HelpMeWalk - A new digital process for orthoses production: Data processing, Workflow and Accuracy

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Abstract. The *HelpMeWalk* project introduces a low-cost, magnetic field–based 3D acquisition system using sensor-embedded textile bandages for digital modeling of lower leg orthoses. The system captures approximately 300–500 spatial points within six seconds, providing data for a model-based surface reconstruction. A multi-step workflow – comprising error cleaning, alignment of measured points to a model surface and form adjustment – enables accurate reconstruction of individual limb geometries. Prototype evaluation demonstrated robust functionality and a final mean surface deviation of 2.89
mm. Remaining inaccuracies were mainly linked to sparse sensor coverage and sensor noise. Future development will focus on optimizing sensor placement protocols, mobile App integration, and machine learning enhanced error detection.

Keywords: Digital orthoses; magnetic tracking; 3D reconstruction; remote healthcare.

1 Introduction

The provision of orthopedic aids such as foot orthoses is still largely based on analog methods like plaster casting, which are labor-intensive, imprecise, and costly – especially when patient transport is needed. Inaccurate molds often require multiple adjustments, reducing comfort and patient adherence, and thereby compromising therapeutic success. With more than 300 custom orthoses produced annually per practice, there is strong demand for precise, reproducible, and efficient digital processes that improve both productivity and patient comfort.

The *HelpMeWalk* project aims to fill this gap by developing a cost-effective, user-friendly digital 3D measurement solution. Washable sensor-equipped bandages (“smart textiles”) capture a point cloud during manual corrective positioning, enabling model-based reconstruction of body structures with high accuracy from relatively few data points.

2 Method

3D point acquisition was achieved using a magnetic field tracking system, which determines the positions of three-axis magnetic field sensors. Trilateration of points is based on precomputed magnetic field maps and generates a point cloud of 300–500 points in under six seconds. Different flexible PCB layouts were employed to effectively capture complex curvatures.

Surface reconstruction is model-based, mapping the acquired point cloud onto a normalized 3D surface model of an average lower leg. The process involves four main steps:

1. **Error Cleaning**: Measurement points are classified using geometric constraints derived from PCB design, comparing theoretical and measured distances. Points are scored by local relations and excluded if distances exceed physical limits [1].
2. **Rigid Pre-Registration and Size Adjustment**: The normalized model and measured point cloud are roughly aligned using artificial landmarks. Alignment includes translation and quaternion-based rotations. The normalized model is then scaled along the main anatomical axes of lower leg and foot to match patient-specific dimensions.
3. **Fine Registration**: An Iterative Closest Point (ICP) algorithm is used to refine alignment between the point cloud and the scaled surface model. This step benefits from error cleaning and a certain degree of similarity as prepared above [2], [3], [4].
4. **Shape Adjustment**: A Thin-Plate-Spline (TPS) algorithm [5] establishes nearest-neighbor correspondences from measured cloud points to the surface model and deforms the model accordingly. Nearest surface points are displaced toward their matched sensor point, while neighboring points are adjusted using a falloff function.

Results were post-processed using (1) a Windowed Sinc Smoothing to remove undetected outliers caused by random noise, (2) a voxel-based surface shrinking to correct for a 3 mm offset caused by the bandage thickness, and (3) a final smoothing to obtain a high-fidelity representation of the surface.

3 Results & Conclusion

Table 1. Geometric deviations between an optimal surface scan and process steps of a test reconstruction

Compare after	**Size Adjustment**	**ICP Registration**	**TPS Adjustment**	**Post-process**
Mean Distance	11,64 mm	4,14 mm	3,63 mm	2,89 mm
75^{th} Percentile	17,04 mm	5,74 mm	5,29 mm	4,07 mm
Mean SE	196,31	26,21	22,04	14,11

A reconstruction test was performed which shows that the individual steps consistently decrease mean distance error down to 2,89 mm when comparing the results to a provided optical surface scan of the reference leg (Table 1). High deviations were mainly found in regions lacking sensors patches or when patches exhibit a consistent spatial offset due to systematic noise.

First results demonstrate the potential of the magnetic sensor patch approach of *HelpMeWalk* for accurate 3D reconstruction of lower limbs. Though broader validation across diverse patient groups and real-world conditions is still required. Accurate results depend on well-defined sensor placement protocols, as patch misplacement introduces early errors. Further research focuses on optimizing patch positioning, refining algorithms and incorporating variable foot angles between lower leg and foot as this is a treatment / costumer requirement. Improved data cleaning with Dynamic Graph CNNs and model selection based on individual patient characteristics are currently being investigated to improve overall accuracy.

References

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