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Estimating a person's age from walking over a sensor floor

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ABSTRACT

Ageing has an effect on many parameters of the physical condition, and one of them is the way a person walks. This property, the gait pattern, can unintrusively be observed by letting people walk over a sensor floor. The electric capacitance sensors built into the floor deliver information about when and where feet get into close proximity and contact with the floor during the phases of human locomotion. We processed gait patterns recorded this way by extracting a feature vector containing the discretised distribution of occurring geometrical extents of significant sensor readings. This kind of feature vector is an implicit measure encoding the ratio of swing-to stance phase timings in the gait cycle and representing how cleanly the leg swing is performed. We then used the dataset to train a Multi-Layer Perceptron to perform regression with the age of the person as the target value, and the feature vector as input. With this method and a dataset size of 142 persons recorded, we achieved a mean absolute error of approximately 10 years between the true age and the estimated age of the person. Considering the novelty of our approach, this is an acceptable result. The combination of a floor sensor and machine learning methods for interpreting the sensor data seems promising for further research and applications in care and medicine.

1. Introduction

The approximate age of a person is recognisable from various bodily features. Medical and forensic age determination is usually based on dental [1,2] or bone properties [3]. Efforts towards solving the task of estimating a person's age with methods of machine learning often work by analysing a photo of the face. An examplary algorithm for age estimation from facial features is found in Ref. [4], which also compares various other published methods and results from humans estimating the age of a person from a portrait. In the present methodological proposal we investigate the possibility of estimating a person's age from walking over a sensor floor. The SensFloor floor sensor we used is a system that captures the time and location of persons walking on it by means of electric capacitance measurements over a grid below the floor covering.

Previously, we introduced an experiment setup and computation method to classify people in risk of falling [5]. For this new purpose of age estimation we evaluated a similiar method with a newly recorded large dataset. Other work in this area already found a principal relation between age and properties of locomotion. In Ref. [6], the stride-to-stride variability was observed when study participants were challenged with a cognitive task while walking. It was found that the effects of dual-tasking were more distinct with increasing age. There, the GAITRite system was used to assess properties of the gait, which is also a floor sensor but with a different mode of operation as it makes use of a pressure-based instead of electric capacitance-based sensor principle. Another approach of gait-based age estimation from locomotion captures with a camera is found in Ref. [7]. Camera-based gait capturing for age estimation was also used in creating a remarkably large dataset of 1728 subjects [8]. A further approach to age estimation is found in evaluating data from Inertial Measurement Unit (IMU) sensors [9]. We intend to demonstrate the potential of the floor sensor data combined with machine learning algorithms for research and applications in medicine and care.

2. Floor sensor

In the present study we used a SensFloor [10] sensor system for recording the gait patterns. The sensor is installed hidden beneath common flooring types like parquets, carpets, tiles or synthetic materials and therefore not interfering with the person walking on it. The sensor is a textile-based underlay with embedded electronics. By performing measurements of the electric capacitance within a discrete spatial resolution, it can detect where people are standing on the floor, and where

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they are resting their feet in the stance phases of the gait cycle. Persons are detected as the human body contains water, which, beside metallic materials, influences the measured electric capacitance. Fig. 1 shows the SensFloor assembly and an exemplary timeline of four consecutive measurements. SensFloor is an event-based sensor which only sends out a current reading whenever the measured capacitance of one triangular sensor-field of a module has changed significantly.

3. Experiment setup and dataset

The dataset was collected at three occasions, at an open house day in a neurologic clinic, a trade fair exhibition stand, and in an office building. We used a SensFloor installation with a length of 6 m and a width of 1 m. At the clinic and office building recording sites, the sensor was installed below a carpet, and at the exhibition stand below parquet. These flooring materials have different absolute permittivities, which influences the measurements of the electric capacitance. However, the sensors are programmed to calibrate themselves to the flooring material on being power-cycled. The calibration happens by measuring the base capacitance when the sensor is unoccupied. The properties of the flooring material can therefore be neglected in the sensor data analysis.

During previous recordings, we observed that it is qualitatively immediately recognisable in the sensor data when a person is distracted amidst walking over the mat. Participants were hence told to focus on a point in the distance, and walk along the sensor area at normal pace and style without deliberately concentrating on their gait. In some cases, the recording was repeated once, and both recordings were used in training the neural network. Besides the instruction to walk normally, no further training was given and no other requests were made to the participants.

Fig. 2 shows the experiment setup and conduct as well as two examples of gait patterns along the walk. We respected the ethical principles of data reduction and data economy by only storing the gait patterns in an anonymised database with a minimum of other personal information. Participants were asked for their age, which we stored in the database together with the gender. Some subjects voluntarily told us about pathologies with a possible influence on the gait, in which case we also noted this down. However, we did not actively demand the information about gait-related conditions. After the recording, participants were offered to take home a print-out of their gait pattern on an infosheet with facts about the sensor and various examples of gait patterns. Besides announcing general information about the gait recording event taking place, there was no targeted invitation or plan to get a certain group of participants recorded. All passers-by at the recording sites were invited to participate in the gait recording. Participants were only excluded from the study if they were not able to walk without a walking aid of any kind like a wheeled walker or crutches, or required support by a care taker. At the clinic, the public consisted of visitors of the open house day, patients and their relatives, and medical staff. In the trade fair, we found a mix of private visitors ranging from school children to seniors, as well as professional visitors and exhibition staff. For the third location in the office building, we recorded people working there on their way to or from the canteen, and locals visiting the building for lunch. Remarkably, the age distributions between the recording sites did not differ a lot.

Participants gave an informed consent to the evaluation of their gait recordings. In total, we recorded the gait patterns of 142 persons. The youngest participant was 13 years old, and the oldest 82 years. Fig. 6 shows the distribution of ages of persons in the dataset.

4. Data analysis

The recorded gait patterns are a time series of events of capacitance changes, as reported by the sensors and collected at the central receiver. The time series was first processed with a feature extraction step, which results in a six-dimensional vector. This feature vector served as input to a neural network, with the normalised true age as output.

4.1. Feature extraction

The feature extraction step compresses properties of the gait from a time series of sensor events into a feature vector. We initially described this kind of feature extraction for SensFloor data in detail in Ref. [5]. The steps of the feature extraction process are shown in Fig. 3. For each point in time t with a recorded event, we calculate the current location of the person as a two-dimensional object position $\overrightarrow{x}_{obj,t} = \{x_{obj}, y_{obj}\}$ on the floor. The object position is calculated as the average position of relevant measurements weighted with the capacitance. The points in P_t are all those with a capacitance above a certain threshold, e.g. $c_{i,t} > 10$ in our case, with a possible range $c_{i,t} \in [0, 127]$.

$$P_t = \{p_{i,t}\} = \{p_{0,t}, p_{1,t}, \cdots p_{n,t}\} \quad \text{with} \quad p_{i,t} = \{\overrightarrow{x}_i, c_{i,t}\}, \overrightarrow{x}_i = \{x_i, y_i\} \tag{1}$$

Considering only these points, the object position follows as:

$$\overrightarrow{x}_{obj,t} = \frac{1}{C_t} \sum_{i=1}^{n} c_{i,t} \overrightarrow{x}_i \quad \text{where} \quad C_t = \sum_{i=1}^{n} c_{i,t} \tag{2}$$

C_t is calculated as the sum of all capacitances of measurement points at a time t with a significant increase of electric capacitance compared to a sensor field that is not occupied. The second row of Fig. 3 shows how this calculation results in the track of the objects position over time. The green dot shows the most recent object centroid as determined from the sensor readings. At each timestamp of the so calculated object trajectory, consisting of the time series of object positions $\overrightarrow{x}_{obj,t}$, we calculate the spread value s_t as the average euclidean distance from the object position to all measurement points that exceed the threshold at this time:

$$s_t = \frac{1}{|P_t|} \sum_{\{\overrightarrow{x}_i, c_{i,t}\} \in P_t} |\overrightarrow{x}_{obj,t} - \overrightarrow{x}_i| \tag{3}$$

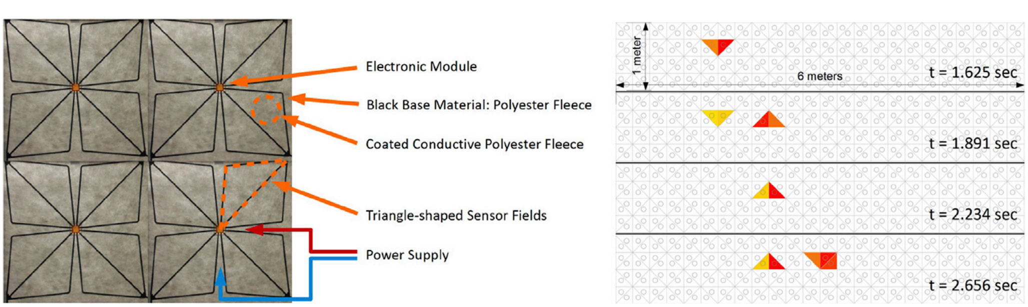

Fig. 1. SensFloor sensor structure and time series of sensor readings. Yellow towards red colours correspond to lower towards higher capacitance readings. White sensor fields denote a capacitance below a threshold interpreted as occupied. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)