Active Capacitive Sensing: Exploring a New Wearable Sensing Modality for Activity Recognition

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Abstract. The paper describes the concept, implementation, and evaluation of a new on-body capacitive sensing approach to derive activity related information. Using conductive textile based electrodes that are easy to integrate in garments, we measure changes in capacitance inside the human body. Such changes are related to motions and shape changes of muscle, skin, and other tissue, which can in turn be related to a broad range of activities and physiological parameters. We describe the physical principle, the analog hardware needed to acquire and pre-process the signal, and example signals from different body locations and actions. We perform quantitative evaluations of the recognition accuracy, focused on the specific example of collar-integrated electrodes and actions, such as chewing, swallowing, speaking, sighing (taking a deep breath), as well as different head motions and positions.

1 Introduction

On-body sensing and activity recognition are a key concept in Pervasive Computing [1,16]. It enables a broad range of applications, from new mobile user interfaces, sports assistant systems, to health and assisted living. Today, the majority of on body activity recognition systems rely on motion sensors, such as accelerometers, gyroscope, magnetic field sensors, and combinations thereof [9,18,28]. On one hand it is due to the availability of cheap, miniaturised devices. On the other hand, motions of body parts are the key factor in almost all human activities. Despite their success motion sensors have some limitations:

1. Not all activities can be sensed from motion. For example, dietary monitoring has recently received significant interest in activity recognition. However, neither chewing nor swallowing can be easily detected by motion sensors [7].
2. Attaching motion sensors is not practicable for every body location. This is particularly true for hands and the head.
3. Signals from motion sensors can be ambivalent (as different actions are for example associated with similar motions) and noise (e.g. as sensor positions

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shift). Thus, even if a particular activity can be captured using motion sensors, the accuracy could benefit from additional sensors that provide complimentary information and have different, independent sources of error.

As a consequence there has been significant interest in alternative sensing modalities. Textile stretch [14] and fibre optical sensors [13] have been proposed to detect posture. Another approach has been to add sensors for environmental parameters such as ambient sound, temperature, or air pressure [20,23].

Finally there are some more experimental approaches involving signals from "inside" the body. Body sound from the wrist has been used to detect hand motions [2] and from the ear to detect chewing [3]. In [10] the use of Electrooculographic eye tracking has been demonstrated for the recognition of reading activity. It has also been shown how to use force sensitive resistors to detect muscle [22,4] activity. Another interesting example is the use of radar directed at the body can detect vital signs [25].

The work presented in this paper falls into the above category of novel sensing approaches that attempt to utilise information from inside the body. It adapts the physical principle of capacitive sensing used in industry (for example to inspect closed boxes on a conveyor belt) to wearable activity sensing. In simple words, we consider a capacitor build out of a conductive textile electrode and the human body as dielectric. We then analyse capacitance changes caused by muscle motion, tissue displacement, electrode deformation, etc. This approach is attractive for activity sensing for the following reasons:

1. It provides information that is difficult to obtain with other unobtrusive sensors. For example, in the quantitative study presented in this paper, we use textile electrodes integrated in a collar to recognise among others, chewing and swallowing.
2. A sensor at a single location provides signals from a broad range of actions and physiological parameters. Thus, in addition to chewing and swallowing, we demonstrate the recognition of speaking, head motions (shaking, nodding), head positions, and deep breathing using the collar setup.
3. The sensing principle can be applied to different body locations. Besides collar and wrist setups, we show signals from the upper leg that can be used for modes of locomotion recognition and signals from the chest that are relevant for vital signs monitoring.
4. The system is based on textile electrodes that can be easily and unobtrusively integrated into clothing. It requires neither direct skin contact nor special fixation beyond the pressure of normal close fitting garments.

Related Work. Specifically for capacitive sensing previous work proposed using basically the same method to measure pulse on the wrist [26]. We have done a preliminary evaluation of this approach for pulse and breathing rate measurements on the chest [12]. There also exists a large body of work on capacitive coupling electrodes for hearth rate monitoring and ECG, e.g. [21,27]. However, our work is based on a fundamentally different principle. Whereas our approach generates an electric field and measures the influence of capacitance changes due to structural changes inside the body, the capacitive coupling electrodes cited above, measure the electric field generated by the body.

Capacitive sensing is widely used in industry for proximity sensing but moreover, to examine the content of closed boxes on a conveyor belt. Taking the idea further, there has been a significant amount of research on electric capacitance volume tomography [29] that attempts to reconstruct complex structures from multiple capacitive measurements.

The use of on-body capacitive sensing for user interfaces has been proposed by [31]. Later the same group has used on-body capacitive sensing for motion tracking in a dance application [8]. In this work the capacitive measurement had been used to measure distance between body parts, which is different from our approach. Capacitive gesture recognition for pervasive computing (but not wearable systems) has been discussed in [30] and in a string of other publication by this group. In the wearable field capacitive sensing is the basis of widely used textile pressure sensors as well [24]. Moreover, it was used for tracking people using electrode arrays embedded in a carpet [19] and as insole system measuring weight bearing [17]. To our knowledge, capacitive sensing had not been investigated for monitoring activities in the breadth attempted in this work.

Paper Contributions. We propose and evaluate a new way to derive activity-related information by "looking inside" the human body with a capacitance sensor.
Specifically the paper makes the following contributions:

– While capacitive sensing in itself is an established principle we have put forward a novel concept for using it in wearable activity recognition.
– Starting from extensive simulations, we designed and implemented the sensing hardware needed to deal with the specific requirements of our approach, in particular, the large dynamic range and very low electronics noise.
– We performed extensive experiments with different electrodes locations and activities. We present selected signals from those experiments and use them to explain the properties and potential of the proposed sensing approach.
– We performed quantitative evaluations of the recognition performance achieved with our system in the specific example of collar electrodes. Our recordings include the activities while working at a computer and while walking (to investigate the impact of motion artifacts).
– To further underscore the potential of this sensing approach, we present initial quantitative results (from the same collar electrode positions) for spotting swallowing in the continuous data stream, distinguishing between different swallowing amounts, and estimating respiration rate for shallow, normal, deep breathing.

We would like to point out that the aim of this work is **not** to prove the utility of the new modality for a particular real life application. Instead, we aim to establish a basic understanding of how to implement and use the modality and what sort of information it can provide. For a new sensing modality, such basic understanding is a necessary pre-condition for conceiving and demonstrating concrete applications. Thus, we aim to lay the groundwork for other researchers to build on, when including this new sensing modality in their systems and enriching their future applications.

2 Sensing Principle

A capacitor is, in essence, a device that can store energy in an electric field. The best known example is the parallel plate capacitor, having two rectangular conductive plates separated by a gap filled with a non-conductive dielectric material. There are no specific requirements on the material from which the conductive plates are made. Thus, enabling conductive textile to be used, which means that they are very unobtrusive and easily integrated in clothing.

The electric field of a capacitor depends on the material placed between the plates, which can "dampen" the field. The damping depends on the molecular properties of the material as well as on its structure and shape. It can be as simple linear dependence like in the parallel plate capacitor, but also arbitrarily complex relationship reflecting elaborate shapes (including cavities) and inhomogeneities in the molecular properties.

The factor determining the voltage V that a given charge Q produces (distance between the plates and the influence of the material between them) are summarised as the capacitance C of the device. The key equation at the heart of the active capacitive sensing is $C = \frac{Q}{V}$, where Q and V can be easily measured, and C depends on the properties of an object including what is hidden inside it. Thus, object of changing structure, cavities, or changing surface, e.g. making it wet, will change C.

Hence, by measuring two electric parameters we can "look" inside an object in a non-invasive way. Clearly the information that we get is very limited: a single scalar value. Consequently, a capacitive measurement with a single electrode pair can not reveal complex structural information. However, it can indicate structural changes that take place within objects.

Capacitive Measurements on the Human Body. Figure 1 shows the simulated electric field distribution in the human body during a capacitive measurement. This data is part of extensive simulation that we have performed as part of our system design. We used the SEMCAD package [11]. The simulation was performed with the following configuration:

- Instead of using two electrode plates, we use just one. The second electrode is then effectively "earth". This is a common approach in many capacitive systems (e.g. touchpads) and allows us to more easily integrate several close-by electrodes.
- We use AC current instead of DC to charge the capacitor. Since the capacitance of different materials varies with the oscillation frequency, this allows us to better optimise sensitivity of the system to certain effects.

Electric field intensity just below the electrode is several orders of magnitude higher then just a few cm further inside the body. Further inside the body the

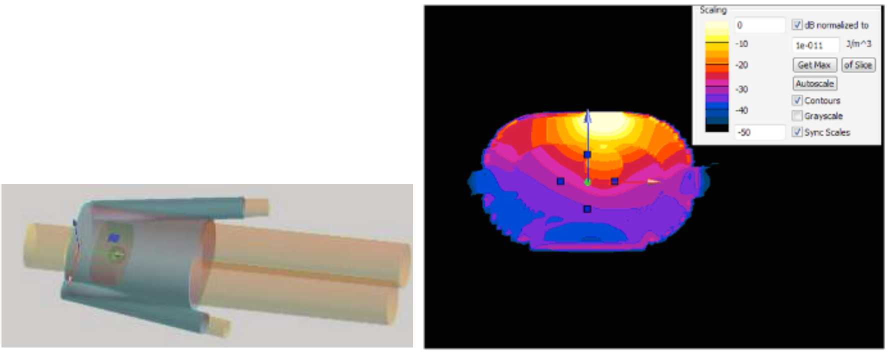

Fig. 1. Simulation of the electric field generate by an electrode on the chest. Left: the simulation setup. Right: the resulting field. Note that the different tones correspond to a dB (logarithmic) scale.

intensity is even lower. With regard to information that the capacitive signal could provide, the following conclusions can be drawn:

1. Any action that produces changes in the position of the electrode (in particular its distance to the skin) will have a very strong effect on the signal. This is on one hand a major source of noise, on the other, it can contain useful information related to motion or posture (when a person moves or changes posture the electrode will in general be displaced or deformed).
2. Any changes taking place directly below the electrode will produce a clear (although much weaker) signal. Such changes can be muscles flexing or hyoid movement during swallowing. The exact range of this regime varies depending on the setup between less then 1 cm to a few cm.
3. Changes deeper inside the body will only produce a distinguishable change in capacitance if they involve a large volume. A good example is breathing, where a large amount of air enters the lungs inside of the body.

3 Sensing Hardware

The overview of our sensing hardware is shown in the top part of Figure 2. We used four front-end boards to provide four independent channels, converting the capacitance into voltage. The voltage is AD-converted and sent out via ZigBee. We used a Tmote mini node for the wireless transmission to a Tmote-sky, which is connected to PC USB port.

The electrode itself is made of conductive textile, which is both thin and flexible. It can be easy integrated by cutting a required shape and sewing into the middle of 4 layers of soft paper (ink eraser tissues).

Front-end Boards. Our simulations have shown that existing commercial solutions for capacitive measurement are not sufficient to meet our demands:

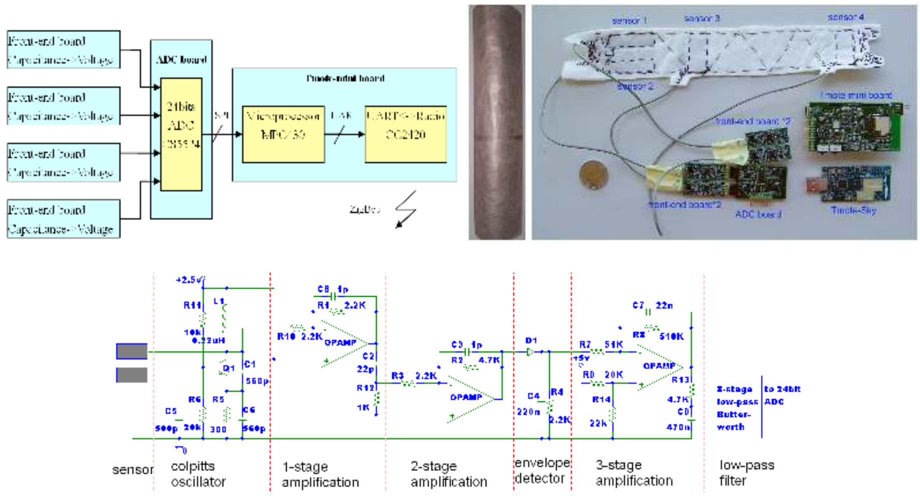

Fig. 2. Top left: top level diagram of the sensing hardware. Top right: implemented hardware including the electrode used for the neck experiments (left side). Bottom: schematic of the analog part of the front-end board.

- Small capacitance and ultra-low noise: the capacitance to be measured varies front several pf to several hundred pf, where information is the signal change, which could be as small as 0.01 pf.
- High measuring frequency: as confirmed by our simulation, the higher frequencies can better penetrate the body , and can thus provide more information inner-body changes.

Theses requirements have to be achieved in a small form factor, battery powered device. We have chosen to design and implement our own measurement circuit as shown on the bottom of Figure 2. The circuit is based on concept from [26]. The capacitor consisting of the conductive textile electrode, the human body, and ground is part of a copitts oscillator that generates a sinusoidal voltage. The oscillation frequency of the circuit is given by

$$f = \frac{1}{2\pi\sqrt{L(C_{circuit} + C_{sensor})}}, \tag{1}$$

where L and $C_{circuit}$ are the characteristic inductance and capacitance of the circuit, and C_{sensor} is the measured capacitance of the electrode. In our system $C_{circuit}$ is 17 MHz.

This sinusoidal signal from the copitts oscillator is differentiated by the capacitor and resistor after a 1st-stage amplification, converting the change of frequency to the change of amplitude. After a 2nd-stage amplification, which isolates and provides enough driving current, this change of amplitude (up to at most 100 Hz) is extracted by an envelope detector. The 3rd-stage amplification then amplifies the change into a proper input range of the ADC.

Fig. 3. Different sensor setups with which experiments were performed. Chest placement, wrist placement, and neck placements. For the neck setup, sensor placement in an elastic band and integration in a pullover collar are shown.

Because the distance between sensor and skin affects the results most, the circuit must provide both broad measuring range and high precision. A 24-bit ADC was used for this purpose. At the same time, signal noise must be suppressed. Common noise removing methods as isolating the power supply with appropriate capacitors or adding resistor for impedance matching, do not work in our case, because they are meant to remove high frequency noise only. Thus, we optimised our hardware design by separating digital and analog circuits, amplifying and digitising close to the front-end, and using multi-stage low-pass filters. Because we focused on human body activity, sample rate was set to 40 Hz, with low-pass filters' 3dB frequency fixed to $\sim$15 Hz. In addition, we used ultra-low noise DC-DC voltage regulators to provide amplifier reference voltage.

For multi-channel measurements, oscillation frequencies of the individual channels must be distinctive. We chose L1 to 0.33 uH, 0.47 uH, 0.68 uH, and R3 correspondingly to 470 Ω, 680 Ω, and 680 Ω. Further, the insulation material between sensor and skin should be either of a high dielectric coefficient or thick enough to avoid crosstalk on nearby channels.

4 Signals Analysis

Using the hardware described in the previous section we have performed extensive experiments with different placement of electrodes and activities to understand what type of signal the proposed method can provide. In this section we give some interesting examples, that illustrate the points made above and relate to the systematic evaluation that are described in Section 5.

Chest Electrodes. In Figure 4 we first look at the signal collected by electrodes on the chest (see 3), showing breathing cycles. This is an example of the third category described above: signals originating far from the electrode, but involving large body volume. The signal from the left electrode has a superimposed component related to the heart beat, as the electrode is in close proximity to the heart. Heart beat becomes more visible when the wearer holds his breath.

Wrist Electrodes. The properties of the proposed sensing approach are well illustrated by the signal from a wrist electrode which is shown in Figure 4. Although the electrode is by far not near to the lungs, there is a clear breathing signal. Even though the electrode is placed far from the chest, the electric field

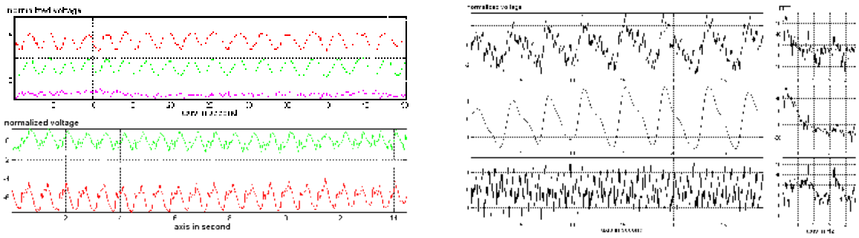

Fig. 4. Left top: breathing and pulse signals from chest electrodes. Signals from left and right electrodes (top and middle trace) and their difference (bottom trace). Left bottom: signals from front and back chest electrode at higher amplification, when wearer is holding breath. The pulse can be clearly seen then. Right: signal from a wrist mounted electrode and spectrogram. Right top: signal showing a mixture of pulse and breathing. Right middle: low pass filtered signal showing breathing. Right bottom: high pass filtered signal showing pulse.

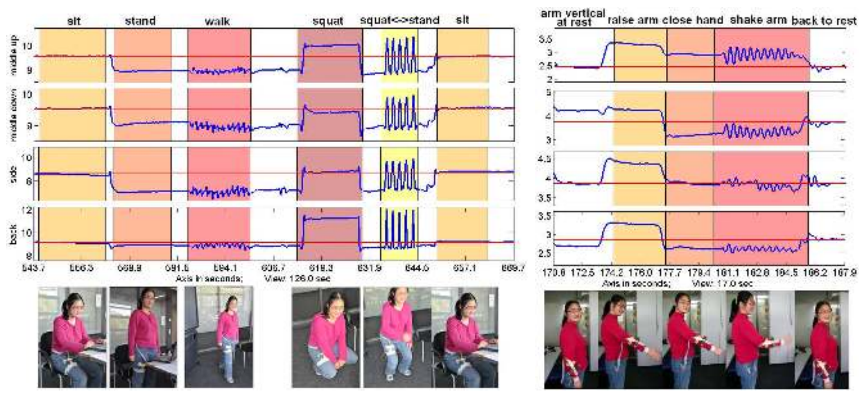

Fig. 5. Left: signals from upper leg electrodes (front middle front up, side and back) during a modes of locomotion experiment. Right: signals from lower arm and wrist electrodes during a movement sequence.

still passes through and around the chest when going towards "earth". This means that the large volume breathing effect is still visible.

The pulse signal is clearly seen even when breathing. In fact, it is even clearer then from the electrode above the heart. This is because the wrist contains many blood vessels directly below the skin surface and the distance to the electrode matters much more than volume of change. This was illustrated in Figure 1.

As Figure 5 shows, arm and wrist signals also contain activity-related information. Raising the arm, closing the hand, or shaking the arm, all produce distinct patterns related to muscle and tissue motion. Note that the muscles and tendons moving fingers are extending from the lower arm, which is why the hand closing gesture (and potentially other palm and finger motions) can be distinguished at the wrist.

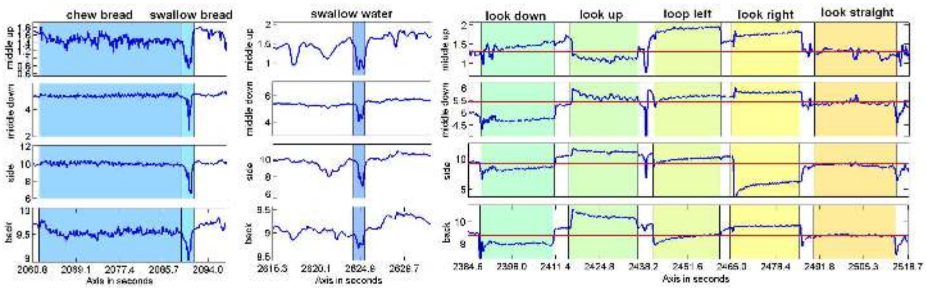

Fig. 6. Signals from the neck electrodes. Left: chewing a piece of bread and swallowing. Middle: swallowing 15 ml of water. Right: different head positions.

Upper Leg Electrodes. The recognition of modes of locomotion (differentiation between sitting, standing, walking etc.) is a standard problem in activity recognition. Figure 5 left shows how the sensor can be used for this purpose, with the electrodes wrapped around the upper leg. Walking, sitting standing and doing crunches all produce different signal patterns. They are mostly due to muscle shape changes compressing top level tissue and skin (potentially also the sensor material). An interesting questions for future research is whether careful electrode placement and elaborated signal processing can provide cues on activation and state of different muscles.

Neck Electrodes. We investigated electrode positions at the neck (see Figure 3). This position was chosen for three reasons.

1. It is a rich source of information as head motions, positions, speaking and chewing, all cause skin and muscle motions directly below the skin. The hyoid moves as people swallow. Veins are covered by thin tissue only.
2. Many of the activities to which those signals relate, are difficult to detect using other non-obtrusive sensors. Head position and motion requires head mounted sensors, which is not always practical. For chewing and swallowing most existing solutions require electrodes to be glued to the skin (although we have also used sound from the ear in previous work [3]).
3. People are used to wearing things like scarfs, ties, collars, etc. on the neck. Our electrodes are just pieces of textile and can be unobtrusively integrated.

Figure 6 shows the signals from chewing and swallowing. Chewing is best seen in front upper electrode as skin motion and deformation caused by jaw motions. To a much lesser extend the signal is present in the other three electrodes. The swallowing signal shape is very clear: in the front electrodes it has a “W”-like shape caused by the hyoid moving up and down. Swallowing water and swallowing bread causes different shapes.

Figure 6 illustrates our analysis of head postures (left, right up, down). Clear differences can be seen in the amplitude levels on the different electrodes. These are due to electrode deformations, tissue compression, and skin movement. The

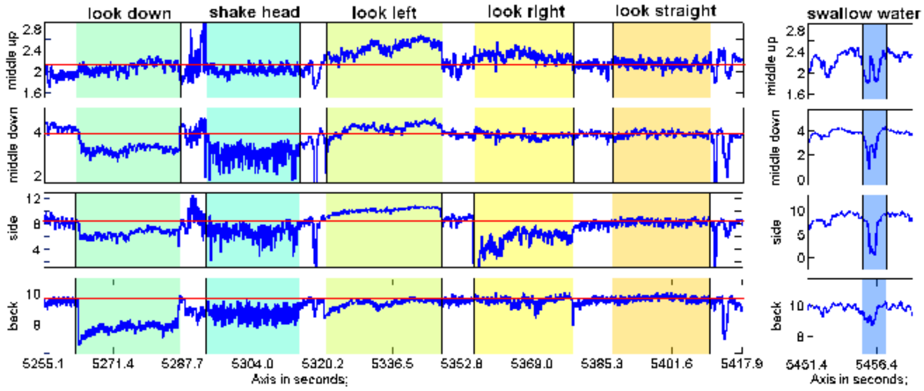

Fig. 7. Influence of motion artifacts on the neck electrodes. Left: signals for different head positions. Right: swallowing water while walking.

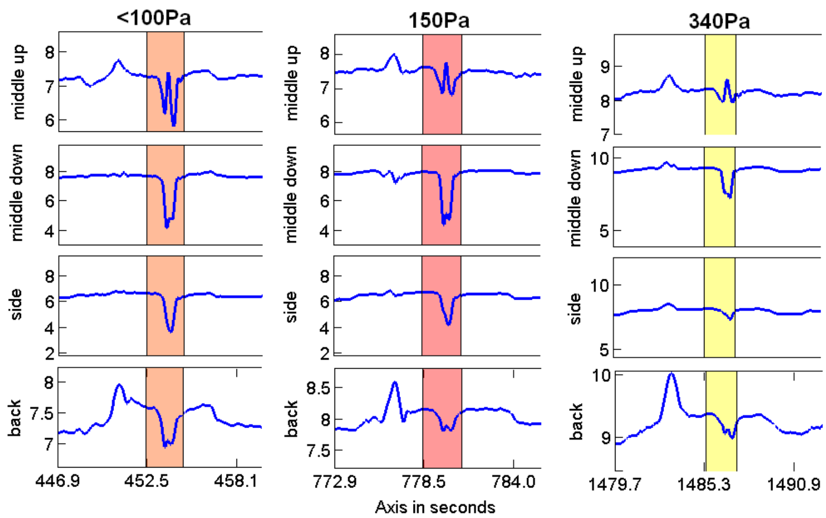

Fig. 8. Swallowing signal when the collar presses the electrode against the neck with 100 Pa, 150 Pa, and 340 Pa

same factors are responsible for the very articulate rhythmic signals for nodding and head shaking. Finally, speaking shows a strong but very variable signal. Nevertheless, in Section 5, we will show that it is distinct enough for a reasonable recognition results.

Motion Artifacts and Electrode Attachment. Previous paragraphs have detailed that the proposed sensor is highly sensitive to a broad range of factors. Thus, motion artifacts and sensor attachment are obvious concerns. To illustrate the effect of motion artifacts, signal for different head position and for swallowing, recorded while a person was walking, are shown in Figure 7. While the noise due to walking can be clearly seen, key features of the specific activity remain visible. Overall, motion artifacts influence signal quality, however they do not completely obscure the signal information content. This is confirmed by dedicated recognition experiments in Section 5.

Concerning sensor attachment, a primary question is how tight the electrode must be pressed onto the body. During the recognition experiments participants were assisted to attach the collar "tight but comfortable". For a more quantitative assessment, we have recorded sample signals while measuring the force, which the collar extended. From this force the pressure on the neck was estimated. The results for pressures of 100 Pa (band extended by 1 mm), 150 Pa and 340 Pa (for comparison, the atmospheric pressure is around 100'000 Pa) are shown in Figure 8. Interestingly, the least pressure leads to the best signal. This is because the main contribution to the signals comes from deformation of skin and soft tissue directly below the electrode, which is suppressed when the collar is to tight.

5 Quantitative Evaluation

In this quantitative evaluation we focus on the collar setup. As detailed in Section 4 this setup provides information related to different activities, such as head motions, chewing and swallowing, which are difficult to detect with other unobtrusive sensors. For the same reason it is also challenging, as the system needs to deal with a broad range of variable signals.

We proceeded in four stages. First we investigate how well the signals corresponding to 11 different activities can be differentiated in isolation. Thus, we check how much relevant information is contained in the signal. Secondly, we investigate how well the swallowing can be spotted in the continuous data stream. We choose swallowing because it is a short subtle signal (as opposed to activities, such as nodding which are longer and repetitive). Swallowing spotting is also relevant for nutrition related applications. Here we demonstrate that relevant activities are not "swamped" by noise from the NULL class. Thirdly, we attempt to distinguish different swallow sizes, this tests the limits of information we can extract. In further testing these limits, we attempt to distinguish different breathing modes, which can be relevant for many sports and health-related applications.

5.1 Recognition of Activities

Experimental procedure. Three subjects (one female, two male; aged between 25 and 45 years) have worn the electrode collar during computer work and when walking in corridors of the office building. In both scenes we asked them to perform a set of head movements for 20 s each: nodding, shaking head, look down, up, left, right, and straight. Moreover, the individuals were asked to drink and swallow water from a cup (10× ∼6 ml), chew and swallow bread pieces (total 5×2 cm^3), and speak (reading a text aloud from the computer screen or talking

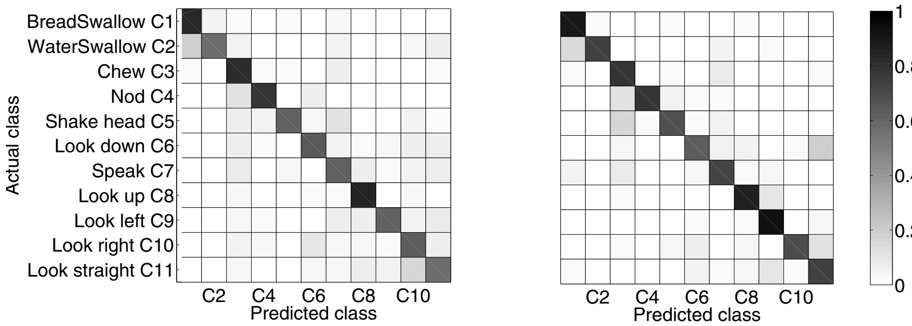

Fig. 9. Activity recognition confusion matrices using three capacitive sensors embedded in the collar. Left: activities while sitting and walking, Acc = 0.69. Right: activities while sitting, Acc = 0.77.

to the experiment observer for 20 s). All actions were repeated for 3 times, in order to introduce natural variability in the recordings. "Nodding" and "looking up" were recorded for the sitting scene only, as these were both exhausting for the participants, and safety critical during the corridor walking. All recordings for computer work and walking were made in one session for each participant.

To maintain electrode position the collar was fixed with an elastic band, the subjects were told to fix it so that it is tight but comfortable. We analysed two front, one side, and one back electrode position in the same way as presented for our signal study in Section 4 above. Preliminary analysis showed however, that the back position did not provide useful information. Thus we did not consider it here. An experiment observer controlled the recording and advised participants on the activities to perform. In addition all recordings were captured on video. The recording lasted for about 70 minutes for each individual, in total ∼4.3 hours of data were acquires. The observer annotated all activities during the recording. These annotations were refined in post processing step based on signal waveforms.

A particular challenge is to accurately annotate natural swallowing [5]. Typically, the swallowing reflex is initiated unconsciously, which makes it difficult to identify and annotate it during recordings. In this study, we asked the participants to indicate swallowing with a hand sign. In addition, we reviewed the sensor data and video material to decide unclear cases of potential swallows. For this purpose we installed the video camera in the computer work scene such that it captured the hyoid movement. This procedure is a standard technique used in swallowing analysis [5,15]. For the walking scene, we had to rely on participant hand signs and review of sensor waveforms.

Analysis method and results. The analysis employed a linear discriminant classifier. Time domain features, such as signal mean, variance, maximum, etc. were derived from all three sensors (45 in total) in sliding windows of 1.5 s length without overlap. We employed 10-fold cross-validation to obtain training (9 parts) and testing (1 part) observations. The training was controlled to avoid class skew. The classification output was compared to our annotation and the class-normalised accuracy computed. We first performed a combined analysis over the sitting and walking segments. For comparison, we analysed the sitting activities separately as well. “Nodding”, “looking up”, and “chewing bread” were excluded from the walking scene for practicability reasons.

Our combined results for sitting and walking activities showed an accuracy of 69%. For the sitting activities 77% were achieved. Figure 9 shows the classifier confusion matrices for both analyses. While the different head postures and movements incurred some confusions, we observed that particular activities such as speaking and chewing could be very well discriminated. Moreover, the discrimination of fluid and bread swallowing is remarkable. Although including walking reduces performance, these results indicate that the sensor can provide useful information in the presence of motion artifacts.

5.2 Spotting of Swallowing

We analysed the viability of spotting swallowing events in the continuous sensor data, as it is an essential component of food and fluid intake [7]. In particular, we were interested to analyse the spotting performance with regard to swallowing pattern variability and the effect of artifacts, such as walking. For this analysis we focused on fluid swallows and utilised the same experimental data as presented in Section 5.1 above. As this dataset included a variety of other activities, we could test the spotting performance under realistic conditions.

Analysis method and results. We used an online pattern spotting procedure, Feature Similarity Search (FSS), developed in previous work [6] to evaluate swallowing detection performance in this work. The procedure uses trained feature patterns to continuously search the sensor data. In the search step, a variable observation window is used to derive features from data section. Between these features and the trained feature pattern we computed the Euclidean distance to compare and select a section. For the selection, a threshold was applied on the computed distances. At each time point only on such section can be correct, hence potential sections are kept in a buffer, until no further section could overlap with such already ones. Both, selection threshold and the variable window bounds were derived during the training step.

In this analysis we used time domain features from all three capacitive sensors, including the same types as described in Section 5.1 above, and three additional feature sets of the same type, describing three equally sized partitions of the section under investigation. This approach allows to convert the temporal swallowing signal pattern into a spatial one. The search was performed at constant time intervals of 0.25 s. We used a 10-fold cross-validation by splitting the dataset into 10 partitions and using nine for training and one for testing at each iteration. The partitions were controlled to not intersect with the swallowing sections.

In our evaluation, we included sitting and walking scenes to study spotting performance under noisy pattern condition. For comparison, we also analysed

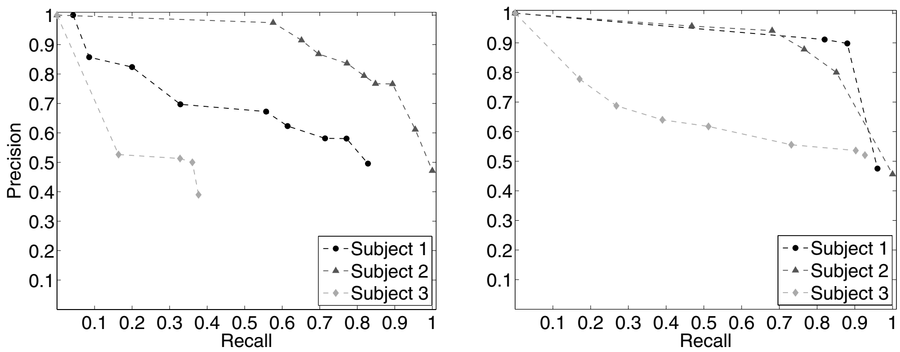

Fig. 10. Precision-recall tradeoff for spotting swallowing in three subjects. Left: swallowing while sitting and walking. Right: swallowing while sitting.

the sitting scene separately. In total 212 swallows were recorded, amounting to 2.8% of the dataset size. Figure 10 shows the precision-recall tradeoff for both spotting situations and the three participants. We observed that the performance was more variable in the combined sitting and walking analysis. Performance increased for the sitting scene, as to be expected from the reduced motion noise. The results show that the spotting is feasible, in particular when not walking. Under calm conditions a performance of 80% recall at 60% precision or more, can be expected. Although our dataset is smaller than the ones investigated for acoustic and electromyography swallowing spotting in earlier works [5], these results are very promising.

5.3 Swallowing Amount Estimation

We investigated the classification of drinking sizes as this information could be used to estimate fluid consumption. For this investigation we used the same collar and setup as in the activity recognition analysis.

We asked three individuals (one female, two male; aged between 25 and 30) that were not the same as in the activity recognition analysis to drink 5 ml and 15 ml water amounts. The amount was controlled using a calibrated glass. The experiment observer filled the glass for each drink. The participants were asked to swallow the fluid at once. A sequence of 10 swallows of each amount was taken and the sequence was repeated for three times, resulting in ∼30 swallows per amount. The recording was annotated and post-processed as the ones before.

Swallowing amount recognition was performed using the features variance, minimum, and maximum from all three sensors (9 features total). The linear discriminant classification was used. Figure 11 shows the Receiver Operator Characteristic (ROC) performance analysis obtained from the classification result. From the ROC, we computed the "Area under the curve" (AUC) for quantitative performance estimation. The results show that a similar AUC can be achieved for all participants. ROC and AUC are the most appropriate illustrations for this two-class problem. As Figure 11 illustrates, is the performance

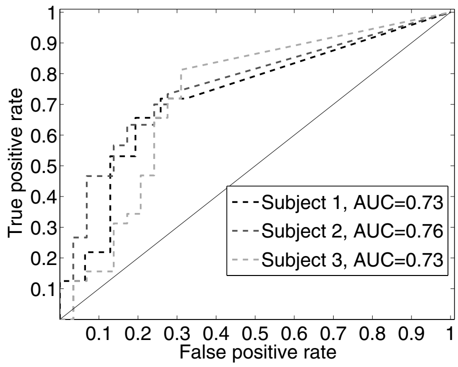

Fig. 11. ROC analysis for classifying 5 ml and 15 ml water swallowing. AUC values indicate the area under the curve.

clearly above the level of random choice. This result indicates that the sensors could be used to assess fluid amount. The result is in a comparable range to previous investigations using audio and Electromyography [5].

5.4 Respiration Rate Detection

As our preliminary signal study showed that breathing could be observed in the sensor data, we investigated the respiration rate detection from the capacitive collar system. We studied breathing with the same individuals who participated in the swallowing analysis (Section 5.3 above).

We asked the participants to breathe in and out in three qualitative modes: deep, normal, and light. We recorded 10 breathing cycles during walking and standing of each mode and repeated this protocol three times. In total ∼30 breathing cycles were recorded per mode, participant, and scene. As not all participants achieved exactly 30 cycles, the numbers were noted and checked in the waveforms. Our post-recording analysis showed that the breathing was difficult to identify from the waveforms during walking, hence we could not verify the number of breaths. Henceforth, we concentrated our analysis on the standing scene.

For this study we chose the capacitive sensor at the neck side, as this showed the largest amplitudes during breathing for all participants. The signal was band-pass filtered using a fourth-order Butterworth filter with $f_{Low} = 0.3\,\text{Hz}$ and $f_{High} = 2\,\text{Hz}$. These frequency ranges reflect the natural variation of the respiratory rate in adults. On the resulting signal a hill-climbing peak detection algorithm was applied with thresholds for positive and negative slope set to $\frac{\sigma}{2}$ of the considered signal. To set the thresholds automatically, a longer observation period could be used, which contains several breathing cycles at high probability. The resulting peak detection count were compared to the annotated counts and the accuracy was computed. Figure 12 shows the detection performance for all participants and breathing modes.

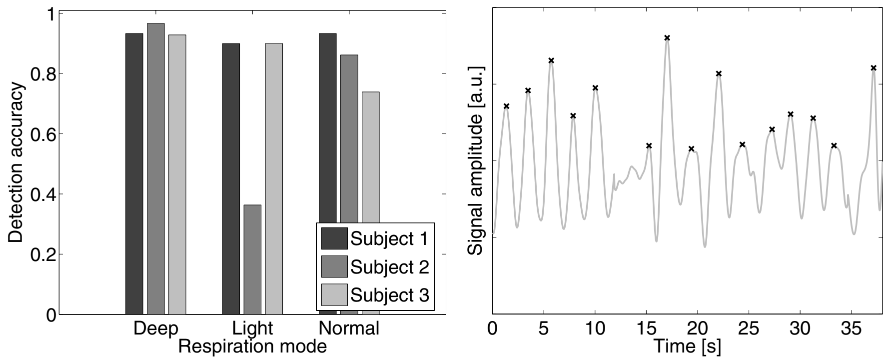

Fig. 12. Respiration rate detection results. Left: accuracy for all participants and breathing modes. Right: deep breathing detection sample.

Although our algorithm performed well to identify breathing, it might fail, if the breathing is held. In this case the peak detection algorithm may pick the heart rate, which is in a similar frequency band and amplitude level as the light breathing. However, under normal breathing using the electrode position at the neck, heart beat is marginally disturbing the breathing detection.

6 Conclusion

While being at an early state, the proposed application of capacitive sensing shows promising results, making it appealing for a wide range of applications. Starting from electric field, we demonstrated that this new sensing concept is well suited for retrieving activity and physiology-related information at multiple body locations. This is particularly interesting as our capacitive sensors are based on textile patches and can be conveniently integrated into regular clothing.

Since head-related activities are key to many activity recognition applications, we selected a collar system for our quantitative analysis. We observed that our approach is sensitive to motion, body shape, and tissue changes in a spectrum of activities, while providing useful information even under noisy walking conditions. From these results, we concluded that capacitive sensing is a viable and highly interesting new sensing concept for wearable monitoring. Moreover, from analysing swallowing and breathing we have seen that the sensor has particular features that promote its consideration for biomedical investigations and healthcare.

In summary, we expect that capacitive sensing will have a vital prospect as modality that is complementary to established concepts in activity monitoring. This work has initially demonstrated its potential. Further work should address the integration and optimisation for individual applications, which can even increase the sensor's reliability.

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