Tracking your Steps on the Track: Body Sensor Recordings of a Controlled Walking Experiment

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ABSTRACT

Monitoring human motion has recently received great attention and can be used in many applications, such as human motion prediction. We present the collected data set from a body sensor network attached to the human body. The set of sensors consists of accelerometers measuring acceleration in three directions that are attached to the upper and lower back as well as the knees and ankles. In addition, pressures on the insoles are measured with four pressure sensors inside each shoe. Two types of motion are considered: walking backwards on a straight line and walking forwards on a figure-8 path. Finally, we study and present basic statistics of the data.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms, experimentation.

Keywords

Time series, body sensor network, acceleration.

1. INTRODUCTION

Monitoring human physical activity is interesting for several reasons. In [5] and [16] for instance, it is shown that by studying the motion and gait variation in elderly, one can detect dementia at an early stage. Also, abrupt changes in activity patterns can be used to detect falling, after which an emergency service can be notified automatically as shown by [3]. A system that can assist memory impaired people was built in [7], which requires the computer system to be aware of several apriori patterns indicating normal behavior. On the border of the lifestyle and medical domain, [4] study how to motivate people stay in shape by giving feedback on their energy expenditure based on activity tracking. Moreover, operational context for programs is given by activity recognition algorithms enabling ambient intelligent systems [17].

Our focus is on wearable devices for activity and motion recognition. There is a wide range of related work in this field, including for example [12], [18] and [13], where a wrist-worn RFID reader is used to monitor objects used by an individual. These measurements are then used to predict the activity in which the subject is involved. The recognized activities include basic daily living tasks, such as preparing a meal, taking medication, cleaning the home, brushing teeth, etc. Another approach employs sensors to determine a person's location at home and deduce similar type of daily living activities [9]. Similarly, [1] uses sensors to predict a person's path at home. An interesting method is to use an on-body accelerometers to infer personal activities. These motion patterns can be used to classify basic activities such as walking, running or sitting, as shown in [2] and [6]. Accelerometers are also used together with other sensors, such as heart rate monitors [14], RFID tags [13], an array of sensors including temperature, infrared, pressure, and others [15], or a house filled with wired and wireless sensors [10]. Basic repetitive motions in activities are identified in [11], which may be used for activity classification.

Small special purpose devices with embedded accelerometers are at the moment available in the market, including also smart phones, e.g., the Nokia 5500 sport mobile [8]. Such devices can be worn on a belt or placed inside ones pants' pocket. We used such devices for the experiment described in Section 2.

In this paper, we concentrate on the acceleration measurements near the chest, hips, ankles and knees, as well as the pressure measurements in the insoles of the feet. Our main **contributions** include:

- describing collected data in a walking experiment, where body accelerometers and pressure sensors are used to generate a data set of 293 time series collected from 26 different body sensors,
- a preliminary analysis of the data revealing simple correlation structures and characteristics of the data.

The remainder of this paper is organized as follows: in Section 2, we describe the designed experiment behind the data collection, in Section 3 we describe the data set itself. Some preliminary data analysis methods identifying time series patterns in the data are run and described in Section 4. Finally, Section 5 concludes the paper.

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2. THE WALKING EXPERIMENT

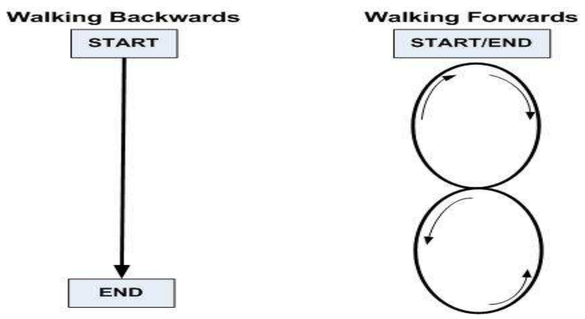

Figure 1: On the left, the display of a backward walking experiment. On the right, the display of a figure-8 walking experiment.

A controlled experiment was conducted for the purpose of data collection. Voluntary students were asked to participate in an experiment, where the test persons would wear the sensors attached to the body and perform the walking tasks. The walking tasks included walking on a straight line backwards (back facing the walking direction) and walking a figure eight formed track (Figure 2. All experiments were repeated twice in order to collect double recordings of all the experiments.

During these experiments, controlled doses of red wine were consumed and the level of alcohol were measured before and after each experiment. These levels are recorded in the data. All the experiments were conducted in the presence of two physiologists monitoring the participants. The motivation behind the alcohol consumption was that it would probably induce slight balance problems which may or may not be reflected in the body sensor measurements. This may be one of the future topics of study with the current data set.

All the participants consented that the data is collected and may be used. Confidentiality of the participants will be respected and privacy preserved.

3. THE BODY SENSOR DATA

The participants wore the body sensor during the experiments described in the previous section. After the task was finished, the collection of the data was terminated. This results in data, where each experiment may have different duration. After each experiment, the data was transferred from the sensors to a central computer for storage. The transfer was done with a wireless radio connection between the sensor nodes and the computer (Bluetooth). As illustrated in the Figure 3, the sensors were positioned at the upper back of the body, lower back of the body, left and right knees, left and right ankles. Acceleration in three perpendicular direction was measured with acceleration sensors. Altogether, we have recordings of three-axis acceleration sensors from six nodes resulting in 18 measurements for body part accelerations. In addition to the acceleration measurements, we have pressure sensors in the insole of the shoe to measure the pressure between the foot and the floor. This is also illustrated in the Figure 3.

Two of the first participants were discarded from the data set, since all the experiments were stored one after the other, and there is no reliable way of separating the data into the correct segments accurately. The data of twelve participants remain in the data set.

Each experiment is stored separately in the data set. They are indexed by the participant, the experiment, and the repetition (first or the second).

The samples were stored with the sampling frequency of 25 Hz. The median duration of the experiment is 12 seconds, that is around 300 samples. The whole distribution of the experiment durations (in seconds) is shown in Figure 3. This is directly proportional to the time series length, which is variable. Notice that from the figure we exclude a single experiment whose duration was approximately 10 minutes. The total number of time series in the data set is 293 and the distribution of their lengths can be easily inferred from Figure 3.

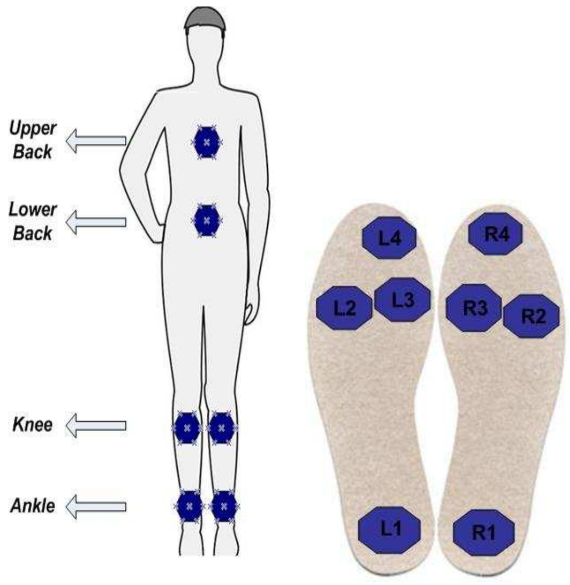

Figure 2: In the left panel, the positions of the acceleration sensors located in the six nodes are depicted. In the right panel, the location of the pressure sensors in the insole of the shoe are shown.

4. EXPERIMENTS: TIME SERIES PATTERN FROM THE DATA

We performed some preliminary data analysis on the data generated in walking experiment. The goal of these experiments is to provide some initial summarization of the data and get some insight about possible correlations of the produced time series.

First, we studied the insole pressure levels of each of the four sensors attached to each sole. Figure 4 shows the foot pressure levels of the front insole sensor of the left foot. The x axis corresponds to the pressure values whereas the y axis is the cumulative percentage of samples. It is interesting to notice that pressure varies for different types of motion (walking backwards and walking forwards on figure-8 path) and different people.

Next, we studied the correlation of the four sensors within each sole. It should be expected that, while walking, when

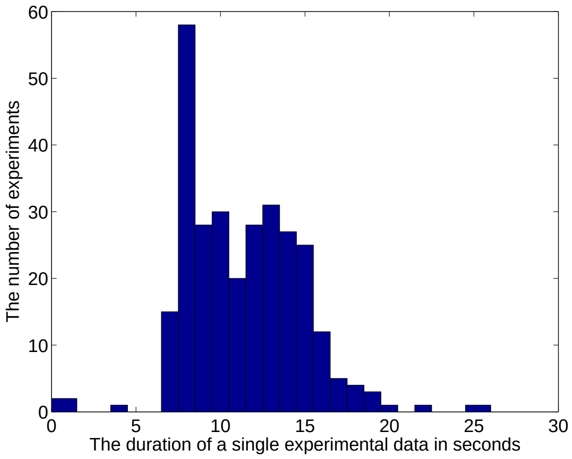

Figure 3: The distribution of the duration of single experiments. The median duration of the experiments is 12 seconds, which corresponds to 300 samples of data, under the sampling rate of 25Hz. The shortest time series were of length 0, 1, and 4 seconds (in the left part of the histogram), the longest time series had a duration of 508 seconds (not visible in the figure).

Sensor	L1	L2	L3	L4
L1	1.00	0.92	0.93	0.92
L2	0.92	1.00	0.91	0.98
L3	0.93	0.91	1.00	0.91
L4	0.92	0.98	0.91	1.00

Table 1: Correlation of the four pressure sensors in the left shoe for participant 3 when walking on a figure-8 path aggregated over all rounds.

L1 has a high pressure then the pressure on L4 should be low and vice versa. The same holds for R1 and R4 respectively. Intuitively, this is highly expected since when one is putting pressure on one foot's back part of the sole (e.g., L1) we should expect the front part of the same foot's sole (i.e., L4) to be almost off the ground. This type of correlation was detected in our data. However, we also detected more interesting patterns for several participants. One such pattern is shown in Tables 1 and 2 where we can see the correlation of the four pressure sensors in the left and right shoe, respectively, for participant 3 when walking on a figure-8 path aggregated over all rounds. Surprisingly, we noticed that while the correlations in the measurements on the right foot sensors abide by the expected correlation scheme described above, this does not hold for the left foot sensors. As shown in Table 1, all four left foot sensors have correlation values close to 1, which actually means that the participant walked in 'flat' steps with his left foot while his right foot moved normally. Such observation may indicate possible left-foot injury.

Finally, in Figure 4 we show an example of the data. In detail, we see the representations of the two 8-bit signal recorded by sensors L4 and R4 of the left and right foot respectively. Both signals were taken when walking on a figure-8 path.

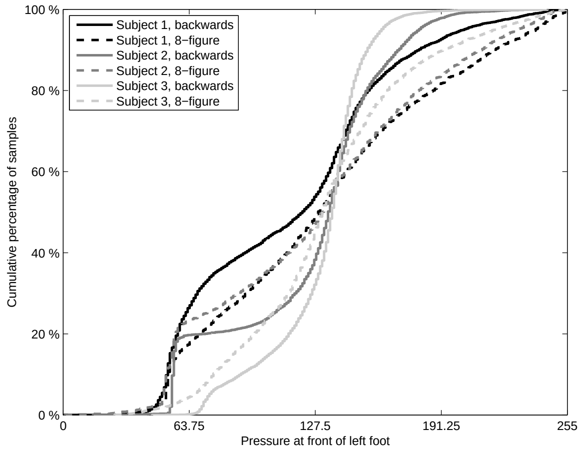

Figure 4: Foot pressure at the front insole sensor *L4* of the left foot over all samples.

Sensor	R1	R2	R3	R4
R1	1.00	0.37	0.15	0.10
R2	0.37	1.00	0.47	0.57
R3	0.15	0.47	1.00	0.46
R4	0.10	0.57	0.46	1.00

Table 2: Correlation of the four pressure sensors in the right shoe for participant 3 when walking on a figure-8 path aggregated over all rounds.

Our implementations, data, and repeatability instructions are available at the authors' web-pages.

5. SUMMARY AND CONCLUSIONS

We have presented a case on body sensor networks for monitoring the acceleration of the body and the pressure on the insole of the shoe during walking experiments under controlled conditions. We describe the locations of the sensors, the measured data and its basic characteristics. Finally, some preliminary analysis is performed to gain some insight into the data. The analysis is far from being complete and many exciting problems remain to be investigated. By releasing the documented data set into research use, we hope that people will find it interesting and use it either as their main resource in body sensor network related research, or as a complementary benchmark data set. It is a nice starting point for those researchers who may not have access to body sensor networks data themselves.

In the analysis of the presented data set, it must be remembered that the data set comes as it is, including all practical problems of sensor malfunctions, faulty experiments, and the like. This must be taken into account when analyzing the data set. We believe that all these characteristics make the data set very interesting start point for those who wish to learn about body sensor networks and the analysis of practical real-life body sensor measurements. This applies to researchers, practitioners, educators, and students alike.

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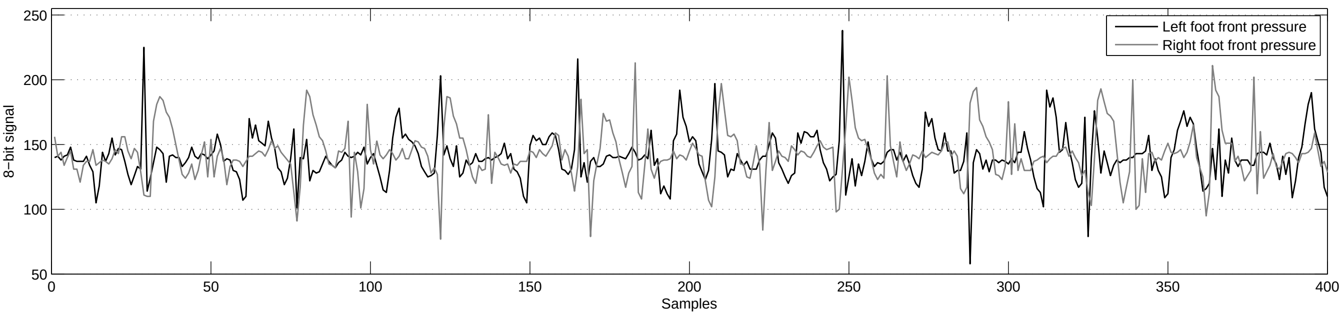

Figure 5: Data set sample.

vices and the logging system in general and who conducted the experiments with the help of two physiologists monitoring the patients during the experiments. We wish to thank the participating students in the experiments. This research has been supported by Algorithmic Data Analysis (Algodan) centre of excellence in research and the Multidisciplinary Institute of Digitalization and Energy (MIDE) at the Aalto University School of Science and Technology. Both funding sources are gratefully acknowledged.

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