CapWalk: A Capacitive Recognition of Walking-Based Activities as a Wearable Assistive Technology

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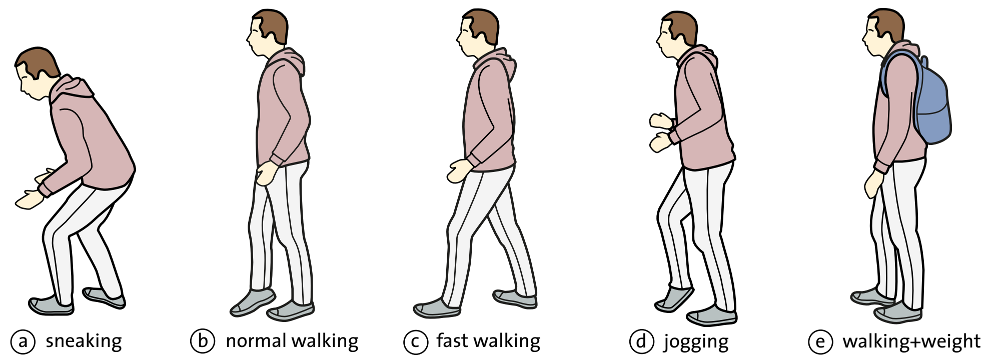

Figure 1. In CapWalk we evaluated the detection of various walking activities while using three self-built prototypes for the recording process. The walking activities are: a) sneaking - 1km/h, b) normal walking - 2.5 km/h, c) fast walking - 4km/h, d) jogging - 5km/h, e) walking while carrying weight - 2.5 km/h

ABSTRACT
In this research project, we present an alternative approach to recognize various walking-based activities based on the technology of capacitive sensing. While accelerometry-based walking detections suffer from reduced accuracy at low speeds, the technology of capacitive sensing uses physical distance parameters, which makes it invariant to the duration of step performance. Determining accurate levels of walking activity is a crucial factor for people who perform walking with tiny step lengths such as elderlies or patients with pathologic conditions. In contrast to other gait analysis solutions, CapWalk is mobile and less affected by external influences such as bad lighting conditions, while it is also invariant to external acceleration artifacts. Our approach enables a reliable recognition of very slow walking speeds, in which accelerometer-based implementations can fail or provide high deviations. In CapWalk we present three different capacitive sensing prototypes (Leg Band, Chest Band, Insole) in the setup of loading mode to demonstrate recognition of sneaking, normal walking, fast walking, jogging, and walking while carrying weight. Our designs are wearable and could easily be integrated into wearable objects, such as shoes, pants or jackets. We envision such gathered information to be used to assist certain user groups such as diabetics, whose optimal insulin dose is depending on bread units and physical activity or elderlies whose personalized dosage of medication can be better determined based on their physical activity.

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Categories and Subject Descriptors
H.5.2 [**Information interfaces and presentation (e.g., HCI)**]: User Interfaces — Input devices and strategies, Interaction styles

General Terms
Performance, Design, Experimentation, Human Factors.

Keywords
Walking Interface; Gait Recognition; Activity Recognition; Autonomous Computing; Capacitive Sensing; Wearable Computing; Assistive Technology.

1. INTRODUCTION
Pervasive computing brought a variety of devices, which are often referred to as smart devices, into every corner of our lives. These devices assist users in everyday situations (e.g. giving directions, monitoring workout status, etc.). Beholding it from a meta-perspective this can be seen as an extension of competence. However, instead of exclusively improving quality of life, the increasing amount of data and information leads to a higher cognitive load [11] or to distractions, when being involved in real world tasks. Activity recognition systems therefore can not only display data the user was not aware of, but also help to adjust the behavior of devices to the user's current activity state by actively utilizing the gathered data. For example, when a system autonomously decides, based on the user's activity status, to not disturb her with incoming phone calls. In such case the user is not actively being involved in a human computer interaction, but rather unconsciously in a heteronomous interaction. We envision this to be the next generation of assistive technology.

Current commonly evaluated activity recognition systems include sleeping and walking detections, which are already implemented into everyday devices such as smartphones [4] or smartwatches and other wearables [28][30]. Technology-wise, accelerometers and gyroscopes remain to be very popular to gain biometric information through data on movement (e.g. step counting or walking speed [25]). Other slightly less popular technologies for wearables are optical sensing systems [34] (e.g. pulse oximetry with LED and Photodiodes), acoustical vibration measuring (e.g. via piezo elements for step counting [29], sleep detection via microphone [2]), and capacitive sensing as well. Capacitive sensing offers a wide range of sensing biometric and vital data or activities such as breathing, sleeping, walking or other body movements [8]. Especially for detecting walking, this technology has several advantages compared to current sensing devices (mostly accelerometry-based). For example, it does not provide erroneous data while walking or running very slowly or when being in accelerated environments, such as when using an escalator, being in the tram or car. However, there can be found many use cases, which would benefit from more accurate step counting and activity recognition. Especially elderlies or patients with pathologic conditions, such as diabetes, could be more precisely medicated while having accurate information on their real activity units.

In this paper, we propose a new way to detect user activities. We developed prototypes and ran studies to prove their feasibility of detecting walking styles with a capacitive sensing, which is invariant to external acceleration, and in terms of step detection accurate for recognizing very slow or specific walking styles. Furthermore, we envision the technology of capacitive sensing to be embedded into widely accepted wearables, such as clothes, insoles, chest bands etc. to assist the user in several proposed scenarios to possibly enhance Autonomous Computing [22].

2. RELATED WORK

The recognition of human activity has been accomplished through various technologies over the last decades. We will briefly describe related work from a technological point of view, while subcategorizing the sensor-based approaches into two subsections (*Wearable Sensing* and *External Sensing*). Furthermore, we summarize various projects that measured activities capacitive and in a wearable context.

2.1 Sensor Setups

2.1.1 Wearable Sensing

Many works concerning wearable sensors show the use of accelerometers in an activity recognition context [5][10][20]. The sensor setups vary in body position and number of sensors. For instance, Bao et al. [5] use multiple accelerometers to recognize activities such as walking, running, stretching, riding an elevator, and more. Other works make use of gyroscopes [1][17] to achieve a detection of mainly rotation-based activities. On top of that, a lot of work focuses on walking based activities, which are mainly detected by the mentioned technologies or with foot placed sensor systems [24][27]. Foot placed sensors thereby often rely on force plates [24], or piezo-electric sensors [3][19].

2.1.2 External Sensing

Additionally, to wearable sensor systems external detection technologies are applied when the user is located in a determined area. A common way to detect walking or gait specifics is to use pressure floors [6], sensor mats that detect pressure exerted by subjects. Another popular technology is Vision Based like RGB [31] or depth cameras, such as MS Kinect [37]. External sensing is usually precise but it is restricted to a specific area.

2.2 Capacitive Sensing

Even though, the theory behind capacitive sensing is much older, beginning with the invention of the Theremin (a musical instrument) in 1917 the measurement of electric fields strongly gained interest. Later, in the early 1970s to 1980s a trend in capacitive sensing brought products like the capacitive switch to a broad market. Most of these technologies have thereby been developed and used in a rather static setup. In 1993 Whalen et al. [35] proposed a method for continuous monitoring of the ground reaction force during daily activities. By applying a single capacitive sensor the system was feasible in distinguishing between different walking speeds to differentiate between the activities walking, standing still, and running. The work of Whalen et al. was a new approach compared to non-capacitive setups as shown by Hennig et al. [16] who proposed a method of measuring the vertical contact stress beneath the human foot. The authors enabled a gait analysis while walking and running by applying an insole with 499 piezoelectric sensors. Other publication such as proposed by Kljajic et al. [18] used a strain gauge setup for gait analysis (9 Sensors). Recently, capacitive sensing technologies experience a renaissance in the field of activity recognition in a mobile context. For example Grosse-Puppendahl et al. [14] recently used a capacitive proximity sensor to enhance the accuracy and application range of an accelerometer-based activity recognition system. Thus a detection of activities such as opening doors, sitting, lying, collecting tools, making a sandwich, eating, drinking, sleeping, and walking has been achieved. Cheng et al. [7] uses a capacitive sensing solution to precisely detect head and throat movements. Included recognitions are: bread swallowing, water swallowing, chewing, nodding, shaking head, speaking, looking up / down / left / right / straight. The signals where gathered by different sensor setups: neck placed (throat band), chest and wrist. Moreover, Sato et al. [32] introduced “Touché”, a frequency-based analysis of capacitive sensing, in which contact with different hand postures on physical objects and water can be detected.

Our capacitive sensing approach is wearable and uses several effects described in former and recent works (e.g. capacitive ground coupling) to enable a detection of multiple walking styles in a mobile context. Moreover, we explore the unique sensing capabilities of our setups, which enable a variety of application scenarios to enhance autonomous computing.

3. CAPWALK

With CapWalk we demonstrate three different prototypes, which are based on capacitive sensing. We conducted small studies to find out on the capabilities of the prototypes. In the main study, we demonstrate how to enable activity recognition by detecting different walking styles. In the following subsections, we will explain the functionality of capacitive sensing and introduce our self-build prototypes in detail.

3.1 Background and Theory

Capacitive sensing is a technology that measures the charge of an established capacitor. There are tree distinguishable methods: Transmit Mode, Shunt Mode and loading mode [33]. In our work we investigated prototypes using the capacitive loading mode, in which a single electrode builds up an electric field to any grounded object nearby. Between these points a virtual capacitor is being established. This capacitance is determined by measuring the charging time. While minimizing the distance to the sensor, the capacitance increases and vice versa.

3.2 Prototypes

To demonstrate the feasibility of capacitive sensing as a mobile technology able to stand on its own, we developed three different prototypes that can be mounted on different positions at the human body: (1) chest, (2) foot, and (3) leg. In terms of sensor setup, we have chosen the capacitive loading mode, because of its simple configuration and versatile use.

3.2.1 Chest Band

The chest band (*see* Figure 2) consists of a fabric electrode, which is connected to the OpenCapSense board [15]. While walking, the capacitive ground coupling takes changes, which is utilized to recognize the stride frequency

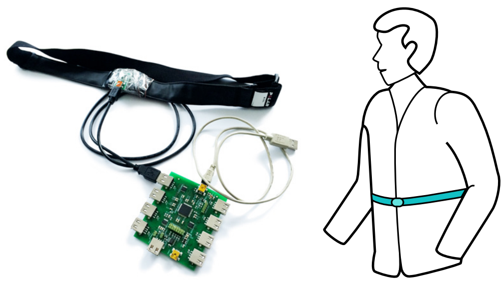

Figure 2. The sensor is a conductive fabric electrode mounted on a chest band that is facing the user.

In this setup the sensor electrode is directly connected to the human body, while facing the chest. This band can be worn underneath the clothes with direct skin contact, but can also be placed on top of garments. In a wearable setup, an additional electrode underneath the shoe facing the ground is required to ensure a ground coupling.

3.2.2 Shoe Insole

Our prototype consists of six copper plates distributed on different spots (*see* Figure 3), which act as the electrodes and thus enable the prototype [19] to measure pressure under the feet with the method of capacitive sensing.

Figure 3. The insole can be inserted in any ordinary shoe and can be connected via USB or wirelessly via Bluetooth.

On top of the electrodes a layer of buffering material keeps distance to the foot. While putting pressure on the insole (e.g. while walking), the distance from foot and electrode is minimizing at different parts of the insole. Hence, the capacity is changing, which is determined by measuring the latency of charging the capacity as usual in loading mode. Besides a walking recognition, the prototype can also be used to distinguish between conscious feet gestures, such as toe pressing, heel tapping, and weight shifting. Implementing sensors in an insole has several advantages, such as putting it in any ordinary shoe where it can be replaced easily and is invisible to other people in public.

3.2.3 Leg Band

As already stated before, the leg band setup (*see* Figure 4) consists of a loading mode sensor, which enables a detection of the passing leg. This functionality is similar to the light barrier principle. While walking, both legs are passing each other at regular time intervals. Thereby, the constantly changing capacity between the legs is measured.

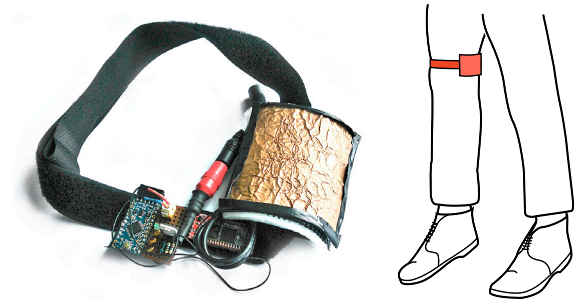

Figure 4. A large copper plate, facing the inside of the opposite leg, mounted on a leg band. The backside of the copper plate has to be isolated, which can be accomplished with a shield electrode or thick plastic layers, which we used

Applying a simple threshold analysis is already sufficient to measure a step counting and thus calculating a precise walking speed (provided the user's leg length is known) or calorie consumption (provided the age and gender is known to the system). The prototype is visibly bulky, but it is conceivable to integrate the sensor in a trouser seam.

4. STUDY DESIGN

To find out about properties and limitations of our built interfaces, we tried to simulate conditions in which users had to perform different walking styles and a cycling activity. In this within-subject study we were measuring the qualitative data of all three devices at the same time. In reality, the condition of a fixed speed mostly does not exist; instead, the user performs each action in various and inconstant speeds and manner. To analyze the bandwidth of the individual execution, we let the user perform a reference activity (cycling on an exercise bike), which is less affected by biometric constraints, such as leg length. Therefore, the user had to adjust the counter resistance on the exercise bike to a level she felt comfortable with.

4.1 Participants

13 participants (including 1 female) performed the within-subjects experiment. The participants had an age of 22 - 49 years and weighed between 58 - 93 kg. Their height was 1.72 - 1.92 m. All participants were within +/- 10% of their optimal body mass index. None of them had walking disabilities.

4.2 Apparatus

All three introduced prototypes, which were simultaneously recording the data, had to be worn by the user (*see* Figure 5). While the chest and leg band could be easily mounted to the user, the insole (European size 43) was required to be put into the subjects shoe or in a prepared shoe, when the insole was too big for the users own shoe. The leg band has always been attached on the left leg above the knee. The insole was also worn in the left shoe. The chest band was mounted slightly over the belly. Except for the leg band, all of the prototypes were wired to a computer. In general to avoid artifacts we shielded our prototypes either

passively or with a shielding electrode. Furthermore, the size of the electrodes has been chosen in respect to the range of measurable proximity to a near-body distance. This way the leg band and the insole did not show any noticeable artifacts near metal objects. The chest band unfortunately suffered of swinging artifacts from cables at very fast movements due to inelastic impacts.
The experiment took place in a lab environment, where the study subjects were walking on a unidirectional treadmill (model: Buffalo MTR 818). The cycling had to be accomplished on an exercise bike (model: MARS top trainer).

Figure 5. Study participant walking on the treadmill (left) and cycling on the exercise bike (right).

4.3 Task and Procedure

In the experiment, the user was instructed to perform different locomotion styles, which had to be executed in the following order: 1. sneaking (1 km/h), 2. normal walking (2.5 km/h), 3. fast walking (4 km/h), 4. jogging (5 km/h), 5. walking while carrying weight (2.5 km/h) and 6. cycling (no fixed speed).

The different walking styles have been carefully chosen to represent a broad spectrum of walking-based activities, beginning with very slow movements (involves steps with very low impact) and fast movements (includes steps with very inelastic hard impacts). The sneaking task had a unique style of execution (slightly ducked posture) to guarantee an elderly walking style with a very slow movement, low impact and a small amount of steps. To gain an insight on the variance of the individual execution of tasks, we used cycling, in which the user could freely perform a speed he was comfortable with.

All users were asked to perform each action for at least one minute, while the study leader was taking the time and controlling the experiment. A technician was taking care of the prototypes and monitoring the data collection process. During the walking on the treadmill (for the fifth task), the user had to carry a backpack with a weight of 8 kg (~10% of the mean weight of all subjects).

4.4 Data-Gathering

The data from the leg band and insole was gathered with a sampling rate of 30 Hz. The chest band gathered data with 100 Hz. For comparison reasons, the data of the chest band was sampled down to 30 Hz. The sensors of the insole only enabled a real sampling rate of 20Hz, which was sufficient for detecting walking styles (for instance, high performance athletes accelerate till 40 km/h and have a step frequency of 5 Hz, which requires at least a sampling rate of 10 Hz).

All sensors provided values of unsigned integers, whereby the range was depending on the proximity to the electrode. The influencing factors can be approximated with the formula (†) of capacitive change for a plate capacitor. This formula explains that the capacity is depending on the surface of the electrode area (A), the proximity between the plates (l), the electric field constant (ε_0), and the relative permittivity (ε_r). The measured delta - represented by an integer value - increases while approaching the sensor. By direct contact to the electrode, the value of the capacity theoretically raises up to infinity while the proximity is very small. An important fact that influences the value of the capacities is the electrode area - larger areas increase the capacitance. Because of the fact that all setups used the capacitive loading mode, the change in capacity was measured by detecting the charging time of the capacities as mentioned.

$$C = \varepsilon_0 \varepsilon_r \cdot \frac{A}{l} \qquad (\dagger)$$

Each of the six activities was recorded for the duration of one minute (approximately 1800 samples per activity). The leg band setup transmitted the data via Bluetooth to a computer where the data stream was saved to a CSV file. The chest band and insole were connected via USB cable and saved to CSV files as well.

5. DATA ANALYSIS

This section gives a detailed view on the results of the data analysis. In the following, we show how the three prototypes performed in classification, and give an overview of the specific overall performance.

5.1 Preprocessing

Using a high-pass algorithm for offset filtering corrected the offset Artifacts. It is realized by applying a moving average to the data.

$$\overline{x} = (a \cdot \overline{x}) + (b \cdot x)$$

The constants to determine the speed of approximation were then set to a=0.8 and b=0.2 (values that delivered the best results).

$$\overline{x} = (0.8 \cdot \overline{x}) + (0.2 \cdot x)$$

To realize a high-pass filter, the average value needs to be subtracted from the current sensor value.

$$x_{filtered} = x - \overline{x}$$

To reduce high frequent noise, the signal was low passed.

$$x_{out} = x_{out} + \alpha \cdot (x - x_{out})$$

The optimal determined α value was set as α=0.2.

$$x_{out} = x_{out} + 0,2 \cdot (x - x_{out})$$

Some extraordinary peaks caused by unintended touches of the electrode (leg band prototype) needed to be filtered out. This was accomplished by applying a median filtering algorithm that cut off the extraordinary peaks.

5.2 Feature Extraction

For the purpose of feature extraction, we took a window size of 512 samples (approx. 17 seconds) and extracted the following features for each prototype: (1) frequency with the highest amplitude, (2) highest significant frequency, (3) spectral centroid and (4) signal energy. As a result, the single sensor setups (chest band, leg band) extracted four features per 512 samples. The very small feature set was intentionally selected to avoid overfitting effects. We selected the features in an empirical investigation to describe the main characteristics of the raw data signal (e.g. stride frequency). Moreover, we wanted to avoid using features that are interdependent and or redundant regarding their characteristics. The rather big window size was chosen to enable the recognition of very slow movements, as commonly performed by elderly people. To compute feature vectors for each activity set of 1800 samples, as given by the raw data recording, the features where generated by overlapping windows. Therefore, the window of 512 samples was sliding over the data with an overlap of 87.5%. In conclusion, the window slides in steps of 1/8 of the current window size over the raw data. As a result, 28 instances with feature vectors of four elements are extracted for each activity. Due to technical issues, the number of instances per subject differed slightly for each sensor setup.

5.3 Classification & Results

Based on the generated feature files, a set of classifiers was trained to analyze the recognition performance. The *Weka* workbench tool in version 3.6.11 was utilized for the evaluation. Figure 6 shows the recall rates for Naïve Bayes (NB), Bayes Net (BN), Nearest Neighbor (NN), C4.5 decision tree and a Random Forest ensemble decision tree classifier, determined by a leave-one-out cross validation. The results show best recognition rates when applying the Naïve Bayes algorithm for the leg band, the Bayes Net classifier for the insole and the Random Forest classifier for the chest band prototype.

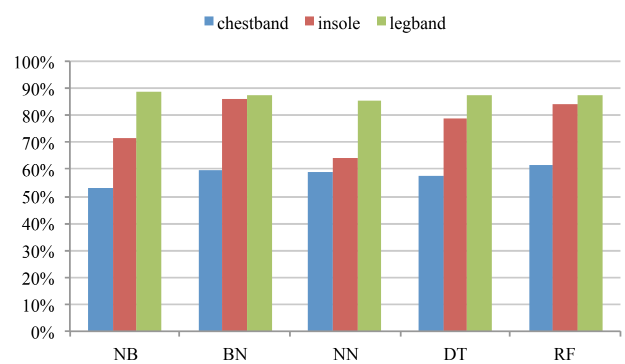

Figure 6. Classifier performance (recall rate) for all setups, determined by a leave-one-out cross validation. Classifiers are Naïve Bayes (NB), Bayes Net (BN), Nearest Neighbor (NN), C4.5 decision tree (DT) and Random Forest (RF).

Table 1 to 3 show the confusion matrices of the specific classifier validation determined for each sensor setup (10-fold-cross-validation). The data shows false positives for the detection of normal walking and normal walking with weight for all prototypes. This is due to the equal speed level in which both activities were performed on the treadmill. A difference can be found in a dropping of feature selectivity for frequency-based features at the weight condition.

Table 1. Confusion matrix for the chest band setup.

a	b	c	d	e	← classified as
218	23	29	17	76	a = sneaking
65	**122**	59	18	86	b = normal walking
42	18	**229**	20	32	c = fast walking
10	18	19	**253**	39	d = jogging
56	52	41	11	**171**	e = walking + weight

Table 2. Confusion matrix for the insole setup.

a	b	c	d	e	← classified as
301	11	0	3	23	a = sneaking
12	**194**	34	14	72	b = normal walking
4	16	**250**	21	21	c = fast walking
15	1	22	**286**	3	d = jogging
18	66	45	9	**189**	e = walking + weight

Table 3. Confusion matrix for the leg band setup.

a	b	c	d	e	← classified as
305	23	1	2	7	a = sneaking
9	**242**	16	0	59	b = normal walking
0	18	**278**	0	5	c = fast walking
0	0	0	**327**	0	d = jogging
14	50	24	3	**236**	e = walking + weight

Because the *leg band prototype* solely relies on recognizing differences in stride frequency and leg distance, it is barely feasible to distinguish variations in weight. A filtering of artifacts (created by touching the electrode) was necessary.

The *chest band prototype* showed false positive recognitions for multiple activities. The main reason for this is due to the sensor position, which was the lower chest for our tests. In this way a simultaneous detection of walking and breathing was enabled technology-wise. We observed that the breathing rate influenced the signal strongly and in fact, the breathing rate and style slightly correlates with the walking style as well. The breathing rate changed with respect to human factors, such as subject, stamina, etc. This made a comparison between all subjects very hard and led to several confusion effects. Technical drawbacks, which negatively influenced the chest band, were: (1) input artifacts caused by subjects touching the data cable and (2) the capacitive ground coupling on the treadmill led to inaccuracies. In contrast, our previous pilot studies yield much more meaningful signal amplitudes when the subjects actually walked on the floor.

The *insole prototype* would be able to distinguish differences while carrying weight, because of the overall changing in terms of signal intensity due to a higher pressure on the buffering layer. In fact, our final data analysis did not yield these results to distinguish both activities, because of an inevitable signal filtering process that filtered out the differences. The filter was applied to overcome a drift effect, caused by the buffering material being squashed between foot and electrode over time.

To evaluate how the classifier performs with unknown data, we applied a leave-one-out cross validation. This kind of analysis leads to more realistic impression on recognition rates and discovers limitations quite exact. Figure 7-9 show the performance of the recognition (recall rate) per subject for all prototypes. The blue colored bars in the figures show the results from the leave-one-out cross-validation with confused values for normal walking and walking with weight. The red bars show the corrected outcome when the activities normal walking and normal walking with weight are being combined

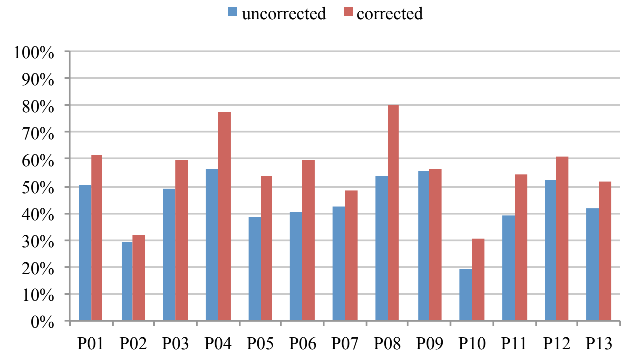

Figure 7. Chest band performance, determined by a leave-one-out cross-validation (Random Forest classifier).

The analysis of the chest band shows a drop in performance, which is due to the reasons we already highlighted before. The insole prototype as well as the leg band provides higher performance than the chest band and yields reasonable detection rates to differentiate the activities.

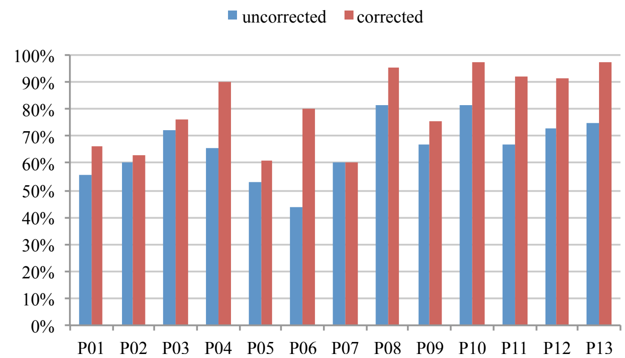

Figure 8. Insole performance for the insole, determined by a leave-one-out cross-validation (Bayes Net classifier).

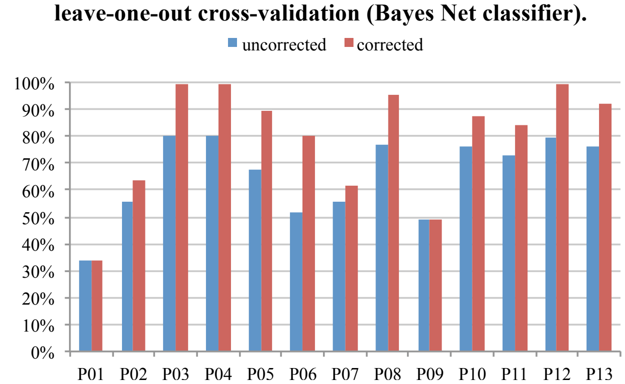

Figure 9. Leg band performance for the leg band, determined by a leave-one-out cross-validation (Naïve Bayes classifier).

We could also identify erroneous datasets (of 3 subjects) and excluded them from the trainings-/ and test-sets. The resulting overall performance of the leave-one-out cross validation for the leg band reached 88.97%, the insole's rate reached 86.17% and, due to the afore mentioned irregularities, the chest band dropped down to 61.54%.

5.4 Individual Factors

The signals showed no influences by metal objects nearby, instead the lack of a fixed speed of execution lead to incomparability. The treadmill is inevitable to guarantee a comparability of walking styles, while controlling variables, such as the amount of speed and a constancy of speed. Due to the high variance in execution of the reference task (cycling), the feature selectivity decreased (*see* Figure 10). This way confusion occurred between all activities. Therefore, in real scenarios the system has to adapt to the user's preference speed with machine learning techniques.

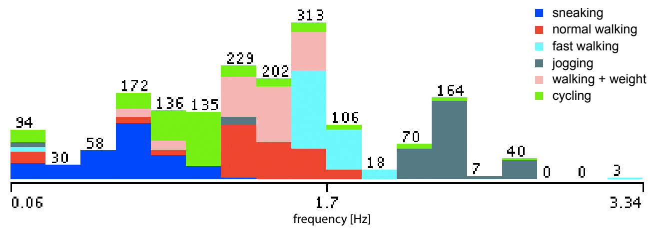

Figure 10. The highest amplitude frequency feature distribution for each activity is indicated in 6 different colors, whereby the green color presents the reference task (cycling) in which the users performed their individual speed.

6. ASSISTIVE SCENARIOS

In this section, we envision several situations where a capacitive sensing of walking styles would assist the user and extend the concept Autonomous Computing. Steiner et al. [22] define this term as a system with a large degree of independence, which in theory autonomously adjusts user interfaces based on the user's condition and environment.

a) *Stress Level Detection:* The user's personal stress level is often indicated by leg movements, such as a nervous shaking of legs while sitting or a different gait style, which is mostly faster than the normal walking speed. With CapWalk these differences can be recognized and therefore this information could be utilized to adjust a computational system, such as switching on assistive technologies while driving a car or notifying communication partners before contacting.

b) *Health Monitoring:* Detecting resting and active states of a user can be essential for elderly and ill people or when sitting long periods at a desk. In these cases, a system could notify the user itself to engage in an activity / take rest or it autonomously adjusts devices or notifies thirds. This could be interesting for occupational safety to help following a suggestion by the health office.

c) *Anomaly Detection*: In some cases, the detection of anomalies can be crucial to ensure an in time assistance. Especially elderly people are prone to falling and are thus often in need of a special care. An insole that is worn by a person with a need for continuous monitoring could identify an abrupt loss of pressure that persists over time. If the incident is taking place at an unusual daytime, the system could identify this as an anomaly or a possible fall. Furthermore, the combination with a chest band set up could complement the detection by applying breathing measurement possibilities.

d) *Workout Performance:* Especially high performance athletes have a high interest in very accurate performance measuring. A high accurate step counting, which also provides information on length of steps, speed, and on what angle the user is hitting the ground with her feet. Additionally, CapWalk also enables to measure the breathing frequency at the same time. Summing up all data would enable new levels of performance measurement that could be presented to the user, but also utilized for adjusting sports equipment.

7. DISCUSSION

When it comes to detecting activities, currently most wearable devices rely on accelerometers or gyroscopes. At first glance, these technologies might already deliver sufficient information on detection of steps and walking speed, but suffer of great accuracy issues in terms of step recognition and walking speed, which is already being analyzed in many papers [12][23]. As a matter of fact, Melanson et al. [23] reported a significant drop of accuracy (up to 74.3% for the worst case) for standard devices such as pedometers at slow walking speeds of about a mile per hour. Because our approach is not dependent on speed and intensity, it does not suffer from this issue. Therefore, we believe in the benefits of using a capacitive sensing to recognize walking activities. In addition to a very simple setup of a capacitive sensor, it also does not consume high power, as it is easily integrable in clothes, which makes it an optimal technology applicable for wearable computing.

Our evaluation showed multiple effects, which influenced the resulting accuracy rates. Reasons therefore can be found in the lack of direction dependent features (prototypes provided only a one-dimensional sensor functionality), as well as hardware issues that can be traced back to the prototyping process. Similar effects were triggered when the cable was being touched accidently. However, the recognition rates for the chest band prototype could be improved by excluding sources of error. In terms of the insole prototype, the buffer material showed a limited performance in long-term measurements and the dependence on feet sizes also caused problems for the insole, which was optimal for european size 43. Artifacts caused by direct leg contact, depending on the specific subject's walking style, sometimes affected the leg band setup. In general, human factors such as height or leg length respectively influenced features such as the stride frequency, since subjects with shorter legs need to increase stride frequency to keep up with taller people at the same speed. Furthermore, all subjects were performing shorter or longer steps for the same activity, which inevitably caused an unwanted variance. Moreover, a natural variation in activity execution affects the classifier training and thus the recognition results, which is indicated by the individual weight distribution on the insole. Especially the sensing of a multi-spot area as applied for the insole enables further fields of application compared to single sensor approaches as most of the acceleration sensor based devices deploy.

We did not investigate the effects regarding pacemakers or metal-made implants, but since the capacitive loading mode only relies on a grounded object for an opposite electrode – to build up an electric field which is dependent on electrode distance, size, and dielectric between both of them - a metal rod in bones as a permanent condition would not affect the sensing principle. Moreover, constant signal artifacts could be determined and subtracted from the signal. Since we do not drive any current through the human body, this technology is considered to be safe. Social Acceptance of wearable devices is definitely a question worth to investigate, but wasn't the focus of this paper. However, in the course of development and embedding of technology into everyday objects, technology becomes less obtrusive und thus possibly more acceptable.

8. CONCLUSION

Previous approaches for detecting activities originally often utilize Optical Sensing, which is affected by bad lighting conditions or a static location-fixed setup. A very popular wearable sensor approach is using accelerometers, which already achieve high accuracy rates in terms of motion detection. However, this sensor approach is due to fail when being in accelerated environments, such as in a train / bus / escalator or when performing very slow movements. In contrast, capacitive sensing is invariant to acceleration and thus is not affected by these issues. In contrast, we presented three capacitive prototypes that are able to recognize diverse walking activities as well. The proposed fields of applications stay in contrast to common accelerometer-based uses and extend the sensing potential for assistive concepts to effectively assist certain target groups, such as elderlies, diabetes or bariatric patients. Integrating a low-power consuming technology, such as capacitive sensing such as in form of conductive thread in a trouser seam, is one of our future visions.

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