Improving Presence Detection For Smart Spaces

Julian von Wilmsdorff
Technische Universität Darmstadt
Darmstadt, 64289, Germany
julian.von.wilmsdorff@igd.fraunhofer.de

Biying Fu
Fraunhofer Institute for Computer Graphics Research IGD
Darmstadt, 64289, Germany
biying.fu@igd.fraunhofer.de

Florian Kirchbuchner
Fraunhofer Institute for Computer Graphics Research IGD
Darmstadt, 64289, Germany
florian.kirchbuchner@igd.fraunhofer.de

Abstract
In this paper, we present a novel sensor for smart spaces based on electric field sensing. It detects and classifies several events around a door to improve presence detection. We are able to detect events including *inside*, *outside*, *entry*, *exit* and *none*. In contrast to photoelectric sensors, it does not require a direct line of sight and also does not react to objects like suitcases with wheels or similar things like wheelchairs. Based on a conducted test study with 12 participants, we showed that we are able to detect the given classes with an overall accuracy of 90.3 %.

Author Keywords
Sensors; Smart Spaces; Electric Field Sensing; Signal Processing

ACM Classification Keywords
Hardware [Sensors and actuators]; Hardware [Digital signal processing]

Motivation
In modern smart spaces, the information of the presence of users is mandatory for many systems. By knowing the number of users in a room, smart objects can adapt their behaviour to fit the current situation. For example, lights can be turned off in case no persons are present to save energy or music speakers can increase the volume when

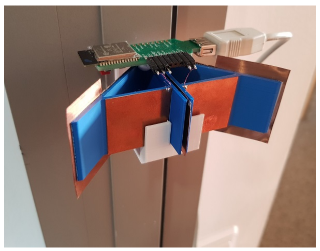

Figure 1: sensor and copper electrodes placed on door

more persons enter the room.

Commonly used presence detectors that are based on infrared detection are not sufficient for this application. If a person enters a room and remains calm, the sensor has no means to know if the person left the room or is sitting nearly motionless in the room.

Optical barriers can improve this situation, but do not cover other aspects of real life situations. If two light barriers are placed at every entrance of a room, directional information of exit- and enter-events can be calculated. But optical systems lack the capability of differentiating between objects and persons.

This is why we implemented a directional sensor (shown in Figure 1) based on electric field sensing. These sensors react very sensitive to steps. That is the reason why objects with wheels are not recognized by the detection algorithm. In addition, compared to mere capacitive sensors, our passive electric field sensors have a higher range.

Related Work

The principle of electric field sensing is well known for over hundred years, but lots of application areas have been revived in the last few decades with emerging new processing algorithms and sensor designs. This technology gained lots of popularity in sense of low power consumption, no emission of electrical fields and high privacy preserving aspects. In the medical domain, applications like remote EEG measurement has been implemented by Prance et al. [6]. The group of Wilmsdorff et al. [7] have showed in their research paper lots of exploratory experiments for different use cases, for example no-touch gesture recognition for wearables and traffic observation using electrical field sensing. Xavier et al. [4] worked with the possibility of using this technology for indoor positioning and even person recognition based on gait patterns on two different days. Similar work for indoor positioning system using electrical potential sensing on a smart floor has been presented by Fu et al. [2]. Cohn et al. [1] made some efforts by applying this technology in gaming context. They augmented a customized gaming pad into a device with multiple input modalities like jumping and stepping without using the control stick on the gaming pad. Examples of wearables based on electric field sensing that can detect movements of legs and even the touch of human hair is shown by [5].

Door as an entry point to a secured location is quite interesting to interact with. Gjoreski et al. [3] showed in their work that it is possible to identify person by just analyzing door accelerations in Time and Frequency domain. In the following sections, we present a novel use-case of electrical potential sensing to be a smart presence detector. We first introduce the hardware implementation, followed by the detection algorithm and finally conclude our findings in the evaluation section.

Hardware Implementation

The sensor contains four core components. These components are:

- A UART to USB bridge for communication purposes
- An ESP32 micro controller of which two ADCs are used in 12bit mode
- Two electric field sensing groups
- Two shielded electrodes for every sensing group

A measurement group consists of an instrumentation amplifier, which meters the voltage between two pre-charged electrodes. To pre-charge the electrodes, half of the supply voltage is linked to both electrodes over two 1GΩ resistors. The current running through these resistors slowly pulls the measured signal back to a defined voltage level, removing some of the wanted signal in the process. To prevent a too strong loss of the signal, these resistors have to have a high value. Omitting these resistors would result in a higher range and increased sensitivity of the sensor, but would also introduce the problem of railing voltages. This happens if a voltage over the supply voltage (3.3V) or a negative voltage is created between the electrodes. Without pre-charging of the electrodes, the voltage level would not (or very slowly) recover to a range measurable by the ADC of the micro controller. By tying the potential of the electrodes to 1.65V, the sensor values will normalize within seconds, even if railing occurred. Figure 2 shows the simplified circuit of a measurement group. If the voltage of the first electrode is p_a and the voltage of the second electrode is p_b, the voltage u given by the instrumentation amplifier will be:

$$u = \frac{1}{2}V_{cc} + (p_a - p_b)$$

The voltage u is sampled by an ADC of the micro controller and further processed. This voltage is influenced by movements of the human body. Since there is a tiny amount of charge on the body, it will attract the opposite charge on the electrodes while approaching the sensor, but not the same amount on every electrode because of the arrangement of the electrodes. The induced potential difference between both electrodes is the input for our instrumentation amplifier.

Detection Algorithm

Since the sensor consists of two measurement modules, every module will output its own measurements. The measurement modules use a scan frequency of 50 Hz, the frequency of the European power grid. In this way, noise created by power outlets and power lines is suppressed by under-sampling.

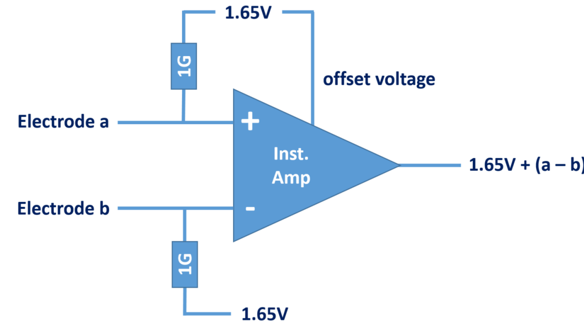

Figure 2: simplified circuit of a measurement group

The two outputs of the sensor will be processed by a pipeline. Every module uses a 12 bit ADC, which is equal to values from 0 (= 0V) to 4095 (= 3.3V). Because of the pre-charging of the electrodes, the normal baseline of a module is 2048, around half of the measurement range. Due to variances of the electrical components and environmental conditions like air humidity and temperature, the baseline can have an offset up to 10% of the original 2048. This is why the first stage of the pipeline is to calculate the real baseline of every measurement module and subtract it so that the values are zero based. This stage will only be active if there were no activities for at least 25ms. Otherwise the sensor would calibrate its baseline to the level of human steps.

The second stage is to form the first derivation of the two signals. This is needed to calculate the moment when the feet of a person hit the ground, which is represented by a local minimum or maximum. Note that no information can be obtained by the distinction of minima and maxima, because this only depends on the charge of a person. If a person is charged negatively, their steps will give a negative amplitude, otherwise a positive. The position of the extremum will be stored, but only if the following conditions are met:

- The first derivation is crossing the zero line. The direction of the crossing does not matter out of the stated reasons.
- The amplitude of the signal has to overcome a certain threshold. Simple noise will be discarded this way.
- The extremum has a certain minimal euclidean distance to the previous extremum. This way, if a single extremum that was corrupted by noise would appear as two or more extrema, the algorithm will only note one extremum.

This stage only operates on the previously calculated positions of the extrema. If no new peaks are detected for at least 25ms, the third stage of the pipeline is processed. For each peak we compute the sign of the difference in amplitude of the two signals. The electrodes of the sensor are placed in such a way that the position of a person in relation to the sensor will give a stronger signal in one measurement module, depending on if the person is moving on the right of the sensor or on the left. When calculated for each peak, this stage of the pipeline will result in a sequence of negative or positive peaks. In a best case scenario, a person which is moving from right to left would give the sequence: +1, +1, ..., +1, -1, -1, ..., -1. Note that the number of peaks is determined by the number of steps of the detected person.

The fourth and last stage of the algorithm is an auto correlation. Four different cases of sequences are evaluated:

- $\{+1, +1, ..., +1, -1, -1, ..., -1\}$: The person is moving from right to left
- $\{-1, -1, ..., -1, +1, +1, ..., +1\}$: The person is moving from left to right
- $\{+1, +1, ..., +1\}$: The person is moving only on the right side of the sensor
- $\{-1, -1, ..., -1\}$: The person is moving on the left side of the sensor

These are ideal sequences. A normal given sequence could contain outliers that obfuscate the sequence. To eliminate those, every +1 or -1 that has no adjacent peak with the same sign will be discarded. For example, the sequence $\{+1, +1, +1, -1, +1, -1, -1\}$ would result in $\{+1, +1, +1, -1, -1\}$. The auto correlation is only computed if three or more peaks are contained in the reduced sequence. Otherwise the result will be unreliable. Such weak signals are discarded because they originate most likely of persons moving at a large distance of the sensor or noise. In these cases, the algorithm will output the none-class. If there are enough peaks, the auto correlation matches the reduced sequence with these four functions:

- person moving left to right: modified Heaviside step function
$$H_1(x) = \begin{cases} -1 & x \leq 0 \\ 1 & x > 0 \end{cases}$$
- person moving right to left: inverted modified Heaviside step function
$$H_2(x) = \begin{cases} 1 & x \leq 0 \\ -1 & x > 0 \end{cases}$$
- person moving on the right: constant positive function
$$P(x) = 1$$
- person moving on the left: constant negative function
$$N(x) = -1$$

Entry	Straight line from Position 1 to Position 4
Exit	Straight line from Position 4 to Position 1
Outside	Starting from Position 1 to circle around Position 2 and return back to Position 1
Inside	Starting from Position 4 to circle around Position 3 and return back to Position 4

Table 1: The selection of pre-marked paths regarding the different classes has been given and each path was taken twice.

The function with the lowest error will be selected and represents the final result of the algorithm.

Evaluation

To illustrate the proof of concept, we conducted a test study with 12 participants. The participants have an average height of 174.9 cm ranging from 163 to 186 cm and contain 5 females and 7 males. We asked the participant to walk on predefined paths as shown in Figure 3. Each path were taken twice to determine the 5 different target classes of {*inside*,*outside*,*exit*,*entry*, *none*}. The approximate sensing range is indicated by the area of the blue circle. Four positions from 1 to 4 have been marked to indicate the path. The walking speed is not constrained. The walking direction was instructed as given in Table 1.

We noted the success- and mismatch-rate for each run to derive the confusion matrix shown in Figure 4.

We did an additional experiment to show that electric field sensing in contrast to photoelectric sensors will not be disturbed by objects. In Figure 5, we plotted two different signals. The upper plot shows the signal, when a person is entering the room rolling a wheel chair, while the plot below shows the signal when a person is entering the room without any objects. As shown, the signals are nearly identical

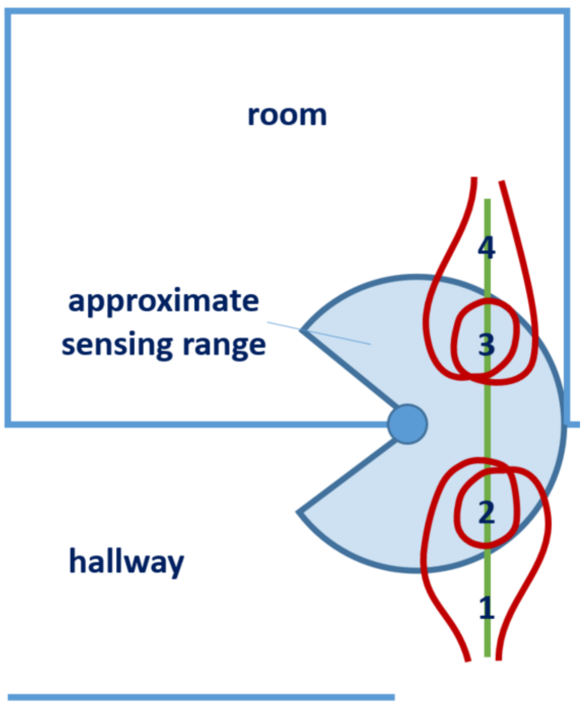

Figure 3: evaluation setup and walking paths

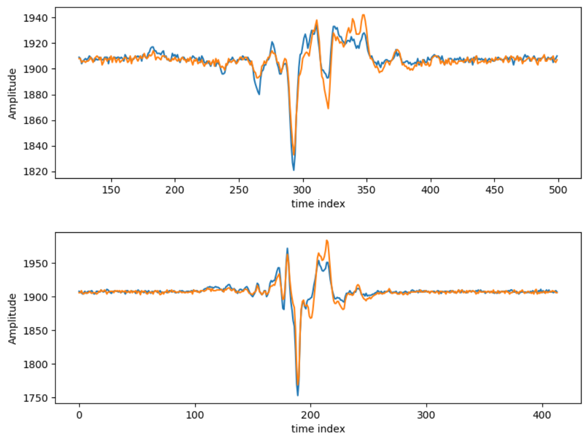

Figure 5: signal of entering the room with (above) and without (below) wheelchair

Figure 4: confusion matrix of the five different classes

and do not contain any features indicating another moving object. Both entry events were classified correctly by the sensor.

Conclusion & Future Work

We presented a novel approach for counting exit- and entry-events with a sensor based on electric field sensing. The evaluation shows that this concept is promising. To improve the performance even more, the placement of the sensor could be further examined and optimized. An important point would be to enhance the implementation to detect multi-user scenarios. Regarding the advantages of this technology like low power consumption, no need for direct line of sight and insensitivity to objects, this technology is very suitable for this use-case.

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