Wang, Lijuan, Yan, Yong, Chen, Chih-Yen, Alessi, Enrico, Gubellini, Luca and Fabio, Passaniti (2025) *Human presence and motion detection through electrostatic sensing*. Measurement: Sensors, 38 (Suppl.). ISSN 2665-9174.

Measurement: Sensors 38 (2025) 101705

Contents lists available at ScienceDirect

Measurement: Sensors

journal homepage: www.sciencedirect.com/journal/measurement-sensors

Human presence and motion detection through electrostatic sensing

ARTICLE INFO

Keywords:
Human motion detection
Non-contact sensing
Electrostatic sensors
Characterisation

ABSTRACT

Human motion detection is essential in a wide range of applications. In view of the advantages of non-contact sensing, high sensitivity, fast response, simple installation and low cost, electrostatic sensors in different sizes and arrangements have been developed for human motion detection recently. This paper evaluates for the first time the performance of electrostatic sensors for human presence and motion detection. Experimental tests were conducted to obtain and analyse sensor signals of typical walking and stepping motions. The effects of sensor location, ambient conditions and the subject under test on the sensor output are quantified through systematic experimental testing.

1. Introduction

Human motion detection plays an important part in the areas such as health care, public safety, access control and smart homes etc. To sense human movement activities, contact and non-contact measurement systems based on inertial measurement unit sensors [1,2], cameras [3,4], radars [5,6], radio frequency devices [7] have been proposed. However, these methods have their limitations such as complex sensor arrangement, high power consumption, high cost and privacy concerns.

In recent years electrostatic sensors have been proposed for human motion detection due to the advantages of non-contact sensing, high sensitivity, fast response, simple installation and low cost. Kurita et al. [8–11] used a single electrostatic sensor with different electrode sizes to sense the motions including stepping, walking, standing up and sitting down. Takiguchi et al. [12] and Li et al. [13] realized steps counting and gait analysis, respectively, with a single electrostatic sensor. Kurita [14] and Tang et al. [15] designed four electrodes in a square configuration and five electrodes in a planar arrangement, respectively, for hand movement detection and gesture identification. The sensors used in the above research are fixed at a certain distance away from the subject under test. Wearable electrostatic sensors attached to the wrist, ankle or chest of a subject have also been proposed to detect the subject movements such as hair touching, scratching, walking, jogging, leg lifting and lowering, arm swing, sitting down and standing up [16–18]. However, the characteristics of the electrostatic sensors for such applications have never been systematically assessed. Such characteristics are important for the understanding and optimised design and applications of electrostatic sensors.

This paper analyses the sensing process of electrostatic sensors through analytical modelling where capacitive coupling between the electrode, human body and the surrounding environment is considered. To evaluate the characteristics of electrostatic sensors for human motion detection, experimental tests were conducted under a range of laboratory conditions. The effects of sensor location, ambient conditions and the subject under test on the sensor output are quantified and their implications for future applications for human motion detection discussed.

2. Modelling of electrostatic sensing

When a person interacts with the surrounding environment, such as walking, stepping, jumping on an insulated floor, the human body becomes triboelectrically charged. As the charge builds up on the body, high electric potential develops. The capacitance between the human body and the ground changes during body movement, mostly due to variations in the distance between the limbs and the floor, resulting in the variation in the electric potential of the body. The variations in the electric field around the human body can be detected using an electrostatic sensor [19].

The charged human body can be modelled as a plate of a capacitor whilst the sensing electrode itself is modelled as the other plate, as shown in Fig. 1. The capacitive coupling between the human body and the electrode is denoted as C. The human body is capacitively coupled to the ground through the air (C_a), shoe soles (C_s) and floor (C_f). Whilst, the electrode is capacitively coupled to the ground through C_e [8,18,20].

Assuming that the net charges on the body and the electrode is Q_b and Q_e respectively, the electrical potential difference U_{be} between the body and the electrode can be expressed as:

$$U_{be} = U_b - U_e = \frac{Q_b}{C_a + \frac{C_s C_f}{C_s + C_f}} - \frac{Q_e}{C_e} \tag{1}$$

It is clear that the changes in the net charges Q_b, Q_e and coupling capacitances C_a, C_s, C_f and C_e will result in the variation in U_{be}. Therefore, there are a few factors including the sensor location, ambient conditions, and materials of clothing, shoe soles and floor which all affect the sensor output. As the parameters in equation (1) are difficult to quantify in practical applications, experimental tests were conducted to evaluate the effects of these factors on the sensor output.

https://doi.org/10.1016/j.measen.2024.101705

Available online 30 December 2024

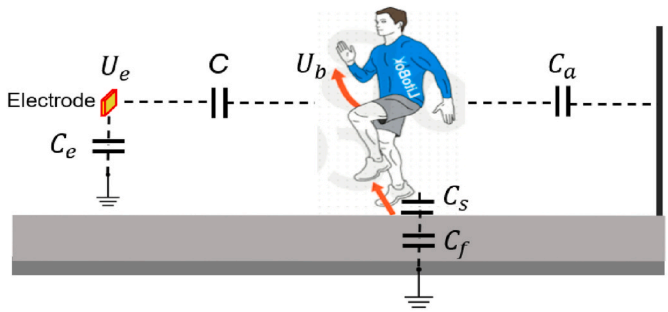

Fig. 1. Modelling of the electrostatic sensing for human motion detection.

3. Experimental results and discussion

3.1. Experimental setup

The electrostatic sensor used in this study is a commercial sensor (Qvar [20]). It is an electrical potential sensing channel able to measure the quasi-electrostatic potential changes. The Qvar sensing channel can work with one or two electrodes. The single electrode configuration with the electrode size of 16.4 mm × 9.4 mm is chosen in the tests. As shown in Fig. 2, the Qvar sensor was fixed on a non-metallic rod facing directly toward the human subject. The human subject was a middle-aged man with a height of 170 cm and a body weight of 65 kg. All the tests were conducted in the same room with PVC flooring. The ambient conditions, including temperature, relative humidity (RH) and dust level (PM2.5 and PM10), were measured and recorded during the tests using a commercial air quality monitoring instrument (TemTOP LKC-1000S). Effort was made to keep the environment conditions as the same as possible. The data sampling rate was set to 240 Hz.

3.2. Sensor signals due to typical motions

A simple test was conducted to observe the sensor output when the human subject performed stepping motion at a fixed location and during walking, respectively. As shown in Fig. 3, each pulse in the sensor output presents a step. As the subject repeats the same motion, the amplitude of the sensor output remains a similar level.

When the subject moves away from the sensor, the amplitude of the sensor output, as shown in Fig. 4, decreases accordingly. When the subject moves towards the sensor, stronger electrostatic induction is sensed by the sensor and hence the higher signal amplitude. In this case, it is possible to identify the directionality of the subject with reference to the sensor location by analyzing the changing trend of the signal amplitude.

3.3. Effect of sensor location

To investigate how the output of the sensor varies with the sensing distance, the angle of the human subject and the sensor height, a series of tests were conducted. The distance between the subject and the sensor varies from 60 cm to 300 cm with an increment of 30 cm and the angle is set to a value between 0° and 180°, respectively. The sensor was fixed on

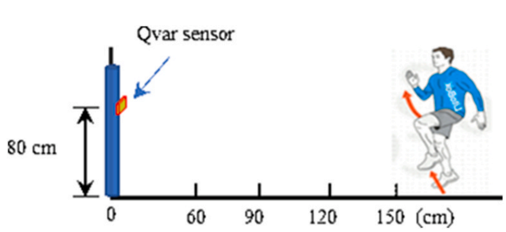

Fig. 2. Experimental arrangement.

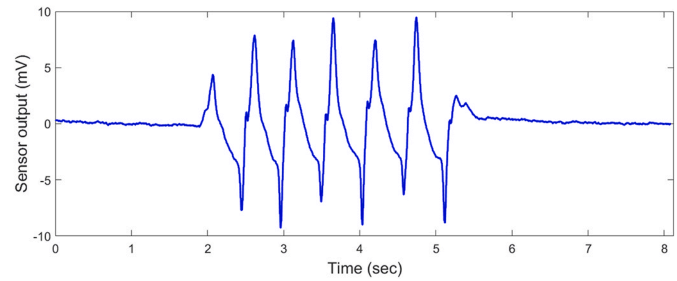

Fig. 3. Sensor output due to subject stepping.

the supporting rod at three different heights, 60 cm, 80 cm and 100 cm. Again, ambient conditions were kept the same during the tests. Meanwhile, the human subject wore the same clothing and shoes. At each location the stepping motion consists of five regular steps and each test repeats for five times.

The RMS values of the sensor signal as a function of the sensor distance and angle for three different sensor heights are plotted in Fig. 5. It is clear that the sensor output reduces rapidly with the distance between the subject and the sensor. This declining trend with the distance is consistent with the theoretical prediction that the sensor output amplitude is more or less inversely proportional to the distance for a human subject. For different sensor heights, the strongest sensor output is always obtained at a distance of 60 cm which is the shortest distance that can be tested. The sensor height affects the sensor output with the 80 cm height giving the highest signal magnitude. It is not surprising that this height is about half of the subject height. Even though the signal becomes very weak at a distance of 300 cm, the human movement is just detectable.

The sensor output as a function of angle for the sensor height of 80 cm is plotted in Fig. 6. As expected, the sensor output at 90° is the strongest and weakest at 0° and 180°. This is because the effective area of the electrode for electrostatic induction at 90° (i.e. perpendicular to the electrode plane) is the largest compared with other angles.

3.4. Effect of ambient conditions

The sensor was fixed at a constant height of 80 cm and faced directly to the human subject. The relative humidity changed from 65 % to 50 % whilst other ambient conditions remained constant. The sensor output under different humidity conditions is depicted in Fig. 7.

The senor output presents consistently a declining trend with relative humidity. As expected, the relative humidity is an important factor affecting the sensor performance. Higher relative humidity gives a lower signal amplitude.

3.5. Effect of clothing

The human subject wearing the same shoes but three different types of clothing, as illustrated in Table I, performed repeated marching motion. The sensor was also fixed at a height of 80 cm. As shown in Fig. 8, the sensor output depends on the type of clothing. At different distances, the sensor outputs for Types II and III clothing are similar but significantly stronger than that for Type I. This is because the whole body of the subject was covered by clothing in Types II and III. However, the thickness of the clothing has less effect on the sensor output.

3.6. Discussion

Experimental results demonstrate the sensing distance of the Qvar sensor can reach as far as 300 cm. This distance may be extended if a larger electrode is used. At the angle of 90° the sensor produces the strongest signal at the same sensor distance. The senor output presents consistently a declining trend with relative humidity, confirming that

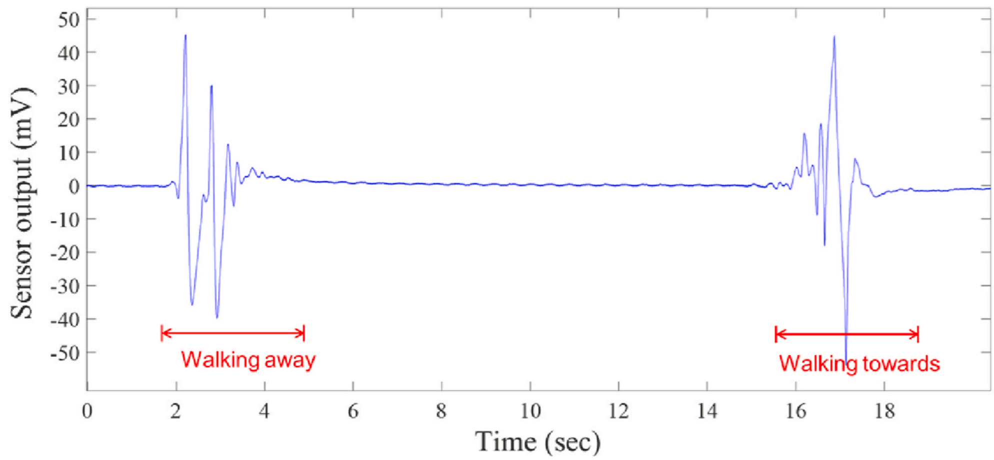

Fig. 4. Sensor output for a subject walking away and towards the sensor.

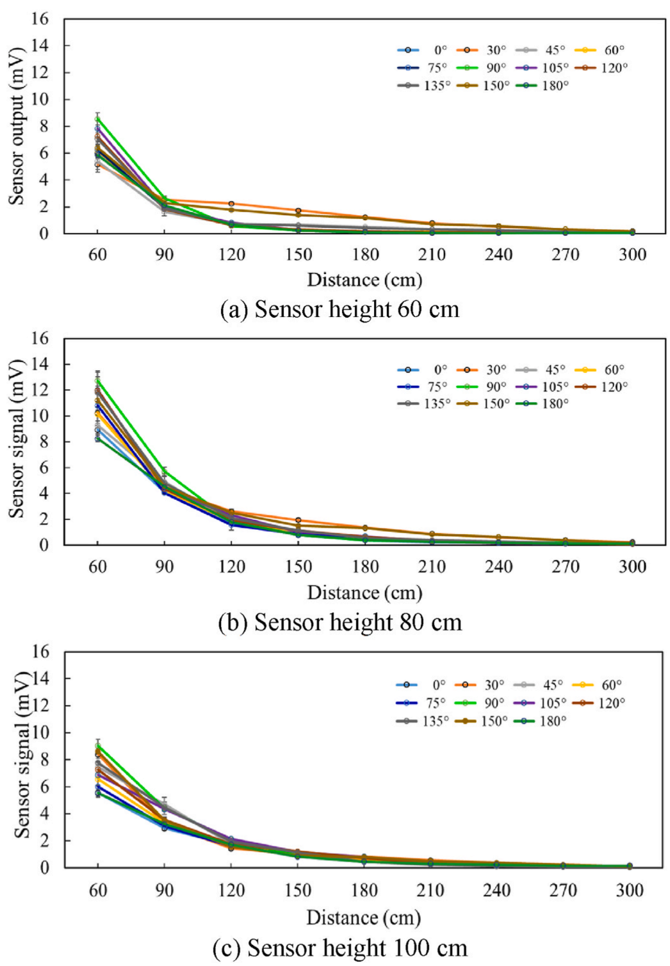

Fig. 5. Sensor output versus distance for three sensor heights.

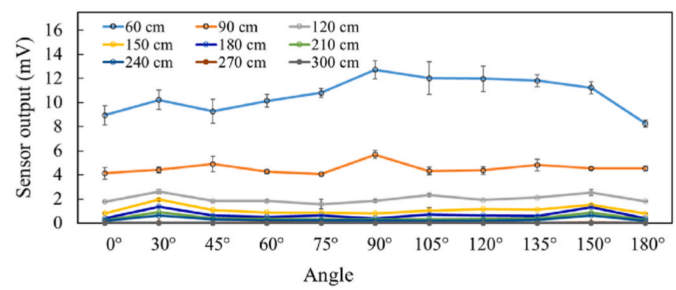

Fig. 6. Sensor output versus angle for sensor height of 80 cm.

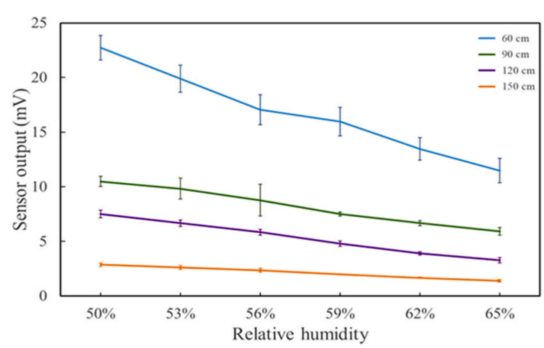

Fig. 7. Sensor output under different humidity conditions.

Table 1
Types of clothing.

Type I	Type II	Type III
Short sleeve T-shirt; Gym shorts	Long sleeve T-shirt; Sport pants	Slim jacket; Long sleeve T-shirt; Sport pants

relative humidity is an important factor. This is a common limitation of all electrostatic sensors though its effect may be compensated if the humidity is measured concurrently with the sensor output. The area of the subject covered by the clothing affects the magnitude of the sensor output, however, the thickness of the clothing has less impact on the sensor output. The effects of other factors, such as materials of shoe soles, floor materials and body conditions of the subject under test will be explored in future.

4. Conclusions

A single electrostatic sensor has been evaluated for human motion detection. To characterize the performance of the sensor, walking and stepping were performed and the effects of sensor location, ambient humidity and the clothing of the subject are evaluated. The experimental results have demonstrated that the electrostatic sensors have potential applications in residential homes, rehabilitation clinics, hospitals, nurseries, smart homes and safety critical environments. Good

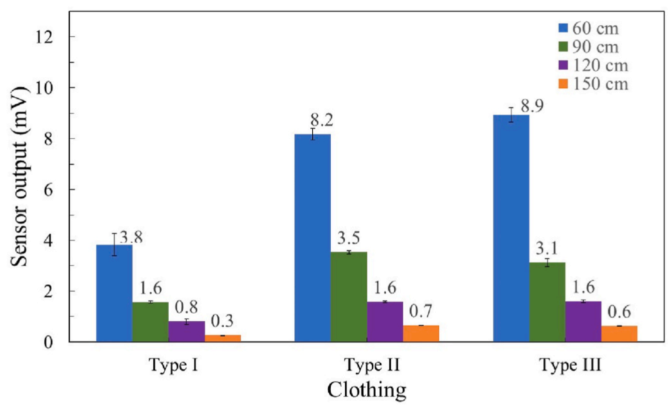

Fig. 8. Sensor output under different clothing conditions.

progress has already been made in applying embedded electrostatic sensors for human presence detection for laptop applications and smart lighting.

References

[1] Q. Macret, G. Gagnon-Turcotte, M. Bielmann, C.L. Fall, L.J. Bouyer, B. Gosselin, A wearable sensor network with embedded machine learning for real-time motion analysis and complex posture detection, IEEE Sensor. J. 22 (2022) 7868–7876, https://doi.org/10.1109/JSEN.2021.3139588.

[2] O.C. Kurban, T. Yidirim, Daily motion recognition system by a triaxial accelerometer useable in different positions, IEEE Sensor. J. 19 (2019) 7543–7552, https://doi.org/10.1109/JSEN.2019.2915524.

[3] S. Motiian, F. Siyahjani, R. Almohsen, G. Doretto, Online human interaction detection and recognition with multiple cameras, IEEE Trans. Circ. Syst. Video Technol. 27 (2017) 649–663, https://doi.org/10.1109/TCSVT.2016.2606998.

[4] Y. Liu, Human motion image detection and tracking method based on Gaussian mixture model and CAMSHIFT, Micropocessors and Microsystems 82 (2021) 103843, https://doi.org/10.1016/j.micpro.2021.103843.

[5] R. Zhang, S. Cao, Real-time human motion behavior detection via CNN using mmwave radar, IEEE Sens. Lett. 3 (2019) 3500104, https://doi.org/10.1109/LSENS.2018.2889060.

[6] N. Maaref, P. Millot, Ch Pichot, O. Picon, A study of UWB FM-CW radar for the detection of human beings in motion inside a building, IEEE Trans. Geosci. Rem. Sens. 47 (2009) 1297–1300, https://doi.org/10.1109/TGRS.2008.2010709.

[7] Z. Dong, F. Li, Z. Li, K. Pahlavan, A study of on-body RF characteristics based human body motion detection, IEEE Sensor. J. 22 (2022) 3442–3453, https://doi.org/10.1109/JSEN.2021.3139735.

[8] K. Kurita, S. Ueta, A new motion control method for bipedal robot based on noncontact and nonattached human motion sensing technique, IEEE Trans. Ind. Appl. 47 (2011), https://doi.org/10.1109/ICEMS.2009.5382670, 2022-1027.

[9] K. Kurita, Human identification from walking signal based on measurement of current generated by electrostatic induction, in: 2011 International Conference on Biometrics and Kansei Engineering, Takamatsu, Japan, Sept. 2011, pp. 19–22, https://doi.org/10.1109/ICBAKE.2011.12.

[10] K. Kurita, S. Morinaga, Noncontact detection of movements of standing up from and sitting down on a chair using electrostatic induction, IEEE Sensor. J. 19 (2019) 8934–8939, https://doi.org/10.1109/JSEN.2019.2921379.

[11] K. Kurita, Non-contact detection technology for individual characteristics of motorcycle riding operation using electrostatic induction, Measurement: Sensors 18 (2021) 100118, https://doi.org/10.1016/j.measen.2021.100118.

[12] K. Takiguchi, T. Wada, S. Toyama, Human body detection that uses electric field by walking, J. Adv. Mech. Des. Syst. Manuf. 1 (2007) 294–305, https://doi.org/10.1299/jamdsm.1.294.

[13] M. Li, P. Li, S. Tian, K. Tang, X. Chen, Estimation of temporal gait parameters using a human body electrostatic sensing-based method, Sensors 18 (2018) 1737, https://doi.org/10.3390/s18061737.

[14] K. Kurita, A novel non-contact hand motion classification technique for application to human machine interfaces, in: SICE Annual Conference, Tokyo, Japan 13-18 Sept, 2011.

[15] K. Tang, P. Li, C. Wang, Y. Wang, X. Chen, Real-time hand position sensing technology based on human body electrostatics, Sensors 18 (2018) 1677, https://doi.org/10.3390/s18061677.

[16] A. Pouryazdan, R.J. Prance, H. Prance, D. Roggen, Wearable electric potential sensing: a new modality sensing hair touch and restless leg movement, in: Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct, 2016, pp. 846–850, https://doi.org/10.1145/2968219.2968286.

[17] G. Cohn, S. Gupta, T.J. Lee, et al., An ultra-low-power human body motion sensor using static electric field sensing, in: Proceedings of the 2012 ACM Conference on Ubiquitous Computing, 2012, pp. 99–102, https://doi.org/10.1145/2370216.2370233.

[18] Y. Hu, Y. Yan, A wearable electrostatic sensor for human activity monitoring, IEEE Trans. Instrum. Meas. 71 (2022) 4009410, https://doi.org/10.1109/TIM.2022.3214295.

[19] Y. Yan, Y. Hu, L. Wang, X. Qian, W. Zhang, K. Reda, J. Wu, G. Zheng, Electrostatic sensors – their principles and applications, Measurement 169 (2021) 108506, https://doi.org/10.1016/j.measurement.2020.108506.

[20] AN5755 Qvar sensing channel. Online [accessed 22 April 2024] https://www.st.com/resource/en/application_note/an5755-qvar-sensing-channel–stmicroelectronics.pdf.

Lijuan Wang[a,*], Yong Yan[a], Chih-Yen Chen[a], Enrico Alessi[b], Luca Gubellini[c], Fabio Passaniti[b]

[a] *School of Engineering, University of Kent, Canterbury, UK*
[b] *STMicroelectronics, Catania, Italy*
[c] *STMicroelectronics, Agrate, Italy*

[*] Corresponding author.
E-mail addresses: l.wang@kent.ac.uk (L. Wang), y.yan@kent.ac.uk (Y. Yan), chihyenorama@gmail.com (C.-Y. Chen), enrico.alessi@st.com (E. Alessi), luca.gubellini@st.com (L. Gubellini), fabio.passaniti@st.com (F. Passaniti).