

**Project title:** SensFloor

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## 1. Introduction

With the ageing of the population elderly care is becoming more important than ever. However, the amount of missing workforces is increasing and expected to be between 280 000 and 690 000 in 2049 in Germany [1]. To help this remaining workforce some steps and processes in their work could be automated. By tracking patients movements accidents can be recognised earlier, be backtracked and safety measurements can be deployed to prevent future incidents. One option for data collection and tracking that is already spread among elderly homes is SensFloor: a sensor-based technology which can be installed under every regular floor.

By embedding doing so, it enables the detection and analysis of human movement patterns mostly used for fall detection. Recent research has leveraged this technology for various data-driven applications, such as estimating the age of individuals [2] or identifying people through characteristic movement profiles [3]. While pose estimation has been studied using other sensing technologies [4], there is no research investigating pose estimation based specifically on data from SensFloor, leaving this an open area for exploration

This project is part of a bigger project aiming to improve the data collected from SensFloor floors, with the goal of gaining deeper insights into human activity and reducing the number of false-positive fall detections.

Our contribution to this project is to research about the estimation and visualization of walking patterns using real-time data collected by SensFloor. The aim of it is visualizing a person walking using only the data provided by SensFloor.

The project will start with a review of existing literature on pose estimation, the use of SensFloor and on similar approaches. Following on this, data will be collected and preprocessed and a model to solve the task will be trained and evaluated. As a last step, the estimated movement patterns will be visualized.

## 2. Literature review

In this section, we review relevant literature related to the research topic. We cover previous work on pose estimation using floor-based data, explore various applications of the SensFloor system, and discuss general approaches in pose estimation.

Leusmann, Mollering, Klack, *et al.* [5] proposed an algorithm to detect human position and movement from the data obtained by a sensor floor. The floor sensors recorded pressure, which was used to recognize walking patterns, falling events, and abnormal movement behaviour. While the method successfully predicted some human behaviours on the floor, it was not tested in real-time due to the computational complexity. Moreover, its estimation of human posture was limited to a small set of behaviour.

Another notable study in this field is by Luo, Li, Foshey, *et al.* [4], who proposed an intelligent carpet system for estimating 3D human poses using tactile data. In their approach, tactile signals were captured via the intelligent carpet, while ground truth 3D poses were obtained using OpenPose. A deep neural network was trained to infer 3D joint positions solely from

pressure data. Their method achieved high accuracy for single-person pose estimation across various activities. However, the model failed to accurately predict certain poses that lacked sufficient physical contact with the floor.

Overall, the existing literature demonstrates the feasibility of using sensor floor data for human activity and pose estimation. However, current systems are limited in the variety of behaviors they can recognize and often lack real-time capability. Additionally, Luo, Li, Foshey, *et al.* [4] focused on 3D pose estimation in both single- and multi-person scenarios, whereas our project aims to estimate walking patterns from SensFloor data.

In [2] the authors present a method for age estimation using SensFloor data and a Multi-Layer Perceptron regression model. This study showcases a novel use of the SensFloor technology and offers practical insights into experimental design and data processing. However, the dataset is relatively small, and potential bias exists due to the lead author's affiliation with FutureShape GmbH, the manufacturer of the SensFloor system. A similar study [6] explores the classification of gait patterns using recurrent neural networks. It provides detailed insights into the data collection and data preparation processes within the SensFloor context. Nevertheless, its results offer limited relevance for the current project, and like the previous study, it may be biased due to the authors' involvement with the SensFloor company.

Human pose estimation (HPE) is a growing field given by its wide range of applications in healthcare, gaming, security or therapy and the advances of Deep Learning methods. Depending on the field the accuracy of the model is very important and thus there have been several studies giving an outline to different evaluation methods.

Zheng, Wu, Chen, *et al.* [7] provides a summary of 260 papers for 2D and 3D approaches for HPE solutions and different evaluation methods. While the study's abstract tries to generalize the problem as predicting poses from input, it does only include Computer vision approaches. The work still gives a detailed evaluation method for general pose estimations.

A more recent study from Elshami, Salah, and Mohsen [8] focuses on 2D pose estimation methods and evaluation methods between 2019 and 2023 also focusing on Computer Vision approaches. It fails to explain why it chooses 2D methods, but it shows similar results as the previous analysis.

Both studies highlight the same evaluation methods: PCK (Percentage of correct keypoints) and average precision (AP) are the most commonly used approaches to evaluate HPE models. They compare the joints and given some threshold commonly a body part label it as correct or falsely predicted.

### 3. Research Question, Hypothesis or Aim and Objectives

The aim of this project is to explore the feasibility of estimating human walking patterns using only SensFloor data and develop a working machine learning pipeline that visualizes these walking patterns. To achieve this, the project addresses the following research questions:

- To what extent can walking patterns be estimated from SensFloor data?
- How accurate are these estimations compared to pose data extracted from camera recordings?
- Which walking patterns can be estimated more accurately, and which are more difficult to detect?

## 4. Research design/methodology

This project follows a quantitative, experimental research design to explore whether it is possible to estimate walking patterns using data from the SensFloor system. The focus lies in developing and evaluating a model that can predict walking patterns based on floor sensor input.

### 4.1. Step Overview

The methodological process consists of several key steps:

1. Setting up the experimental environment
2. Collecting the SensFloor and camera data
3. Preprocessing and aligning the data
4. Training a machine learning model
5. Evaluating the results
6. Visualizing the estimated walking pattern

All these steps follow the goal of the project to estimate and visualize poses based solely on the data collected by SensFloor.

The whole development phase is planned to be an iterative process starting with the collection of data. Data collection takes place in the CAIRO Room at THWS, where the SensFloor system is installed. A single camera is positioned to record participants as they move on the floor. To keep the setup manageable, members of the project team act as participants. Data collection begins with one person at a time to validate the methodology. If successful, additional data with multiple persons may be conducted in a later state of the project. During data collection, the SensFloor records movement data while the camera capture video footage. The pose estimation software OpenPose will be used to extract joint positions from the videos. These will be aligned with the corresponding SensFloor signals to create a labeled dataset. Next, a yet to be evaluated machine learning model is trained to solve the supervised learning task of mapping floor signals to pose outputs. The model's performance is evaluated using the evaluation metrics percentage of correct key points, average position and average recall proposed in the survey [7]. Depending on the results of the evaluation the whole process of collecting data, model training and evaluation is repeated to refine the performance of the model. During the first iteration we also implement a way of visualizing the estimated walking patterns using Unity.

### 4.2. Limitations and Obstacles

This study faces some limitations and potential challenges. The number of participants will be very small, omitting the diversity of movement data. Furthermore, the analysis is restricted to one camera which limits the visualization to one point of view.

Another obstacle could be that the SensFloor system is not yet installed at the beginning of the project, potentially delaying data collection. Additionally, the floor is located in an area that is publicly accessible to all AI students, making undisturbed data collection difficult when others are present.

## 5. Expected Outcome

The final deliverable of this project is a prototype of a machine learning pipeline that estimates and visualizes walking patterns using only SensFloor data. If the approach proves effective, it opens up several potential applications. For example, tracking and visualizing movement patterns of care home residents. Furthermore, it provides an insightful way to demonstrate the results of the overarching project. In addition to that, knowing which walking patterns can be predicted better can provide a valuable basis for future research.

## 6. Project plan

The Gantt chart in Figure 1 presents the project timeline for estimating and visualizing walking patterns using SensFloor data. The timeline begins with a literature review and methodology planning, followed by an iterative process of developing the machine learning pipeline and visualizing the results. Scientific writing runs in parallel with the development, with the primary focus on writing beginning during the later stages of model development and evaluation. A buffer period is included at the end to accommodate potential delays and help ensure timely project completion.

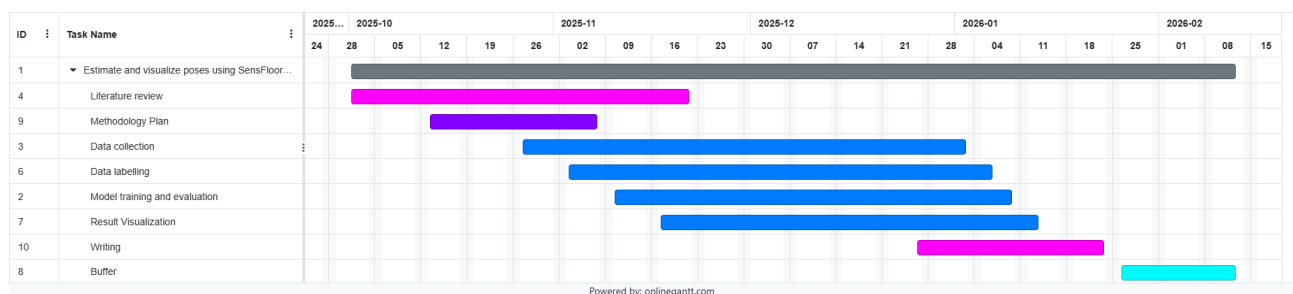


Figure 1: Gantt chart for SensFloor project

## 7. Ethical Consideration

Since the data collection takes place in a building during the semester we must ensure that our system is only being used to track the participants and should be shut down otherwise. We also need to make others aware of the ongoing data collection

## References

- [1] Statistisches Bundesamt, *Bis 2049 werden voraussichtlich mindestens 280 000 zusätzliche Pflegekräfte benötigt*, [https://www.destatis.de/DE/Presse/Pressemitteilungen/2024/01/PD24\\_033\\_23\\_12.html](https://www.destatis.de/DE/Presse/Pressemitteilungen/2024/01/PD24_033_23_12.html), 2024.
- [2] R. Hoffmann, C. Lauterbach, J. Conradt, and A. Steinhage, “Estimating a person’s age from walking over a sensor floor,” *Computers in Biology and Medicine*, vol. 95, pp. 271–276, 2018.
- [3] G. Qian, J. Zhang, and A. Kidané, “People Identification Using Floor Pressure Sensing and Analysis,” *IEEE Sensors Journal*, vol. 10, no. 9, pp. 1447–1460, 2010.

- [4] Y. Luo, Y. Li, M. Foshey, W. Shou, P. Sharma, T. Palacios, A. Torralba, and W. Matusik, “Intelligent Carpet: Inferring 3D Human Pose from Tactile Signals,” en, in *2021 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Nashville, TN, USA: IEEE, 2021, pp. 11 250–11 260.
- [5] P. Leusmann, C. Mollering, L. Klack, K. Kasugai, M. Zieffle, and B. Rumpe, “Your floor knows where you are: Sensing and acquisition of movement data,” in *2011 IEEE 12th International Conference on Mobile Data Management*, ISSN: 2375-0324, vol. 2, 2011, pp. 61–66.
- [6] R. Hoffmann, H. Brodowski, A. Steinhage, and M. Grzegorzec, “Detecting Walking Challenges in Gait Patterns Using a Capacitive Sensor Floor and Recurrent Neural Networks,” *Sensors*, vol. 21, no. 4, p. 1086, 2021.
- [7] C. Zheng, W. Wu, C. Chen, T. Yang, S. Zhu, J. Shen, N. Kehtarnavaz, and M. Shah, “Deep Learning-based Human Pose Estimation: A Survey,” en, *ACM Computing Surveys*, vol. 56, no. 1, pp. 1–37, 2024.
- [8] N. E. Elshami, A. Salah, and H. Mohsen, “A Comparative Study of Recent 2D Human Pose Estimation Methods,” in *2024 6th International Conference on Computing and Informatics (ICCI)*, New Cairo - Cairo, Egypt: IEEE, 2024, pp. 528–537.