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# Ultrasound Bone Detection Using Patient-Specific CT Prior

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***Abstract*— Registration of pre-operative CT datasets to intra-operative 3D freehand ultrasound has been of high interest for computer assisted orthopedic surgery. Feature-based registration relies on an accurate detection of the bone surface in the B-mode ultrasound images. In this work we present a fully automatic bone detection approach for US. The pre-operative CT is utilized to create a patient-specific bone model for our joint detection-registration framework. The model provides a geometric constraint for accurate and robust detection. Simultaneously to the detection, our method yields a close estimate of the rigid transformation from US to CT, which can be used as an initialization for further refinement through sophisticated intensity-/feature-based registration methods. We evaluated our approach on datasets of the human femur acquired in a cadaver study and demonstrate a mean bone detection error of below 0.4*mm*.**

## I. INTRODUCTION

Orthopedic surgery rapidly becomes more common considering the increasing amount of elderly people due to the demographic shift. Common orthopedic interventions include hip and knee replacement, reparations of femoral neck and trochanteric fractures and placement of pedicle screws. Computer-Aided Orthopedic Surgery (CAOS) provides assistance in the pre-operative planning phase and navigation during surgery.

In most of CAOS procedures, a computer tomography (CT) scan of the region of interest (ROI) is acquired prior to surgery, showing clear information about the bone for diagnosis and pre-operative planning. Intra-operatively, this information can be utilized for navigation when the patient's real-world position and the pre-operative CT are registered into a common reference frame. This is often achieved with invasive reference objects drilled into the bone or fiducial markers for point-based registration.

In this work, we investigate a non-invasive approach, which is based on registration of intra-operative 3D freehand ultrasound (3DUS) to a pre-operative CT dataset. More specifically, point-based registration is performed between the bone surface extracted from 3DUS and CT. Our main novelty is the fully automatic bone surface detection in US, together with a simultaneous and mutually inter-dependent registration to the pre-operative CT. We demonstrate that as a consequence, the detection accuracy is improved and a close registration of the detected bone surface in US to CT is yielded, which can be used as an initialization for a subsequent image-based registration refinement step.

We design our proposed approach towards several criteria relevant for surgery; besides robustness, accuracy and quick execution time – which includes performing interactive tasks like manual pre-alignment of the CT-dataset – the procedures is conceptualized to fit into the surgical workflow without exhaustive training of the physician.

## II. STATE OF THE ART

Most feature-based CT-3DUS registration algorithms rely on an accurate detection of the bone surface in the acquired 3DUS datasets, which is then registered to a pre-operatively generated bone surface from CT (e.g. a mesh). While bone segmentation is relatively straightforward in CT, the main challenge lies in the detection of bone in US images, which are view-dependent and additionally affected by speckle noise and artifacts.

Bone in ultrasound datasets usually appears as a bright and connected ridge with a shadow region afterwards. Kowal et al. [13] use these features directly in an approach combining threshold, morphological and connectivity operations to estimate the bone contour. Jain et al. [9] captured these characteristics in a Bayesian probabilistic framework giving the probability of every pixel for belonging to the bone surface. Other methods use concepts like fuzzy logic [5], dynamic programming [6], or local phase information of the ultrasound signal, which can be extracted through 3D-Log-Gabor-filters applied on the 3DUS data [8]. The latter method makes bone detection less dependent on the intensity values and the configuration of the ultrasound machine.

CT-US registration of bone anatomy can be generally categorized into feature- and intensity-based approaches. Feature-based approaches are commonly performing point-based registration between the bone surface extracted from 3DUS and CT, using the Iterative-Closest-Point (ICP) algorithm [4] or comparable methods. In [2], the manually delineated US bone surface was registered to CT, with a simultaneous optimization of calibration parameters. In a similar way Beek et al. [3] performed the registration for scaphoid fixation assisted by intra-operative tracked US. In [1], the US surface was registered to a surface instantiation from a Statistical-Shape-Model (SSM) of hip or femur bones in order to alleviate the need for a pre-operative CT.

Intensity-based approaches include the work in [14], where an intermediate image representation is registered in form of a bone probability map extracted from both CT and US. In Wein et al. [16], US was simulated from CT and registered with a new similarity measure denoted $LC^2$. In [12], the $LC^2$ similarity measure was utilized for the registration of a SSM of the lumbar spine. Subsequently, the approach was refined in [11] with biomechanical constraints in a group-

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wise registration framework. It should be noted that intensity-based registration methods require a good initialization in order to not get trapped in local minima far away from the desired optimum.
In this work, the US bone detection and registration is viewed as an inter-dependent process, providing: 1) fully automatic and accurate US bone detection and 2) good initialization for intensity-based registration methods.

## III. METHOD

### A. Pre-alignment and Initialization Workflow

The partial visibility of the bone surface in ultrasound makes an adequate initialization for any registration method necessary, which is also true for our joint detection-registration approach. Since our approach incrementally registers US and CT during acquisition, we require only a rough initialization in the beginning, which basically aims at determining the main body axes. In the case of femur, we estimate the long axis of the bone in cranial-caudal direction and the rotation around this axis. To this end, we propose a quick and easy procedure which can be easily integrated into the surgical workflow. Our initialization workflow is based on three points $[cp_1, cp_2, cp_3]$, which we refer to as *correspondence points* (CP), where $[cp_1, cp_3]$ define the principle axis and $cp_2$ the rotation/orientation of the bone (Fig. 1a). While the pre-operatively acquired CT-dataset can be labeled manually or via a comparison with a pre-defined atlas model before the intervention, the points for the US can be defined at the beginning of the surgery by placing the tracked US-transducer at *roughly* the same spots as in the CT. These correspondence points are then pre-aligned (Fig. 1b) using an arbitrary point-based registration method. In this work, we use Umeyama's method [15], which accounts for obligatory differences between both point sets by calculating a least-squares estimate of the required transformation from US to CT.

### B. Joint Registration and Detection

After pre-aligning the CT and the world coordinate systems using the proposed initialization workflow, the acquisition of ultrasound data begins. For the first acquired US slice, our algorithm assumes that the bone boundary is clearly visible and approximately in the image center. Again, this requirement can be easily integrated into the surgical workflow by letting the physician place the US transducer accordingly when starting the acquisition. In practice, and as we also experienced in experiments on several volunteers, it is easy and quick to initially place the transducer in this way, e.g. by positioning the transducer in the middle of the upper leg and adjusting the transducer pose such that the femur boundary appears in the image center.
In our joint registration-detection approach (Fig. 2), we focus on the bright appearance of the bone surface. The registration step of our approach is patient-specific and model-based, for which we *pre-operatively* generate a well-defined segmentation of the femur from CT. In this work, a state-of-the-art semi-automatic segmentation approach was used, namely random walks segmentation [7]. Alternatively, fully automatic approaches can be used, such as [10], which demonstrated good accuracy for the femur.
In the US bone detection step, we can exploit the pre-operative bone model from CT by excluding unlikely bone regions in the US images through intensity weighting. Following our proposed acquisition workflow, the bone surface is initially expected to be at the image center, therefore a two-dimensional ellipsoidal Gaussian function with a peak at the image center is applied for the first detection.

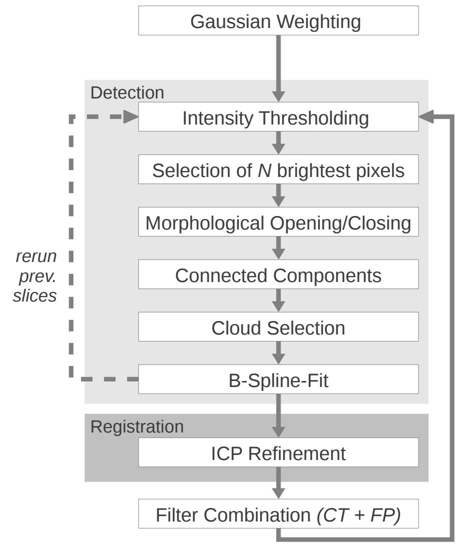


Fig. 2. Overview of the proposed joint registration and detection algorithm.

In order to detect US pixels belonging to the bone surface and suppress surrounding structures, the B-mode intensities are adaptively thresholded before selecting the $n = 5$ brightest pixel per scanline[1], similar to the approach of Kowal et al. [13]. Since the bone surface appears as a connected ridge, morphological closing and opening remove outliers. Next, a connected components approach is used for binding pixels into groups, which Kowal et al. refer to as clouds [13]. The selection of clouds representing the bone surface or at least parts of it is done via determination of the cloud including the highest sum of intensities. Finally, $m = 7$ points distributed equally along the x-axis and at their respective ridge centers are selected, which then form support points of a cubic B-spline smoothing the detection.

The subsequent registration is based on the detected US bone contours, which are fitted to the bone model from CT. For surface-to-surface registration, we used ICP [4] with multiple initializations for increased robustness, since ICP snaps directly to the closest points and may thus get stuck in local minima. Therefore, a grid-search approach is applied

[1]Scanline refers to the direction of ultrasound waves outgoing from the transducer. In case of a linear transducer, the scanlines would be the columns of the image matrix.

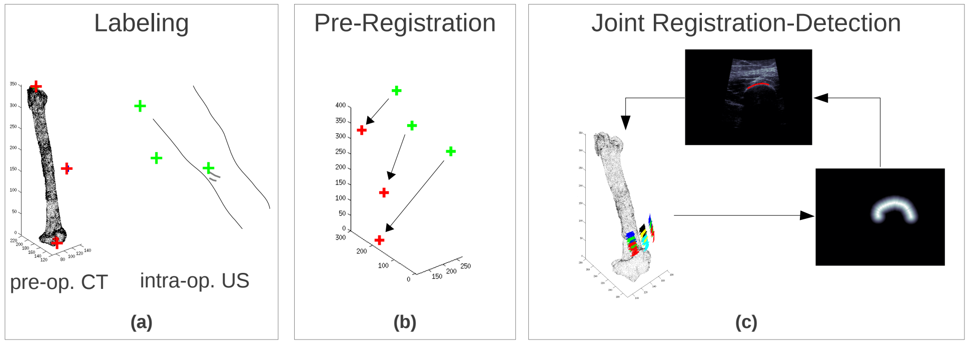


Fig. 1. Overview of the proposed workflow, (a) shows the labeling of the correspondence points in both modalities, (b) the pre-alignment towards point-based registration and (c) the combined registration and bone detection approach in ultrasound.

in which the initial position of the surface is varied in rotation and translation (Fig. 1c) while selecting the registration with the lowest mean square distance from the CT surface as reference.

Given the assumption that a continuous sweep is acquired, relatively small differences in the location of the contour can be expected. Therefore, in all acquired US images after the first detection, a combination of the previously detected contour and the registered CT-bone is used to weight intensities and suppress surrounding tissue responses (Fig. 1c). This is implemented through a distance-based weighting filter $f$, defined as:

$$f(x, \partial C) = \begin{cases} \frac{1-d(x)}{r}, & \text{if } x \in C \text{ and } d(x) < r \\ 1, & \text{if } x \in \partial C \\ 0, & otherwise \end{cases} \tag{1}$$

$$d(x) = \min \|x - \hat{x}\| \text{ , } \hat{x} \in \partial C \tag{2}$$

where $x$ is a point in the US image domain $C$, and $\partial C$ a contour set. Subsequently, both previous detection and CT prior are combined as:

$$g(x) = f(x, \partial U_{i-1}) + f(x, \partial S) \tag{3}$$

where $\partial U_{i-1}$ is the contour in the previously detected US image $U_{i-1}$, and $\partial S = U_i \cap S(T)$, i.e., the contour from intersecting $U_i$ with the CT surface $S$, given the estimated rigid registration pose $T_{i-1} \in \mathbb{R}^{4,4}$. Contour points that are likely to be located in shadow regions are removed from $\partial S$. Specifically, the intersection image plane is sampled from top-to-bottom, based on the transducer orientation, and only the first contour points identified along each scanline are retained.

## IV. RESULTS

For the evaluation, CT and 3D freehand US data were acquired from a femur in a cadaver study, following all ethical guidelines. The US was acquired using a Siemens X150 ultrasound machine with a VF-105 transducer that was tracked with an NDI Aurora magnetic tracking system. The acquired images had a resolution of $1024 \times 768$ and an isotropic pixel spacing of $0.102 \times 0.102mm$. The CT was acquired with a Phillips Brilliance 64 system and a voxel spacing of $0.63 \times 0.63 \times 0.5mm$. Subsequently, the femur was segmented and the surface extracted.

We compared our automatic bone detection approach against a manual delineation of the bone surface using a total of 384 US images. The robustness of the algorithm was tested towards variation in translation and rotation of the correspondence points for the ultrasound scan. More specifically, $cp_1$ and $cp_3$ were shifted randomly in x-,y- and z-direction for a maximum length of $20mm$ while $cp_2$ was randomly rotated around the long axis spanned by $cp_1$ and $cp_3$ for a maximum of $\pm 30$ $degree$, for a total of 44 random trials. We used the root mean square distance (RMSD) between the manual and automatic bone delineation as error measurement in our experiments. The results are presented in Fig. 3, exemplary detections are shown in Fig. 4. The low mean of $0.38mm$ and standard deviation of $0.83mm$ indicate a highly accurate and robust detection for a large number of images. To evaluate the registration accuracy a manual reference registration was performed between the acquired 3DUS and CT. Subsequently, the RMSD was evaluated between the manual reference and the ICP-based registration. The resulting error (in RMSD [mm]) was: $\mu = 11.2$, $\sigma = 8.4$, $min = 1.37$, $max = 42.5$. These results are not surprising given the view-dependency and US specific artifacts that cause partial-only visibility of the bone surface. Moreover, the largest part of the RMS distance is contributed by deviation along the long femur axis, which is again not surprising since the bone surface is smooth and provides little salient surface features between joints, where the largest part of our data sweep was acquired. Nevertheless, the accuracy is sufficient enough to provide a good initialization for more sophisticated feature-/intensity-based approaches (see related work) which can deliver the necessary accuracy required in the clinical scenario.

The bone detection was implemented in C++ using OpenCV and requires $20 - 30ms$ for a single frame on an Intel Core i7 3.4 GHz, while the workflow procedure and registration was implemented with Matlab.

## V. DISCUSSION AND OUTLOOK

In this paper, an automatic approach for bone detection in 3D freehand US was presented. For the initialization of the registration, we proposed an easy and quickly executable

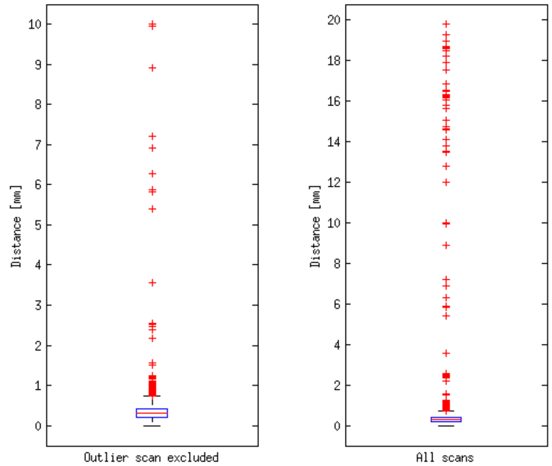


Fig. 3. Evaluation of bone detection for random study. Left image without outlier-experiment and right image with all random experiments. In both cases 0.7% of the study set was marked as outliers in the box-plots.

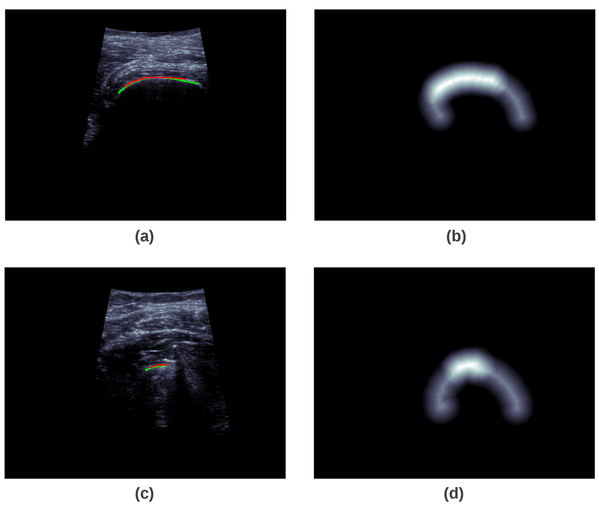


Fig. 4. Detection of bone surface, (a) and (c) showing the result of the automatic detection (red) and the manual delineated ground truth (green) for clearly visible (a) and artefacted (c) bone surfaces and the matching filters (b) and (d) combining the previous detection with the current CT-registration.

workflow based on three correspondence points defining the principle axis and orientation of the bone in both modalities. The joint registration-detection approach yields highly accurate bone surface detection in US, has proven to be robust even for noisy images. Limitations mainly lie in the registration step, which is currently only relying on distance-based surface-to-surface matching, which can fail if the bone shape does not feature enough salient geometric features, e.g. along the long axis of the femur bone. It can be expected that multiple sweeps containing various views and including distinguishing shape regions such as the knee joint would increase the confidence of the registration, possibly to the point of reaching the desired accuracy for surgery.

However, our experiments show that registration is accurate and quick enough to serve as a very good initialization of further refining registration steps, e.g. with intensity-based approaches, and is thus complementary to the current state-of-the-art. Our future work includes the evaluation of the joint detection-registration for multiple views as well as the detection of multiple bones in one ultrasound sweep. Furthermore, we aim at analyzing the clinical applicability of the proposed initialization workflow under simulated and real-life OR conditions.

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