstruction using a robotized ultrasound probe. *The Fourth IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, 884–888. https://doi.org/10.1109/BioRob.2012.6290782