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A Contactless Sensor for Human Body Identification using RF Absorption Signatures

Javed Iqbal, Arslan Arif, Osama Bin Tariq, Mihai Teodor Lazarescu, Luciano Lavagno
Department of Electronics and Telecommunications (DET)
Politecnico di Torino, Italy
email: javed_iqbal; arslan.arif; osama.bintariq; mihai.lazarescu; luciano.lavagno@polito.it

***Abstract*—Indoor human detection and localization sensors are at the base of many automation and monitoring systems. This work presents an indoor tagless passive human body identification method. It uses a load-mode capacitive sensor to detect the differences in the conductive and dielectric properties of the human body due to differences in body constituency. The experimental results show that four male individuals with similar height but different body mass index (BMI) standing at 70 cm in front of a chest-level 16 cm x 16 cm sensor plate determine different capacitance-frequency characteristics over a 5 kHz - 160 kHz range, which can be used to identify the person.**

Keywords: Capacitive Sensors; Dielectric Properties; Human Sensing; Identification; Monitoring

I. Introduction

The development of low-power and low-cost contactless sensors for indoor human detection, localization, tracking, activity monitoring and identification has earned a great interest from the research and scientific community in the recent years. In the past, many solutions have been devised for human identification, for both indoor and outdoor environments. Some existing solutions are either video or infrared-based face and gait recognition. Ding et. al. [1] presented a comprehensive survey on video-based face recognition. Muramatsu et. al. [2] and Semwal et al. [3] performed a gait-based person identification with a very good accuracy. Ghiass et. al. [4] presented a literature review on infrared-based face recognition approach. Moreover, pyroelectric infrared sensors are also being widely used in various configurations for human motion detection and identification in indoor static environments [5].

The human identification techniques discussed in [1], [2], [3] and [4] provide a very good accuracy and detailed information about the subject, but have high power requirements. These solutions are expensive in terms of hardware and computational resources.

Many scenarios do not require high accuracy and detailed information about the subject. For example, to monitor the activity of elderly people living alone, a low power capacitive sensing technique can be employed [6]. It provides enough information about the activity patterns of the person, without invading the individual's privacy, which is not the case with solutions provided in [1], [2], [3] and [4].

The electrical permittivity and conductivity of biological tissues are much different than those of the free space, and have strong and non-linear dependencies on frequency. Studies have shown that the average values of electrical conductivity and permittivity of the whole human body is almost equal to two-thirds of the muscle tissues [7]. Hence, the dielectric properties of the human body differ from one tissue type to the other. For example, there is a significant difference between the dielectric properties of mammary gland and mammary fat, bones with low amounts of bone marrow and high amounts of bone marrow etc. [8].

Moreover, the dielectric properties and specific absorption rate (SAR) of human body also change with age [9], [10], [11]. Huayue et. al. [12] reported some age-related changes in microstructures of cortical bones and trabecular bones. Stolzing et. al. [13] observed a notable and progressive decrease in human bone marrow from childhood to the old age. From the observations given in [8], it is evident that the dielectric properties of an aged person must be notably different from a young adult or child.

Capacitive sensing can exploit the dielectric properties of human body for contactless indoor detection, localization and tracking [14], [15]. The use of capacitive sensors is also being studied for activity monitoring of independently living senior citizens [6].

A loading mode or single plate capacitive sensor measures the capacitance between its electrode and the environment. The capacitance greatly depends on the distance between the electrode and other conductive objects nearby, as well as the electrical properties of the environment, as shown in Fig. 1. C_{pb} is the capacitance from the human body to the sensor plate, C_{pg} is the capacitance from plate to ground and C_{bg} is the capacitance from body to ground. The dielectric properties of the body also contribute to the overall capacitance of the sensor plate.

Assuming a static environment, when an individual comes near the sensor the effective permittivity of the environment is modified, which in turn determines a different value of capacitance. This change in capacitance depends upon many factors e.g., physical traits of the person (obese or skinny), distance of the individual from the plate and specific electric and dielectric properties of the body etc. If the distance between the plate and the individual is kept constant, the change in capacitance just depends upon the physiology of the person, its gender [8] and age group [9].

This work is an experimental study of capacitive sensors for human identification. Wang [16] discussed a capacitive

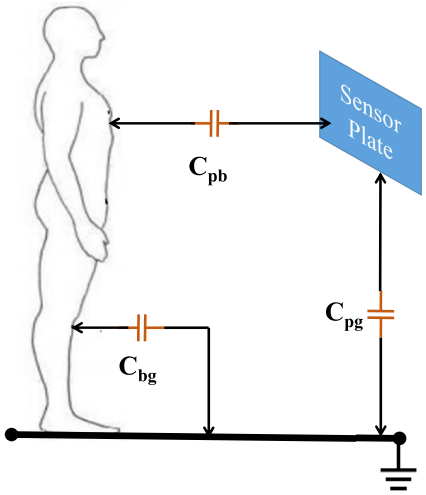

Fig. 1. Capacitance of a single plate capacitor

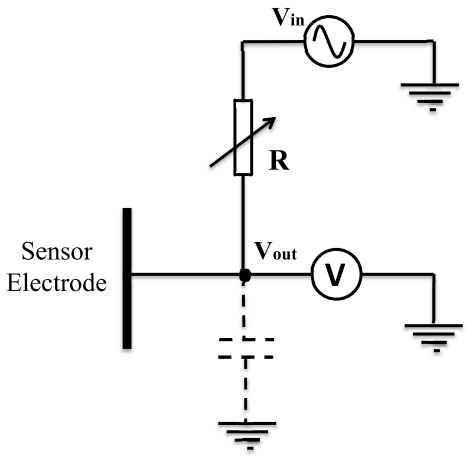

Fig. 2. Setup for tuning the RC filter

sensor topology for human recognition, and there is not much reported work in literature in this regard.

We selected four male individuals with the same height but different weights, and performed capacitive sensor based experimentation to discriminate among them. We only considered physical differences i.e., different weights of the body. Gender and age-related differences would be studied in future works. Moreover, the distance between the individual and the sensor(s) can be estimated, and thus factored out, using techniques like those reported in [14]

The rest of the article is organized as follows: In Section II, we explain our main contributions. In Section III we present the methodology of experimentation as well as our experimental setup. In Section IV, the experimental results and some discussion are presented. Section V provides some possible future work and suggested improvements. Section VI consists of the conclusions drawn from our results.

II. Our Main Contributions

As mentioned in Section I, the video-based and infrared-based human sensing systems comprise of expensive hardware and they have to perform too much computations before taking a decision, hence requiring powerful computational resources to achieve a good response time. They also provide a lot of unwanted redundancy in many situations. For example for healthcare monitoring of elderly people, we do not want too much details about the subject. The pyroelectric infrared (PIR) sensor based systems rely on the motion detection and need to keep track of the system history in order to localize a person, which needs extra memory resources. The perfomance of PIR sensors is degraded in case of stationary objects. Moreover, they could not be efficiently employed for human identification. On the contrary, capacitive sensor based human sensing systems require cheap front-end circuitry and comparatively much less computational power, hence offering a low-cost and low power solution for indoor human detection, localization, tracking, identification and activity monitoring.

This work is a primary experimental attempt towards the development of a capacitive sensor based robust human identification system for indoor applications. As capacitive sensors are already being used for human detection, localization, tracking and activity monitoring, we aim to add the human identification feature to the capacitive sensor based human sensing systems, so that a single low-cost, low-power and battery-powered portable system can perform all the tasks including detection, localization, tracking, activity monitoring and identification simultaneously.

III. Methodology

We use a loading mode capacitive sensor, in a lowpass filter configuration. We measure the human body response to electric fields at various frequencies by measuring the RC filter magnitude response, which we call “Body Signature”of the body under test. The sensor used is a square metallic plate with a side length of 16cm, installed at the chest height of an average height adult.

A. Experimental Procedure

We connect the capacitive sensor in lowpass filter configuration as shown in Fig. 2. The input frequency is initially set to the minimum measurement frequency f_m, in our case 5 kHz and the value of R is adjusted, so that without anybody near the sensor we have,

$$\frac{V_{out}}{V_{in}} = 0.707 \tag{1}$$

This means that the minimum input frequency f_m is equal to the cutoff frequency of the filter. We measure the value of the resistance R_o, i.e., the value of the resistance at cutoff frequency f_o and increase the value of the resistance 10 times. This implies that the cutoff frequency is lowerd by a factor of 10 i.e., the new cutoff frequency, $f_o = 500$ Hz.

Thus, the minimum measurement frequency f_m is now 10 times higher than the cutoff frequency i.e., f_m=10f_o. This shift is necessary to move all measurement frequencies in the asymptotic response region of the RC filter.

Then we measure the input and output voltages and calculate the gain in dB.

$$\text{Gain in dB} = 10\log_{10}(\frac{V_{out}}{V_{in}}), \tag{2}$$

Then we set the measurement frequency to $2f_m$, $4f_m$, $8f_m$, $16f_m$ and $32f_m$ and measure the input and output voltages for each frequency and calculate the gains in dB. This set of gain values measured at different frequencies is regarded as the "Body Signature". We repeat this procedure for different people, standing at a fixed distance of 70 cm from the sensor, to measure their Body Signatures.

B. Experimental Setup Design

The block diagram in Fig. 3 shows the design of the front-end interface circuitry to measure the body signatures. An AD9837, Direct Digital Synthesis (DDS) programmable waveform generator chip is programmed through the SPI interface of an 8-bit AVR microcontroller, ATMEGA328P to generate the sinusoidal signal of desired frequency, f given by Eq. (3). The AD9837 provides a DDS resolution of 0.06 Hz at 16 MHz. The output level of the DDS is 600 mV_{pp}, with a DC offset of 300 mV, which implies that the whole signal is above the ground level. To remove this offset, a 0.1uF series capacitor is used at the outout of the signal generator. The waveform generator is programmed to sequentially generate the frequencies given by,

$$f = 2^n f_m \tag{3}$$

where, $f_m = 5$ kHz and $n = 0, 1, 2, 3, 4, 5$.

The amplifier A_1 provides a gain of 5 to get a 3 V_{pp} signal at the input of the RC filter. As our minimum measurement frequency, f_m is 10 times higher than the cutoff frequency, even at $f_m = 5$ kHz, we get an output signal level around 350 mV_{pp}. As we increase the frequency to $2f_m$, $4f_m$, $8f_m$, $16f_m$ and $32f_m$, the signal is very much attenuated. In order to improve the signal strength, we introduce a gain, $A_2 = 10$ at the output of the filter to keep the signal within the measurable range.

The sensor is a 16 cm $\times$ 16 cm metallic plate and picks a lot of noise from the environment. Moreover, the presence of various metallic objects in the room also modify the electric field. We assume that these modifications are almost static for all measurement subjects and should cancel out in relative measurements.

Since we know the values of the input frequencies, we remove the noise using a filter bank as shown in Fig. 3. The filter bank consists of 6 fourth-order Butterworth bandpass filters with quality factor, Q = 5 each centered at a frequency, f given by Eq. (3). Ideally, we would like to get a passband gain of 1, but due to the difference between the calculated values of the components and the nominal values of the

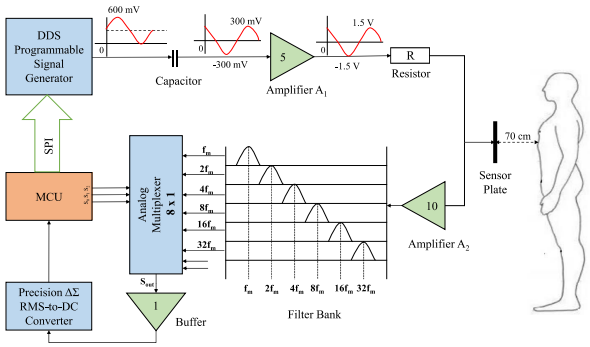

Fig. 3. Design of front-end interface circuitry to measure the RF absorption signatures

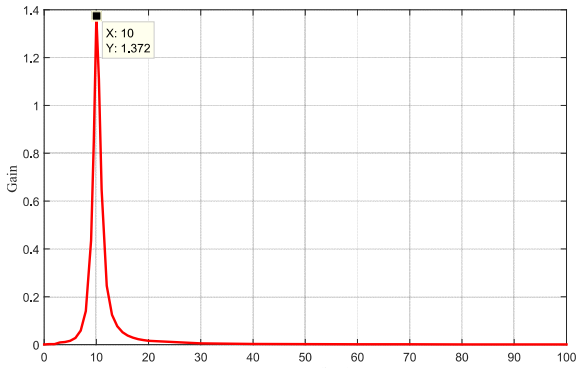

Fig. 4. Measured frequency response of 4th-order Butterworth bandpass filter with Q = 5 and f_c = 10 kHz

components, we end up with a slightly different gain at center frequency. Moreover, the filters with high Q-factor are highly sensitive to component tolerances. For instance, the measured frequency response of the filter centered at $2f_m$ i.e., 10 kHz is shown in Fig. 4. Since the gain at the center frequency for each filter is not exactly 1, the frequency response for each filter is measured. In this way, we were able to determine the overall gain for each frequency from sensor output to buffer output, hence we were able to accurately compute the output of the sensor. At the output of the buffer, a precision $\Delta\Sigma$ RMS-to-DC converter converts the RMS value of the signal to DC, which is sampled by the built-in ADC of the MCU.

When the MCU programs the DDS to generate a certain frequency given by Eq. (3), it also selects the corresponding filter. As the input signal RMS value is already known, it becomes quite straight forward to compute the gain in dB for each frequency. Fig. 5 shows a snapshot of the front-end interface circuitry, while the complete experimental setup is shown in Fig. 6.

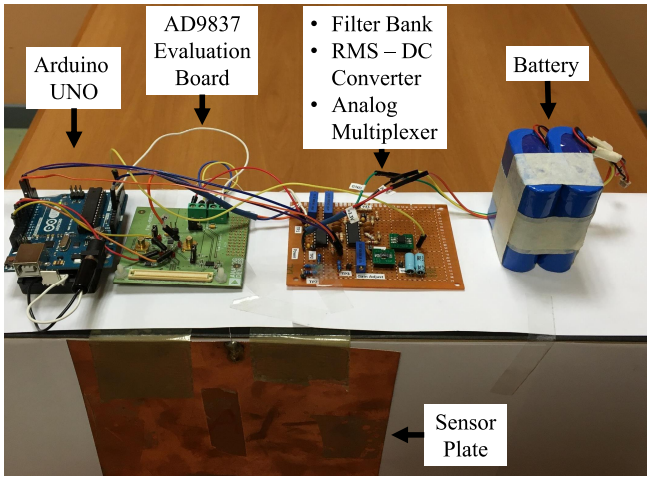

Fig. 5. Front-end interface circuitry

Fig. 6. Experimental setup

IV. Experimental Results and Discussion

Using the automatic experimental setup given in Section II, the experiment was initially performed in a static environment, i.e., without anybody near the sensor, and the gain values were recorded. Next, four different people from the same age group and with same height but with different weights were selected for experimentation. This implies that the selected individuals had a different Body-Mass-Index (BMI). The same experiment at the aformentioned set of frquencies was performed for each individual, standing at a fixed distance of 70 cm, facing the sensor plate.

Fig. 7 shows the measured RF absorption signatures of the four different bodies, with different BMI in the 5 kHz to 160 kHz frequency range. We observe that the gain curves have a significant distance between them for the people with significantly different BMI. For example, body 1 and 2 differ in weight just by 5 kg, so we have a smaller distance between their respective gain response curves. On the other hand body 2 and 3 have a difference of 17 kg, so we have a notably larger distance between their gain response curves. It can also be seen that higher frequencies provide better sensitivity.

Fig. 8 shows the gain response curves plotted against the body weights for different frequencies. The sensitivity to BMI is very low at frequencies f_m and $2f_m$, but as we go from $4f_m$ to $32f_m$, the gain curves show a significant sensitivity.

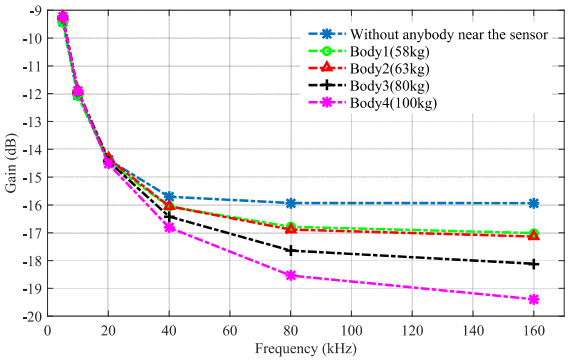

Fig. 7. Measured RF absorption signatures for different bodies

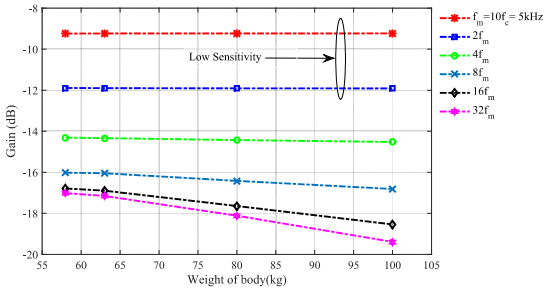

Fig. 8. Measured gain vs. weight of the body

A. Positive Aspects

Our sensor consists of cheap and low-power hardware and a simple front-end interface circuitry, which makes it possible to implement a portable battery powered sensor node. Moreover, contrary to other solutions, our sensor node needs to transmit just a small set of measurements, when connected in a wireless sensor network (WSN) configuration.

Furthermore, since we exactly know the input sinusoidal excitation frequencies, it is very easy to implement filters with high Q-factor to suppress the unwanted noise.

B. Observed Deficiencies and Possible Solutions

The results presented in this paper are based on the measurements taken by a single capacitive sensor node, while the subject standing at a fixed distance and fixed body orientation. It is observed that in order to achieve robustness we need to use multiple sensor nodes in a WSN configuration, and train the system for distance scaling and different body orientations. Afterwards, various classification algorithms could be employed for the decision making.

Another observed weakness of the sensor is the effect of low frequency noise from the mains supply lines at the input of the RMS-to-DC converter, which causes a small error in the measurements. This problem could be resolved by introducing two notch filters centered at the first two harmonic frequencies of the mains power, at the input of the RMS-to-DC converter.

Moreover, the filters with high Q-factor have low tolerance resilience in terms of passive component values. The implementation of filters require higher levels of sophistication and adeptness to exactly match the calculated values to the real values. The availability of passive components with very small values of tolerence can solve this problem.

V. Future Work and Suggested Improvements

In the future, we intend to study whether capacitive sensors could be employed to sense gender and age-related changes of the electrical properties of the human body, in order to distinguish between a male, a female, a child, an adult or an old person.

A. Optimal Measurement Frequency Band Exploration

As mentioned in section I, the electrical properties of human body are strong and nonlinear functions of frequency. So, it is worth exploring that in what frequency range we get the highest sensitivity to human proximity. We are keen to extend our measurement frequency range from a few kHz to several MHz in order to find a set of frequencies over which we get the highest variance of capacitive sensor impedance due to interaction with different human bodies with distinct physiological traits.

B. Distance Scaling and Moving Objects

We aim to experimentally study the effects of distance scaling, body orientation and moving objects on the response of the sensor. It requires multiple measurements and repeated experimentation to collect enough data for the classification purpose.

C. Multiple Sensor nodes in WSN Configuration

In future, we target to experiment with at least four sensor nodes in WSN configuration, installed on the four walls of a 3m$\times$3m room. Each node would transmit its measurements to a central data-processing unit, for different positions and orientations of the human body. Then we shall determine, how many repeated measurements for different weight catagories are required to take a robust and accurate decision on the identity of the person under test.

D. Hardware Optimization and Power Management

The present work was done using on bench hardware. In the future we shall optimize the hardware for minimum power consumption by using least possible computational resources and low power analog components.

In our application, the sensor node does not need to keep awake all the time, rather it is enough to repeat measurements once in a few seconds. So we shall experimentally compute the time required to take one set of measurements over the selected frequencies. Then, we shall determine the wake and sleep cycles for the sensor node. This would bring the overall power consumption of the sensor to a sufficiently low level.

VI. Conclusion

This work presents an experimental study to examine the use of capacitive sensors for human identification. We checked, whether human bodies with different BMI have different influences on electric fields at different frequencies. In order to do this, we used a loading mode capacitive sensor i.e., a square metallic plate of side 16 cm in lowpass filter configuration and measured its magnitude response by placing different human bodies at a distance of 70 cm from the sensor. We selected four male individuals with almost the same height but different body weights and measured the RC lowpass magnitude response for each at different frequencies. The experimental results show significantly different response curves for each body, proportional to the weight. From our experimental results, we conclude that capacitive sensors can successfully distinguish between the people with significantly different physical traits, such as weight in our case.

Moreover, from our results, we are able to infer that if we increase the number of sensors, we may be able to design an indoor human identification system, which can discriminate among people with distinct physiological properties with better accuracy. We expect that our sensor can be used to implement indoor wireless sensor networks (WSN) for smart indoor monitoring solutions for healthcare of elderly people.

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