

MEASURING RELATIVE BONE POSE INSIDE A BI-LATERAL ANKLE EXOSKELETON USING A-MODE ULTRASOUND

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# Measuring relative bone pose inside a bi-lateral ankle exoskeleton using A-mode ultrasound.

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Abstract-In this study, we present a non-invasive method for directly quantifying tibiofibular pose in-vivo in a bi-lateral ankle exoskeleton during plantar & dorsiflexion. 26 A-Mode US transducers were used, held in place by a rigid, 3D-printed brace without using additional tracking methods to live track the transducer positions. The brace contains holders with a user friendly mechanism to find proper US-reflective bone surfaces. A window-based method was used for peak detection, Iterative Closest Point algorithm was used for bone segmentation registration. Passive optical markers were used for evaluation of the bone pose estimation accuracy. During plantar & dorsiflexion swings registration errors were 6.22±1.17mm and estimation errors were 35.40±8.33mm. This study did not perform cadaveric accuracy studies. Thanks to being non-invasive, non-radiative and highly compatible with wearable robotics, A-mode ultrasound skeletal motion capturing has the potential to obtain high-accuracy skeletal kinematics in robot-assisted rehabilitation & computeraided surgery.

*Index Terms*—A-mode ultrasound, point set registration, skeletal motion capture, exoskeleton, real-time

### I. INTRODUCTION

**I** N an increasing rate, wearable robotics are being developed for rehabilitation of motoric disorders [1]. Wearable robotics, or exoskeletons, provide an assistive force or torque to the impaired part of the body to fulfill motoric tasks such as normal gait or climbing a staircase. During these tasks the bone moves with respect to the exoskeleton. This aspect is largely overlooked in exoskeleton design, leading to inaccurate control strategies and discomfort to the user [2].

Mechatronic design often aims to develop lightweight devices employing as few actuators as possible. Therefore, complex joint kinematics are simplified by reducing the number of degrees of freedom (DoF) [3]. In case of the ankle joint, a single rotation DoF is assumed, while in reality a combination of rotation and translation along non-trivial planes make up the joint kinematics due to the complex shape of the talus and tibia [4].

Assessing performance of simplified devices on complex joint kinematics is often solely based on external factors [5] (e.g. metabolic cost reduction [6], joint kinematics [7] and spatiotemporal parameters [8]. However, internal aspects that assess the human-machine interface, such as the relative motion between a joint and an exoskeleton, are usually overlooked [2].

Besides performance assessment motives, relative skeletal motion measurements can also be used for improving assistas-needed control strategies. One approach to generating such control strategy is by using EMG-driven neuromusculoskeletal (NMS) modelling [9], [10]. This approach captures the user's motion intention through EMG data and uses a subject-specific NMS model to simulate the supplemental assistance needed to fulfil a locomotion task in real-time [11]. The kinematic data necessary to drive NMS models is usually obtained from marker-based measurements, using inertial measurement units (IMUs). One of the drawbacks of using IMUs, is that it requires inverse kinematics to convert marker data to model kinematics. Inverse kinematics is a computationally heavy algorithm, limiting the suitability for real-time applications [11]. Moreover, IMUs are likely to move with respect to the bone as well, leading to errors otherwise known as soft-tissue artifacts (STAs) [12]. These limitations call for a direct method of quantifying relative skeletal motion.

1

In other words, a method is required that measures skeletal motion in-vivo, in a direct manner while doing dynamic locomotion tasks. Moreover, the method must be compatible with the available exoskeleton workspace. Under these requirements, many methods disqualify. High-accuracy intracortical bone-pins are invasive [13], thus not suitable for in-vivo applications. Fluoroscopy provides high fidelity, but is radiative to the subject, as well as not being easily interfaceable with a wearable exoskeleton due to the size of the system [14] Computed Tomography (CT) & Magnetic Resonance Imaging (MRI) are accurate, but high-cost methods that only work with non-metallic exoskeletons [15]. Moreover, CT & MRI typically have a low framerate and do not offer freedom of movement for measuring during dynamic tasks [16].

A(mplitude)-mode ultrasound (US) offers a feasible method for recording relative skeletal motion that meets these requirements. Mahfouz et al. [17] & Amin et al. [18] proposed a method that places an array of compact A-mode US transducers (USTs) on the skin to measure the depth of bone surface underneath at various locations. By tracking the position of each transducer, the obtained depths are converted to coordinates in 3D space, resulting in a point cloud of bony points. A detailed bone model is then fitted to the acquired cloud of US reflection points. Ultimately, an anatomical coordinate system is assigned to the registered bone model to measure position & orientation with respect to the exoskeleton.

This method has been adopted by Niu et al. to develop a system capable of measuring tibiofemoral kinematics [19]. The system was validated with cadaver experiments, reporting rotational errors of  $1.51 \pm 1.13^{\circ}$ ; translational errors of  $3.14 \pm$ 1.72mm for quantification of tibiofemoral kinematics. Amstutz et al [20] reported an root-mean-square error of  $0.49 \pm 0.20$ mm for a computer-aided surgery system for otorhinology and skull base surgery. Chong et al. [21] explored the use



Fig. 1: a) A-mode USTs transmit & measure sound waves. Signal peaks indicate transition to a denser medium, bone tissue. The time at which a peak occurs is translated to a depth using equation 1. b) Multiple transducers measure bone tissue depth at various locations. These depths are converted to points in a global 3D reference frame. c) Using registration algorithms, a detailed pre-operative bone segmentation is aligned with the obtained point-cloud. d) An anatomically relevant reference frame is assigned to the registered bone model which is compared to the exoskeleton reference frame.



Fig. 2: Left: Achilles exoskeleton equipped with the 3D-printed brace. Each slot has a mechanism that is highlighted on the right. Holders allow axial translation and roll & pitch rotations.

of A-mode US to detect the position of the residual femur within a stump. Accuracy errors were reported between 2.9 and 14.4mm for in-vivo measurements.

Other advantages of A-mode US are the high degree of configurability, mobility and fast processing of A-mode signals compared to B-mode images [22]. Moreover, A-mode transducers are low-cost and can be easily replaced by any technician.

A bi-lateral ankle exoskeleton (Achilles exoskeleton, University of Twente) [23] is used. The anterior side of the exoskeleton offers plenty of room to attach a brace holding the transducer array in place. Figure 2 shows the exoskeleton with the brace. Within this workspace, the pose of the tibia & fibula, relative to the exoskeleton, will be estimated.

In this study, we present a non-invasive method for directly quantifying tibiofibular pose under dynamic conditions using 26 A-Mode US transducers that are being held in place by a 3D-printed brace. The brace can be worn in combination with the Achilles exoskeleton. The aim of this study is to determine whether A-mode US can be interfaced with wearable robotics. Also, in an attempt to minimize equipment usage, bone pose estimation is done using only data from the anterior-distal part of the lower leg. It is investigated whether this method can operate with requiring an optical motion capturing system for tracking transducer positions. Optical data will however be recorded for evaluation of the bone pose estimation accuracy. Experiments were done in-vivo on one healthy subject with static trials in 4 dorsiflexion angles, and a dynamic trial consisting of 5 plantar & dorsiflexion swings.

### II. METHOD

# A. Working Principle

An overview of A-mode US-based tibiofibular motion tracking is shown in figure 1. The ankle exoskeleton is equipped with a brace that snaps to the exoskeleton and can hold up to 26 transducers, covering the distal half of the anterior tibia and fibula. At every transducer, the depth of bone tissue underneath the skin is found by applying a peak detection algorithm to the US signal. These depths are converted to points in 3D space by using the local-to-global transformation matrices of every transducer. Next, a segmented bone model is fitted, or better, registered to the US point cloud using registration algorithms. Then, a coordinate system is assigned to the registered bone model. Ultimately, an anatomically relevant point will be derived from the registered bone model to track its trajectory within the exoskeleton coordinate system.



Fig. 3: A high-quality US signal is shown with the x-axis already converted to distance using equation 1. The raw & low-pass filtered signals, filtered window sample envelope and identified depth of reflective bone surface are shown.

# B. Brace Design

The brace was designed using Solidworks (D'Assault Systèmes, Vélizy-Villacoublay, France). The gimbal-based holder design offers 3 DoFs for manipulating the transducers, ensuring good contact between transducer and skin. Its user friendly design allows bone surface perpendicular to the transducer to be found more easily. See figure 2. To create a geometry that fits the exoskeleton, readily available CAD files from the exoskeleton were used. A surface scan of the leg was made with a Sense 3D scanner (3D Systems, Rock Hill, USA) to create a fitting inner surface of the brace. A manually segmented bone model from MRI data was aligned to the leg surface model and was used to aim the holders at the bone surface in nominal position. The brace prototype was made with Selective Laser Sintering 3D-printing technique (tolerance:  $\pm$  0.1mm; FORMIGA P110, EOS, Munich, Germany) from Nylone (PA2200, EOS, Munich, Germany). The individual transducer positions were assumed to be kept constant with respect to the exoskeleton. Therefore, the brace was assumed rigid. This way, considerable material & space is saved compared to equipping every transducer with three optical markers to track each transducer's positioning in 3D. Rigidity was simulated under a load case of a force of 50 N along the top edge of the brace, pointing forward. The results showed a simulated total deformation of 0.2mm. See appendix D.

# C. Point Cloud Generation

US data was acquired using the system developed by Niu & Sluiter [12]. The system consists of 30 A-mode transducers (Imasonic SAS, Voray / l'Ognon, France), the Diagnostic Sonar FI Toolbox (Diagnostic Sonar Ltd., Livingston, Scotland) and its acquisition software, which was written in LabView 2014 (National Instruments, Austin, United States). US data is saved in TDMS format and converted to CSV



Fig. 4: Three groups of four optical markers each are shown. Groups are placed on the exoskeleton (orange), brace (blue) and on the lateral & medial tibia condyles, tibia tuberosity & approximately 10cm down on the tibia diaphysus (green).

using the python pyTDMS library for offline post-processing. Transducers transmitted waves with a frequency of 7.5 MHz. Sampling frequency of the transducer is 50 MHz to record the amplitude of incoming reflected waves over time. The frame rate (the rate at which full waveforms are transmitted and recorded) of the system lies between 20 and 90 Hz, depending on the number of transducers used and its configuration. This is related to signal multiplexing, which is further explained in appendix A.

The raw US signals were filtered with a High-Pass filter  $(2^{nd})$ order, 3.5 MHz cut-off frequency) to remove the transducerinherent low-frequency behaviour. Linear Time-Gain Compensation (TGC) was applied to enhance signal content from deeptissue reflective surfaces, such as the more proximal areas of the fibula. During measurements, a live preview of the signal was used to define the window where US reflective points could be expected. Within this window, the signal was filtered using a Low-Pass filter  $(2^{nd} \text{ order}, 1 \text{ MHz cut-off frequency}).$ US reflective points were identified at the onset of the peak, which is found by taking the maximum of the  $2^{nd}$  derivative of the sample on a positive slope. The  $2^{nd}$  derivative is associated with peak quality since it approximates the sharpness of the peak. Sharp peaks are the result of perpendicular reflection off the bone surface. Figure 3 shows how a US depth is obtained from raw data. A threshold was set on the 2nd derivative of the peaks, disqualifying insufficiently sharp peaks from further point cloud generation. To convert the found peaks from time to spatial domain, equation 1 is used, with  $v \approx 1590$  m/s as the sound velocity in human tissue:

$$x_{bone} = \frac{vt}{2} \tag{1}$$

Keep in mind that the sound waves are transmitted & reflected, travelling the distance twice, hence division by 2.

Converting the calculated depths to points in the 3D reference frame of the exoskeleton (i.e. the global reference frame)

is done by multiplying the depths with transformation matrices **T**, as given by equation 2.

$$\mathbf{x_{global}} = \mathbf{T} \ \mathbf{x_{local}}$$
$$\begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} \mathbf{R} \\ \mathbf{R} \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} T_x \\ T_y \\ T_z \\ 0 \end{bmatrix} \begin{bmatrix} x_{bone} \\ 0 \\ 1 \end{bmatrix}$$
(2)

where the 4-by-4 matrix T is an affine, rigid transformation matrix containing a 3x3 rotation matrix R and 3x1 translation vector. Appendix B explains more in-depth how T was acquired.

### D. Pre-registration

After successfully calculating a point cloud of US reflection points, a detailed bone model is registered to the point cloud. The resulting transformation matrix is then applied on the full bone segmentation to find the final bone pose estimation.

An initial, coarse estimation of the bone pose is found by doing pre-registration, which is only done for the first frame. Pre-registration is a point-to-point registration algorithm using Horn's method [24], see equation 3

$$f(\mathbf{R}_{pr}, \mathbf{P}_{pr}) = \frac{1}{n} \sum_{i=1}^{n} w_{i} ||x_{i} - (\mathbf{R}_{pr}u_{i} + \mathbf{P}_{pr})||^{2}$$
(3)

The source point cloud  $x_i$  (4 pre-registration points from the bone segmentation) is registered to the target point cloud  $u_i$ (US points from holders 1, 5, 23 & 26). Weights  $w_i$  are used to account for US points with low localization confidence. The weights are given by the peak sharpness of the US point. The outcome is a transformation matrix that contains translation vector  $\mathbf{P_{pr}}$  and rotation matrix  $\mathbf{R_{pr}}$ , placing the bone model from original positioning to the pre-registered positioning. The selection of  $x_i$  points is further explained in appendix C.

Although this step can take several minutes, it can be done as a calibration step before doing real-time measurements. Therefore, pre-registration is not included in computational speed evaluation.

The accuracy of any registration process is defined by the root-mean-squared error between source & target point cloud. The error is calculated by

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} ||u_i - x_i||^2}$$
(4)

# E. Iterative Closest Point

This study uses the ICP algorithm written by Martin Kjer & Jakob Wilm for finer registration [25]. Before transforming, ICP finds the closest points on the target point cloud to the source points using the kdTree algorithm. Then, the closest points are transformed onto the target points and the RMSE is evaluated again. This process is iterated until a termination condition is reached.

Weighted point-to-plane ICP is used. For point-to-plane registration, surface normal vectors at the vertices (not the face centroids) of the target point cloud are required. Therefore, the anterior distal side of the segmented bone model is first used as the target point cloud. Peak sharpness is used as weighting coefficients and a maximum of 20 iterations is set on the algorithm as the used ICP function did not have an error or convergence termination criterion. At first, the iteration with the lowest RMSE is chosen. However, if this iteration leads to the velocity of the bone segmentation between two frames being higher than 100mm/s, the iteration is rejected and the next lowest RMSE iteration is chosen. In case of 20 rejected iterations, registration from the previous frame is used.

After ICP, the rotation matrix is inverted, and the translation vector is multiplied by -1. These are combined in a transformation matrix and applied to the full bone segmentation. This way, the bone segmentation transforms to the US point cloud. Frames with rotation matrices that are not properly invertible are skipped and reuse bone pose estimation from the previous frame.

The accuracy of the registration algorithm is quantified with the RMSE between US point cloud ( $u_i$ , n=26 when all US points have sufficient sharpness) and its nearest points on the anterior distal bone surface point cloud ( $x_i$ ).

### F. Motion Tracking

Relative motion of the registered bone segmentation is obtained by tracking an anatomically relevant point on the bone segmentation. This point is found by assigning an anatomical reference frame to the tibia & fibula by the Cappozzo reference frame definition [26] [27]. The origin of the anatomical reference frame is then tracked within the exoskeleton reference frame.

### G. Performance Assessment

The performance of this method is assessed by the quality of the bone pose estimation, the magnitude of error sources along the process & computational speed. The required data for assessment is obtained by performing ultrasonic measurements and running the US data through the post-processing steps described in this sections II-C, II-D & II-E. For the ultrasonic measurements, the system described in section II-C is used. The identified error sources include:

- Navigation errors due to mismatch between CAD & actual geometry and deformation of the exoskeleton & brace. Calculation & results on navigation errors can be found in appendix D.
- Registration error as quantification of the misalignment between bone segmentation & US point cloud. The registration error of pre-registration was not taken into account.
- Estimation error as quantification of the misalignment between registered bone segmentation & optical data from anatomical sites on the knee.

Errors due to improper ultrasonic point localization (UPLE) could not be obtained directly. However, a lower UPLE can be expected for signals of high quality with sharp peaks, i.e. perpendicular orientation of the transducer towards the bone surface. In this context, the quality of each point is calculated



Fig. 5: (x,y,z) motion of the anatomical reference frame origin, with respect to the exoskeleton reference frame. Data is obtained from the dynamic trial.

(maximum 2nd derivative of the filtered US sample) [12] and used as a measure for the UPLE. For each trial, the mean peak sharpness among qualifying US points for every frame is used.

To evaluate the final bone pose estimation, the pose of the registered bone model is compared to passive optical marker data using the Qualisys 6+ camera system (Qualisys AB, Göteborg, Sweden). Figure 4 shows the marker placement. The estimation error is defined as the RMSE of the distance between marker positions on the skin  $x_i$  (tibial tuberosity, medial & lateral condyle, and anterior diaphysis) and respective points from the registered bone segmentation  $u_i$ . Due to obstruction by the brace & exoskeleton, the malleoli could not be tracked with the optical setup. However, estimation errors are expected to be largest at the proximal end of the bone regardless, due to the point cloud being generated from the distal end only. Any misalignment on the distal end of the bone will linearly propagate towards the proximal end. Optical data was not recorded in parallel with US data, thus synchronization of the two datasets was not possible. However, when evaluating the optical data, it was found that the optical markers moved with a standard deviation of 0.99mm. Since comparing pose estimation to optical recordings is just a practical evaluation and not a precise validation, the time-average marker positions are used. For complete method validation, a cadaver study would have to be done, which is outside the scope of this study. Besides estimation evaluation, optical data is also used for validating rigidity assumptions about the exoskeleton & brace, which is further explained in appendix D.

Also, a registration simulation is run using the nominal target point cloud. The nominal point cloud consists of bone points that the holders in the CAD geometry are originally aimed at. All nominal points lie precisely on the bone segmentation, so a minimal registration error is expected. Registration remains an optimisation algorithm, so only an approximation of the perfect registration can be achieved. This simulation



Fig. 6: Error categories during dynamic trial. The peak sharpness (dotted line) is plotted on the right y-axis.

is done to investigate the effect of point cloud quality on registration algorithm performance.

Measurements will be done on one healthy subject, consisting of 4 static trials at approximately 0, 5, 10 & 15 degrees dorsiflexion & 1 dynamic trial during which the subject performs 5 swings of the ankle joint, ranging from 20 degrees plantar flexion & to 15 degrees dorsiflexion. A small rig was constructed to fix the subject leg in the respective angles. See appendix E.

### **III. RESULTS**

The relative motion of the anatomical reference frame origin to the exoskeleton reference frame during 5 plantar & dorsiflexion swings is shown in figure 5. It is hard to recognise the swinging motion in the line trends. A closer look is taken at the error contributions.

The error sources of the dynamic trial, excluding navigational errors, are shown in figure 6. The peak sharpness line shows the clearest oscillating behavior, with increasingly noisy content for the registration error & estimation error. Peak sharpness is inversely proportional to the registration & estimation errors. Five oscillations can be identified.

Navigation errors were found to be small and acceptable at the distal end of the brace, but at the proximal end, the displacement of the brace with respect to the exoskeleton was  $4.86 \pm 2.05$ mm. The brace itself and the exoskeleton showed a maximum deformation of 1.16mm &  $0.6\pm0.1$ mm respectively.

The quality of the points cloud was quantified by the mean peak sharpness among transducers during one frame. Figure 7 shows the peak sharpness during each trial. The boxplots contain 53, 59, 53 & 73 frames respectively.

Figure 8 shows the registration errors per trial. Besides the static 10 degrees trial, trials show similar registration errors.

Figure 9 shows the estimation error per trial. Static 15 degrees heavily outperforms the other trials. This is in line with our experience during measurements. The brace provided the best contact between skin and transducer under 15 degrees



Fig. 7: Boxplot of the mean peak sharpness per frame.



Fig. 8: Boxplot of the registration error per frame. Registration error is defined by equation 4, with  $x_i$  being US points and  $u_i$  being the closest bone model points.

dorsiflexion. Even at that position, the achieved estimation error is roughly 22mm, which is too big to speak of an accurate bone pose estimation.

Registration of the bone segmentation onto the nominal point cloud resulted in a registration error of 3.0mm. The resulting bone pose estimation is shown in figure 10.

In terms of computation time, ICP registration at the first frame takes on average 0.27s, while the following frames only take 0.05s. Without taking the first 4 frames into account, ICP takes  $0.05\pm0.002s$  per frame. There was no significant difference in processing time among the five trials. In 75% of the frames, the iteration with the lowest registration error was also in compliance with the velocity contraint.

### IV. DISCUSSION

The purpose of this study was to develop a method to measure the relative position of the tibia & fibula with



Fig. 9: Boxplot of the estimation error per frame. Estimation error is defined by equation 4, with  $x_i$  being the anatomical points on the registered bone model and  $u_i$  being the anatomical optical markers.



Fig. 10: The bone segmentation (shaded grey) is registered onto a nominal point cloud (red). The blue dots show that the estimation does not match with the optical markers. Registration error is 3.0mm. Estimation error is 40mm.

respect to an exoskeleton, in-vivo, during a dynamic task, without using optical marker tracking to live track transducer positioning. Although the final evaluation of the bone pose estimation does not validate the results, it can be stated that this method is able to make an estimation off a given point cloud. Using non-optimized software, a rate of estimation of approximately 10Hz was reached. Compared to bone pins or fluoroscopy, A-mode US is a feasible technology for obtaining relative skeletal kinematics in living subjects for applications in wearable robotics, NMS modelling & minimally invasive (computer-aided) surgery.

The dynamic trial clearly shows an inversely proportional relation of the mean peak sharpness to the registration & estimation error. With values of 25mm at best, the estimation error fails however to meet acceptable accuracies. Moreover, the complete animation of all frames shows discontinuous motion. For simple plantar- & dorsiflexion it is observed that peak sharpness, registration error & estimation error show oscillating behaviour, although in decreasing degree due to presence of artefacts. The artefacts are likely the result of picking the lowest error ICP registration that obeys the velocity constraint.

To evaluate registration algorithm performance, results were compared with a simulation that used a nominal target point cloud, obtained directly from the bone segmentation (no manually defined window involved). A registration error of 3.0mm was achieved in the simulation, thereby outperforming US-based point clouds. From this, it can be concluded that the registration algorithm is sensitive to point cloud quality. Surprisingly, the estimation error was larger: 40mm. For the calculation of estimation errors, some limitations can be pointed out. First, the optical marker data could not be synchronized, both in time and space, because data was recorded in two different sessions and points had to be handpicked from the bone model. Moreover, disagreement between CAD geometry & experiment geometry was too large near the proximal end of the brace. A displacement of approximately 5mm was found at the top edge of the brace with respect to CAD geometry. Taking these error sources into account, it is expected that the estimation error still exceeds practical values.

The static trials fail to show clear correlation between peak sharpness within the window and registration error. Even though the peak sharpness is much higher for all frames during 15 degrees dorsiflexion, only half of those frames show a lower registration error than the other trials. It is believed that the window-based peak detection algorithm caused peaks to qualify within the window that are actually not bone points. With identical windows among trials, this leads to low variability between point clouds and thus the same registration regardless of point cloud quality.

This study has several limitations. Firstly, the final bone pose estimation is only roughly evaluated without actually validating the results. A cadaver experiment with intracortical bone pins would be needed to confidently quantify the accuracy of this method [12]. Interpreting these results remains dubious as a ground-truth is missing. Secondly, significant skill with ultrasonic equipment is required to find reflecting bone surface with confidence. It takes multiple hours to position the transducers and update window settings. Thirdly, only a point cloud of the anterior distal side of the tibia & fibula was calculated which caused a small misalignment at the distal end to grow in proximal direction. This means that taller bones lead to larger estimation errors. On top of that, this study did not estimate tibia & fibula pose independently, but used a model with a rigid connection between the two. Finally, transducer positions were assumed to be constant and in agreement with CAD data but it was found that this is only partially true. Taking this into account, it must be concluded that more work needs to be done for this method of recording skeletal motion to be used in NMS modelling, gait analysis and computeraided surgery.

To improve upon this work it is recommended to use an automatic peak detection algorithm. Example algorithms include:

- Kurtosis-based peak detection [28].
- Cross-correlation [29].

This way, there is less bias towards the probable peak depth that is found in static window-based peak detection. Overall quality is not compromised by user-defined windows & thresholds. The drawback of using a fully automatic peak detection algorithm is that the algorithm will always select a peak in the first few millimetres, as US signal suffers from noisy artifacts at the first few millimetres of data, containing huge peaks compared to US reflection points. Forcing TGC over that part of the signal will also remove bone reflection content. A better method to overcome early signal instability is to equip transducers with a gel bed between skin and transducer. It is recommended to use a medium that is stickier than standard US aqua gel, because aqua gel will easily flow away. Also, this brace used 26 transducers which took a long time to prepare. Minimizing the number of necessary US transducers will benefit practical viability of this method. A rigid connection to the exoskeleton at the top of the brace would reduce navigational errors significantly.

Sure enough, this study also has its strengths. This study has shown that ultrasound skeletal motion capturing can be interfaced with wearable robotics without adding much weight, exceeding the volume of the exoskeleton, or making the whole configuration overly complex. The registration algorithm is fast and, with optimized software, real-time applications are well within reach. The brace prototype could use some improvements but it showed that the gimbal holder design allows plenty of configurability to establish and maintain proper skin contact with the transducers. The prototype was tailor-made for one leg, but a generalized version would function equally well, making real-time ultrasound motion tracking more accessible. Measuring constrained, relative skeletal motion among a wide base of users would allow to study the different motion patterns & assess the performance of a simplified exoskeleton on complex motion pattern in terms of the human-device interface. An analogy could be drawn here with fitting a shoe. A fitting shoe not only provides a comfortable shape, it also provides suiting freedom and support of motion.

A-mode US-based skeletal motion tracking is a truly noninvasive, lightweight technique, on top of being highly configurable to suit any given workspace. With a wide variety of exoskeleton designs available, this technique can grow independently of advancements in wearables design. Ultrasound is especially compatible with soft robotics, a category of wearables that allows more freedom of movement through flexible structures. A-mode ultrasound can also be used to measure muscle expansion upon contraction, allowing to explore the feasibility of an alternative to sEMG for muscle-based Human-Machine Interface [30].

## V. CONCLUSION

In this study, we present a non-invasive method for directly quantifying tibiofibular pose in-vivo in a bi-lateral ankle exoskeleton during plantar- & dorsiflexion. 26 A-Mode US transducers were used, held in place by a rigid, 3D-printed brace without using additional tracking methods to live track the transducer positions. The gimbal-based holder design offers a user-friendly mechanism to adjust & fix transducer position. Even though bone pose estimation could not be validated with ground-truth data, it was found that A-mode US-based motion tracking is highly interfaceable with wearable robotics. After the necessary improvements, this technology has the potential to record skeletal motion data in-vivo, in real-time for many applications including gait analysis, rehabilitation, NMS modelling, soft robotics & computer-aided surgery. The window-based peak detection algorithm could be replaced by a fully automatic method that is not biased to one point cloud shape and does not rely on the skill of the US operator. It was shown that ICP is a fast and robust registration algorithm that is mainly limited by US point cloud quality. A cadaver study is necessary to validate the accuracy which will allow to effectively assess maturity of this skeletal motion tracking method.

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### REFERENCES

- T. Yan, M. Cempini, C. M. Oddo, and N. Vitiello, "Review of assistive strategies in powered lower-limb orthoses and exoskeletons," *Robotics* and Autonomous Systems, vol. 64, pp. 120–136, Feb. 2015.
- [2] D. Torricelli, C. Cortés, N. Lete, I. Bertelsen, J. E. Gonzalez-Vargas, A. J. del Ama, I. Dimbwadyo, J. C. Moreno, J. Florez, and J. L. Pons, "A Subject-Specific Kinematic Model to Predict Human Motion in Exoskeleton-Assisted Gait," *Frontiers in Neurorobotics*, vol. 12, Apr. 2018.
- [3] K. Junius, M. Degelaen, N. Lefeber, E. Swinnen, B. Vanderborght, and D. Lefeber, "Bilateral, Misalignment-Compensating, Full-DOF Hip Exoskeleton: Design and Kinematic Validation," 2017.
- [4] C. Swank, S. Wang-Price, F. Gao, and S. Almutairi, "Walking With a Robotic Exoskeleton Does Not Mimic Natural Gait: A Within-Subjects Study," *JMIR Rehabilitation and Assistive Technologies*, vol. 6, no. 1, p. e11023, 2019.
- [5] D. Torricelli, A. J. del Ama, J. Gonzalez, J. Moreno, A. Gil, and J. L. Pons, "Benchmarking Lower Limb Wearable Robots: Emerging Approaches and Technologies," in *Proceedings of the 8th ACM International Conference on PErvasive Technologies Related to Assistive Environments*, PETRA '15, (New York, NY, USA), pp. 51:1–51:4, ACM, 2015. event-place: Corfu, Greece.
- [6] L. M. Mooney, E. J. Rouse, and H. M. Herr, "Autonomous exoskeleton reduces metabolic cost of human walking during load carriage," *Journal* of *NeuroEngineering and Rehabilitation*, vol. 11, p. 80, May 2014.
- [7] E. H. F. van Asseldonk, J. F. Veneman, R. Ekkelenkamp, J. H. Buurke, F. C. T. van der Helm, and H. van der Kooij, "The Effects on Kinematics and Muscle Activity of Walking in a Robotic Gait Trainer During Zero-Force Control," *IEEE transactions on neural systems and rehabilitation engineering: a publication of the IEEE Engineering in Medicine and Biology Society*, vol. 16, pp. 360–370, Aug. 2008.
- [8] M. Arazpour, A. Moradi, M. Samadian, M. Bahramizadeh, M. Joghtaei, M. Ahmadi Bani, S. W. Hutchins, and M. A. Mardani, "The influence of a powered knee-ankle-foot orthosis on walking in poliomyelitis subjects: A pilot study," *Prosthetics and Orthotics International*, vol. 40, pp. 377– 383, June 2016.
- [9] M. Sartori, D. G. Llyod, and D. Farina, "Neural Data-Driven Musculoskeletal Modeling for Personalized Neurorehabilitation Technologies," *IEEE Transactions on Biomedical Engineering*, vol. 63, pp. 879–893, May 2016.

- [10] G. Durandau, M. Sartori, M. Bortole, J. C. Moreno, J. L. Pons, and D. Farina, "Real-Time Modeling for Lower Limb Exoskeletons," in *Wearable Robotics: Challenges and Trends* (J. González-Vargas, J. Ibáñez, J. L. Contreras-Vidal, H. van der Kooij, and J. L. Pons, eds.), Biosystems & Biorobotics, pp. 127–131, Springer International Publishing, 2017.
- [11] G. Durandau, D. Farina, and M. Sartori, "Robust Real-Time Musculoskeletal Modeling Driven by Electromyograms," *IEEE Transactions* on Biomedical Engineering, vol. 65, pp. 556–564, Mar. 2018.
- [12] K. Niu, "Ultrasound based skeletal motion capture: the development and validation of a non-invasive knee joint motion tracking method," Feb. 2018.
- [13] M. A. Lafortune, P. R. Cavanagh, H. J. Sommer, and A. Kalenak, "Threedimensional kinematics of the human knee during walking," *Journal of Biomechanics*, vol. 25, pp. 347–357, Apr. 1992.
- [14] J. Bingham and G. Li, "An Optimized Image Matching Method for Determining In-Vivo TKA Kinematics with a Dual-Orthogonal Fluoroscopic Imaging System," *Journal of Biomechanical Engineering*, vol. 128, pp. 588–595, Jan. 2006.
- [15] D. Forsberg, M. Lindblom, P. Quick, and H. Gauffin, "Quantitative analysis of the patellofemoral motion pattern using semi-automatic processing of 4d CT data," *International Journal of Computer Assisted Radiology and Surgery*, vol. 11, pp. 1731–1741, Sept. 2016.
- [16] K. Zhao, R. Breighner, I. Holmes, David, S. Leng, C. McCollough, and K.-N. An, "A Technique for Quantifying Wrist Motion Using Four-Dimensional Computed Tomography: Approach and Validation," *Journal of Biomechanical Engineering*, vol. 137, pp. 074501–074501– 5, July 2015.
- [17] M. Mahfouz, W. Hoff, R. Komistek, and D. Dennis, "A Robust Method for Registration of Three-Dimensional Knee Implant Models to Two-Dimensional Fluoroscopy Images," *IEEE Transactions on Medical Imaging*, vol. 22, no. 12, pp. 1561–1574, 2003.
- [18] D. V. Amin, T. Kanade, A. M. Digioia, and B. Jaramaz, "Ultrasound Registration of the Bone Surface for Surgical Navigation," *Computer Aided Surgery*, vol. 8, pp. 1–16, Jan. 2003.
- [19] K. Niu, V. Sluiter, J. Homminga, A. Sprengers, and N. Verdonschot, "A Novel Ultrasound-Based Lower Extremity Motion Tracking System," in *Intelligent Orthopaedics: Artificial Intelligence and Smart Imageguided Technology for Orthopaedics* (G. Zheng, W. Tian, and X. Zhuang, eds.), Advances in Experimental Medicine and Biology, pp. 131–142, Singapore: Springer Singapore, 2018.
- [20] C. Amstutz, M. Caversaccio, J. Kowal, R. Bächler, L.-P. Nolte, R. Häusler, and M. Styner, "A-mode ultrasound-based registration in computer-aided surgery of the skull," *Archives of Otolaryngology–Head & Neck Surgery*, vol. 129, pp. 1310–1316, Dec. 2003.
  [21] S.-Y. Chong and O. Röhrle, "Exploring the Use of Non-Image-Based
- [21] S.-Y. Chong and O. Röhrle, "Exploring the Use of Non-Image-Based Ultrasound to Detect the Position of the Residual Femur within a Stump," *PLOS ONE*, vol. 11, no. 10, p. e0164583, 2016.
- [22] K. Niu, J. Homminga, V. I. Sluiter, A. Sprengers, and N. Verdonschot, "Feasibility of A-mode ultrasound based intraoperative registration in computer-aided orthopedic surgery: A simulation and experimental study," *PLOS ONE*, vol. 13, p. e0199136, June 2018.
- [23] C. Meijneke, S. Wang, V. Sluiter, and H. van der Kooij, "Introducing a Modular, Personalized Exoskeleton for Ankle and Knee Support of Individuals with a Spinal Cord Injury," in *Wearable Robotics: Challenges and Trends* (J. González-Vargas, J. Ibáñez, J. L. Contreras-Vidal, H. van der Kooij, and J. L. Pons, eds.), Biosystems & Biorobotics, pp. 169–173, Springer International Publishing, 2017.
- [24] B. K. P. Horn, "Closed-form solution of absolute orientation using unit quaternions," JOSA A, vol. 4, pp. 629–642, Apr. 1987.
- [25] H. M. Kjer and J. Wilm, "Evaluation of surface registration algorithms for PET motion correction," p. 97.
- [26] G. Conti, L. Cristofolini, M. Juszczyk, A. Leardini, and M. Viceconti, "Comparison of three standard anatomical reference frames for the tibiafibula complex," *Journal of Biomechanics*, vol. 41, pp. 3384–3389, Dec. 2008.
- [27] A. Cappozzo, F. Catani, U. Della Croce, and A. Leardini, "Position and orientation in space of bones during movement: anatomical frame definition and determination," *Clinical Biomechanics*, vol. 10, pp. 171– 178, June 1995.
- [28] J. M. Fresno, R. Giannetti, and G. Robles, "A survey of time-of-flight algorithms to determine bone positions in movement," in 2017 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), pp. 1–6, May 2017.
- [29] R. S. Frenkel, "Coded Pulse Transmission and Correlation for Robust Ultrasound Ranging from a Long-Cane Platform," p. 94.

[30] W. Xia, Y. Zhou, X. Yang, K. He, and H. Liu, "Toward Portable Hybrid Surface Electromyography/A-Mode Ultrasound Sensing for Human–Machine Interface," *IEEE Sensors Journal*, vol. 19, pp. 5219–5228, July 2019.

# APPENDIX A MULTIPLEXING

To prevent interference between transmitted sound waves, adjacent transducers never transmit & receive simultaneously. The array of transducers is divided in 4 groups, as shown in figure 11. Each color corresponds to one of the groups. Every group gets a fixed amount of time (135  $\mu s$ , approximately equivalent to 100 mm) to transmit & receive sound waves. By grouping together transducers that do not interfere significantly, less time is needed to traverse the whole array, compared to sequencing every transducer individually. This leads to a higher frame rate and a compressed data file in the end (reduction factor of 7.5 in data size).

# APPENDIX B CONVERTING US DEPTHS TO COORDINATES

To obtain transformation matrix T for depth-to-coordinate conversion of US reflective points, 2 subsequent transformations matrices are required:

• Transformation from the adjusted transducer position during recording to the nominal transducer position  $T_2$ . Caps, offset pieces & angles of each holder during trials was written down. The angular DOFs permitted by the holders can be interpreted as the pitch & roll Eulerian angles, where  $\theta$  is the pitch angle and  $\phi$  is the roll angle. The order of multiplication of two rotation matrices is unique since additions of angles in 3D space are non-interchangeable. The rotation part of  $T_2$  is obtained by



Fig. 11: Each color shows to which group of simultaneously active transducers the holders belong.

multiplying the Eulerian rotation matrices in this order:

$$\mathbf{R_2} = \mathbf{R_{pitch}} \mathbf{R_{roll}}$$
$$= \begin{bmatrix} \cos(\theta) & 0 & \sin(\theta) \\ 0 & 1 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \sin(\phi) & \cos(\phi) \end{bmatrix}$$
(5)

- Transformation from nominal transducer positions to the global coordinate system T<sub>1</sub>. T<sub>1</sub> was extracted from the brace CAD geometry.
- T is found by multiplying  $T_1 \& T_2$  in this order:

$$\mathbf{T} = \mathbf{T_2}\mathbf{T_1} \tag{6}$$

**T** is multiplied with the depth vector, resulting in a 3D point cloud of US reflective points in the reference frame of the exoskeleton.

# APPENDIX C Pre-registration

Before pre-registration it is unknown which source points  $x_i$  register the best to the target points  $u_i$ . Optimal source points are found by doing a brute force search to the lowest error point combination among the points inside the pre-registration areas. First, the pre-registration area point cloud is down sampled to a grid size of 15mm. Then, every possible combination of 4 points (1 point from each pre-registration area) is tested with Horn's algorithm. The point combination that result in the lowest error is saved. Then on the native pre-registration point cloud, around these 4 points, all points within a 10mm radius are identified and tested, again in every possible combination. The lowest error point combination is used for pre-registration. Figure 12 shows an example of the optimal source points combination for one of the trials.

# APPENDIX D RIGIDITY ANALYSIS

When calculating the point cloud from US data, a transformation matrix is used that is based on CAD geometry. Thereby, it is assumed that the exoskeleton & brace are rigid bodies and do not move with respect to the global coordinate system. This assumption was tested by performing a quick



Fig. 12: Example result of the brute-force search to the best performing point set for pre-registration in one of the trials. Points on the diaphysis are not on the edge of the pre-registration areas, meaning that the pre-registration area has been chosen sufficiently large.

# APPENDIX E Experiment Rig



Fig. 13: Results of a quick structural simulation. Total deformation is simulated to be sub-millimeter, being the highest near the proximal end.

strength analysis in Ansys Workbench, predicting a maximum deformation of 0.17mm at the proximal end. See figure 13.

Optical measurements were done to verify the simulation by equipping the configuration with 3 groups of 4 reflective markers on the exoskeleton, brace & knee. See figure 4. Between the 4 markers placed on the brace, 6 lines can be identified. The strain of each line is calculated with

$$\varepsilon = \frac{L_1 - L_0}{L_0} \tag{7}$$

With  $L_0$  being the length in unloaded condition, and  $L_1$  being the length during recording. Here, rigidity can be assumed when strain is less than 2%. The maximum strain during dynamic measurements was 1%, thereby passing the rigidity criterion. 1% strain is equivalent to an elongation of 1.16mm of the line in question. Even though the result is one order of magnitude higher than the simulation, it is still an acceptable navigation error for bone pose estimation.

The displacement of the brace with respect to the exoskeleton is also calculated. The length between markers 1 & 5 showed a maximum deformation of 1.3mm, meaning that the brace was attached firmly to the leg. However, between marker 5 and its equivalent point from CAD data, a displacement of 4.42mm was found. Between markers 2 & 6, the maximum deformation was 0.45mm. Therefore it can be concluded that navigation errors propagate from the distal end to the proximal end, reaching navigational errors that exceed typical STA error values. Something to attach the brace to the exoskeleton at the proximal end would greatly benefit the reduction of navigational errors.



Fig. 14: A small improvised rig to hold the subject leg & exoskeleton in fixed dorsiflexion angles for the static trials.