An Ultra-Low-Power Human Body Motion Sensor Using Static Electric Field Sensing

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ABSTRACT

Wearable sensor systems have been used in the ubiquitous computing community and elsewhere for applications such as activity and gesture recognition, health and wellness monitoring, and elder care. Although the power consumption of accelerometers has already been highly optimized, this work introduces a novel sensing approach which lowers the power requirement for motion sensing by orders of magnitude. We present an ultra-low-power method for passively sensing body motion using static electric fields by measuring the voltage at any single location on the body. We present the feasibility of using this sensing approach to infer the amount and type of body motion anywhere on the body and demonstrate an ultra-low-power motion detector used to wake up more power-hungry sensors. The sensing hardware consumes only 3.3 µW, and wake-up detection is done using an additional 3.3 µW (6.6 µW total).

Author Keywords

Activity sensing, low-power sensing, electric field sensing

ACM Classification Keywords

H.4.m. Information systems applications: Miscellaneous.

INTRODUCTION

Wearable motion sensors have been used in high-impact applications such as activity recognition, health and wellness sensing, and elder care. As a result of their popularity, considerable work has been done to optimize the power consumption of these sensors. The lowest power commercially available accelerometers typically consume 400-1000 µW, and the latest research devices consume as little as 36 µW [6]. With these low-power devices, accelerometers are now being widely deployed in a wide range of applications. We present a novel sensing approach which extracts similar human motion information as accelerometers, but at orders of magnitude lower power. We demonstrate

UbiComp' 12, Sep 5 – Sep 8, 2012, Pittsburgh, USA.

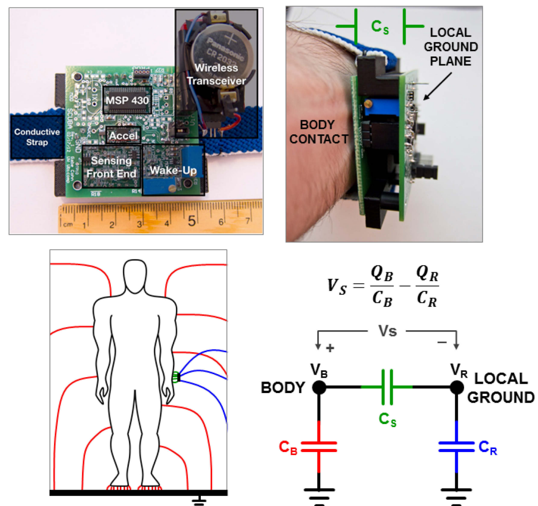

Figure 1. Static EF sensing utilizes capacitive coupling between the body, the sensor's local ground plane, and the environment. *Top Left:* Prototype sensing platform. *Top Right:* Side view of sensor platform showing spacing between the body and the local ground plane. *Bottom Left:* Capacitive coupling indicated by field lines, closer lines indicate stronger coupling. *Bottom Right:* Circuit model of sensing technique.

the ability to classify human activity using a 3.3 µW sensor. The power consumption of our approach is so low that the power consumed by the sensor is now virtually negligible.

Our approach for sensing the user's movement builds on work in the space of electric field (EF) sensing, which has been used in Human-Computer Interaction work to sense gestures for user input [1,2,3,4,5,7,8]. Previous work has used *active* sensors, consisting of a transmitter which emits a *time-varying* signal (typically 10–1000 kHz) and a receiver which senses the signal at a different location. In contrast, our sensing approach is completely *passive*; relying on the existing *static* electric field between the body and the environment. We do not transmit any signal and simply measure a voltage at any *single* location on the body.

The ultra-low-power consumption of our approach makes this an ideal sensor for continuously sampling coarse-grain body movement. This information can either be used for simple activity recognition or in order to wake up other sensors such as the more power hungry accelerometers or

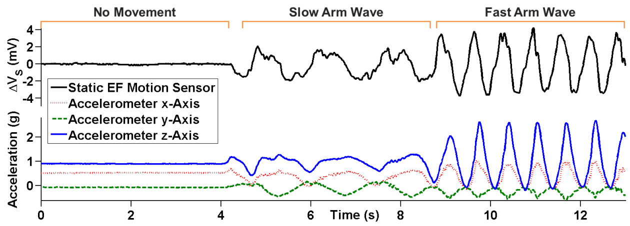

Figure 2. Example static EF sensing signal showing three different levels of movement along with accelerometer data.

gyroscopes. As an added advantage, the sensor can reliably sense movement on other parts of the body, even when the sensor itself is held completely still, thus providing capabilities not offered by accelerometers or other inertial sensors. In this paper, we describe the theory of operation and hardware that enables this sensing approach, and demonstrate that this technique works in any environment (*e.g.*, indoors, outdoors, in a Faraday cage, etc.). We also describe a small study that explores the capabilities of this new sensing technique, its ability to sense different types of body movements, and how this technique can be used for ultra-low-power (6.6 µW) motion-based wake-up.

THEORY OF OPERATION

Our sensing technique relies upon the capacitive coupling between the human body and its environment, as shown in Figure 1. Our sensor measures the voltage across a capacitor (C_S) in which one side of the capacitor is connected to the body, and the other side of the capacitor is a small local ground plane on the sensor board. In addition to this sensing capacitor, both the body and the local ground plane are capacitively coupled to the environment (*i.e.*, earth ground) through C_B and C_R, respectively. This system can therefore be modeled simply using three capacitors, as shown in Figure 1. Note that the capacitors in the model are lumped elements and represent the coupling among many different objects in the environment. Using this model, we can derive the relationships between physical changes (*i.e.*, body movement) and the sensed voltage (V_S).

The voltage across a capacitor is governed by ratio of the charge on either side, and its capacitance. Using this relationship, we obtain an expression for our sensing voltage (V_S) by taking the difference between the voltage on the body (V_B) and the local ground plane of the sensor (V_R), as shown in the equation in Figure 1. From this equation, it is clear that we will sense a change in V_S if there is a change in either the charge or the capacitance on either side of our sensing capacitor C_S. For this sensing approach, a static electric field must be established across C_S (*i.e.*, there must be charge on the capacitor). We inject this charge through a small bias current supplied by our sensing hardware. Experimentation confirms that the charge on C_S is dominated by that supplied by the bias current and not triboelectric charge from the body's friction with the environment.

When either the body or other objects in the environment move, all of the variables in the equation for V_S are likely to change. However, we believe that the charge is held relatively constant and therefore changes in V_S are primarily due to changes in the capacitance of C_B or C_R. For example, consider a user lifting their leg off of the ground with our sensor on their wrist. Since neither the local ground plane on the sensor nor any objects in the environment are moving, C_R should remain constant. However, C_B will change because the coupling between the body and the environment (*i.e.*, earth ground) changes significantly by lifting the leg. This action will therefore cause a change in V_S.

Our sensing hardware (shown in Figure 3) measures *changes* in V_S in order to infer body movement. This example highlights the ability of our sensor to detect body motion even when the sensor itself does not move (*e.g.*, the arm and sensor are perfectly stationary, but the leg is moving). This gives our sensor capabilities which accelerometers and other inertial sensors do not have.

Like accelerometers and other inertial sensors, our sensor can measure body movement at the location where the sensor is attached. In this case, the body movement causes changes in C_B, but since the sensor is also moving in the environment, there are also large changes in C_R. Once again, we detect these body movements by observing *changes* in V_S which are caused by changes in the capacitive coupling to the environment. An example signal produced by waving an arm is shown in Figure 2 along with the signals obtained from a 3-axis accelerometer at the same location on the wrist. Refer to the video figure to see more example signals. Although our signal is correlated to the data from the accelerometer, it is important to note that we are not measuring acceleration; we are simply measuring changes in the position of the body to its surroundings. While this means that we have to explicitly deal with small changes in V_S as objects in the environment move near the body, it also provides the unique ability to detect body motion independent of movement of the sensor itself.

Furthermore, because the human body can be considered a perfect conductor [7], our sensor can be placed at *any* location on the body as long as it has direct contact with the skin, and is fixed rigidly to the body so that C_S is constant. Additionally, since we are measuring capacitive coupling between the body and the environment and not utilizing any emitted electromagnetic waves, our sensing approach works in any environment. To verify this, we conducted tests indoors, outdoors, in a Faraday cage, and in a large open field at least 0.6 km from the nearest power lines.

HARDWARE

We have implemented a hardware device to passively sense body motion using existing static electric fields as described in the previous section. Our sensing platform, shown in Figure 1, measures 4.4 cm x 4.4 cm x 1.5 cm, and consists of a conductive fabric strap to make contact to the body, an analog front-end for measuring body motion, wake-up detection circuit, Analog Devices ADXL335 3-axis accelerometer for direct comparison, TI MSP430F5172 microcontroller, and a TI eZ430-RF2500 2.4 GHz wireless transceiver for streaming live data off the device. The device is

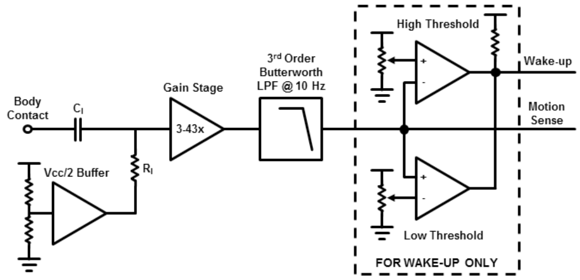

Figure 3. Block diagram of hardware for motion sensing.

powered by two CR2032 3V lithium batteries: one for the eZ430-RF2500 transceiver and one for all other circuitry.

The block diagram for the analog sensing front-end and wake-up detection circuitry is shown in Figure 3. This hardware was implemented using ultra-low-power off-the-shelf components. The voltage sensed on the body (V_S) is AC coupled and biased to mid-rail using C_I and R_I, and a Vcc/2 virtual ground using an Intersil ISL28194 op-amp. Next, the signal is amplified using a Microchip MCP6041 op-amp between 3 and 43 times so that the full-scale range of values observed for normal actions swings from rail to rail. To filter out the high amplitude 60 Hz signal on the body (*i.e.*, radiated noise from power lines), we apply a 3rd-order Butterworth lowpass filter with a corner frequency of 10 Hz using a Sallen-Key active filter. This was implemented using another ISL28194 op-amp. The power consumption of this front-end is 3.3 µW (*i.e.*, 1.1 µA at 3 V).

EXPLORATION OF CAPABILITIES

To explore the capabilities of our new sensing approach, we collected data from 6 users (3 female). Each user performed 6 different actions 9 times each in 2 locations within a building. The actions were chosen to show a variety of different types of movement: (1) rest (*i.e.*, not moving), (2) typing, (3) using a computer mouse, (4) small arm movements (*i.e.*, users were asked to sort cards), (5) walking, and (6) jogging. The 9 examples were collected in 3 *sessions* of 3 *examples* each which were separated in time, and the order of the actions was randomized within each session. Each example consisted of a 5 second period in which the user continually performed the specified action.

Low-Power Wake-Up

As shown in Figure 2, the change in the sensed voltage (V_S) is near zero when the user is not moving and non-zero when the user is moving. It is therefore reasonably easy to use this signal to detect when the user is moving. Furthermore, we hypothesized that different levels of movement can also be extracted from our static EF sensing signal using only a simple threshold. To test this, we grouped the data collected in our user study into 4 classes representing increasing levels of movement. We then generated receiver operating characteristic (ROC) curves by sweeping the threshold, shown in Figure 4. We used the following four classes to represent the level of movement: (1) rest, (2) mousing and typing (*i.e.*, hand and finger movements), (3) small arm movements, and (4) whole body movements (*i.e.*, walking and jogging). To generate the ROC curves, we divided our

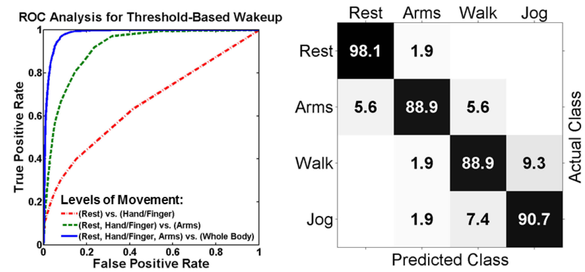

Figure 4. *Left:* ROC curves for threshold-based wake-up. *Right:* Confusion matrix of motion type classification.

dataset into 250 ms windows. Each window above the threshold was classified as being in the more active class. Therefore the false positive rate is defined as the number of misclassifications over the total number of windows.

From the ROC curves shown in Figure 4 we can see that it is difficult to use a simple threshold to determine the difference between rest from finger and hand movements. This makes sense because small movements of the fingers and hands do not have a large effect on the overall capacitance of the body to its environment. Therefore, given the sensitivity of our current hardware implementation, we would suggest that we cannot reliably use a simple threshold to perform wake-up when the user makes small hand and finger movements. As seen in Figure 4, it is much easier to choose a threshold which can robustly perform a wakeup when transitioning to higher levels of movement. For example, this may augment existing accelerometer-based activity sensing systems by going into a sleep state when the users stops moving and then wake-up to run the accelerometer again once more movement is detected.

To demonstrate the ability to perform ultra-low-power wake-up, we use two Maxim MAX9120 comparators to wake up the MSP430 on our prototype sensing platform. Including the comparators, the total power consumption of the analog circuitry is 6.6 µW (*i.e.*, 2.2 µA at 3 V), and including the MSP430 in deep-sleep, the board consumes only 9.3 µW while waiting for body motion to wake-up.

Body Motion Classification

In addition to threshold-based wake-up, we hypothesized that the static EF sensing signal may contain enough information to determine the type of motion that the user is performing. To test this hypothesis, we posed the problem as a machine learning classification problem, in which we are trying to classify different user actions. If we are able to build a classifier that can robustly determine the user actions, then it is feasible that this signal can be used for activity recognition in some of the same ways that accelerometers are currently used. From our threshold-based wake-up analysis we learned that it is very difficult to sense hand and finger movements. Therefore, in this analysis we only considered the following 4 actions from our user study: rest, small arm movements, walking, and jogging.

We expect our static EF signal for body movement to be similar to an acceleration-based model, so we leverage classification features from accelerometer-based activity recognition research. We used six features that capture both time and frequency domain characteristics. For deriving frequency domain features we compute the power spectral density (PSD) using the Welch method. The distribution of the energy in a PSD is often a good indicator of the type of activity. For example, running results in more energy in the higher frequency range than slower activities like walking or resting. We derive two features from the PSD: the median power and median frequency. The latter is the frequency that divides the area under the PSD curve into two equal halves. The energy distribution for walking and running often overlap, which requires additional time-domain features in order to obtain robust classification.

We compute 4 time domain features. First, we compute the standard deviation across the entire 5 s window to capture the overall variability in the signal. Activities involving less motion result in lower variability, providing enough information to partition between resting and motion, but not enough to distinguish between various movements. Second, we compute the number of zero crossings of the derivative, which approximates the number of peaks in the signal. Third, we count the number of high magnitude, rapid changes in the signal by thresholding the absolute value of the derivative with a constant static threshold. This was calculated so that resting activity did not generate a count. Finally, the magnitude of the first peak of the autocorrelation was computed to capture the periodicity of the signal, which differentiates periodic motion (*e.g.*, walking and jogging) from random motion.

Using these 6 features, we trained a k-nearest-neighbor classifier with k=1, using the Weka machine learning toolkit. We performed a 3-fold cross-validation in which we folded the data by *session* in order to avoid over-fitting (*i.e.*, training and testing sets would never contain examples from the same session). We ran our 4-class classifier per user, per location (*i.e.*, 12 classification runs) and averaged the results to obtain an overall accuracy of 91.7% (σ=7.0%). The confusion matrix for this classification is shown in Figure 4.

Our ability to achieve motion classification at nearly 92% accuracy using a single low-power sensor on the body is very promising. To further test the capabilities of the static EF sensor, we configured a more realistic machine learning scenario in which we train using only *one* of the 6 sessions (*i.e.*, there are 6 sessions of data from each user; 3 from each location), and then test on the other 5 sessions. We performed a 6-fold cross-validation (*i.e.*, folding by session) for each user and obtained 80.0% accuracy (σ=7.5%), thus suggesting the possibility of developing a deployable motion recognition system using only the static EF signal.

DISCUSSION AND FUTURE WORK

We described a technique that researchers can use for body motion sensing using a novel approach which leverages static electric fields around the human body. Our sensing approach provides coarse-grain body motion data, allows for ultra-low-power wake-up of other sensors, and shows promise for detecting the type of motion without the need for an inertial sensor.

There are a number of application areas in which our approach for low-power motion and activity sensing is ideally suited. The sensitivity of our approach to footsteps makes it ideal for pedometer-based physiological calorimetry (*e.g.*, FitBit and similar products), and gait analysis. In addition, we have shown correlation between our signal and an accelerometer, which consumes 1-2 orders of magnitude more power than our approach. The lowest power commercially-available accelerometers typically consume 400-1000 μW, and the latest research devices consume about 36 μW [6], which is much higher than our 3.3 μW. We are excited about the simplicity of our approach and the fact that it can be done without significant specialized hardware.

In future iterations, we would like to improve the hardware used for sensing. Although we have not experienced any issues, voltage signals produced by changes in charge rather than capacitance could potentially confuse our system. One problem with charge is that it is a result of unpredictable static electricity. One way to reduce the effect of charge buildup is to periodically short the sensing capacitor.

We could even more dramatically reduce the power consumption of the front-end hardware by implementing a custom analog IC. Although our power consumption is already very low, it was implemented on higher bandwidth commercial off-the-shelf parts. Since our signal has an extremely low bandwidth of 10 Hz, we estimate that a custom analog IC could be created which performs the same task as our current hardware, but between 1 and 10 nW (*i.e.*, 3 order of magnitude lower power than our existing prototype).

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