# TPM Framework: a Comprehensive Kit for Exploring Applications with Textile Pressure Mapping Matrix


Bo Zhou*, Jingyuan Cheng‡, Ankur Mawandia*, Yujiang He‡, Zhixin Huang‡, Mathias Sundholm*, Muhammet Yildrim*, Heber Cruz*, Paul Lukowicz*†

*German Research Center for Artificial Intelligence
†TU Kaiserslautern, Germany
‡TU Braunschweig, Germany
bo.zhou@dfki.de, j.cheng@tu-braunschweig.de, ankur.mawandia@dfki.de,
yujiang.he@tu-braunschweig.de, zhixin.huang@tu-braunschweig.de,
mathias.sundholm@dfki.de, muhammet.yildrim@dfki.de,
heber.cruz@dfki.de, paul.lukowicz@dfki.de



***Abstract*—Based on a series of projects with textile pressure mapping matrix (TPM) for ubiquitous and wearable activity recognition in various scenarios, we have accumulated the knowledge and experience to develop an open-access hardware and software framework, which enables a broader education and allows the scientific community to build their own TPM applications. The hardware framework includes all the necessary resources to manufacture the sensing equipment and instructions to build the fabric sensors for an up to 32×32 TPM. The software framework 'Textile-Sandbox' contains ready-to-use tools and modules that support both running experiments and data mining. The framework is evaluated with 10 master students working in 4 groups. 4 applications are developed from scratch and validated within only 40 hours. We present this framework and the evaluated applications in this paper.**



***Keywords–Software Framework; Pressure Matrix; Smart Textile; Rapid Prototyping.***


## I. INTRODUCTION

Textile pressure mapping matrix (TPM) is a sensing modality that measures the planar pressure intensity distribution of the sensing textile, which is related to the people (parts of their body) and analyze a complete modular and miniaturized hardware system, software chains, and data processing and data mining algorithms.

With every new application, we discover:

1) TPM can be a *general sensing modality* for most of the activity recognition applications, as most activities are initiated by interactive force or support surface counter force. Even for contact activities, force can be propagated onto the floor. TPM can also be fixed on-body to measure the muscle activities. Pressure force mapping provides both temporal and spatial information about the activities, very distinct from the dominating sensing modalities, such as inertial measurement units in activity recognition. Its output is similar to a video in the sense of data format and processing methods.
2) Various applications share certain *similar exploration procedures*, as summarized in Fig. 2. The smart fabric produced by Sefar [1] is tailored to fit specific application scenarios [2]. From the hardware perspective, various versions of data acquisition electronics are developed to explore implementation varieties of the scalable modular architecture we proposed in [3]. Different data mining and machine learning methods are also evaluated according to the signal nature of various applications.

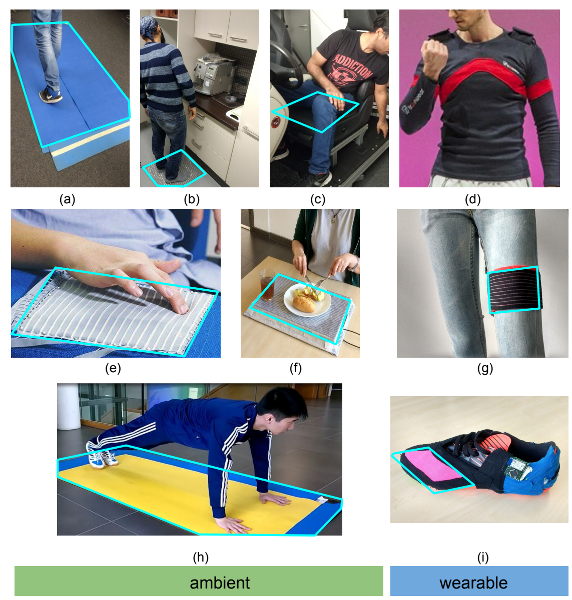



Figure 1. Various applications enabled by textile pressure mapping matrix (TPM)

It has come to a point that certain processes can be generalized in both the hardware and software domain to form a framework, which can greatly reduce time and effort of the idea-to-implementation cycle. Though there are much more application possibilities that can be interesting to be evaluated, we work on developing and improving this open-access framework, that can promote TPM in education and the broader research community, and more developers can be inspired to easily build their own applications.

The major contribution of this paper lies in:

1) We offer the manufacturing resources and firmware builds for the refined data acquisition system.
2) We present Textile-Sandbox, a well documented software framework for application exploration with TPM, including two labeling tools for ground truth annotation and a three-layered Matlab-based data mining tool, which can be both ran by a single click and adjusted in depth.
3) We validated the framework with 10 developers working in small groups, and 4 applications have been prototyped within 40 hours (see Table I). The developers are computer science students with very limited knowledge in the sensing modality and data mining. Therefore, our framework can not only reduce the time and effort spent in new application exploration, but also greatly lower the entry barriers.
4) We open all the code, resources, documentation and ethics templates to the research community [4] [5].

We hope the TPM framework can support more researchers in validating and exploring their own applications with textile pressure sensing matrix.

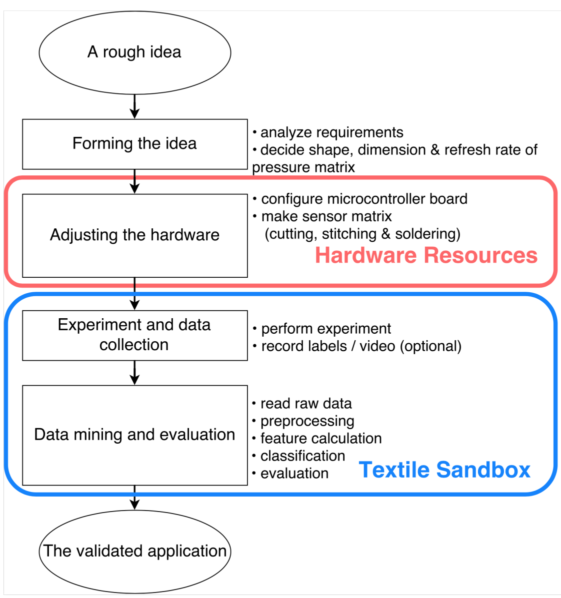



Figure 2. Typical procedures in new application exploration with textile pressure sensing matrix: the "Textile Sandbox" serves as the general framework for data recording and mining

## II. Related Work

### A. Planar pressure mapping development scene

In ubiquitous computing, planar pressure sensing is used in shoes to analyze gait information [6] [7], on chair/seat to detect user posture [8] [9] or recognize driver's identity [10], on furniture to recognize daily activities of the elderly [11]. A pressure sensing matrix equipped bed can recognize on-bed rehabilitation exercises or monitor sleep posture and stage [12] [13] [14]. Different kinds of pressure sensitive floors have been used for indoor positioning [15] [16], gait and person identification [17] [18] [19] and human computer interaction [20] [21]. Similar to our own previous research, these works focus on creating or enhancing concrete hardware design, on creating data processing algorithms for specific applications. No open-access software framework is available from said works for a broader community to explore their own applications.

There are also a few off-the-shelf pressure sensing matrices. Sensingtex [22] provides a development kit for capturing pressure data using prefabricate hardware serving as seat cover, fitness mat and mattress mat. Tekscan provides both single pressure sensors and sensing matrices, that are used in shoes, mat, seat and bed [23]. Texisense provides a sensor matrix for monitoring walking and seating, accompanied by TexiMonitor-SLT, a custom software for data readout [24]. These commercial products come with fixed hardware, that is, the shape, dimensions, sample rate, etc. are all pre-fixed. Software is provided mainly for data read-out or for feature analysis and only for certain applications. The freedom of adapting these systems to new scenarios is thus greatly limited.

In summary, to the best of our knowledge, there is no existing open-access framework that is based on customizable hardware, and meanwhile provides ready-to-use data acquisition and data mining tools, thus enabling easy and quick exploration of new applications based on pressure sensing matrix. Moreover, our work focuses on textile based pressure mapping, instead of thin film based methods, which is the case with most of the above-mentioned works.

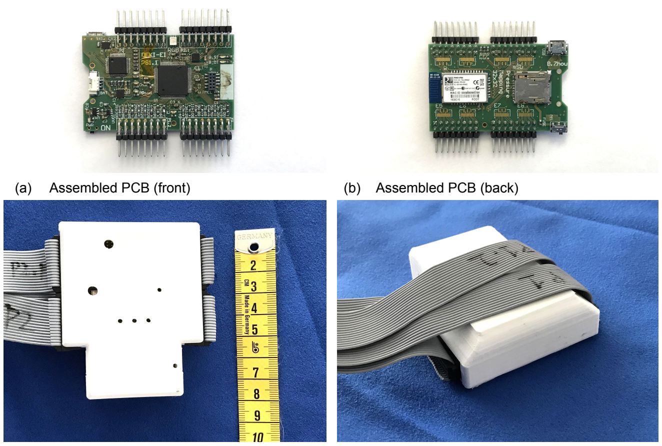
### B. Frameworks for ubiquitous computing applications

To ease application exploration in ubiquitous computing, a large number of frameworks were developed. A systematic review on them can be found in Guinea et al.'s work in 2016 [25], based on 132 approaches. Below we name a few, which inspired our Textile-Sandbox.

The iStuff toolkit [26] is composed of multiple physical devices and a supporting software framework, which includes a dynamically configurable intermediary to simplify the mapping of devices to different applications, thus greatly simplifying the exploration of novel interaction techniques in post-desktop era of multiple devices. CRN Toolbox [27] as a modular framework not only allows flexible sensor configuration and sensor data processing, but also provides a graphical configuration editor so that users can intuitively drag modules from library into workspace. It thus enables fast implementation of activity and context recognition systems. The Funf Open Sensing Framework [28] is an extensible sensing and data processing framework for mobile devices, which enables the collection, uploading and configuration of a wide range of data signals accessible via mobile phones. It reduces greatly the app developers' effort through its 3rd-party developer API.

As to smart textile, Buechley built a construction kit consisting of hardware components that can be stitched on garments to create interactive textiles [29]. Interactex [30] serves as a visual, integrated development environment specifically designed for smart textiles, including support on application development, testing and circuit design. Plushbot [31] contains a pattern interface for users to create and trace a plush toy; in the background, the program combines the plush toy pattern with computational pieces, allowing even children to create and customize programmable toys.

In summary, supporting tool-kits and frameworks for ubiquitous computing started to appear around 15 years ago. They all share the common characters of modular design and easy to configure, aim at enabling larger number of developers (specially software developers) to explore their own applications with reduced time, effort and cost. We took these as guidelines while developing our Textile-Sandbox.



(a) Assembled PCB (front) (b) Assembled PCB (back)

(c) 3D printed Enclosure (d) 3D printed Enclosure

Figure 3. The up-to-date hardware module from the hardware resources

## III. TPM APPLICATIONS: THE GENERAL WORKFLOW

The operation principles and detailed hardware designs of our TPM has been presented in [32] [3]. In short, a TPM sensor consists of 3 layers in a sandwich-like structure. The top and bottom layers are made of the same fabric, composed of evenly spaced parallel metallic stripes on a PET fabric substrate. The middle layer is a pressure sensitive semi-conductive fabric. The bottom layer is 90 degree rotated from the top layer. Each cross-section acts as a pressure sensor. The resistances at all cross-sections are turned to voltage by simple voltage-dividers and then turned from analog signal into digital data by ADCs (Analog-to-Digital Converter) scanning through the whole matrix. A complete scan of the matrix results in a pressure mapping imagery. Repeated scans produce a video-like data stream of pressure mapping imagery.

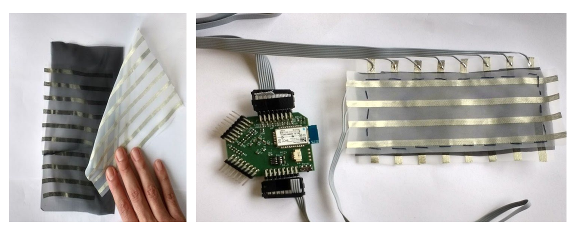
Exploring a application with TPM normally involves 4 steps (Fig. 2):

1) *Forming an idea*: Motivated by a general scenario, first a rough analysis on involved activities shall be carried out and a draft list of the activities shall be defined, then the hardware settings shall be fixed, including: where to put and how to fix the sensor matrix, the dimension and resolution of the matrix, the scanning speed, the electronic placement and cable routing. This step defines the hardware specifications for the next steps.
2) *Adapting the hardware*: Using pre-manufactured electronics, the specific hardware for this application can be made by: 1) tailor the smart fabrics to fit the target surface, 2) connect the sensing fabric to the electronics by careful soldering, 3) prepare the firmware of the electronics (change of scanning ports and speed) 4) fit the hardware into the experiment setting. A small-scaled matrix normally can be made within several hours (see Fig. 4). After this step, raw data can be gathered and visualized using our data acquisition tool in real-time, available at [33].
3) *Experiment and data collection*: Data can be collected by several participants for an abundant amount of repetitions. The ground truth (labels) are generated either at runtime or offline. This step generates the dataset for the next step.
4) *Data mining and evaluation*: The dataset is split into the training set and the testing set. Features are calculated for all the activities and the result is evaluated through n-Fold cross-validation.

## IV. HARDWARE RESOURCES

Through the accumulation of our previous works, we have developed a mature hardware system to drive a sensing matrix of up to 32×32 sensing points. The electronics, alone measures at 6×4 cm, are centered around a dsPIC microcontroller, powered by a Li-Po battery with onboard charging and protection circuits. It can be charged with a microUSB (Universal Serial Bus) cable. The data transmission is possible through Bluetooth Classic, USB 2.0 or serial port streaming, or local SD card logging. Several LEDs including a full-color LED (Light-Emitting Diode) provides a rich range of status indication. It also has a 9-axis onboard IMU (Inertial Measurement Unit) for sensor fusion purposes, and optional ESD (Electrostatic Discharge) protection at the smart textile connection ports.

With USB connection, a 32-by-32 sensor matrix can be sampled at 40 frames per second with 12-bit analog resolution, which is limited by the ADC sampling rate. With Bluetooth, the refresh rate is limited to approximately 19.5 frames per second due to the Bluetooth bandwidth (30KB/s). However, as the matrix resolution decreases, the refresh rate can be improved. For example, with USB data transmission, a 16-by-16 matrix can be scanned at 160 frames per second.



(a) raw material (b) assembled TPM hardware

Figure 4. With the instructions in the Textile-Sandbox, developers can easily assemble tailored TPM sensors from raw material

In the open-access resources, the manufacturing files are available together with the micro-controller firmware builds, which streams out data of the full scan of 32 × 32 matrix. The parameters can be easily modified to accommodate different matrix resolutions. The 3D model of an enclosure (22×62×76 mm) for the electronics and the battery is also available. The electronics connects to the smart fabric through 2.54cm-pitch 8×2 headers, which can be clamped onto widely available 1.27cm-pitch ribbon cables. All resources needed to produce a hardware as shown in Figure 3 can be accessed in [4].

## V. Software Framework: Textile-Sandbox

### A. Design Guidelines of the Textile-Sandbox

As our goal is to reduce application exploration effort, and our target users are the computer science students and researchers, who are new to pressure sensing, we identify the following basic requirements on the software framework:

- *Per step support*: Tools should be provided for data recording and data processing/mining. We provide two tools for data labeling, and a Matlab-based data mining tool for feature extraction and classification.
- *Configurable*: Application-specific parameters (matrix size, refresh rate, preprocessing parameters, data path) are configured by an editable .cvs file.
- *Fast kickstart*: Together with the framework, we provide a compact example of labeled dataset and configurations. After downloading the framework, users can execute the whole data processing chain by calling a single function and a few more mouse clicks.
- *Modular design*: We divide our framework into three-layered modules. User can sequentially execute each module and validate its output. The intermediate outcome of former steps are automatically saved, so that the user can resume the data processing from any step.
- *Documented*: An on-line "help" documentation is created, serving as the nexus for resource downloading, tutorials of experiment design, and how to use the labeling tools and data mining tool (open access at [33]).

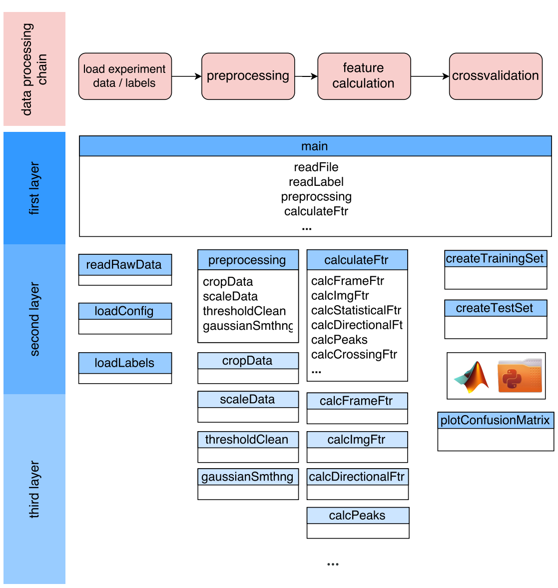



Figure 5. Data processing flow and corresponding design in Textile-Sandbox

### B. Data Labeling Tools

As we follow the typical supervised learning method in application exploration, generating accurate labels for recorded data is the base for all data mining tasks afterwards. We developed two labeling tools according to the nature of two types of activities. The first type of activities can be easily controlled by the test subject him/herself to be finished within a predefined period in predefined order. For example, using forefinger to *plot a circle* or to *write "A"* on the pressure mat. The second type of activities shall happen in a more natural way at the speed and the order that the test subject feels comfortable. For example, having a meal contains activities like *eating salad*, *eating bread* and *drinking water*. The test subject however, would most likely want to mix the activities, adapt the duration and sequence of each activity according to his/her own eating habit. We developed a light-weight online labeling tool for the first type and an offline labeling tool for the second (open access at [34]).

### C. Data Mining Tool

We followed the general data processing chain in Figure 5 and developed a data mining tool, which allows the user to process the pressure distribution dataset with minimal or no coding. We implemented all the functions in Matlab with self-developed algorithm, except the step "classification", where the Classification Learner app in Matlab [35] is used. The data mining tool is divided into three layers. On the first layer is the main function, which calls the functions on the second layer in a sequence way, so that the end result based on given dataset can be obtained by executing just one function and few clicks. The second layer matches each step in the data processing chain. These functions further call the functions on the third layer, where sub-tasks are performed.

In the data processing chain, first the raw data, the configuration in the .cvs file, and the labels are loaded. The preprocessing step utilizes several methods, such as DC removal, upscaling, filtering to enhance the data quality within each frame (the reasons for applying these methods and the implementations are reported in our former work [32]).

The next step is essential for the final classification performance of every new application. Here the features are extracted from the preprocessed data. We provided 21 basic features, which are generally useful for most of the applications. These features offer an initial classification result, to explore the feasibility of using TPM for the application with little overhead effort. If the user decides to further improve the result, the second layer also supports custom features.

For each event, the 21 basic features are defined as follows:

*Statistical features from the time series of frame descriptors (10 features)*: two descriptors are calculated from each frame: sum of all pixels and the number of pixels after thresholding. From the time series of these two descriptors within the event, the maximum, minimum, mean, number of peaks and number of mean-crossing are calculated.

*Pressure center shift (4 features)*: Three frames from each activity event, the first, the last, and the frame with the highest pixel-sum, are selected. The center of weight [x,y] of these frames are calculated. The difference of [x,y] between the first and the last frame, and between first and the highest pixel-sum frame, are considered as another 4 features.

*Image descriptors the average frame (7 features)*: Each pixel in the average frame is the average of the pixel location within the event period. The 7 Zernike image moments [36] of this frame are calculated as features.

The third layer performs cross-validation using the features from the second layer with the Matlab Classification Learner.

TABLE I. SUMMARY OF THE APPLICATIONS FROM THE 10-PARTICIPANT WORKSHOP

| Project | Matrix | Classes | participant × repetitions | Evaluation* | Accuracy |
|---|---|---|---|---|---|
| SpyOnMe | $32 \times 8$ 2cm pitch | 6 [1] | $3 \times 5$ | Bagged Trees 8-fold | 91%** |
| Win Your Heart | $16 \times 16$ 2cm pitch | 6 | $1 \times 10$ | Random Forest 10-fold | 84% |
| Pressure Password | $16 \times 16$ 1cm pitch | 5 [3] | $2 \times 10$ | SVM 5-fold | 76% |
| Smart Pillow | $16 \times 16$ 2cm - 4cm pitches*** | 5 [4] | $3 \times 10$ | Bagged Trees 10-fold | 87% |

* all projects used the 21 basic features provided by the Textile-Sandbox
** the asymmetric pitch is used to accompany the length of the pillow
[1] typing, writing, sketching with a pen, internet surfing or playing computer games (both mouse and keyboard), idle, and absence.
[2] scratching, hugging, holding the toy's upper part, holding the lower part, beating, pinching and touching with the face (simulating kissing).
[3] five distinct passwords.
[4] 4 sleep positions (supine position, prone position, lying on the left side, lying on the right side) and 1 kneeing posture

This three layered design allows users with varying levels of expertise to benefit from the data mining tool. With the first layer the user can quickly get an impression on the process and check the initial results by running only a few functions plus a few clicks in the Matlab Classification Learner. The user can then get deeper by checking the output of each step on the second layer. As he/she gets more insights, the third layer provides him/her enough freedom to influence the final result with some small changes in the code. The user can then modify the modules even on higher levels. By then the users shall have already gained enough knowledge to develop their own data mining algorithms. Our data mining tool has thus completed its mission in supporting application exploration. From that moment on, it shall serve mainly as a starting point for the user towards the more comprehensive application development.

### *D. Documentation*

A web documentation is created and can be accessed at [33]. It is indexed and can be searched upon, containing: (1) An overview of the application exploration chain; (2) Description of the hardware and operational instructions; (3) Description of the labeling tools; (4) Description of the data mining tool, including detailed description to all the Matlab functions; (5) Links to all source code, tools, introduction powerpoint slides (used in the practicum, details in section VI) and one labeled dataset for an easy start without own data recording and labeling.

## VI. APPLICATION EXPLORATION USING TEXTILE-SANDBOX

To evaluate to what degree our Textile-Sandbox can support new application exploration, and to provide computer science students the hands-on experience with hardware and the activity recognition related data processing, we created a workshop for master students majored in Computer Science or System Techniques, where the students develop from scratch their own application. From 10 participants, only 3 had background knowledge on ubiquitous computing through some earlier lectures. Four groups were formed voluntarily. All the groups managed to individually propose and explore one application within only 40 hours (The applications are shown in Fig. 6, detailed time distribution is listed in Table II). All applications are based on general ready-to-use electronics, which are developed by our lab in [37]. It drives one matrix of maximum 32×32 channels and transfers the data via Bluetooth to a mobile phone. The scanning rate is set to 60Hz.

TABLE II. TIME DISTRIBUTION IN APPLICATION EXPLORATION WITH TEXTILE-SANDBOX.

| Task | time spent |
|---|---|
| Introduction lecture | 6 hr |
| Software practice with existing dataset | 4 hr |
| Propose an application | 3 hr |
| Making matrix | 4 hr |
| Data recording and evaluation with Textile-Sandbox | 20 hr |
| Presentation on the explored applications | 0.5 hr |
| Sum | 37.5 hr |

The motivations of the applications are described below, the physical hardware are shown in Figure 6, and the settings and results are listed in Table I. Since the educational purpose of this workshop is our main focus, the level of innovation and dataset size are limited to only establish a pilot prototype.

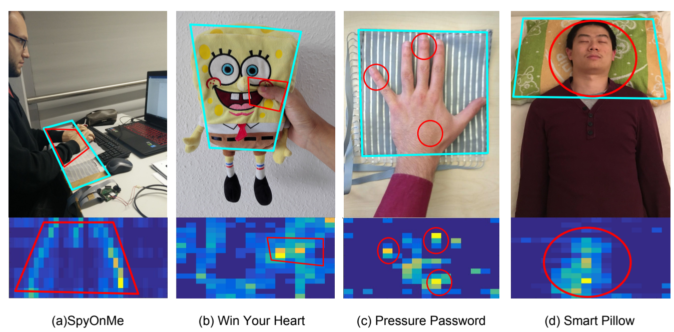



Figure 6. Applications explored using Textile-Sandbox, along with the representing pressure distribution of one selected activity, (a)SpyOnMe (two arms lying on the table while tying on keyboard), (b)Win Your Heart (grabbing with thumb), (c)Pressure Password (pressing with the middle and the little fingers), (d)Smart Pillow (supine position)

### *A. SpyOnMe: activity monitoring at workplace*

Modern office workplace normally has a similar setting: a work desk, a computer with keyboard and mouse, paper, etc. Detection of typical activities like typing on keyboard, browsing web or away from work can give insights into the person's role, his/her methods and performance at work place. SpyOnMe is proposed, as an non-intrusive method to monitor work space activities based on pressure between forearms and the desk.

TABLE III. FEEDBACK RECEIVED FROM 10 PRACTICUM PARTICIPANTS, SCALED FROM 1 (LOWEST) TO 5 (HIGHEST)

| Criteria | avg score | min score |
|---|---|---|
| well documented | 4.9 | 4 |
| intutive to use | 4.4 | 3 |
| applicable to multiple scenario | 4.3 | 3 |
| richness of tools | 4.1 | 3 |
| faster application development | 4 | 2 |

### B. *Win Your Heart: a toy for children behavior analysis*

Toys have been widely used, for educational, behavioral training, emotional companion and other purposes. This application aims to enable non-obtrusive monitoring of children's behaviour and their mental status by identifying their interactions with a pressure sensitive toy.

### C. *Pressure Password: motionless unlocking*

Pattern or numerical locks are fairly common on mobile devices and keyless entry systems. However, pattern based locks have been shown to be highly insecure as intruders can observe movements and easily crack the pattern [38]. Numerical entry systems, such as in ATM machines have been shown vulnerable to thermal cameras [39]. We explored a motionless password system based on the born shape of palm and length of fingers, and the combination of multiple fingers at different intensity of pressure. All the combinations look the same, making the password hard to copy by observing.

### D. *Smart Pillow: sleep position detection*

One third of our life is spent sleeping, which has a high impact also on the other two thirds. A pillow covered with pressure sensing matrix can help monitor the sleep posture and enhance sleep quality.

### E. *Developer feedback*

Anonymous questionnaires were given to the ten participants to collect their feedback to the Textile-Sandbox (see Table III). In general, we received a very positive response. Most of the students agree that the framework is easy and intuitive to use, allows them to create and develop applications faster. Eight out of ten students agree that they can independently develop applications with the support from Textile-Sandbox. Two students got inspired to create features suiting their applications. All reported improvement in the understanding of smart textile and its application after developing their own application with Textile Sandbox.

It is suggested to combine the data acquisition app and the online labeling tool into one tool to reduce annotation effort. It is also suggested that more prior applications shall be introduced at the beginning. (We will thus accumulate applications developed within this workshop as example for future students.)

## VII. CONCLUSION

We present in this paper our open access framework to explore wearable and ubiquitous applications with textile pressure mapping matrix (TPM), which includes hardware resources and the software framework, Textile-Sandbox. We have explored its application in various activity recognition related domains. To pave its path towards a wider adoption in the research community, we developed the framework to inspire and assist developers new to smart fabric or TPM, but interested in exploring their own applications using this sensing modality. We evaluated this framework with computer science master students, who successfully explored applications proposed by themselves independently within only 40 hours.

In our future work, we plan to keep pushing out hardware and software revisions. A Python port of the software framework is also in the plan. Also, manual mode will be added to the online labeling tool, as suggested by students, so that labels can also be freely generated by the experiment supervisor during the experiment. To further reduce the exploration time and lower the barriers to entry, more features shall be implemented and provided as ready-to-use module. A graphical user interface shall be created, which shows the data processing chain and provides "drag and drop" function for adding and removing modules. We will also look into packaging the functions for using the TPM into APIs that can act as a third-party plugin for other smart textile frameworks, such as Interactex [30]. We are looking forward to further suggestions from the research communities as well.

We believe the TPM hardware sensing platform and the Textile-Sandbox framework, shall free the imagination of a boarder research community, and project another type of light (the gravity and other forces) onto the secrets hidden in human activities and behaviors.

## REFERENCES


[1] "Sefar." [Online]. Available: http://www.sefar.com/

[2] S. P. Consortium, "Simpleskin project final report - 4.1.3.1 wp1 textile technologies," Tech. Rep., 2016. [Online]. Available: http://simpleskin.org/downloads/final_report.pdf

[3] B. Zhou, J. Cheng, M. Sundholm, and P. Lukowicz, "From smart clothing to smart table cloth: Design and implementation of a large scale, textile pressure matrix sensor," in ARCS. Springer, 2014, pp. 159–170.

[4] A. Mawandia and J. Cheng, "Textile sandbox: source codes, resources and documentation on-line," http://wearcomlab.com/wcldocumentation/sites.google.com/site/resistivesensingdocumentation/resources.html, last access: Feb. 2017.

[5] S. Doda, M. S. Singh, B. Zhou, and J. Cheng, "Ethics templates for experiments with resistive sensing matrix," http://simpleskin.org/?ethics, last access: Feb. 2017.

[6] L. Shu, T. Hua, Y. Wang, Q. Li, D. D. Feng, and X. Tao, "In-shoe plantar pressure measurement and analysis system based on fabric pressure sensing array," Information Technology in Biomedicine, IEEE Transactions on, vol. 14, no. 3, 2010, pp. 767–775.

[7] W. Xu, M.-C. Huang, N. Amini, J. J. Liu, L. He, and M. Sarrafzadeh, "Smart insole: a wearable system for gait analysis," in Proceedings of the 5th International Conference on PErvasive Technologies Related to Assistive Environments. ACM, 2012, p. 18.

[8] J. Meyer, B. Arnrich, J. Schumm, and G. Tröster, "Design and modeling of a textile pressure sensor for sitting posture classification," Sensors Journal, IEEE, vol. 10, no. 8, 2010, pp. 1391–1398.

[9] W. Xu, M.-C. Huang, N. Amini, L. He, and M. Sarrafzadeh, "ecushion: A textile pressure sensor array design and calibration for sitting posture analysis," Sensors Journal, IEEE, vol. 13, no. 10, 2013, pp. 3926–3934.

[10] X. Xie, B. Zheng, and W. Xue, "Object identification on car seat based on rough sets," in 2011 IEEE 3rd International Conference on Communication Software and Networks, 2011, pp. 157–159.

[11] J.-H. Lim, H. Jang, J. Jang, and S.-J. Park, "Daily activity recognition system for the elderly using pressure sensors," in EMBS 2008. 30th Annual International Conference of the IEEE. IEEE, 2008, pp. 5188–5191.

[12] M.-C. Huang, J. J. Liu, W. Xu, N. Alshurafa, X. Zhang, and M. Sarrafzadeh, "Using pressure map sequences for recognition of on bed rehabilitation exercises," Biomedical and Health Informatics, IEEE Journal of, vol. 18, no. 2, 2014, pp. 411–418.

[13] J. J. Liu, W. Xu, M.-C. Huang, N. Alshurafa, M. Sarrafzadeh, N. Raut, and B. Yadegar, "Sleep posture analysis using a dense pressure sensitive bedsheet," Pervasive and Mobile Computing, vol. 10, 2014, pp. 34–50.

[14] L. Samy, M.-C. Huang, J. J. Liu, W. Xu, and M. Sarrafzadeh, "Unobtrusive sleep stage identification using a pressure-sensitive bed sheet," Sensors Journal, IEEE, vol. 14, no. 7, 2014, pp. 2092–2101.

[15] D. Savio and T. Ludwig, "Smart carpet: A footstep tracking interface," in AINAW'07. 21st International Conference on, vol. 2. IEEE, 2007, pp. 754–760.

[16] Y. Kaddoura, J. King, and A. S. Helal, "Cost-precision tradeoffs in unencumbered floor-based indoor location tracking," in 3rd International Conference on Smart Homes and Health Telematics, Sherbrooke, Québec, Canada, 2005, pp. 75–82.

[17] L. Middleton, A. Buss, A. Bazin, M. S. Nixon et al., "A floor sensor system for gait recognition," in Automatic Identification Advanced Technologies, 2005. Fourth IEEE Workshop on. IEEE, 2005, pp. 171–176.

[18] R. J. Orr and G. D. Abowd, "The smart floor: a mechanism for natural user identification and tracking," in CHI'00 extended abstracts on Human factors in computing systems. ACM, 2000, pp. 275–276.

[19] G. Qian, J. Zhang, and A. Kidané, "People identification using gait via floor pressure sensing and analysis," in Smart sensing and context. Springer, 2008, pp. 83–98.

[20] P. Srinivasan, D. Birchfield, G. Qian, and A. Kidané, "A pressure sensing floor for interactive media applications," in Proceedings of the 2005 ACM SIGCHI International Conference on Advances in computer entertainment technology. ACM, 2005, pp. 278–281.

[21] S. Rangarajan, A. Kidané, G. Qian, and S. Rajko, Design Optimization of Pressure Sensing Floor for Multimodal Human-Computer Interaction. INTECH Open Access Publisher, 2008.

[22] S. Sensing Tex, "Sensing tex smart textiles," http://sensingtex.com/development-kits, last access: Feb. 2017.

[23] Tekscan, "Pressure mapping, force measurement, & tactile sensors — tekscan," https://www.tekscan.com/products-solutions, last access: Feb. 2017.

[24] T. Company, "Texisense textile pressure sensor: Teximat and teximat-slt," http://www.texisense.com/home_en, last access: Feb. 2017.

[25] A. S. Guinea, G. Nain, and Y. Le Traon, "A systematic review on the engineering of software for ubiquitous systems," Journal of Systems and Software, vol. 118, 2016, pp. 251–276.

[26] R. Ballagas, M. Ringel, M. Stone, and J. Borchers, "istuff: a physical user interface toolkit for ubiquitous computing environments," in Proceedings of the SIGCHI conference on Human factors in computing systems. ACM, 2003, pp. 537–544.

[27] D. Bannach, O. Amft, and P. Lukowicz, "Rapid prototyping of activity recognition applications," IEEE Pervasive Computing, vol. 7, no. 2, 2008.

[28] N. Aharony, W. Pan, C. Ip, I. Khayal, and A. Pentland, "Social fmri: Investigating and shaping social mechanisms in the real world," Pervasive and Mobile Computing, vol. 7, no. 6, 2011, pp. 643–659.

[29] L. Buechley, "A construction kit for electronic textiles," in Wearable Computers, 2006 10th IEEE International Symposium on. IEEE, 2006, pp. 83–90.

[30] J. Haladjian, K. Bredies, and B. Brügge, "Interactex: an integrated development environment for smart textiles," in Proceedings of the 2016 ACM International Symposium on Wearable Computers. ACM, 2016, pp. 8–15.

[31] Y. Huang and M. Eisenberg, "Steps toward child-designed interactive stuffed toys," in Proceedings of the 10th International Conference on Interaction Design and Children. ACM, 2011, pp. 165–168.

[32] J. Cheng, M. Sundholm, B. Zhou, M. Hirsch, and P. Lukowicz, "Smart-surface: Large scale textile pressure sensors arrays for activity recognition," Pervasive and Mobile Computing, 2016.

[33] "Textile sandbox." [Online]. Available: http://goo.gl/hiowPc

[34] "Textile sandbox online labeling toll." [Online]. Available: http://wearcomlab.de/resources/exptool

[35] MathWorks, "Matlab classification learner app," https://www.mathworks.com/products/statistics/classification-learner.html, last access: Feb. 2017.

[36] A. Khotanzad and Y. H. Hong, "Invariant image recognition by zernike moments," IEEE Transactions on pattern analysis and machine intelligence, vol. 12, no. 5, 1990, pp. 489–497.

[37] B. Zhou, H. Koerger, M. Wirth, C. Zwick, C. Martindale, H. Cruz, B. Eskofier, and P. Lukowicz, "Smart soccer shoe: monitoring football interaction with shoe integrated textile pressure sensor matrix," in Proceedings of the 2016 ACM International Symposium on Wearable Computers. ACM, 2016, pp. 64–71.

[38] G. Ye, Z. Tang, D. Fang, X. Chen, K. I. Kim, B. Taylor, and Z. Wang, "Cracking android pattern lock in five attempts," 2017.

[39] K. Mowery, S. Meiklejohn, and S. Savage, "Heat of the moment: characterizing the efficacy of thermal camera-based attacks," in Proceedings of the 5th USENIX conference on Offensive technologies. USENIX Association, 2011, pp. 6–6.