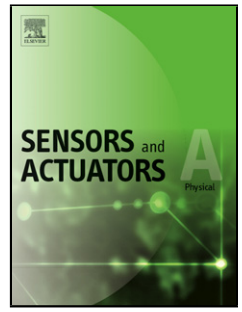


Smart-Cover: A Real time sitting posture monitoring system

Arif Reza Anwary, Deniz Cetinkaya, Michael Vassallo, Hamid Bouchachia, IEEE

PII: S0924-4247(20)31766-0

DOI: https://doi.org/10.1016/j.sna.2020.112451

Reference: SNA 112451

To appear in: *Sensors and Actuators: A. Physical*

Received Date: 28 March 2020

Revised Date: 27 August 2020

Accepted Date: 17 November 2020

Smart-Cover: A Real Time Sitting Posture Monitoring System

Arif Reza Anwary[a,*], Deniz Cetinkaya[b], Michael Vassallo[c] and Hamid Bouchachia[b], Senior Member, *IEEE*

[a] *Swansea University Medical School, Swansea University, UK*, [*]correspondence email a.r.anwary@swansea.ac.uk
[b] *Department of Computing and Informatics, Bournemouth University, UK*
[c] *Royal Bournemouth Hospital, UK*

Graphical abstract

Figure 1: Architecture of the proposed prolonged and asymmetric sitting posture monitoring system

Highlights

- Design and develop new hardware and a novel pressure sensing architecture embedded in the seat covering to a) study human sitting biomechanics, b) reduce sensor noise through filtering, c) transfer collected data to a cloud using IoT and d) develop a wireless charging facility. Considering the manufacturability, customizability and adaptability of the equipment.
- Classify the level of asymmetry of sitting posture using a rule-based system.
- Design and develop a new end-point device application that uses IoT to a) summarise and show an overview of sitting balance and posture, b) using visual displays that provide sitting information including level of asymmetry, active and static sitting and c) deduce a day based summary score.

***Abstract*— Prolonged asymmetrical sitting is common and can exacerbate musculoskeletal back pain and spinal deformities. Monitoring sitting posture can help maintain correct posture and prevent health problems. Currently posture is assessed by expert clinicians using subjective visual observation. More objective methods involve the use of a gold-standard motion capture system in Laboratories, which is expensive and not widely available. We develop a Smart-Cover, an automatic system to provide real time visualization and information about sitting posture. A Sitting Pressure Sensor (SPS) is built using Velostat, conductive fabric and foam to collect pressure distribution information within the seat surface. The data are collected from 10 healthy young subjects where each subject sits for 30 minutes and are transferred to a cloud server using Internet-of-Things (IoT). A rule-based classifier is used to provide timely notification to users about sitting duration and level of asymmetry. A new end-point device application is developed to show sitting balance. Dial based displays show level of asymmetry, active and static sitting, and daily summary score. Our system is**

user friendly, inexpensive, automatic and quantitative method for evaluating posture in real time, which has the capability of providing quantitative information about sitting behaviour. The results show that our system can be used for objective monitoring of sitting posture which has medical and social benefits. Smart-Cover can support the management of patients during their rehabilitation by monitoring pressure areas and balance when seated. In addition, it offers users at home, schools and offices the means to improve their sitting posture.

Index Terms— **Wearable Sensors; Prolonged Sitting; Sitting Disease; Posture Monitoring; Pressure Sensors; Sitting Asymmetry; Internet of Things; Fuzzy Classifier.**

1. Introduction

SITTING in a straight, upright, symmetrical and stable posture is not only associated with good health, but also depicts a positive image of a dynamic person, alongside being a good practice to avoid the 'sitting disease'. It has been reported that 43% of adults and 83% of students spend more than 10 hours a day seated on a chair [1]. Indeed, prolonged sitting seems to be the new norm for many. Significant changes in social behaviours and arrangements, related to one's work, commute, communication, entertainment and home are often leading people to prolonged periods of sitting [2-4]. On the other hand, the benefits of exercise are well recognized; but prolonged sitting has only been associated with a wide range of medical ailments including musculoskeletal, cardiovascular, cerebrovascular disease (strokes), type 2 diabetes mellitus, decubitus ulcers, early death and some malignancies [4, 5].

Prolonged sitting results in ergonomic spinal deformity and asymmetry [6]. The risk of pressure ulcer development over one's buttocks is high during prolonged sitting as the soft buttock tissue gets squashed between two hard surfaces: the seat and the bones of one's pelvis [7]. Sitting asymmetry caused by prolonged incorrect posture such as slouching to one side, resting one's chin on a hand or resting on folded arms; leads to one's spine being bent abnormally. In addition to this keeping one's arms crossed, knees and ankles bent, or carrying thick objects such as wallets or phones in rear pockets, while seated; often results in pelvic asymmetry and lack of posture alignment with the rest of the spine. Such ergonomic deformity can result in non-neutral spine positioning which in turn might cause spinal muscular spasm and spinal imbalance [6] finally leading to permanent deformity such as scoliosis, lordosis, kyphosis and chronic low back pain [8, 9]. Such postures are not recommended even for short time periods. The asymmetry discussed above results in a reduction in pan-seat contact area [10].

The economic impact of this is significant. Back pain alone is one of the common causes of absence from work and disability worldwide [11]. Back pain increases with age but can occur across all ages. Studies indicate that 7.3% (540 million people) of the world population can be affected by it at any time. With an ageing world population this burden is set to get worse in the future particularly for low to middle income earners [12]. Although no causal effect of poor posture on low back pain has not been proven [13], occupational groups that are more likely to be associated with poor posture and prolonged sitting for several hours at a time are more likely to get back pain [14].

The need to assess posture is therefore clear. The methods used however are often subjective and based on visual observation by trained practitioners such as physicians, physiotherapists or researchers [15]. They use clinically validated scales such as Postural Assessment Scale [16] or Posture Index [17] but interpretation of these is subjective and dependent on visual observation, clinical expertise and experience; sometimes resulting in poor inter-rater reliability. In addition, such assessments often take place in artificial conditions that are not the norm for the subjects being assessed. Subjects are often assayed in laboratories, clinics or hospitals on equipment they are not familiar with [15]. More objective gold-standard benchmarks such as a Motion Capture System [18] can analyse posture. This equipment is not widely available as it is expensive and laboratory based. In addition, this requires technically trained clinical staff to operate them. They also require the patients to attend in person to dedicated clinics for an assessment. There are other systems in development for posture monitoring. For instance in [19], a flexible three layers printed pressure sensing system is proposed, classifying four leaning sitting angles (forward, backward, right and left). The top layer is screen printed to form conductive interdigital electrodes on a polyethylene terephthalate sheet, a sensing layer is printed on the bottom sheet for pressure sensing and an adhesive layer is used in the middle for spacing and adhesion. The polyethylene terephthalate sheet is hard and may be uncomfortable to sit on. In addition, there is no information about the durability of the adhesive to repeated mechanical sensor deforming with sitting. In [20], a bank of real-time textile pressure sensors is introduced as a building block of a sitting posture correction system. The sensors consist of conducting Ni-Ti alloy fiber and a pressure-sensitive polyurethane elastomer resulted in reliable capacitance change by an applied pressure. Although, the system shows high accuracy and responsiveness, the Ni-Ti alloy fiber elastic material approaches its yield stress, the sensitivity may be compromised as the plastic phase begins and the change in separation distance becomes less observable and with elastic hysteresis. The elastic hysteresis characteristics change with many parameters (e.g. weight of the individual subject, longitudinal uses and many more) which may affect the accuracy. Closer to the proposed system, the authors in [21] described a piezoresistive pressure distribution sensor for sitting analysis. Such a sensor is designed with Velostat and matrix of electrodes where surfaces are covered with adhesive vinyl films. The sensors are placed on a rigid acrylic board. Sitting on an acrylic board will be neither comfortable, nor compatible with conventional chairs. Four load cells are used to assess in real-time six different postures of a seated person [22]. The load cells are placed four locations on a chair and a cushion is placed on the top of the load cells. The size of the load cell covers a small area and it measures only the vertical downward pressure. The majority of the pressure is distributed outside the load cell region, while the cushion is not rigid. Hence, a slight change in the same sitting position may result in a different output signal. Based on these studies, it becomes clear that there still is a need to develop innovative ways of evaluating posture that can provide real-time feedback to users.

In this study, we design, develop and implement a novel user-friendly smart seat cover to monitor sitting posture. The users can visually assess and get feedback through a mobile phone application linked via Bluetooth to the seat cover. IoT technology enables such data to be gathered, processed, stored and finally visualized on end-point devices such as computers, tablets, smart-phones etc.

This study is the improvisation of our previous work [23] that investigated the basic sensor architecture which displayed instantaneous values without categorizing level of asymmetry and validation with subjects. This study therefore has three main contributions:

1) Design and develop new hardware and a novel pressure sensing architecture embedded in the seat covering to a) study human sitting biomechanics, b) reduce sensor noise through filtering, c) transfer collected data to a cloud using IoT and d) develop a wireless charging facility. Considering the manufacturability, customizability and adaptability of the equipment.
2) Classify the level of asymmetry of sitting posture using a rule-based system.
3) Design and develop a new end-point device application that uses IoT to a) summarise and show an overview of sitting balance and posture, b) using visual displays that provide sitting information including level of asymmetry, active and static sitting and c) deduce a day based summary score.

2. System Architecture and Design

We combine hardware and software components to develop a dynamic automatic sitting posture monitoring system, Smart-Cover that is able to study prolonged and asymmetrical sitting information. Figure 1 illustrates the architecture of the system identifying the various stages and processes involved.

Figure 1: Architecture of the proposed prolonged and asymmetric sitting posture monitoring system

2.1. Sitting Pressure Sensing (SPS)

A Smart-Cover that can measure pressure force, is constructed using woven silver conductive fibre, piezoresistive conductive film, polyethylene foam and conductive thread fabricated in layers. The resistivity of piezoresistive material changes when deformed, making them the ideal choice for use as pressure sensors [24, 25]. For our project we chose the anti-static Velostat, which is a type of piezoelectric conductive material with the characteristics of flexural modules 40,000-50,000 psi, usual thickness 104 µm, volume restively < 500 ohm·cm and tensile strength of 1,700-2,000 psi [26]. Conductive fabric consists of woven silver coloured yarns with the consistency of polyester (70±3%), copper (16±5%), nickel (14±2%) and plated nylon [27]. It has a resistance of less than 1 ohm per square foot. This material complies with ROHS requirements for being halogen free, washable, stretchable, and durable. Topping all that, it can also bend. These characteristics are crucial to integrate electronic functions in wearable devices.

According to our design, in between the Velostat layers, a layer of electric insulator is required. Polyethylene foams are widely available and commonly used for packing, storing and handling objects. They are ideal as they can be used in several ways, materials can easily be added to them and are easily used in the manufacturing process. We chose Cell-Aire® polyethylene foam for our project. It is 2.5 m thick, has a density of 1,2 pounds/cubic foot and punching test resistance of 5.5N in relation to standard SAC-PL 012 when damage free from damage [28]. The material also provides strong support and protection to the various layers of the seat.

We use conductive thread for wiring the sensors with the circuit. It is made from nylon, polyester and cotton coated with a metallic mesh consisting of a silver nanowire. Examples of non-conductive thread would essentially be cotton, nylon and polyester as they are insulators for electricity.

Force sensor architecture in [29] and [30] used a Velostat placed between two copper layers. With such a design prolonged use results in a tightening of the copper layer with the Velostat resulting in a loss of sensitivity. For this reason, we adopted the multi-layered architecture of the SPS using foam as demonstrated in Figure 2(a). A 2.5 mm polyethylene foam layer is placed between two Velostat layers and the whole is then sandwiched between two silver conductive fabric layers. These two Velostat layers are sewed using non-conductive thread to stop any slippage of the layers, which might occur when the seat is in use, as a result of pressure.

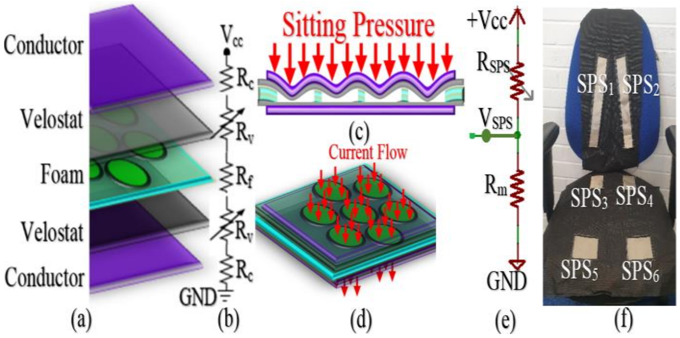


Figure 2: Sitting pressure sensing system; (a) Multi-layered architecture and components; (b) Schematic diagram of current path geometry (R_c, R_v and R_f are the corresponding resistances of woven silver conductive fabric, Velostat and polyethylene foam); (c) View of the loaded contact area due to sitting pressure; (d) Schematic diagram of the current path through contact layers; (e) Analog output reading V_{SPS} using voltage divider configuration; and (f) SPS1 to SPS6 arrangements on the face of a chair

The foam between the two Velostat layers has holes cut in a circular shape shown in Figure 2(a). When pressure is applied its shape squeezes and becomes thin and flexes due to sitting. Current then flows through these circular holes in a top to bottom direction. When there is no sitting pressure the foam regains its original shape and current stops flowing.

Figure 2(b) shows the modelling of the electrical components for use in the sensor. Let the resistance of conductive fabric be R_c, Velostat resistance be R_v and foam resistance be R_f. To increase the accuracy of the SPS output a correction is made for the contact resistance R_{cv} between conductive fabric and the Velostat. SPS resistance can therefore be calculated as $R_{SPS} = 2R_c + 2R_{cv} + 2R_v + R_f$. A number of assumptions had to be made to derive to the above formula, namely: since the conductive fabric is made of silver we assume resistance $R_c \approx 0$. Conversely foam resistance with no-load $R_f \approx \infty$ and load condition is $R_f \approx 0$. Using the Holm and Greenwood [31] formula, $R_{cv} = (\rho_1 + \rho_2)/4na$ where ρ_1 and ρ_2 are the electrical resistivity of the two materials in contact, a is the radius of contact area and n is the number of contact areas. As pressure increases the number of contact area increases (Figure 2c). As pressure is progressively applied, the upper surface of the SPS is deformed while the bottom remains flat decreasing the thickness of the layer. When pressure is applied there is a decrease in the distance between the filler particles inside the piezoresistive film, thus decreasing its resistance [30]. We have incorporated an air vent at the lower end of the SPS to enable air trapped between the conductor and Velostat to escape. This will lead to a sudden decrease in R_{cv}, and R_v between the conductive fabric and the Velostat followed by a flow of current from the top to bottom (blue arrows in Figure 2d). The blue arrows demonstrate the effective areas of contact. In reality they are much greater at a microscopic level due to the roughness of the surfaces [32]. In order to convert this pressure to voltage we design a voltage divider that measures and configures the resistance change from the SPS and match for impedance as shown in Figure 2(e). We therefore introduce R_m which is the resistance of the voltage divider. The output from the SPS can be expressed as $V_{SPS} = (R_{SPS} * V_{cc})/(R_m + R_{SPS})$ where V_{cc} is the supply voltage. In order to determine R_m we calculate the changes in V_{SPS} output arising from different pressures applied to the SPS in increments of Kgs getting a measure of force vs resistance [33]. For our work we set the value of R_m as 1K Ω and the supply voltage as +3.7V

Another important factor that determines the accuracy of the results is the location on the chair where the SPS are placed. The design of the SPS is to monitor symmetry of posture for extended periods of sitting. The location therefore needs to be based on analysis of the dimensions of the human body [34]. In a sitting position, shoulder width ranges from 375-505 mm, height 505-646 mm and hip width 310-405 mm [35]. Each SPS measures 50 x 300 mm in shoulder area and 70 x 100 mm in the seat cover.

Repetitive deformation due to sitting on the chair is an important issue for piezoresistive sensors [36]. The SPS accuracy is measured using a controlled load digital universal testing machine. We assume that the range of human body weight is between 50 kg and 100 kg and that the human sitting position covers 80% of a seat area amounting to 350 x 300 mm. The range of minimum to maximum pressure per square cm is then 0.06 kg to 0.12 kg. Therefore, the range of minimum to maximum pressure for the area of each SPS is from 4.2 kg to 8.4 kg. A digital universal testing machine is used to apply dynamic force from 1 kg to 10 kg and record the corresponding resistance of the SPS. The procedure is repeated 10 times for 10 days. The result of this experiment is shown in Figure 3.

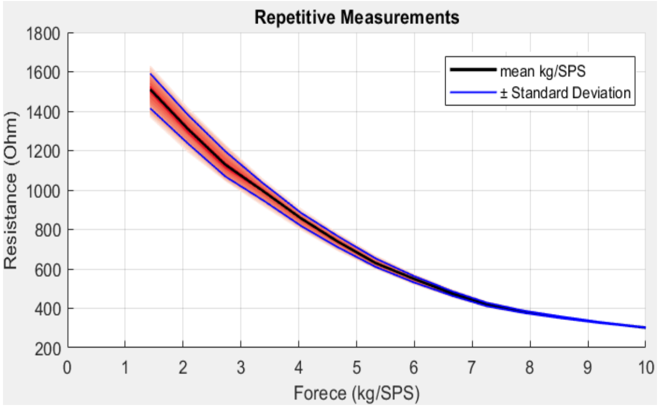


Figure 3: SPS deformation characteristics for 100 times repetitive measurements

The black line shows the mean estimation, while the blue lines show the ± standard deviation of 100 repetitive measurements. The error spread is high (approximately ±10%) during the low pressure (0 to 2kg) and gradually decreases (approximately ± 1%) during high pressure (9 to 10 kg). The average error for the region between 4.2 kg to 8.4 kg when a person sits on the chair is approximately ± 4%. The repeatability error for our case is lower where it shows up to 15% error performed with a controlled load machine [37]. As the purpose of this research is to show sitting asymmetry by measuring the relative difference between right and left sided pressure, this error will have minimal output effect. However, the process of minimizing this error will be explored in future work.

Human anatomy has also been taken into consideration. When sitting the bones of the spine need to align on top of each other to permit the paravertebral muscles to relax. This will result the lower back in a lordosis that will lengthen and relax the spine. The area covered by the shoulder can therefore vary from individual to individual. To sense the pressure from both shoulders we place the SPSs with a slight inclination to pick up input from people of small and large build.

For maximum coverage the seat cover is divided into 6 regions. The backrest is divided into right shoulder area and left shoulder area across the midline. The seat is divided into 4 regions.

1) Right lower back 2) Left lower back 3) Right thigh and 4) Left thigh. Two SPS are placed at the top of the centre line of the seat for the right and left thighs and two attached below the centre for right and left lower back as shown in Figure 2(f). These positions have been chosen to delineate the sitting pressure distribution for all these regions.

2.2. Raw Data Processing

As the SPS sensors are very sensitive, they record some noise. When at rest with no pressure the sensors demonstrate some minor activity. When activated the SPS sensors record noise arising from flicker noise, mechanical and stretching stimuli, temperature changes and calibration errors [38]. The readings are made of noisy spikes that need to be removed before analysis. We do this using a Kalman filter that uses advanced optimal reclusive filter techniques [39] in a two-step process. It estimates the current state variables in the first step. The estimates are updated using a weighted average, with more weight being given to estimates with higher certainty in the second step. It is recursive and it can run in real time, using only the present input measurements and the previously calculated state and its uncertainty matrix; therefore, no additional past information is required. Implementation of this Kalman filter results in significant noise reduction, hence obtaining a clear and usable distortion-free stable signal from the sensors [40]. Data is then transmitted wirelessly to the cloud using IoT cloud communication layer.

2.3. IoT Cloud Connectivity for SPS

The IoT communication layer uses pre-set rules to establish wireless connectivity between the sensors and cloud data storage [41]. This enables quick data storage and real-time data-analysis, enabling users to see results instantaneously. Communications are usually established using W-Fi [42], Bluetooth [43], ZigBee [44], and even cellular network. We use Wi-Fi and ESP8266 development board [45] as the conduit for data transmission to cloud server ThingSpeak^{TM} [46]. This enables the creation of a user account. A user can then make sensor-logging applications; applications that track location and a social network that enables status updates. This also allows the data to be stored from various IoT applications, using Wi-Fi, not only as a data packet carrier between the sensors and the ThingSpeak^{TM} cloud but also as a link to MATLAB for data analysis. The format we use is date (*dd/mm/yyyy*), time (*HH:MM:SS.ss*), clock (ms), and SPS (SPS_1, SPS_2, SPS_3,SPS_4, SPS_5, SPS_6).

2.4. Power Management

To maintain an extended active period of the equipment, an efficient power supply is required. The battery is charged using the Qi wireless power standard [47] inductive power transfer [48] technology. A DC 3.7 Volt 4000 mAh capacity battery is to operate the circuit. To extend the battery life we lower the duty cycle between the ThingSpeak^{TM} and Wi-Fi. Power is controlled by a push button switch with an On/Off option. The ON position activates the processor to start reading the SPS, the Wi-Fi transmitter to start data transfer and the circuit to become active. The circuit automatically reverts to sleep mode if no pressure changes are detected for a user defined period of time considered to be the threshold; and switches on by itself upon detection of pressure data by the SPS.

2.5. Circuit Design

In Figure 4(a) we demonstrate the block diagram of the circuit and the inductive wireless charging system. For the circuit we used Proteus ISIS Professional simulation software [49] developed by Labcenter Electronics Corporation Figure 4(b). Figure 4(c) demonstrates a 3D view of the circuit. More information on the PCB and 3DS files is provided in the supporting document. The circuit and the corresponding wireless charging system is shown in Figure 4(d).

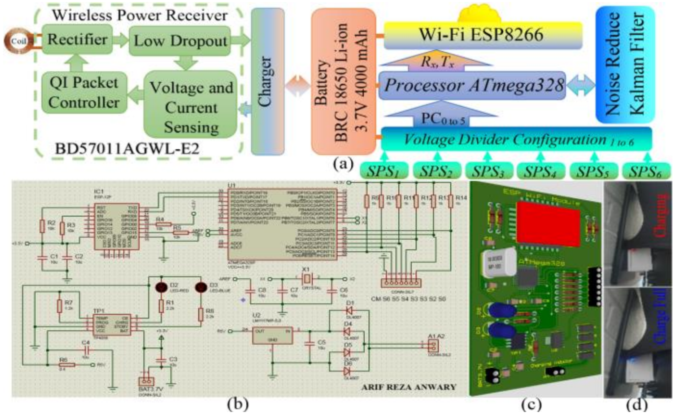


Figure 4: Hardware implementation (a) Circuit block-diagram, (b) Circuit schematic, (c) 3D view of the simulated circuit, and (d) Implemented circuit and wireless inductive charging

ATmega328 processor is used in the circuit. Six SPS are connected with a voltage divider configuration (Figure 4(a)). The outputs are connected with six analogue pins ($PC_{0\ to\ 5}$). The SPS sampling rate by the processor is 5Hz. Data gathered by $PC_{0\ to\ 5}$ is transmitted to ThingSpeak^{TM} cloud server using ESP8266 Wi-Fi. This uses UART serial communication to receive (*Rx*) and transmit (*Tx*) data. The *Rx* and *Tx* pins are connected with ATmega328 Pin PD_0 and PD_1. The inductive wireless QI receiver (BD57011AGWL-E2) is used to receive electrical energy. The QI receiver coil patch can charge up to 1000 mAh, 5V which is a faster charge and a higher conversion rate. TP4056 linear charging is used to charge a BRC 18650 Li-ion 3.7V 4000mAh capacity battery. When charging we put an LED marker that shows red and this turns blue when fully charged.

3. Data Collection and Analysis

3.1. Ethical Approval and Subject Selection

Ethical approval for this research is granted by the Bournemouth University ethical review committee and each subject is given a Participant Information Sheet and signs an informed Participant Agreement Form. We recruit a convenient group of 10 healthy young subjects (8 males, age mean ± standard deviation: 32.42 ± 4.32 years, range: 24 to 40 years, weight mean ± standard deviation: 73.68 ± 13.6 Kg, range: 44.5 to 93.9 Kg and height mean ± standard deviation: 174.13 ± 7.23 cm, range: 161 to 188 cm). The chosen subjects, each are known to have full time office jobs where they had to spend long hours being seated on a chair, despite of which, they still have not yet experienced any sign of back pain or sitting disease. The exclusion criteria for selecting these young subjects were identifiable movement dysfunction, pain, and/or pathology in the spine or lower extremities requiring treatment, musculoskeletal or neurological pathology, contraindication to exercise, fracture or muscle injury, impairment attributable to other cause by history or other health conditions during the preceding six months and sitting disease may adversely impact the outcomes of the study. In this initial part of our study and development we purposefully select young healthy subjects to find the measurement of normal sitting pressure ranges.

3.2. Experimental Protocol and Data Collection

This experiment is conducted in an office environment. Each subject is given a chair and is asked to sit on it, maintaining a normal posture, using the lever to adjust the height of the chair seat, depending on their body types so that the feet are completely in contact with the ground. The normal sitting posture as described in [50, 51], is explained to each subject and they are then asked to sit up with their back straight, shoulders pushed back, and buttocks aligned to the rear most part of the seat, such that their back is straight in line with the backrest. It is therefore ensured that the subject's body weight is evenly distributed on both hips. Each subject is asked to bend their knees at a right angle, such that they are at the same level of higher than the hips. The normal sitting posture is shown in Figure 5(a). This position is considered as normal or best sitting posture with mild asymmetry. We then collected the sitting pressure data for a period of 10 min for each subject. Subjects are then asked to sit cross legged; with right leg over the left knee; which is considered to be a moderate asymmetry posture as shown in Figure 5(b). Another set of pressure data is collected for this posture for the same time period. Lastly, the subjects are asked to sit leaning high to right side, cross-legged with right leg over the left knee in a severe asymmetry posture as shown in Figure 5(c). Another set of data is collected for each subject for 10 min. The collected data is streamed and stored in the cloud ThingSpeak™ server. These positions are chosen after discussion with 5 clinicians (3 physiotherapists, 1 chiropractor and 1 doctor) who regularly assess posture in their work.

Figure 5: Front (top) and side (bottom) views of sitting postures with a) Normal or mild asymmetry, b) Moderate asymmetry, and c) Severe asymmetry

3.3. Data Importation and Interpretation

ThingSpeak™ MATLAB toolbox reads and imports SPS data using a secure channel ID and API key. In Figure 6, we demonstrate raw cloud data collected from the group of SPS sensors in each seat.

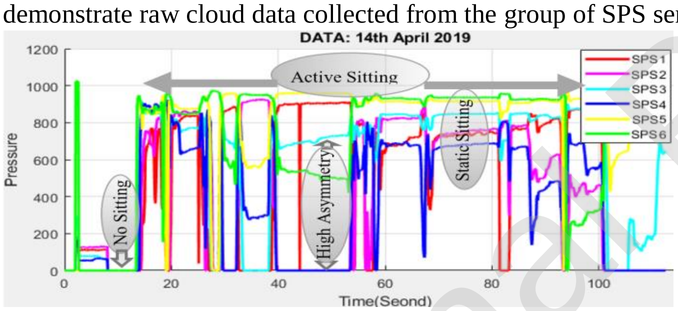


Figure 6: Graphical output of the SPS raw data from ThingSpeak™ IoT cloud

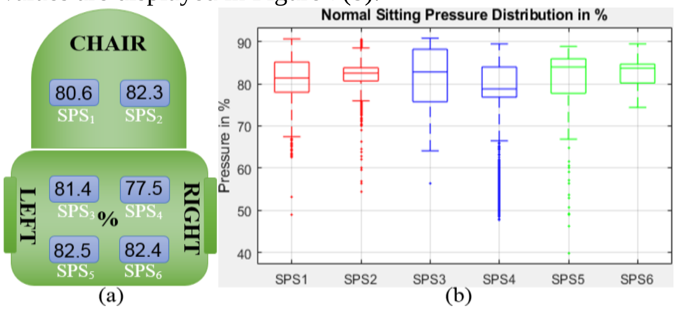
Figure 6 shows the data collected from the sensors shown in Figure 2(f). SPS1 (red) is the pressure reading from the right shoulder, SPS2 (pink) from left shoulder, SPS3 (cyan) from right lower back, SPS4 (blue) left lower back, SPS5 (yellow) right thigh and SPS6 (green) left thigh. $SPS_{1\ to\ 6}$ shows zero at *no sitting* condition (Figure 6). When a subject sits and changes posture, the pressure values rise sharply and is referred to as an active sitting period. After a while readings become constant and is referred to as *static sitting*. The output of the SPS sensor gives a value between 0 and 1023 based on the sitting pressure. A change in the sitting position results in a sharp increase and decrease in the signal. Asymmetrical sitting is identified from a signal difference between right and left sided signals from the various regions. An example of this is shown in the cyan and blue lines indicating that the pressure is highest on the right lower back area compared to the left. Such a difference can occur while sitting with the left leg crossed over the right leg. Next, collected data requires to be processed for unwanted noise that can potentially bias the data and give wrong information. Eventually, we reach the next step which is calibration.

3.4. Calibration

The Piezoresistive conductive film in the SPS is very sensitive to pressure force and stretch. In practice, when the seat is at rest, with nobody sitting on it, we shall receive no data ideally; however, a signal is still generated. This may be due to intrinsic resistance of the material or the mechanical structure of the film, thus making it necessary for the signal output to be calibrated, before the data can be analysed. The calibration is done by measuring the signal generated while the seat is at rest position, with no one sitting and saving these data as 'initial baseline values' for future reference. A subject is then asked to sit on the chair and move in different directions. This enabled the maximum threshold values for each SPS to be recorded. The initial baseline values are subtracted from the threshold values, giving the true "zero" value for each SPS. The threshold value and the true zero value, for each SPS, is stored in a log file. In our system we use adaptive calibration to factorize the different weights of subjects. To achieve this, we continually follow the values in the no sitting state and continually update the calibration limits.

3.5. Measurement of Normal Sitting Range

The normal sitting posture data from all subjects are analysed to estimate the sitting range in percentage using the equation $\frac{RealTimePressure}{Max(Pressure)} * 100$. The mean of percentage from SPS1 to SPS6 are shown in Figure 7(a) and the distribution of percentage values are displayed in Figure 7(b).



(a) (b)

Figure 7: a) Mean of percentage of sitting pressure (SPS1 to SPS6) estimated from all subjects, b) Distribution of the percentage of sitting pressure (SPS1 to SPS6) from all subjects

The mean of percentage of sitting pressure in shoulder areas is 80%, back thigh areas is around 79% and front thigh areas is around 82% for normal sitting from all subjects. The values indicate that the sitting pressure is distributed equally to all locations. Figure 7(b) shows the distribution of the percentage of sitting pressure for SPS1 to SPS6 from all subjects in Boxplots. The percentage distribution shows that most data lies between 70 to 90% for normal sitting posture. The boxes of interquartile ranges of SPS1, SPS3 and SPS5 show greater variation than SPS2, SPS4 and SPS6. It means that left side pressure variations are higher comparing with right side pressure. All the subjects in this study are right handed and hence have controlled movement. However, the investigation of association between right and left handed person with their sitting pressure distribution will be of our interest in future.

3.6. Measurement of Asymmetry Levels

The sitting pressure is distributed almost equally for the mild asymmetry or normal sitting posture, hence the sitting pressure variation between right (SPS2, SPS4 and SPS6) and left (SPS1, SPS3 and SPS5) sides are low shown in Figure 8.

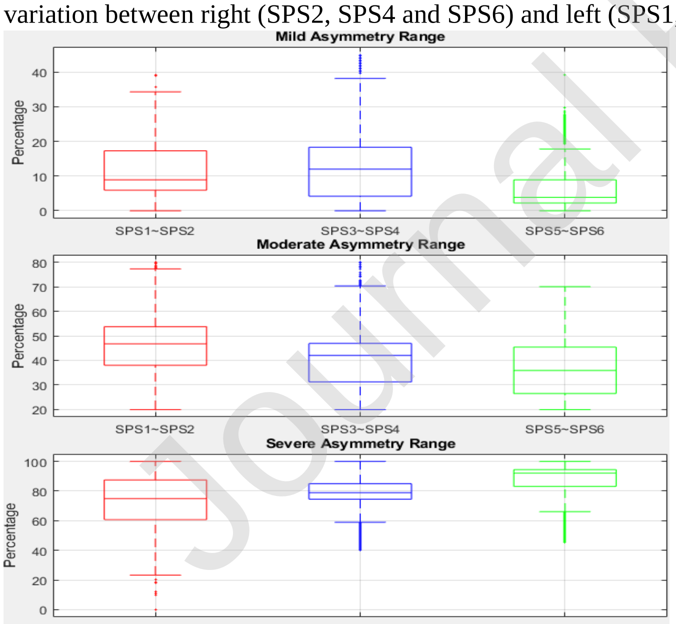


Figure 8: Boxplots of sitting postures for Mild, Moderate and Severe asymmetry

For the moderate asymmetry sitting posture, subjects sit with right leg over the left knee which means the sitting pressure is higher on left side; hence the left side sensors SPS1, SPS3 and SPS5 regarding is higher comparing with right side sensors SPS2, SPS4 and SPS6. For the severe asymmetry sitting posture, subjects sit leaning high to right side with right leg over the left knee which means most of the sitting pressure is distributed on the left side and almost no pressure is on the right side; hence the left side sensors SPS1, SPS3 and SPS5 regarding is higher than right side sensors SPS2, SPS4 and SPS6. The shoulder asymmetry (SA=|SPS1-SPS2|), lower back asymmetry (BA=|SPS3-SPS4|) and thigh asymmetry (TA=|SPS5-SPS6|) are estimated. The asymmetry values are then converted to percentage using equation mentioned in Section 3.5 and generated Boxplots shown in Figure 8. Mild asymmetry Boxplots show that percentage range is from 0 to 40 and more than 75% data lie between 0 to 20. Moderate asymmetry Boxplots show that percentage range is from 20 to less than 80 and more than 75% data lie between 20 to 55. The percentage range is from 20 to 100 (shoulder), 60 to 100 (lower back) and 65 to 100 (thigh) for severe asymmetry shown in Boxplots. More than 75% data lie between 60 to 100. These results are presented to 5 above mentioned (Section 3.2) medical professionals and discussed about selecting ranges. It has been therefore decided that the mild asymmetry range is ±0~25% with maximum sitting time of 15 min, moderate asymmetry range is ±26~65% with maximum sitting time of 10 min and severe asymmetry range is ±66~100% with maximum sitting time of 5 min.

3.7. A Rule Based Approach to Monitor Sitting Behaviours

To prevent the adverse consequences of bad posture, it is important to provide clear and useful real-time information that can be interpreted by everyday people to prompt an improvement in sitting posture. In addition to detecting and monitoring bad posture, there is a need to classify prolonged asymmetric posture. Support vector machine, decision trees and Bayesian network are three such classification techniques. The signals from different sitting positions are approximated over time for each SPS which are fuzzy (Figure 5). To interpret this, we use fuzzy logic as a technique that classifies the fuzziness of the SPS signal. Fuzzy logic deals with reasoning that is fixed or approximate as opposed to fixed and exact and is a form of many-valued logic. Variables have a truth value range between 0 and 1 [52]. Fuzzy logic is advantageous as it avoids categorical (yes/no) computer analysis. It allows outputs between a range of 0 to 1 enabling it to monitor sitting behaviour and to act as a rule-based system. Such an analysis imitates human thinking and evaluation of a complex and changing situation of a human sitting in a chair and all the subconscious movements that occur. However the detail that it delivers in the analysis is not possible to derive by human observation alone improving on a clinician's performance observing sitting behaviours [53]. This system delivers a quick real-time information and feedback for users to quickly understand their sitting posture and helps improve sitting behaviour.

The steps in designing a fuzzy logic algorithm are: 1) fuzzification, 2) an inference, 3) a fuzzy rule base, and 4) defuzzification [54]. Sensor data inputs are "fuzzified" according to rules set by the system designer to break down all possible variants in input into degrees of membership. Each membership function is set a range with minimum and maximum values. Each of these ranges can have several shapes for distribution i.e. Gaussian, Triangular or Trapezoidal. In this study, Trapezoidal shaped membership function is used as the level of asymmetry range is not discrete. The fuzzy set formed by setting the minimum input for each function to the centre point of the previous membership function. A counter is used to record sitting time (ST) when there is a non-zero reading generated from the six SPS sensors.

1) Design of Fuzzy Rule based system

Figure 9 shows the basic structure of the system to monitor sitting behaviour. The Fuzzy Logic system takes input from four (SA, BA, TA and ST) inputs and outputs one result of level of asymmetry. This output refers to the real-time sitting posture and is presented as Mild, Moderate or Severe asymmetry.

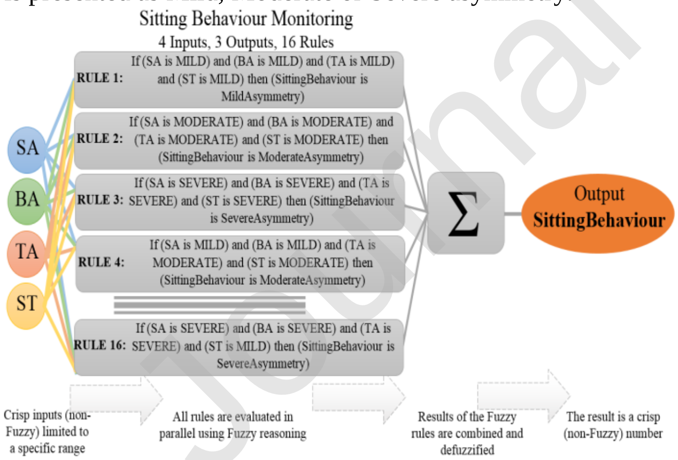


Figure 9: The basic structure of the Fuzzy Rule based sitting behaviour monitoring system

The input information is process according to 16 rules. These rules run in parallel and is an important aspect of the design of the system. The information flows logically along regions where the system facilitates the flow to occur depending on which rule is being satisfied. This removes the need for sharp switching between modes based on breakpoints.

2) Developing the fuzzy logic algorithm: Input, output variables and Fuzzy Rules

The four input variables SA, BA, TA and ST are and the corresponding membership functions are shown in Figure 10(a).

In the ideal scenario when there is no sitting pressure to generate a reading the values of SA, BA and TA should be zero with no difference in pressure between right and left regions. In reality the sitting pressure is not perfectly symmetrical. We therefore set ranges expressed as a percentage. Mild asymmetry is: SA 0-20, BA 0-20 and TA 0- 20. During sitting, pressure is highest in the lower back compared to the thigh or shoulder regions. The range is the lowest in the BA since there is less asymmetry in the lower back when maximum pressure is released. We calculated moderate asymmetry ranges as follows: SA 21-60, BA 21-60 and TA 21-60. Severe asymmetry ranges are: SA 61-100, BA 61-100 and TA 61- 100. The ST ranges are 0-15 min, 0-10 min and 0-5 min for mild, moderate and severe asymmetry respectively.

There is one output "Sitting Behaviour". This refers to the condition of the sitting posture at any one point in time and the corresponding membership functions as shown in Figure 10(b). Output is classified as Excellent, Good and Poor with ranges of 6-10, 3-6 and 0-3 respectively. The higher the value, the higher the level of asymmetry indicating a worse posture. These ranges are selected based on the basis of laboratory observations. However further validation by experts such as physiotherapists, medical doctors and biomechanics is needed.

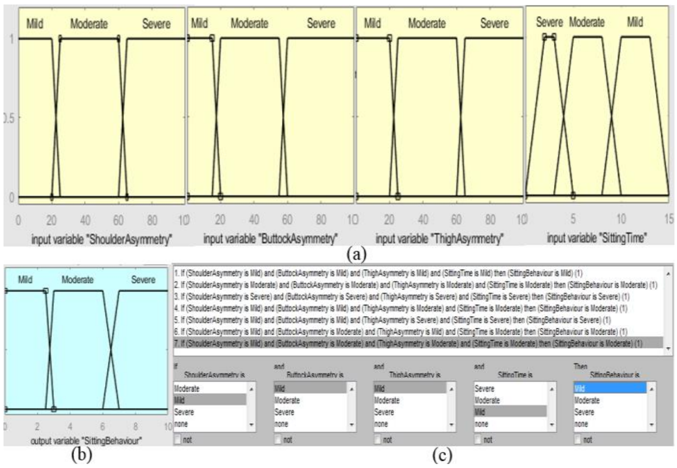


Figure 10: (a) Input variables membership functions of SA, BA, TA and ST; (b) Output variable membership functions of "SittingBehaviour"; and (c) Fuzzy Logic System Rules sample

Defining the Fuzzy Rules is crucial for the function of the fuzzy inference system and determines the quality of results. In this work we include 16 rules that cover all the possible scenarios. We obtain the rules using the formula $N=r_1 \times r_2 \times \ldots \times r_n$ where N is the number of possible (combinations of the input variables) rules for a Fuzzy system and r_n is the number of linguistic terms for the input linguistic variables. We determined the rules on the basis of assumptions. These assumptions will need to be validated. Some of the rules are shown in Figure 10(c).

3) *Fuzzyfication and Defuzzification*

Our system uses the Mamdani Fuzzy inference [55] mechanism approach available in MATLAB. It uses a logical combination of inputs that depend on each other. The system has one output that describes the sitting posture as a fuzzy term. This crisp value output is determined by a defuzzification process after estimating its input values. An example of what results one can expect is shown in Figure 11 where inputs are given as SA=15.5, BA=7.47, TA=6.32 and ST=12.2. Based on these inputs the Fuzzy Logic engine gives a result of 1.35 which is indicative of mild asymmetry.

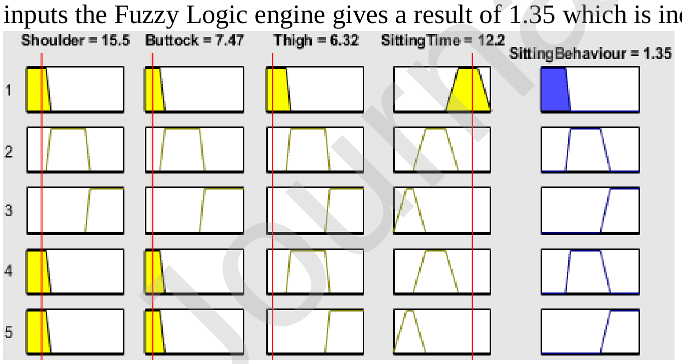


Figure 11: MATLAB- rule viewer and simulation result for fuzzy logic Sitting Monitoring system

3.8. Visualization

We use a purposely designed app loaded onto a Wi-Fi enabled smart phone to visualize the output from our system. To visualize sitting posture we use the readings of minimum and maximum thresholds for SPS_1 to SPS_6 restored from the cloud. We then draw a circle from θ=0 to 2π of duration of 0.01 using $x=\sin(\theta), y=\cos(\theta)$. The interval α=50 is defined and the value of each increment (δ) is calculated using the equation $\delta=(\max-\min)/\alpha$. The value of each incremental step (δ) is calculated using $\delta=(\max-\min)/\alpha$. The interval angle ω is estimated using $\omega=\lambda*\pi/\alpha$ with λ =1. The scale is represented from 0 to α using $\gamma=-\lambda*\pi/i*n+\lambda*\pi$, for n= 0 to α. The small scale line is then drawn using $x=\sin(\gamma), y=\cos(\gamma)$. The minimum and maximum values of the scale are mapped between -100 to +100. The indicator line (β) is then set with the instantaneous difference between left and right value of the feature (η) using $\beta = -\omega * (\eta - \min) / \delta + \lambda * \pi$. The indicator line is drawn from 0 to β. The asymmetry (SA, BA and TA) values between right and left of shoulder, lower back and thigh are estimated described in Section 3.6. A summary picture of the overall sitting posture is demonstrated in Figure 12.

(a) (b) (c)

Figure 12: (a) Display of sitting pressure in percentage; (b) Dial based asymmetrical sitting posture visualization; (c) Sitting score and summary for a day

To illustrate the case in Figure 5(a) we see a subject sitting in normal posture. Figure 12(a) demonstrates the asymmetrical measurements using a dial format. In a situation of perfect symmetry, the pressure distribution is equal on right and left sides and should give dial readings of 0 (zero). In the example shown all the dials are demonstrating asymmetry for all the areas of the shoulder, thigh and lower back. One can also note that the level of asymmetry varies. For example, in Dial 1 the reading is +8.7 and pointing to the right alternatively described as a positive deflection indicating that the pressure is higher on the right shoulder than the left. Conversely if the deflection of the dial is to the left indicates that the pressure on the left shoulder is higher than the right. The higher the deflection the greater the asymmetry and the lower the deflection i.e. the more central the pointer is, the better the posture. Our app has the facility to record daily readings, record the total sitting time and the time spent in active, static and asymmetric sitting state. Active sitting is calculated from the time when there is a non-zero reading from all six SPSs. Static sitting is the time when the dials lie lower than ±25 and symmetric sitting refers to the duration when the dial is ±20 for more than 5 minutes. A percentage static sitting score is estimated using the formula: STATIC = (duration of static sitting/duration of active sitting) x 100. A percentage asymmetric sitting score is estimated using ASYMMETRY = (duration of asymmetric sitting/duration of active sitting) x 100. Figure 12(c) shows the summary results. A low score is indicative of good sitting posture.

4. Discussion

Smart-Cover is embedded with SPSs and IoT platform whose operation is based on a Fuzzy classifier. It generates a score and a visual representation of the state of posture with the aim of prompting a correction in bad posture and promote better sitting behaviour. Kalman filter and Fuzzy logic are used to reduce noise and classification of asymmetry level respectively. A built-in adaptive calibration system is also developed to improve the versatility of the system so it can be employed by different users in an adaptive way. The advantage of our Smart-Cover is that using an IoT platform, the system provides sitting posture information without interfering in the user's daily routine and promotes healthier sitting behaviour with the aim of preventing and reducing the severity of musculoskeletal problems. This research is still in its initial stages and what we have shown is that such a system can work and provide clinically useful results. Much work still needs to be done to validate in a clinical setting with the help of experts in the field, the input/output variable ranges used for Fuzzy classification. More research is needed to quantify and evaluate long term data. Future work will also need to investigate the possible therapeutic benefits of the use of such equipment.

There are a number of limitations in this study. We only included 10 subjects and they were predominantly male of a young age. This study therefore can only be considered as a proof of concept for the development of the system and cannot be used to determine normal posture in specific genders or different age groups. We also do not have any information about disease specific conditions. Our results show that there is a greater variation of sitting posture on the left compared to the right. All our subjects were right handed and this raises the possibility that there is a right/left variation in posture depending on whether the person is right or left handed. These will be addressed in future work. While there are other sitting postures such as cross legged sitting on the floor or squatting, we only consider sitting posture on a chair at 3 levels of asymmetry i.e. mild, moderate and severe. Such postures are common in some countries but are not considered.

Adopting the correct sitting position is essential for maintaining good posture and a healthy back spine. Most people can improve their sitting posture by following a few simple guidelines. Our system provides real time information about duration and level of asymmetry of sitting which can help users to improve their sitting behaviour.

5. Conclusion

We developed a sitting posture monitoring system called Smart-Cover where a chair seat cover is embedded with SPSs and that, uses an IoT platform whose operation is based on a rule based classifier. We also developed an accompanying Android app to monitor the sitting behaviour and to detect extended periods of sitting in an asymmetrical posture. We build a SPS system embedded in the piezoelectric interface on a chair seat cover to sense sitting pressure taking into consideration human biomechanics. The multi-layer architecture that is proposed can provide a novel seat cover for manufacturing and real world use. The flexible fabric based nature of the sensors provide the opportunity to adapt and make bespoke design for people with varying anthropomorphic parameters such as different human back sizes and variations in chair shapes. The IoT communication layer transfers sensor data to the cloud server and makes such data available for use to other interested third parties. Our inductive charging system maximizes battery life. The auto cut feature protects the battery from over charging. The Fuzzy rule based classifier provides real-time information about sitting posture using our Android App. This offers an easy and user friendly way of visualizing and monitoring sitting posture which can be used for treatment and rehabilitation purpose of musculoskeletal conditions associated with sitting in hospitals, clinics, work, school and home. This study enhances the current literature demonstrating a new visual method to show real-time sitting posture that enhances the reliability and validity of monitoring posture.

AuthorStatement

DR. ARIF REZA ANWARY
Innovation Technologist
Accelerate – Healthcare Technology Centre
Institute of Life Science 1
School of Medicine
Swansea University
Singleton Park, Swansea, SA2 8PP

ACKNOWLEDGMENT

The authors would like to thank all participants and clinicians that helped in the study.

References

[1] Y. Song, The self reported symptoms of spine diseases and related factors in adolescents, Kyunggi University, Disertation of master's degree (2013).
[2] N. Krause, R. Rugulies, D.R. Ragland, S.L. Syme, Physical workload, ergonomic problems, and incidence of low back injury: A 7.5- year prospective study of San Francisco transit operators, American journal of industrial medicine 46(6) (2004) 570-585.
[3] J.Y. Chau, H.P. Van Der Ploeg, J.G. Van Uffelen, J. Wong, I. Riphagen, G.N. Healy, et al., Are workplace interventions to reduce sitting effective? A systematic review, Preventive medicine 51(5) (2010) 352-356.
[4] U. Ekelund, J. Steene-Johannessen, W.J. Brown, M.W. Fagerland, N. Owen, K.E. Powell, et al., Does physical activity attenuate, or even eliminate, the detrimental association of sitting time with mortality? A harmonised meta-analysis of data from more than 1 million men and women, The Lancet 388(10051) (2016) 1302-1310. http://www.sciencedirect.com/science/article/pii/S0140673616303701.
[5] A. Biswas, P.I. Oh, G.E. Faulkner, R.R. Bajaj, M.A. Silver, M.S. Mitchell, et al., Sedentary Time and Its Association With Risk for Disease Incidence, Mortality, and Hospitalization in Adults: A Systematic Review and Meta-analysisSedentary Time and Disease Incidence, Mortality, and Hospitalization, Annals of Internal Medicine 162(2) (2015) 123-132. https://dx.doi.org/10.7326/M14-1651.
[6] G. Harris, R. Pudlowski, E. Abraham, E. Millar, Thoracic suspension: quantitative effects upon seating pressure and posture, Spinal Cord 25(6) (1987) 446.
[7] I. Review, Pressure ulcer prevention: pressure, shear, friction and microclimate in context. A consensus document, Wounds International (2010).
[8] J. Dubousset, Pelvic obliquity: a review, Orthopedics 14(4) (1991) 479-481.
[9] M.-J. Kim, C.-G. Son, D.-S. Heo, K.-E. Hong, Analysis of clinical tendency of spinal disorder in primary, middle and high school students in Korea, THE ACUPUNCTURE 27 (2010).
[10] D. Viggiani, M. Noguchi, K.M. Gruevski, D. De Carvalho, J.P. Callaghan, The Effect of Wallet Thickness on Spine Posture, Seat Interface Pressure, and Perceived Discomfort During Sitting, IIE Transactions on Occupational Ergonomics and Human Factors 2(2) (2014) 83-93.
[11] J. Hartvigsen, M.J. Hancock, A. Kongsted, Q. Louw, M.L. Ferreira, S. Genevay, et al., What low back pain is and why we need to pay attention, The Lancet (2018).
[12] R. Buchbinder, F.M. Blyth, L.M. March, P. Brooks, A.D. Woolf, D.G. Hoy, Placing the global burden of low back pain in context, Best practice & research Clinical rheumatology 27(5) (2013) 575-589.
[13] B. Kwon, D. Roffey, P. Bishop, S. Dagenais, E. Wai, Systematic review: occupational physical activity and low back pain, Occupational medicine 61(8) (2011) 541-548.
[14] N. Gupta, C.S. Christiansen, D.M. Hallman, M. Korshøj, I.G. Carneiro, A. Holtermann, Is objectively measured sitting time associated with low back pain? A cross-sectional investigation in the NOMAD study, PLoS ONE 10(3) (2015) e0121159.
[15] M. Mock, K. Sweeting, Gait and posture-assessment in general practice, Australian family physician 36(6) (2007) 398.
[16] C.-W. Chien, J.-H. Lin, C.-H. Wang, I.-P. Hsueh, C.-F. Sheu, C.-L. Hsieh, Developing a short form of the postural assessment scale for people with stroke, Neurorehabilitation and neural repair 21(1) (2007) 81-90.
[17] G. Fröhner, Objectification of posture and trunk flexibility in children and adolescents, Haltung Bewegung 2 (1998) 5-13.

[18] J.L. Garrido-Castro, R. Medina-Carnicer, R. Schiottis, A.M. Galisteo, E. Collantes-Estevez, C. Gonzalez-Navas, Assessment of spinal mobility in ankylosing spondylitis using a video-based motion capture system, Manual therapy 17(5) (2012) 422-426.
[19] J. Ahmad, H. Andersson, J. Sidén, Sitting posture recognition using screen printed large area pressure sensors, 2017 Ieee Sensors, IEEE, 2017, pp. 1-3.
[20] M. Kim, H. Kim, J. Park, K.-K. Jee, J.A. Lim, M.-C. Park, Real-time sitting posture correction system based on highly durable and washable electronic textile pressure sensors, Sensors and Actuators A: Physical 269 (2018) 394-400.
[21] P. Manapongpun, P. Mattayasinchai, D. Bunnjaweht, Development of a Piezoresistive Sitting Pressure Distribution Sensor: Experiments on Standard Shape Objects, 2020 8th International Electrical Engineering Congress (iEECON), IEEE, 2020, pp. 1-4.
[22] J. Roh, H.-j. Park, K.J. Lee, J. Hyeong, S. Kim, B. Lee, Sitting posture monitoring system based on a low-cost load cell using machine learning, Sensors 18(1) (2018) 208.
[23] A.R. Anwary, H. Bouchachia, M. Vassallo, Real time visualization of asymmetrical sitting posture using flexible pressure sensor based on piezoresistive conductive film, The 16th International Conference on Mobile Systems and Pervasive Computing (MobiSPC), Halifax, Canada, 2019.
[24] R.W. Christiansen, W.M. Westberg, Conductive elastomeric fabric and body strap, Google Patents, 1983.
[25] H. Yousef, M. Boukallel, K. Althoefer, Tactile sensing for dexterous in-hand manipulation in robotics—A review, Sensors and Actuators A: physical 167(2) (2011) 171-187.
[26] L. Bolton, B. Foleno, B. Means, S. Petrucelli, Direct-current bactericidal effect on intact skin, Antimicrobial agents and chemotherapy 18(1) (1980) 137-141.
[27] S.W.E.C. Ltd, Woven Conductive Fabric. https://cdn-shop.adafruit.com/product-files/1168/Pn1168_Datasheet.pdf.
[28] S. Air, Cell-Aire® polyethylene foam. https://sealedair.com/product-care/product-care-products/cell-aire-polyethylene-foam-packaging-products.
[29] B.W. Lee, H. Shin, Feasibility study of sitting posture monitoring based on piezoresistive conductive film-based flexible force sensor, IEEE Sensors Journal 16(1) (2016) 15-16.
[30] M. Kalantari, J. Dargahi, J. Kövecses, M.G. Mardasi, S. Nouri, A new approach for modeling piezoresistive force sensors based on semiconductive polymer composites, IEEE/ASME Transactions on Mechatronics 17(3) (2012) 572-581.
[31] R.L. Jackson, R.D. Malucci, S. Angadi, J.R. Polchow, A simplified model of multiscale electrical contact resistance and comparison to existing closed form models, 2009 Proceedings of the 55th IEEE Holm Conference on Electrical Contacts, IEEE, 2009, pp. 28-35.
[32] R. Holm, Electric contacts: theory and application, Springer Science & Business Media2013.
[33] Y. Zhang, J. Ye, Z. Lin, S. Huang, H. Wang, H. Wu, A Piezoresistive Tactile Sensor for a Large Area Employing Neural Network, Sensors 19(1) (2019) 27.
[34] H. Dreyfuss, H.D. Associates, A.R. Tilley, The measure of man and woman: human factors in design, Whitney Library of Design1993.
[35] W.G. Allread, E.W. Israelski, Anthropometry and biomechanics, Handbook of Human Factors in Medical Device Design, CRC Press2010, pp. 106-160.
[36] D. Giovanelli, E. Farella, Force sensing resistor and evaluation of technology for wearable body pressure sensing, J. Sens. 2016 (2016).
[37] Z. Del Prete, L. Monteleone, R. Steindler, A novel pressure array sensor based on contact resistance variation: Metrological properties, Review of Scientific Instruments 72(2) (2001) 1548-1553.
[38] J. Heikenfeld, A. Jajack, J. Rogers, P. Gutruf, L. Tian, T. Pan, et al., Wearable sensors: modalities, challenges, and prospects, Lab on a Chip 18(2) (2018) 217-248.
[39] X. Yun, E.R. Bachmann, Design, implementation, and experimental results of a quaternion-based Kalman filter for human body motion tracking, IEEE transactions on Robotics 22(6) (2006) 1216-1227.
[40] R.E. Kalman, A new approach to linear filtering and prediction problems, Journal of basic Engineering 82(1) (1960) 35-45.
[41] F. Xia, L.T. Yang, L. Wang, A. Vinel, Internet of things, International Journal of Communication Systems 25(9) (2012) 1101.
[42] W.-F. Alliance, Wi-Fi Protected Access: Strong, standards-based, interoperable security for today's Wi-Fi networks, White paper, University of Cape Town (2003) 492-495.
[43] J.C. Haartsen, Bluetooth radio system, Wiley Encyclopedia of Telecommunications (2003).
[44] P. Kinney, Zigbee technology: Wireless control that simply works, Communications design conference, 2003, pp. 1-7.
[45] N. Team, Nodemcu-an opensource firmware based on esp8266 wifi-soc, URL http://nodemcu. com/index en. html (2014).
[46] M.A.G. Maureira, D. Oldenhof, L. Teernstra, ThingSpeak–an API and Web Service for the Internet of Things, World Wide Web (2011).
[47] G.A. Covic, J.T. Boys, Inductive power transfer, Proceedings of the IEEE 101(6) (2013) 1276-1289.
[48] D. Van Wageningen, T. Staring, The Qi wireless power standard, Proceedings of 14th International Power Electronics and Motion Control Conference EPE-PEMC 2010, IEEE, 2010, pp. S15-25-S15-32.
[49] h.w.l.c. Labcenter Electronics Corporation, Proteus ISIS Professional, 1989-2015.
[50] K. O'Sullivan, P. O'Sullivan, L. O'Sullivan, W. Dankaerts, What do physiotherapists consider to be the best sitting spinal posture?, Manual therapy 17(5) (2012) 432-437.
[51] NHS, How to sit at your desk correctly: Healthy body. https://www.nhs.uk/live-well/healthy-body/how-to-sit-correctly/, 2019 (accessed 23/08/2019 2019).
[52] L.A. Zadeh, The role of fuzzy logic in modeling, identification and control, Fuzzy Sets, Fuzzy Logic, And Fuzzy Systems: Selected Papers by Lotfi A Zadeh, World Scientific1996, pp. 783-795.
[53] J.H. Bates, M.P. Young, Applying fuzzy logic to medical decision making in the intensive care unit, American journal of respiratory and critical care medicine 167(7) (2003) 948-952.
[54] L. Kuncheva, Fuzzy classifier design, Springer Science & Business Media2000.
[55] E.H. Mamdani, Application of fuzzy logic to approximate reasoning using linguistic synthesis, Proceedings of the sixth international symposium on Multiple-valued logic, IEEE Computer Society Press, 1976, pp. 196-202.

Biography

Arif Reza Anwary is currently working as an Innovation Technologist in Medical School at Swansea University. He worked as an Assistant Professor in Computer Science and Engineering Department at United International University, Bangladesh. He also worked as an Assistant Professor in Computer Science and Engineering Department at University of Asia Pacific, Bangladesh. He received PhD from Bournemouth University (UK), MPhil from University of Wolverhampton (UK), M.Sc. from Gyeongsang National University (South Korea), and B.Sc. from University of Asia Pacific (Bangladesh). He has long research experience on multidisciplinary industrial projects (Sensors: Wearable, Ambient and Vision; Signal Processing, Image Processing, IoT/Cloud, Machine Learning, Movement Analysis, Morphological Shape Analysis, Fuzzy System, Assistive Technology, Healthcare and Rapid Prototyping).

Deniz Cetinkaya is a Lecturer in Computing at Bournemouth University (BU). Prior to joining BU, she worked as an Assistant Professor in Software Engineering Department at Atılım University, Ankara, Turkey. She graduated from Department of Computer Engineering at Hacettepe University, Ankara, Turkey with honors in 2002. She received her MSc degree in Computer Engineering from Middle East Technical University, Ankara, Turkey in 2005. She received her PhD degree in Systems Engineering from Delft University of Technology (Technische Universiteit Delft) in the Netherlands in 2013. Her research focuses on software engineering, domain specific modelling, model driven development and simulation modelling.

Michael Vassallo is currently a Consultant Geriatrician with the Royal Bournemouth Hospital, U.K. He has a research interest in falls and rehabilitation and has published widely in the area.

Hamid (Abdelhamid) Bouchachia is a Professor at Bournemouth University, leading the Machine Intelligence Research Group, Department of Computing and Informatics, Faculty of Science and Technology, UK. Abdelhamid received the Engineering degree and Master in Informatics, respectively from the University of Oran and the University of Sciences and Technology, Oran, Algeria, and the Ph.D. degree in Informatics from the University of Klagenfurt, Austria. In 2001 he spent one year as post-doc at the University of Alberta, Department of Computer and Electrical Engineering, Edmonton, Canada. His research interests cover Machine Learning, Data Mining, Computational Intelligence, Ambient Intelligence and Telecare. He published more than 130 papers in international journals and conferences. He edited dozen of volumes and special issues. He founded the International Conference on Adaptive and Intelligent Systems (ICAIS). He serves as program committee member for numerous international conferences. He also serves as Associate Editor of Evolving Systems and acts as member of Evolving Intelligent Systems (EIS) Technical Committee (TC) of the IEEE Systems, Man and Cybernetics Society, the IEEE Task-Force for Adaptive and Evolving Fuzzy Systems and the IEEE Computational Intelligence Society.