Smart Cushion-Based Activity Recognition

Prompting Users to Maintain a Healthy Seated Posture

by Congcong Ma, Wenfeng Li, Raffaele Gravina, Juan Du, Qimeng Li, and Giancarlo Fortino

In the emerging wearable world, a plethora of smart devices are being designed to facilitate our daily life. More activities, such as student learning, desk office work, or driving are requiring human beings to spend a significant portion of their daily life sitting on a chair. As a result, there is increasing interest in the development of technologies that monitor and support seated users. The most iconic examples of this are the smart chair and the smart cushion. To prompt users to maintain healthy sitting posture and to encourage them to have a short break after prolonged sitting, several studies focus on the detection, monitoring, and analysis of sitting postures. The smart cushion, in particular, is a very promising device in this context because it is noninvasive and can be conveniently deployed on the seat or backrest, making an ordinary chair, sofa, or even a car seat suddenly smart. This article reviews our previous research studies and the results related to sitting posture recognition using the smart cushion. We will show that very diversified applications can be enabled, spanning medical applications (e.g., back pain or pressure ulcers avoidance) and even human communication (body language detection).

Digital Object Identifier 10.1109/MSMC.2019.2962226
Date of current version: 21 October 2020

2333-942X/20©2020IEEE

Activity Recognition

In the context of body area networks (BANs) [1], many wearable devices have emerged in recent years [2], [3] that are changing people's lifestyles in various ways, such as health care, fitness, sports [4], and entertainment. Along with multisensor data fusion techniques [5], many kinds of useful information have been extracted and valuable decisions can be made to better guide daily life activities.

Initially, activity recognition was addressed with vision-based approaches that introduced relevant privacy concerns; additionally, video-based approaches are significantly more power consuming and require complex processing algorithms. Therefore, research interest gradually shifted toward wearable motion sensors, thanks to their noninvasiveness, limited cost, and practical implementation. The most popular wearable sensor for activity recognition is the inertial measurement unit (IMU) [6], especially for its accelerometer. Different features were extracted, and diversified machine-learning methods were used to better recognize physical activities and static postures. For dynamic activities such as walking, running, jumping, or falling, accelerometer sensors offer advantages. However, for sitting postures [7], sleeping activity [8], or some gait posture recognition [9], pressure sensor-based devices are actually more suitable than IMUs, as they are easy to implement and are often deployed on objects the user has not worn, whose iconic example is the smart cushion.

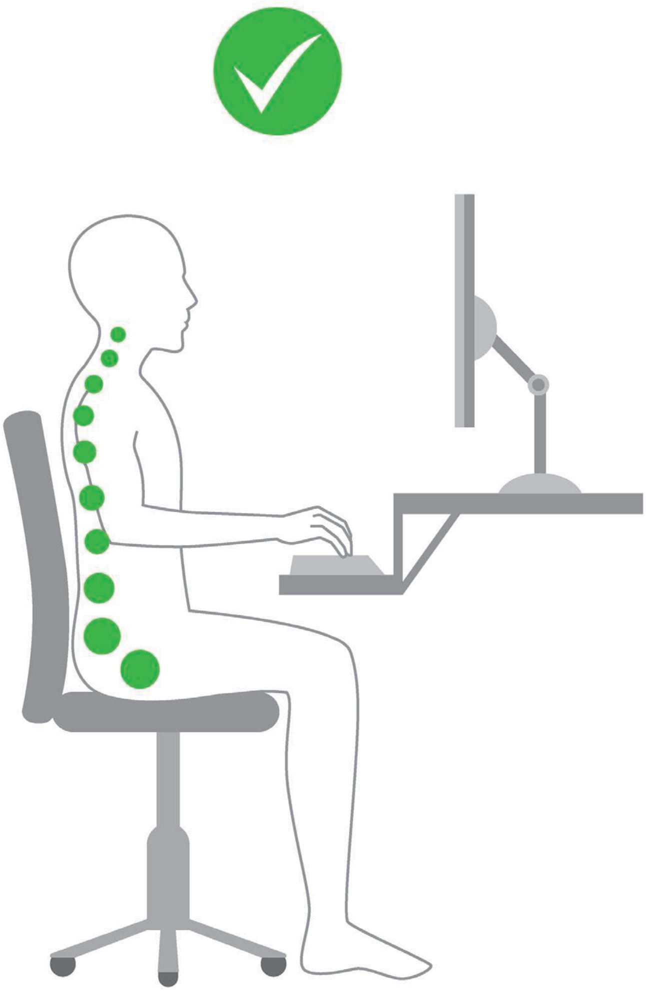
This article provides a comprehensive overview of activity recognition and human–machine interaction applications based on the pressure-sensing smart cushion and particularly reviews our related previous research studies and results. Different from the Intelligent Wheelchair, our article is the first to focus on a smart cushion-based chair/wheelchair that was used to recognize sitting-related activities.

Literature Review of Sitting Posture Recognition Using Smart Cushions

An important part of the global population (e.g., desk workers, truck and bus drivers, and wheelchair-bound users) spends most of their daily time in a seated condition, resulting in a sedentary lifestyle. Smart devices used in BANs, such as the smart cushion, appear to better understand individuals' sitting-related activities while in standard chairs or wheelchairs [10], [11]. Smart cushions are realized using two alternative technological approaches: dense pressure sensor arrays or sparse pressure sensor arrays. In the following section, a state-of-the-art review for each approach is reported.

Smart Cushions With Dense Pressure Sensor Arrays

Many studies have adopted e-textile solutions that can contain more than 1,000 sensor units. Xu et al. [12] proposed a textile-based sensing system: the pressure sensor data were represented by binary pressure distribution data and then converted to gray-scale images for posture recognition. Also, a sensor matrix system composed of more than 2,000 pressure sensors and commercialized by Tekscan [13] was adopted by several studies on sitting posture monitoring. Tan et al. [14] used the Tekscan to analyze sitting pressure distribution in the form of gray-scale image maps. Mota and Picard [15] also employed the Tekscan, proposing a three-layer feedforward neural network to recognize nine different sitting postures. Meyer et al. [16] developed a capacitive textile pressure sensor array cushion and proposed the naïve Bayes classification method to recognize 16 sitting postures. Liu et al. [17] developed a smart cushion with 32 × 32 pressure sensors; a convolutional neural network (CNN)-based algorithm was used



to detect eight sitting postures with 95.5% accuracy.

Other studies exploited an 8 × 8 sensor matrix, and machine-learning methods were used to recognize the postures. Kamiya et al. [18] used an 8 × 8 pressure sensor matrix, and a radial basis function-based support vector machine (SVM) algorithm was used to recognize postures. Fard et al. [19] proposed a system using an 8 × 8 pressure sensor matrix on the seat to prevent pressure ulcers. Kim et al. [20] developed a sensing cushion by mounting 8 × 8 pressure sensors to classify five kinds of children's sitting postures. The authors proposed a CNN-based method and compared the results with other approaches [naïve Bayes, Decision Tree (DT), a regression model, and the Support Vector Machine]. CNN obtained the highest recognition results, with an average accuracy of 95.3%. Xu et al. [21] presented a cushion deployed on the seat and backrest, and the pressure sensors data were converted to binary values ("true" or "false," according to a given pressure threshold) to recognize nine postures. All of the analyzed literature works using smart cushions with dense pressure sensor arrays are summarized in Table 1.

There is increasing interest in the development of technologies that monitor and support seated users.

Smart Cushions With Sparse Pressure Sensor Arrays

Dense pressure sensor arrays are costly solutions, so several studies proposed sparse pressure sensor array methods. Based on different classification approaches, these studies mainly consist of machine-learning methods and threshold-based algorithms.

Works that adopted machine-learning methods are discussed in this section. Multu et al. [22] used the Tekscan [13] to detect significant pressure-sensing points, and then, to support the recognition of sitting postured, it identified an optimal deployment composed of 19 sensors. Hu et al. [23] proposed the use of PoSeat equipped with an accelerometer and pressure sensors. A hybrid SVM classifier was used to recognize sitting postures for chronic back pain prevention. Benocci et al. [24] proposed a system based on five pressure sensors and k-nearest neighbor (kNN) to detect five postures. Min [25] developed a real-time sitting posture monitoring system (SPMS) that prompts users to keep correct postures. Zemp et al. [26] developed an instrumented chair with force and acceleration sensors, with five different machine-learning methods compared, resulting in an average accuracy of 90.9%. Fu and Macleod [27] proposed a system based on eight pressure sensors placed on a chair backrest and seat. A hidden Markov model (HMM) was adopted to analyze sitting posture sequences. Kumar et al. [28] designed a system named *Care-Chair*, using four pressure sensors on the backrest to recognize users' complex sedentary and emotion-related activities.

In our previous research [29], we used three pressure sensors placed on a smart wheelchair seat to detect users' sitting postures. Liang et al. [30] proposed a practical sitting posture recognition system using a sparse pressure sensor array. User-invariant features were extracted and the sitting posture was recognized using an AdaBoost classifier. They also proposed two prototype applications of video game control and wheelchair control using the sitting posture recognition results, including lean left (LL), lean right (LR), lean forward (LF), and sit upright.

Also, in [31], the authors demonstrated an effective sensor placement and an ensemble learning classifier capable of recognizing 15 fine-grained postures with an accuracy of 98%. Roh et al. [32] proposed an SPMS using four low-cost load cells. Six postures could be recognized and a 97.2% classification accuracy was achieved using an SVM classifier. Bibbo et al. [33] adopted pressure cushions on the backrest and seat to assess cognitive engagement based on sitting recognition results. Ren et al. [34] suggested a health-promoting system for relaxation and fitness microbreaks at work. In addition to cardiac monitoring, the authors detected sitting behaviors using an artificial neural network applied to data acquired from six pressure sensors placed on the seat.

Table 1. The state of the art on smart cushions with dense pressure sensor arrays.

Reference	Sensor Array Type	Placement of the Cushion
Xu et al. [12]	E-textile	Seat
[13]	E-textile	Seat and backrest
Tan et al. [14]	E-textile	Seat and backrest
Mota and Picard [15]	E-textile	Seat and backrest
Meyer et al. [16]	Textile pressure sensor	Seat
Liu et al. [17]	32 × 32 sensor array	Seat
Kamiya et al. [18]	8 × 8 sensor array	Seat
Xu et al. [21]	Seat 6 × 8, backrest 2 × 8	Seat and backrest
Fard et al. [19]	8 × 8 sensor array	Seat
Kim et al. [20]	8 × 8 sensor array	Seat

Works that adopted other kinds of algorithms such as threshold-based methods are described in this section. Bao et al. [35] presented a density-based clustering method to recognize sitting postures from a pressure cushion. Diego et al. [36] proposed a system using pressure sensors, which detect pressure relief tilts to prevent causing pressure ulcers of the wheelchair users. Seo et al. [37] implemented a distraction estimation system for the students based on the analysis of sitting postures. In their system, eight pressure sensors were placed on a smart cushion, and the average posture recognition rate achieved 99.04%. Barba et al. [38] detected sitting postural changes in an e-learning environment to indicate users' affective states. Halabi et al. [39] presented a driver's postures recognition system using two 4 × 4 force sensor arrays deployed in a driver's seat and backrest. They used the Unity3D game engine to develop a 3D graphics driving simulation environment to recognize 10 driving actions.

The most popular wearable sensor for activity recognition is the inertial measurement unit.

Ishac and Suzuki [40] utilized a smart cushion on the backrest to detect sitting postures. The device is composed of nine pressure sensors in an array of 3 × 3, with four vibration motors located at each quadrant of the cushion. This cushion can alert the user to their improper posture and encourage the upright sitting position; the classification accuracy reached 94.1%. Kim et al. [41] designed a real-time sitting posture correction system using 10 textile pressure sensors directly touching the surface of the hips, thighs, and back of a chair. The system could obtain nearly 100% of recognition results via a display alert about the users' unhealthy sitting postures in real time.

There are also two commercial smart cushions used for posture and sitting habits monitoring, namely, DARMA [42] and SENSIMAT [43]. DARMA uses fiber-optic sensors to track a user's sitting posture and sitting time and provides a user's stand up reminder and posture advice. SENSIMAT was used to monitor a wheelchair user's sitting postures and offers suggestions about trunk movement exercises.

Table 2 lists the literature works based on sparse sensor arrays. It is worth mentioning that, because many of the analyzed studies used custom-designed smart cushion systems, an accurate comparison of advantages and limitations is difficult.

Hardware Design of Our Proposed Smart Cushion

Following the sparse pressure sensor array approach, we designed a smart cushion that is able to detect sitting postures [44]. The prototype of the smart cushion and sensor deployment are depicted in Figure 1. It is divided in two main units: the sensing module and the signal processing module.

The sensing module consists of multiple force-sensitive resistor (FSR) pressure sensors (Interlink FSR-406) [45] that detect sitting postures and a 9-degree-of-freedom IMU [46] to detect body movements. The signal processing module is realized using an Arduino [47] board placed on the top-left part of the circuit [see Figure 1(c)]; a Bluetooth communication module, vibration motor unit, and power supply unit complete this module. The circuit board is eventually inserted in the foam filling of the cushion for user comfort. Usually, the foam has a size of 40 × 40 cm with a thickness of roughly 20 mm. Using the designed smart cushion, a high-level system architecture is depicted in Figure 2.

Table 2. Smart cushions with sparse pressure sensor arrays.

Reference	Number of Sensors on Seat	Number of Sensors on Backrest
Multu et al. [22]	11	8
Hu et al. [23]	2	4
Benocci et al. [24]	4	1
Min [25]	4	2
Zemp et al. [26]	10	4
Fu and Macleod [27]	4	4
Kumar et al. [28]	0	4
Ma et al. [29]	2	1
Liang et al. [30], [31]	10 or 20	0
Roh et al. [32]	4	0
Bibbo et al. [33]	4	4
Ren et al. [34]	6	0
Bao et al. [35]	5	0
Arias et al. [36]	4	0
Seo et al. [37]	8	0
Barba et al. [38]	8	8
Halabi et al. [39]	16	16
Ishac and Suzuki [40]	0	9
Kim et al. [41]	6	4
Darma Inc. [42]	6	0
SENSIMAT Systems Inc. [43]	6	0

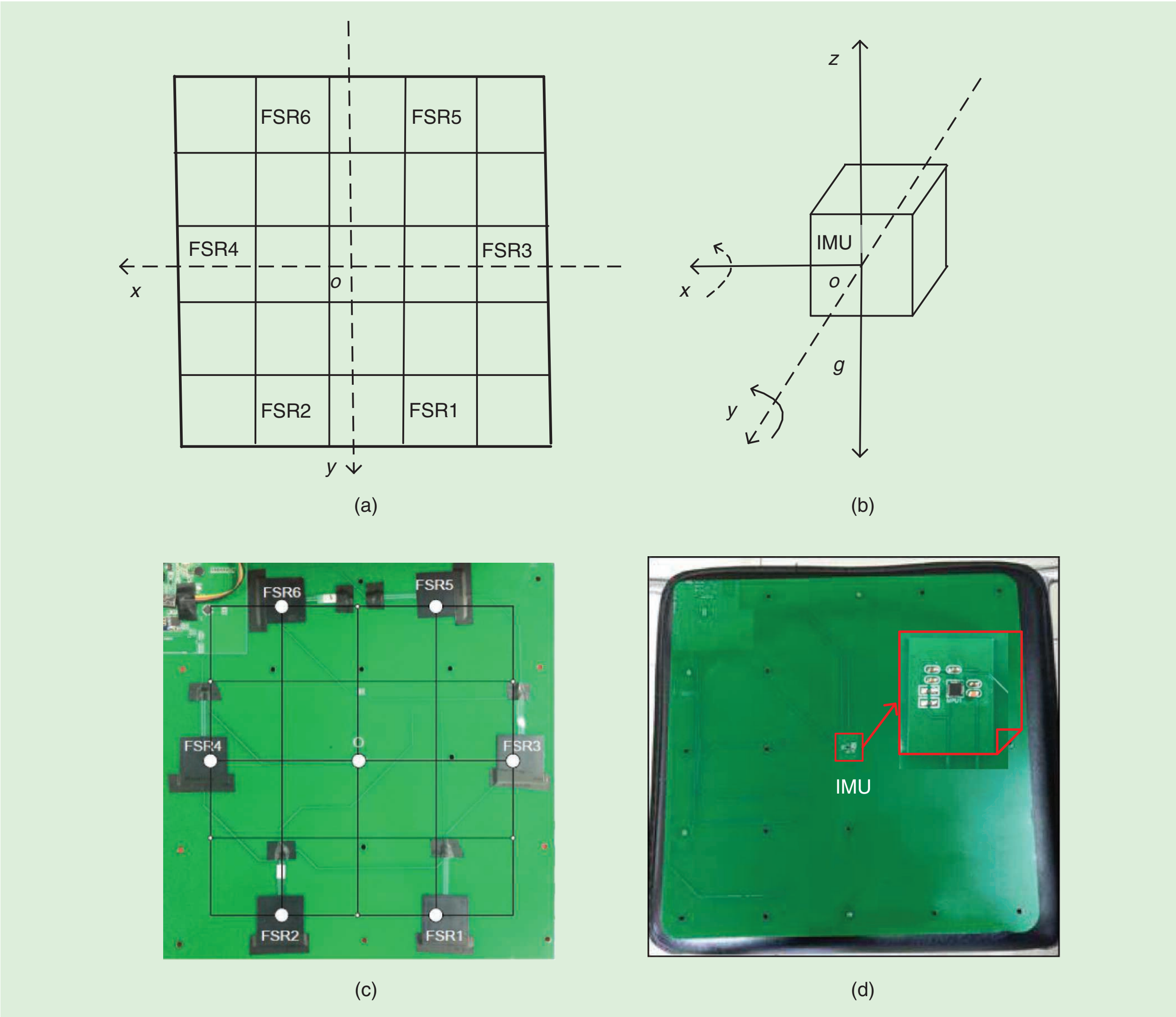


Figure 1. The sensor deployment of the smart cushion and the circuit board. (a) A schematic diagram of the sensors deployed on the base board, (b) the IMU sensor and the three-axis representation, (c) the top side of the circuit board, and (d) the bottom side of the circuit board.

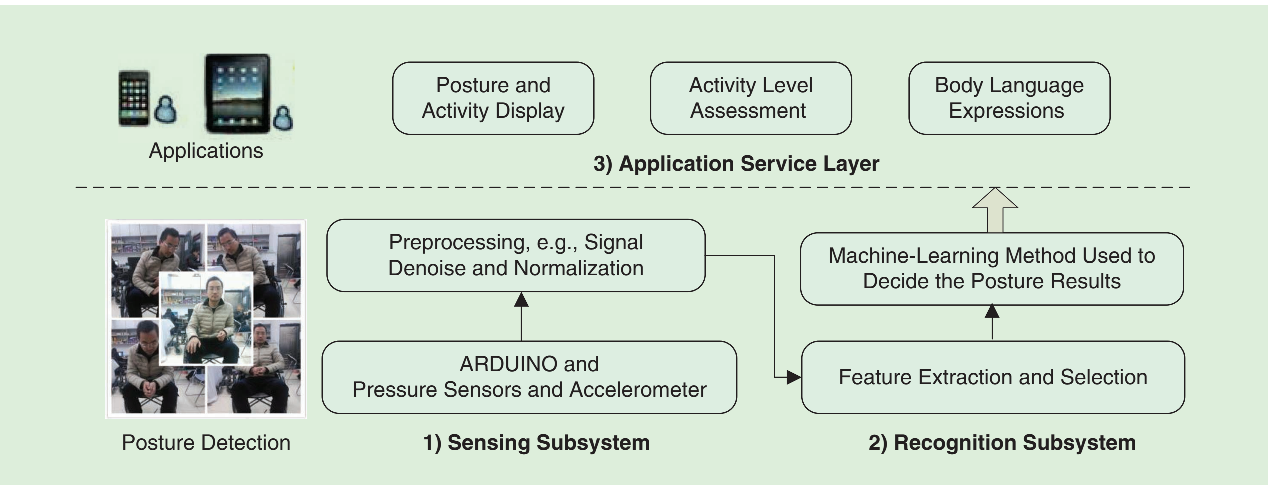


Figure 2. An architecture of the smart cushion system.

Posture and Activity Recognition

Activity Recognition Based on Adaptive Sliding Windows

Among the elderly population and people who suffer from motor disabilities, there is often prolonged use of wheelchairs, with health risks including chronic back pain and pressure ulcers. The smart cushion was used to detect the following basic seated postures: proper sitting (PS), LL, LR, LF, and lean backward (LB). We implemented the machine-learning method based on DT in the Arduino platform.

We can distinguish different activity categories using combinations of the postures, examples of which are provided in Table 3 and include the following:

- *Stable posture activities* are postures that are kept for a meaningful amount of time. A PS activity is exemplified in Figure 3(a).
- *Transitional posture activities* consist of a sequence of different individual sitting postures, such as the pressure relief activity useful in wheelchair users to prevent pressure ulcers. A relevant example of left pressure relief activity is depicted in Figure 3(b).
- *Noncumulative posture activities* refer to sporadic sitting actions (see Figure 4) and include trunk exercises, which could strengthen core stability and promote the prevention of several medical complications such as chronic strokes [48].

In previous research [49], we proposed an adaptive sliding window (ADW)-based classification algorithm focused on the activities listed in Table 3. We collected data from several subjects using the smart cushion deployed on a wheelchair in static and dynamic conditions.

We implemented the algorithm in MATLAB. DT and kNN were chosen to test our algorithm. In both static and dynamic conditions, our algorithm obtained a higher F-score (a combined metric of precision and recall). Table 4 lists the results of static condition between fixed-size windows and ADWs.

PS	PS	PS	PS	PS	PS

(a)

PS	PS	LL	LL	PS	PS

(b)

Figure 3. Examples of cumulative posture activity. (They were composed by a series of postures listed in the boxes.) (a) Posture-stable activity and (b) posture-transitional activity.

Activity Level Assessment for Sedentary Lifestyle Users

It is well known that a sedentary lifestyle is strongly correlated with several health issues, therefore, medical guidelines agree on the importance of constant motivation to maintain an active lifestyle. Activity level assessments can provide statistical information in a given period and recommend that the users increase physical exercise. In a previous study [44], we proposed an activity level assessment system specifically conceived for wheelchair users. The architecture of the system, displayed in Figure 5, consists of two layers:

- *data preprocessing*: time series of sampled data are collected and instance vectors are generated from the pressure sensors and IMU.
- *activity assessment index calculation*: significant features are extracted and machine-learning methods are used to recognize the activity levels. Three activity levels are identified and categorized according to their intensity, as summarized in Table 5.

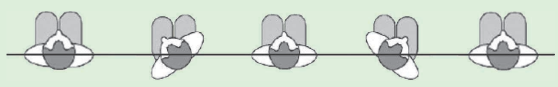


Figure 4. Noncumulative-posture activity examples (trunk-rotation exercise).

Table 3. The activity categories and their examples.

Activity Category	Activity Example
Stable posture activity	PSA, LSA, RSA
Transitional posture activity	LPR and RPR
Noncumulative posture activity	TTL and TTR

PSA: proper sitting activity; LSA: left sitting activity; RSA: right sitting activity; LPR: left pressure relief; RPR: right pressure relief; TTL: trunk turn left; TTR: trunk turn right.

Table 4. The results of F-score using the two time window selection methods in a static environment.

	PSA	LSA	RSA	LPR	RPR	TTL	TTR
DT and FW	0.93	0.93	0.93	0.81	0.81	0.68	0.72
kNN and FW	0.93	0.91	0.91	0.7	0.84	0.67	0.76
DT and AW	0.94	0.95	0.94	0.92	0.86	0.87	0.85
kNN and AW	0.95	0.93	0.94	0.89	0.87	0.82	0.84

FW: fixed-size windows.

The proposed system achieved >89% accuracy for activity recognition and >98% for activity level recognition. These results demonstrated that by using our designed smart cushion, the activity levels of the seated users could be seen to encourage physical exercise, when necessary, especially for the wheelchair users, as they suffer from prolonged exposure to high pressure of the buttocks, which may cause pressure ulcers [19].

Body Language Expressions Recognition

The recognition of seated postures and activities not only supports health-care applications (such the ones discussed previously), but it effectively enables completely different scenarios. The automatic recognition of postures and body movements can promote the analysis of kinesics (often referred to as *body language*). In our research [50], we designed a method to recognize emotion-relevant activities based on the analysis of seated actions. We were specifically interested in daily life basic seated activities (in terms of postures combined with gestures) with emotional valence.

The processing workflow, depicted in Figure 6, is composed of the following three main tasks:

1) posture and gesture synthesis
2) data synchronization and normalization; the posture and gesture data are synchronized and normalized to generalize feature sets for emotion-relevant activity recognition
3) feature fusion and classification.

Our approach employs a hierarchical classification: first, posture and gestures are classified independently, and then posture and gestures are organized in form-sequence vectors, which are, in turn, classified using HMMs. An HMM is effective to model the sequence of states and finds wide application in pattern recognition. In our method, each type of activity is modeled using a dedicated trained HMM; therefore, when a new discrete observation sequence is available, the appropriate HMM is found through maximum likelihood. The results obtained from the recognition of four different body language expressions (interest, frustration, sadness, and happiness) are promising, with an average accuracy of 91.8%.

Conclusion and Future Directions

In this article, we reviewed methods, technologies, and applications of an emerging smart object known as a *smart cushion*. We showed its great potential application value, as it is very suitable for monitoring several parameters of people performing tasks that require them to be seated. The article widely covered the current state of the art, though it is focused on our previous related research studies and results. We presented a diversified plethora of applications enabled by our designed smart cushion, spanning medical scenarios to automotive setups.

Although there is consolidated research on activity recognition based on the smart cushion, there still exists several open research challenges. The following open research directions and challenges are the most interesting:

- *Smart cushion design*: New types of materials should be applied to improve the smart cushion design. To make the recognition of activities more precise, more sensing parameters should be added, e.g., from biological signals such as electrocardiograms and electromyograms.
- *Big data issues*: Human daily life activities will generate a huge volume of data, so it is critical to effectively exploit cloud technology [51], [52] and big data analytics [53] to develop more user-centric applications.

Table 5. The activity levels and the representative activity examples.

Activity Level	Examples of Activities
Light intensity	Reading, desk work, and conversation
Moderate intensity	Swing left-right or front-back
Vigorous intensity	Upper body exercises

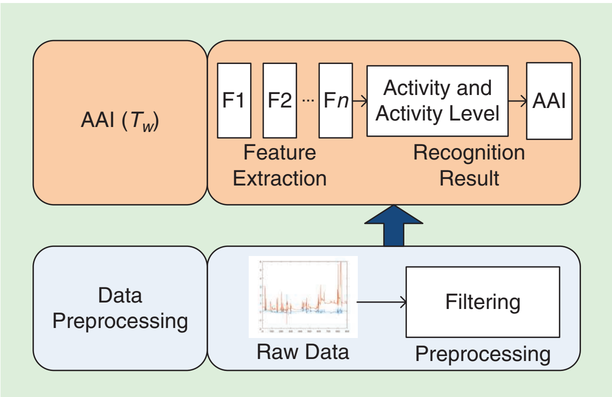


Figure 5. The activity level assessment workflow. AAI: activity assessment index.

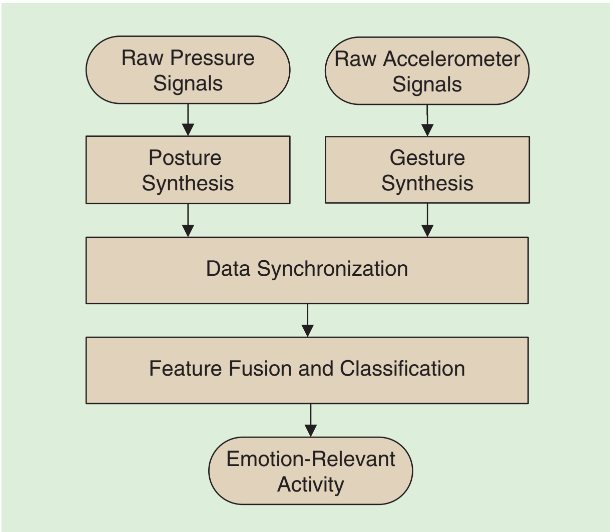


Figure 6. The emotion-relevant activity processing workflow.

- *The Internet of Things-collaborative body sensor networks (CBSNs) integration*: In the context of CBSNs, it is relevant to recognize group activities. In elder care centers, for example, it would be beneficial for wheelchair users and caregivers to exchange information automatically, so as to relieve the workload of caregivers.

Acknowledgments

Our research is financially supported by the National Natural Science Foundation of China (grants 61571336, 61502360, and 61603280). It was also partially supported by the Cogito Project, funded by Italian National Operating Program "Research and Innovation" (2014–2020), and the European structural and investment funds under grant ARS01-00836.

About the Authors

Congcong Ma (macc@whut.edu.cn) earned his B.S. degree from Shaanxi University of Science and Technology, Xi'an, China, his M.S. degree from South China Normal University, Guangzhou, China, and his Ph.D. degree from Wuhan University of Technology, China, in 2009, 2012, and 2018, respectively. He has been a lecturer with the School of Software at Nanyang Institute of Technology, China, since 2018. He is a Member of IEEE.

Wenfeng Li (liwf@whut.edu.cn) earned his B.S. degree from Zhengzhou Institute of Light Industry, China, in 1986, his M.S. degree from Huazhong University of Science and Technology, Wuhan, China, in 1990, and his Ph.D. degree from Wuhan University of Technology, China, in 2000. Currently, he is a professor with the School of Logistics Engineering, Wuhan University of Technology. He is a Senior Member of IEEE.

Raffaele Gravina (r.gravina@dimes.unical.it) earned his B.Sc. and M.Sc. degrees in computer engineering from the University of Calabria (UniCal), Rende, Italy, and his Ph.D. degree in computer and systems engineering, also from the University of Calabria, in 2003, 2007, and 2012, respectively. He is an assistant professor of computer engineering in the Department of Informatics, Modeling, Electronics and Systems, UniCal. He is a Member of IEEE.

Juan Du (dujuan-0218@163.com) earned her B.Sc. and M.Sc. degrees in information engineering from Zhengzhou University, China, in 2009 and 2012, respectively. She is a lecturer of communication engineering at Nanyang Institute of Technology, Singapore.

Qimeng Li (qimeng.li@unical.it) earned his M.Sc. degree in electronic engineering from the University of Calabria (UniCal), Rende, Italy, in 2017. He is currently pursuing his Ph.D. degree in the Department of Informatics, Modeling, Electronics and Systems, UniCal. He is a Student Member of IEEE.

Giancarlo Fortino (g.fortino@unical.it) earned his B.Sc. and M.Sc. degrees in computer engineering from the University of Calabria (UniCal), Rende, Italy, in 1995, and his Ph.D. degree in computer engineering from UniCal in 2000. Currently, he is a professor of computer engineering in the Department of Informatics, Modeling, Electronics and Systems, UniCal. He is also an adjunct professor at Wuhan University of Technology, China. He is a Senior Member of IEEE.

References

[1] G. Fortino, R. Giannantonio, R. Gravina, P. Kuryloski, and R. Jafari, "Enabling effective programming and flexible management of efficient body sensor network applications," *IEEE Trans. Human–Mach. Syst.*, vol. 43, no. 1, pp. 115–133, 2013. doi: 10.1109/TSMCC.2012.2215852.

[2] M. Zheng, P. X. Liu, R. Gravina, and G. Fortino, "An emerging wearable world: New gadgetry produces a rising tide of changes and challenges," *IEEE Syst., Man, Cybern. Mag.*, vol. 4, no. 4, pp. 6–14, 2018. doi: 10.1109/MSMC.2018.2806565.

[3] S. Galzarano, R. Giannantonio, A. Liotta, and G. Fortino, "A task-oriented framework for networked wearable computing," *IEEE Trans. Autom. Sci. Eng.*, vol. 13, no. 2, pp. 621–638, 2014. doi: 10.1109/TASE.2014.2365880.

[4] Z. Wang et al., "Using wearable sensors to capture posture of the human lumbar spine in competitive swimming," *IEEE Trans. Human–Mach. Syst.*, vol. 49, no. 2, pp. 194–205, 2019. doi: 10.1109/THMS.2019.2892318.

[5] R. Gravina, P. Alinia, H. Ghasemzadeh, and G. Fortino, "Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges," *Inform. Fusion*, vol. 35, pp. 68–80, May 2017. doi: 10.1016/j.inffus.2016.09.005.

[6] S. Qiu, Z. Wang, H. Zhao, K. Qin, Z. Li, and H. Hu, "Inertial/magnetic sensors based pedestrian dead reckoning by means of multi-sensor fusion," *Inform. Fusion*, vol. 39, pp. 108–119, Jan. 2018. doi: 10.1016/j.inffus.2017.04.006.

[7] C. Ma, W. Li, R. Gravina, and G. Fortino, "Posture detection based on smart cushion for wheelchair users," *Sensors (Basel)*, vol. 17, no. 4, p. E719, 2017. doi: 10.3390/s17040719.

[8] Y.-S. Hong, "Smart care beds for elderly patients with impaired mobility," *Wirel. Commun. Mob. Com.*, vol. 2018, no. 3, pp. 1–12, 2018. doi: 10.1155/2018/1780904.

[9] D. Chen et al., "Smart insole based indoor localization system for internet of things applications," *IEEE Internet Things J.*, vol. 6, no. 4, , pp. 7253–7265, 2019. doi: 10.1109/JIOT.2019.2915791.

[10] L. Yang, W. Li, Y. Ge, X. Fu, R. Gravina, and G. Fortino, "People-centric service for mHealth of wheelchair users in smart cities," in *Internet of Things Based on Smart Objects. Internet of Things (Technology, Communications and Computing)*, G. Fortino and P. Trunfio, Eds. Cham, Switzerland, Springer-Verlag, 2014, pp. 163–179.

[11] L. Yang, Y. Ge, W. Li, W. Rao, and W. Shen, "A home mobile healthcare system for wheelchair users," in *Proc. 2014 IEEE 18th Int. Conf. Computer Supported Cooperative Work in Design (CSCWD)*, pp. 609–614. doi: 10.1109/CSCWD.2014.6846914.

[12] W. Xu, M. Huang, N. Amini, L. He, and M. Sarrafzadeh, "eCushion: A textile pressure sensor array design and calibration for sitting posture analysis," *IEEE Sensors J.*, vol. 13, no. 10, pp. 3926–3934, 2013. doi: 10.1109/JSEN.2013.2259589.

[13] Tekscan Inc. Accessed on: Nov. 2019. [Online]. Available: http://www.tekscan.com/

[14] H. Z. Tan, L. A. Slivovsky, and A. Pentland, "A sensing chair using pressure distribution sensors," *IEEE/ASME Trans. Mechatronics*, vol. 6, no. 3, pp. 261–268, 2001. doi: 10.1109/3516.951364.

[15] S. Mota and R. W. Picard, "Automated posture analysis for detecting learner's interest level, in *Proc. Computer Vision and Pattern Recognition Workshop*, vol. 5, 2003, p. 49. doi: 10.1109/CVPRW.2003.10047.

[16] J. Meyer, B. Arnrich, J. Schumm, and G. Troster, "Design and modeling of a textile pressure sensor for sitting posture classification," *IEEE Sensors J.*, vol. 10, no. 8, pp. 1391–1398, 2010. doi: 10.1109/JSEN.2009.2037330.

[17] W. Liu, Y. Guo, J. Yang, Y. Hu, and W. Dapeng, "Sitting posture recognition based on human body pressure and CNN," *AIP Conf. Proc.* vol. 2073, no. 1, p. 020093, 2019. doi: 10.1063/1.5090747

[18] K. Kamiya, M. Kudo, H. Nonaka, and J. Toyama, "Sitting posture analysis by pressure sensors," in *19th Int. Conf. Pattern Recognition*, 2008, pp. 1–4. doi: 10.1109/ICPR.2008.4761863.

[19] F. Fard, S. Moghimi, and R. Lotfi, "Evaluating pressure ulcer development in wheelchair-bound population using sitting posture identification," *Engineering*, vol. 5, no. 10B, pp. 132–136, 2013. doi: 10.4236/eng.2013.510B027.

[20] K. Yong, Y. Son, W. Kim, B. Jin, and M. Yun, "Classification of children's sitting postures using machine learning algorithms," *Appl. Sci.*, vol. 8, no. 8, p. 1280, 2018. doi: 10.3390/app8081280.

[21] L. Xu, G. Chen, J. Wang, R. Shen, and S. Zhao, "A sensing cushion using simple pressure distribution sensors," in *Proc. 2012 IEEE Conf. Multisensor Fusion and Integration for Intelligent Systems (MFI),* 2012, pp. 451–456. doi: 10.1109/MFI.2012.6343048.

[22] B. Mutlu, A. Krause, J. Forlizzi, C. Guestrin, and J. Hodgins, "Robust, low-cost, non-intrusive sensing and recognition of seated postures," in *Proc. 20th Annu. ACM Symp. User Interface Software and Technology*, New York, ACM, 2007, pp. 149–158. doi: 10.1145/1294211.1294237.

[23] H. Yu, A. Stoelting, Y. Wang, Z. Yi, and M. Sarrafzadeh, "Providing a cushion for wireless healthcare application development," *IEEE Potentials.*, vol. 29, no. 1, pp. 19–23, 2010. doi: 10.1109/MPOT.2009.934698.

[24] M. Benocci, E. Farella, and L. Benini, "A context-aware smart seat," in *Proc. 4th IEEE Int. Workshop on Advances in Sensors and Interfaces (IWASI)*, 2011, pp. 104–109. doi: 10.1109/IWASI.2011.6004697.

[25] S-D. Min, "System for monitoring sitting posture in real-time using pressure sensors," U.S. Patent 20 160 113 583, 2016.

[26] R. Zemp et al., "Application of machine learning approaches for classifying sitting posture based on force and acceleration sensors," *Biomed. Res. Int.*, vol. 2016, no. 1, pp. 1–9, 2016. doi: 10.1155/2016/5978489.

[27] T. Fu and A. Macleod, "IntelliChair: An approach for activity detection and prediction via posture analysis," in *Proc. Int. Conf. Intelligent Environments*, 2014, pp. 211–213. doi: 10.1109/IE.2014.39.

[28] R. Kumar, A. Bayliff, D. De, A. Evans, S. K. Das, and M. Makos, "Care-Chair: Sedentary activities and behavior assessment with smart sensing on chair backrest," in *Proc. IEEE Int. Conf. Smart Computing*, 2016, pp. 1–8. doi: 10.1109/SMARTCOMP.2016.7501682.

[29] C. Ma, W. Li, R. Gravina, and G. Fortino, "Activity recognition and monitoring for smart wheelchair users," in *Proc. 2016 IEEE 20th Int. Conf. Computer Supported Cooperative Work in Design (CSCWD)*, pp. 664–669. doi: 10.1109/CSCWD.2016.7566068.

[30] G. Liang, J. Cao, X. Liu, and X. Han, "Cushionware: A practical sitting posture-based interaction system," in *Proc. Chi '14 Extended Abstracts on Human Factors in Computing Systems*, 2014, pp. 591–594. doi: 10.1145/2559206.2574778.

[31] G. Liang, J. Cao, and X. Liu, "Smart cushion: A practical system for fine-grained sitting posture recognition," in *Proc. IEEE Int. Conf. Pervasive Computing and Communications Workshops*, 2017, pp. 419–424. doi: 10.1109/PERCOMW.2017.7917599.

[32] J. Roh, H. J. Park, K. J. Lee, J. Hyeong, S. Kim, and B. Lee, "Sitting posture monitoring system based on a low-cost load cell using machine learning," *Sensors (Basel)*, vol. 18, no. 1, p. E208, 2018. doi: 10.3390/s18010208.

[33] D. Bibbo, M. Carli, S. Conforto, and F. Battisti, "A sitting posture monitoring instrument to assess different levels of cognitive engagement," *Sensors (Basel)*, vol. 19, no. 3, p. 455, 2019. doi: 10.3390/s19030455.

[34] X. Ren, B. Yu, Y. Lu, B. Zhang, J. Hu, and A. Brombacher, "Lightsit: An unobtrusive health-promoting system for relaxation and fitness microbreaks at work," *Sensors (Basel)*, vol. 19, no. 9, p. 2162, 2019. doi: 10.3390/s19092162.

[35] J. Bao, W. Li, J. Li, Y. Ge, and C. Bao, "Sitting posture recognition based on data fusion on pressure cushion," *Telkomnika Indones. J. Elect. Eng.*, vol. 11, no. 4, pp. 1769–1775, 2013. doi: 10.11591/telkomnika.v11i4.2329.

[36] D. E. Arias, E. J. Pino, P. Aqueveque, and D. W. Curtis, "Unobtrusive support system for prevention of dangerous health conditions in wheelchair users," *Mobile Inform. Syst.*, vol. 2016, pp. 1–14, July 2016. doi: 10.1155/2016/4568241.

[37] J.-Y. Seo, Y.-H. Noh, and D.-U. Jeong, "Implementation of distracted estimation system based on sensor fusion through correlation analysis with concentration," *Sensors (Basel)*, vol. 19, no. 9, p. 2053, 2019. doi: 10.3390/s19092053.

[38] R. Barba, P. Ángel, and J. G. Boticario, "Development of an inexpensive sensor network for recognition of sitting posture," *Int. J. Distrib. Sensor Netw.*, vol. 11, no. 8, Art. no. 161, Jan. 2015. doi: 10.1155/2015/969237.

[39] O. Halabi, S. Fawal, E. Almughani, and L. Al-Homsi, "Driver activity recognition in virtual reality driving simulation," in *Proc. Int. Conf. Information and Communication Systems*, 2017, pp. 111–115. doi: 10.1109/IACS.2017.7921955.

[40] K. Ishac and K. Suzuki, "A smart cushion system with vibrotactile feedback for active posture correction," in *Proc. Int. Asiahaptics Conf.*, 2016, pp. 453–459. doi: 10.1007/978-981-10-4157-0_76.

[41] M. Kim, H. Kim, J. Park, K. K. Jee, and M. C. Park, "Real-time sitting posture correction system based on highly durable and washable electronic textile pressure sensors," *Sens. Actuator A Phys.*, vol. 269, pp. 394–400, Dec. 2017. doi: 10.1016/j.sna.2017.11.054.

[42] Darma Inc. Accessed on: Nov. 2019. [Online]. Available: http://darma.co/

[43] SENSIMAT Systems Inc. Accessed on: Nov. 2019. [Online]. Available: http://www.sensimatsystems.com/

[44] C. Ma, W. Li, R. Gravina, J. Cao, Q. Li, and G. Fortino, "Activity level assessment using a smart cushion for people with a sedentary lifestyle," *Sensors*, vol. 17, no. 10, pp. 2269, 2017. doi: 10.3390/s17102269.

[45] Interlink Electronics Inc. Accessed on: Nov. 2019. [Online]. Available: http://www.interlinkelectronics.com

[46] TDK, "MPU-9250 Nine-Axis (Gyro + Accelerometer + Compass) MEMS MotionTracking Device," InvenSense Inc., San Jose, CA. Accessed on: Nov. 2019. [Online]. Available: https://www.invensense.com/products/motion-tracking/9-axis/mpu-9250/

[47] "Arduino Pro Mini." Accessed on: Feb. 2020. [Online]. Available: https://store.arduino.cc/arduino-pro-mini

[48] S. H. An and D. S. Park, "The effects of trunk exercise on mobility, balance and trunk control of stroke patients," *J. Korean Soc. Phys. Med.*, vol. 12, no. 1, pp. 25–33, 2017. doi: 10.13066/kspm.2017.12.1.25.

[49] C. Ma, W. Li, J. Cao, J. Du, Q. Li, and R. Gravina, "Adaptive sliding window based activity recognition for assisted livings," *Inform. Fusion*, vol. 53, pp. 55–65, Jan. 2020. doi: 10.1016/j.inffus.2019.06.013.

[50] R. Gravina and Q. Li, "Emotion-relevant activity recognition based on smart cushion using multi-sensor fusion," *Inform. Fusion*, vol. 48, pp. 1–10, Aug. 2019. doi: 10.1016/j.inffus.2018.08.001.

[51] R. Gravina, C. Ma, P. Pace, G. Aloi, W. Russo, W. Li, and G. Fortino, "Cloud-based activity-aaservice cyberphysical framework for human activity monitoring in mobility," *Future Gener. Comput. Syst.*, vol. 75, pp. 158–171, Oct. 2017. doi: 10.1016/j.future.2016.09.006.

[52] G. Fortino, G. D. Fatta, M. Pathan, and A. V. Vasilakos, "Cloud-assisted body area networks: State-of-the-art and future challenges," *Wirel. Netw.*, vol. 20, no. 7, pp. 1925–1938, Oct. 2014. doi: 10.1007/s11276-014-0714-1.

[53] G. Fortino, S. Galzarano, R. Gravina, and W. Li, "A framework for collaborative computing and multi-sensor data fusion in body sensor networks," *Inform. Fusion*, vol. 22, pp. 50–70, Mar. 2015. doi: 10.1016/j.inffus.2014.03.005.

SMC