TriboGait: A deep learning enabled triboelectric gait sensor system for human activity recognition and individual identification

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ABSTRACT

Accurately and continuously measuring and collecting data on human gait is critical for human activity recognition and individual identification, enabling various applications in smart homes/buildings, including security authentication, personal healthcare, and intelligent automation. Many sensing technologies have been investigated by researchers recently, such as camera-based, laser-based, and mobile approaches, which have limitations in particular sensing situations, such as environments with fewer privacy concerns, line-of-sight, and the use of wearables, etc. On the other hand, the floor with the embedded sensor is stable and robust to different circumstances, enabling non-intrusive gait recognition and human identification. Therefore, a triboelectric nanogenerator (TENG)-based gait sensor system installed on the floor is proposed in this paper. Our approach has many advantages in comparison to the existing gait recognition systems, including low cost, simple fabrication, lightweight, and high durability. The TENG-based sensors can be simply embedded into a smart carpet to discern mechanical motions through electrical signals. Furthermore, a deep learning model, deep residual bidirectional long short-term memory network with dense layers (Residual Dense-BiLSTM), is proposed for multichannel floor-based gait recognition. By utilizing this model to analyze the electrical outputs, our system can accurately detect various human activities and distinguish different individuals' walking patterns, with a recognition rate over 98% and 97%, respectively. We conclude that the proposed deep learning enabled triboelectric gait sensor system has broad applications in security and healthcare.

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UbiComp-ISWC '21 Adjunct, September 21–26, 2021, Virtual, USA

ACM ISBN 978-1-4503-8461-2/21/09…$15.00
https://doi.org/10.1145/3460418.3480410

CCS CONCEPTS

• **Human-centered computing** → **Ubiquitous and mobile computing**; • **Computing methodologies** → *Machine learning*; • **Computer systems organization** → *Embedded and cyber-physical systems*.

KEYWORDS

floor sensor, deep learning, activity recognition, human identification

ACM Reference Format:
Jiarong Li, Zihan Wang, Zihao Zhao, Yuchao Jin, Jihong Yin, Shao-Lun Huang, and Jiyu Wang. 2021. TriboGait: A deep learning enabled triboelectric gait sensor system for human activity recognition and individual identification. In *Adjunct Proceedings of the 2021 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2021 ACM International Symposium on Wearable Computers (UbiComp-ISWC '21 Adjunct), September 21–26, 2021, Virtual, USA.* ACM, New York, NY, USA, 6 pages. https://doi.org/10.1145/3460418.3480410

1 INTRODUCTION

Rapid advancements in intelligent sensors and communication technology have enhanced the growth of the Internet of Things (IoT) and empowered the deployment of countless devices interconnected with each other as well as transmitting data to the cloud center, allowing the applications of human activity recognition and personal identification in smart building [9]. Efficiently measuring human gait data is effective in the case of continuous information detecting and gathering for activity recognition and individual authentication. The camera-based technique is one of the most efficient ways for observing gait movements, and it is widely used in the workplace, and home environment [12]. However, it raises potential serious privacy issues in today's society and has temporal constraints in a specific location on the measurement. To properly protect people's privacy, a laser-based technique like laser beam detection has been suggested [1], but the obtained sensory knowledge is limited, and the laser source is easily obscured from interference. Besides, the installation and maintenance of laser-based methods are expensive. In addition, accelerometers/gyroscopes provide a portable method for gait analysis, but they cannot provide comprehensive and precise data for gait analysis, and it is inconvenient for people to wear a module of the sensory system all the time [5]. Thus, designing gait recognition devices that are simple to use, low-cost, and capable of reliable identification continues to be a challenge.

The floor with the embedded sensor is inherently stable and resistant to light change and other ambient disruptions [7, 14]. Normally, all critical spatial or temporal variables of gait, including stride length, duration, and cadence, can be measured using data obtained from an effective floor sensory system. The unobtrusive design of the floor sensor can measure natural gaits and motions outside of a laboratory or clinic, which enables the collection and analysis of gait signals in daily life without drawing attention to the users' awareness. Thus, with the help of deep learning algorithms, the vast amount of data accessible from the floor sensor enables comprehensive gait analysis to collect sufficient sensory information from human gait and realize the applications of activity recognition, human identification, and personal health care. When it comes to the design of floor sensors, the most frequently used transducer systems involve capacitive, resistive, piezoelectric, and triboelectric structures. Among them, triboelectric nanogenerator (TENG) utilizes electrostatic induction and contact electrification to transform mechanical stimuli into electrical signals with the numerous advantages of high power density, outstanding output performance, high energy efficiency, lightweight, and low-cost [4]. Owing to its numerous advantages, TENG has been exhibited as an effective solution in various practical applications under the rapid development of IoT [3, 8, 13, 15, 16].

This study reports a TENG-based gait sensor system for activity recognition and human identification, which can be easily installed in a smart carpet, allowing non-invasive gait recognition by detecting human steps from electrical impulses. Compared with the previous work, our system offers various benefits, including low cost, easy to fabricate, lightweight, and high durability, offering great potential to provide fast mass production and realize practical applications. Besides, the proposed deep learning model, deep residual bidirectional long short-term memory network with dense layers (Residual Dense-BiLSTM), utilizes residual bidirectional long short-term memory (BiLSTM) and dense layers in stacks to obtain more information from time-series data. It effectively recognizes multichannel time-series gait signals and accurately recognizes different activities and users' identities when people are walking through. Experimental results show that our method can accomplish human activity recognition and individual identification with an average success rate of over 98% and 97%, respectively, achieving competitive performance to the state-of-the-art gait recognition system based on floor sensor. The gait sensor system offers new opportunities for sensing and recognizing human gait. The main contributions of the article are summarized as follows.

- A triboelectric gait sensor system is proposed for human activity recognition and individual identification.
- The TENG-based gait sensor unit is designed, and the fundamental theory, fabrication, and manufacturing process are introduced.
- An improved deep learning model, Residual Dense-BiLSTM, is developed for processing and analyzing multichannel gait sensor data.
- Comprehensive experiments and analyses are conducted to evaluate the performance of our method.

The remainder of this paper is organized as follows. Section 2 introduces the overall system architecture. Section 3 presents the design of the TENG-based gait sensor system. Section 4 shows the details of the algorithm for gait recognition. Section 5 illustrates the experimental results of gait recognition. A conclusion of the study is given in Section 6.

2 SYSTEM ARCHITECTURE

The fundamental theory of the TENG-based gait sensor depends on the contact and separation movement induced by the coupling of the triboelectric effect and electrostatic induction. As described in Figure 1, the triboelectric gait sensor system consists of a sensing module, including gait data collection, pre-processing, deep learning model for classification, activity recognition, and individual identification parts.

The design of the sensor unit is illustrated in Figure 2, including a schematic diagram, sensor design, and mechanism. The gait sensor's output signal is collected and delivered to a computer through an 8-channel analog-to-digital converter (ADC). The computer is used to store and analyze gait data. First, several pre-processing steps are applied to the obtained data. Then, the Residual Dense-BiLSTM model, shown in Figure 3, is trained to realize gait recognition.

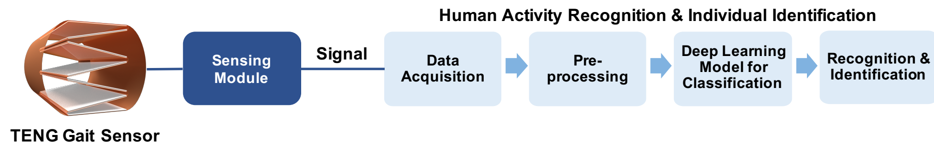

Figure 1: System architecture.

3 TENG-BASED GAIT SENSOR SYSTEM

The TENG-based gait sensor system is embedded in a smart carpet for gait recognition. When an individual walks on the smart carpet, the electrical signals produced by the motion of each walking step can be collected to monitor the person's behavior and personal identity. In our design, the TENG-based gait sensor utilizes the mechanism of converting gait motion to electrical signals. Under the principle of the triboelectric effect and electrostatic induction, it allows the collection of gait motion signals to convert into electrical signals without external signal conditioning circuits.

The system is made of two footprint sensory modules distributed on the carpet in reference to human stride. The design of the module is based on the physical model for human walking. Studies on gait analysis show that horizontal foot pressure is mainly concentrated on the front and rear of the foot during the walking process [2], which means the signals can be well collected in these positions with a higher signal amplitude as well as better sensitivity. Based on the distribution of pressure density, two TENG-based sensor units are located at the front and rear of the footprint module. To further measure gait signals, two additional sensor units are placed parallel to the center of the footprint module to collect additional signals.

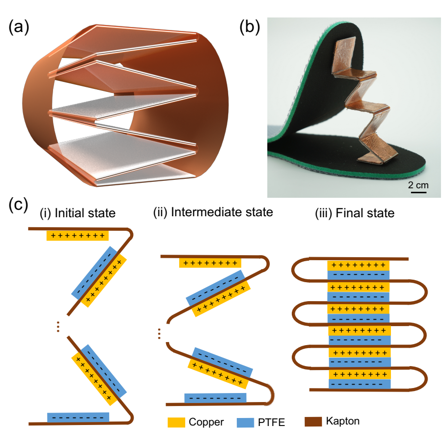

Figure 2: TENG-based gait sensor unit. (a) Schematic design. (b) Photograph. (c) Working mechanism.

The single TENG-based sensor unit comprises six layers of device components, three facing the front and three facing the back. The design sketch of a single sensor unit is shown in Figure 2(a). The photograph of the sensor deployed in the front of the footprint module is illustrated in Figure 2(b), which is embedded in a carpet. A thin, flexible polyimide (Kapton) substrate connects and supports the six-layer framework and devices. Each layer unit is constructed on two sides of the substrate in a zigzag shape, and multiple layer units are stacked vertically. To increase the electrical signal production with the multiple layer structure, the circuit connection of each layer unit in a sensor module is in parallel, and the output signal generated by each one can be accumulated simultaneously.

In principle, the single-layer unit is an individual sensory device and works in contact-separation mode. A thin Kapton film with a thickness of 150 μm has been chosen as the substrate for its characteristics for the proper rigidity, flexibility, lightweight and low price. The Kapton film was twisted into a zigzag shape by producing evenly distributed deformations. The zigzag structure allows the TENG-based units to operate on both sides of the Kapton film. The front/contact electrode includes a thin film of polytetrafluoroethylene (PTFE) coated with a copper foil, and a thin copper film was placed as another electrode on the back of PTFE. Specifically, for the front electrode of every single layer, the 60 μm copper with the size of 3.0 cm x 2.5 cm was adhered to the substrate using 3M foam tapes, and the PTFE thin film was formulated and adhered above with the untreated side exposed. For the back electrode, a copper foil of the same size was coated to the other side of the substrate using the tapes in the corresponding areas. Copper wires were used to link six layers in parallel. The single TENG-based sensor was packaged by a striped Kapton surrounding the deformable zigzag-shaped multi-layer structure and assembling them together. The constructed sensor is flexible with suitable stiffness to generate electrical signals from pressing.

The working mechanism of the sensor is illustrated in Figure 2(c). The TENG operates based on the combination of the triboelectric effect and electrostatic induction. Because of the triboelectric effect, when PTFE and copper get in touch with each other as an external force is applied, surface charge transfer happens. On the PTFE side, negative triboelectric charges are produced due to a higher electronegativity to acquire electrons than copper. The generated electrons flow reciprocally between two plates by the triboelectric charges while a periodic force is exerted. An alternating current signal is generated as a result.

4 ALGORITHM FOR GAIT RECOGNITION

In this section, a deep learning model, Residual Dense-BiLSTM, is proposed for multichannel floor-based gait recognition. A systematic diagram of the model is presented in Figure 3, which provides a multi-layer stacked architecture for multi-class gait recognition and classification.

As compared to previous work, the model architecture realizes the combination of the use of BiLSTM to gain access to additional temporal information [11], residual layers to overcome gradient vanishing challenge [19], with several long short-term memory

(LSTM) layers and fully connected layers in stacks to obtain more information as well as strengthen feature propagation [18].

Provided a series of labeled input data X_t, the main algorithm of LSTM [6] are as follows

$$\begin{aligned} f_t &= \sigma\left(W_f \cdot [h_{t-1}, X_t] + b_f\right) \\ i_t &= \sigma\left(W_i \cdot [h_{t-1}, X_t] + b_i\right) \\ \tilde{C}_t &= \tanh\left(W_C \cdot [h_{t-1}, X_t] + b_C\right) \\ C_t &= f_t * C_{t-1} + i_t * \tilde{C}_t \\ o_t &= \sigma\left(W_o \cdot [h_{t-1}, X_t] + b_o\right) \\ h_t &= o_t \cdot \tanh\left(C_t\right) \end{aligned} \tag{1}$$

where $f_t, i_t, \widetilde{C_t}, C_t, o_t$, and h_t represent the forget gate, the input gate, two state-persistence memory cells, the output gate, and the hidden layer, separately. W_f, W_i, W_C, and W_o are the component weights, while b_f, b_i, b_C, and b_o are the component biases. $\sigma(*)$ is a sigmoid activation function that is used to add nonlinear characteristics into the architecture.

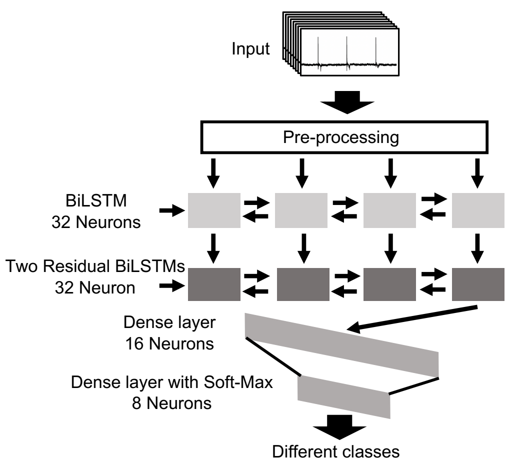

Figure 3: Proposed Residual Dense-BiLSTM architecture for gait recognition.

The algorithm is developed in Python with the use of Pytorch library [10]. A sequential model of BiLSTM, residual, dropout, flattened, and dense layers are used. Since the sensor collects multi-channel gait data in time series, it is critical to prepare the training samples according to the LSTM's criteria for training and testing. The input data to our LSTM architecture is multidimensional, with eight channels of current signal data in time series. Thus, the model begins by reshaping these eight concurrent 1-D time series data into the three-dimensional configuration expected by an LSTM, which includes the memory steps, batch sizes, and the number of sensor channels in the three dimensions, respectively. Then, the bidirectional input layer contains 32 neurons that utilize the previous data points. Furthermore, two residual BiLSTM layers were stacked in our model to consider a more profound time dependence when estimating the next value. Ultimately, the network was transformed into a classifier using a fully connected hidden dense layer with 16 neurons followed by an output dense layer with eight neurons to obtain probabilistic classes' assignments from the raw data. Besides, to deal with the multi-class classification situation, the SoftMax function is applied. The dropout component with probabilities $P_{drop} = 0.5$ is utilized in the LSTM network to prevent overfitting and improve the network generalization. The model was trained offline using an Adam optimizer configured with a 0.0015 learning rate, which operated with a GeForce RTX 3090 GPU on an Ubuntu server.

5 EXPERIMENTAL RESULTS

In this section, we conduct a comprehensive experiment and evaluate the performance of the gait sensor system.

5.1 Experimental Setup & Data Acquisition

The TENG-based gait sensor system is embedded in the square carpet that can be easily assembled with each other. Two footprint sensor modules, each containing four triboelectric sensor units and are embedded inside the carpet and measured by an 8-channel current ADC. To protect the ADC and ensure the stability of the current signal, a 10 MΩ resistor is connected in series to each triboelectric sensor unit. Users are supposed to step on the footprint modules while walking through the smart carpet. The 8-channel analog current signals generated by the sensory system are converted to digital signals by the ADC and store in the computer. Gait data of five different activities, including standing, jogging, walking, running, and jumping, are collected by our system for further analysis on activity recognition. Besides, gait data of eight users walking through the smart carpet are measured as the dataset for individual identification. Figure 4 shows the sample 8-channel current output signals for different users walking on the footprint modules through the carpet. Because each person's walking gait pattern is unique and signal characteristics of activities are different, it can generate a distinct output signal for recognition and classification. Thus, two different models are trained with the two datasets to validate the effectiveness of the proposed system separately.

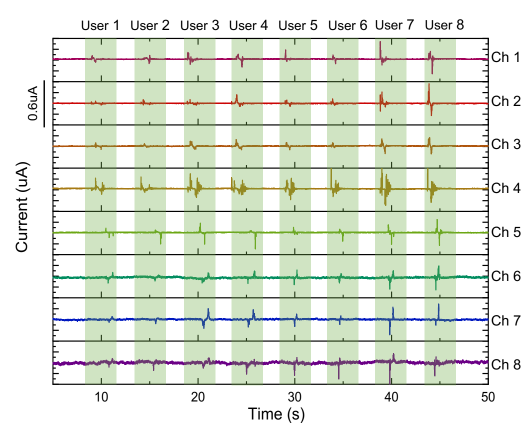

Figure 4: The sample eight-channel current output signals of eight different users collected by our system.

5.2 Data Pre-processing

The original signals measured by the gait sensor are required to be pre-processed as follows to satisfy the input dimension of the neural network and increase the prediction accuracy of the proposed model.

5.2.1 Low-pass filter. Since walking steps are typically in a frequency lower than 10 Hz, we first employ a Butterworth low-pass filter to eliminate high-frequency components.

5.2.2 Scaling and normalization. Each channel's data is given with a specific scale, and a variety of distinct value ranges depending on the fabrication of the triboelectric sensor and the measurement process. Because the deep learning model training with large current values from different channels may lead to training bias, it is required to normalize the data input. Our system employs a method called mean and variance normalization as $x^* = (x - \mu)/\sigma$, where μ, σ are the mean value and standard deviation, separately.

5.2.3 Segmentation and Sampling. The input to the model consists of a series of data sequences with the length designed as 128 to balance recognition accuracy and processing time. According to the regular frequency of human walking steps and the recording time of every single activity, the time interval of the sliding window is set to three seconds. Then, the window is moved forward with a step size of 0.02 seconds to formulate the following sample data, whose overlap is to preserve temporal information and provide more redundancy. Since the sampling frequency of the ADC is 500 Hz, the number of original data points in a sliding window is 1500, which will be downsampled into 128 data points by selecting points from original data in equal distance. It can be concluded that each class has a total number of about 5350 samples, and 80% of the samples are chosen for training while 20% of them are for testing randomly. Every sample contains eight channels with 128 data points in one channel. It's worth mentioning that we chose these proposing parameters adaptively and empirically [17] to obtain appropriate segments for training the model.

5.3 Performance Evaluation

5.3.1 Results for activity recognition. The training procedure of the deep learning model for activity recognition is illustrated in Figure 5. Figures 5(a) and 5(b) demonstrate the convergence of the training and testing accuracy as well as loss function, which indicates that the proposed model can achieve high classification accuracy and robustness. The confusion matrix of predicted and true labels in the testing set after 50 rounds of training is shown in Figure 6. The TENG-based gait sensor system can identify different users with an average prediction accuracy as high as 98.3%.

5.3.2 Results for individual identification. The number of classes is changed to eight for individual identification, and the other training process follows the above steps. The recognition rate can be achieved to 97.6% after 500 epochs with the confusion map shown in Figure 7.

6 CONCLUSION

In conclusion, we propose a TENG-based gait sensor system for human activity recognition and individual identification, and develop

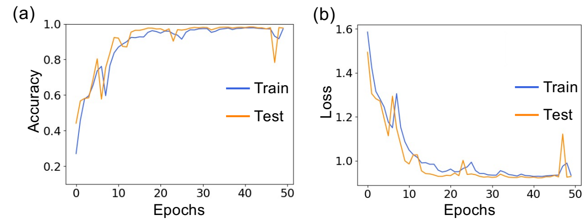

Figure 5: Model training results for activity monitoring. (a) Accuracy. (b) Loss.

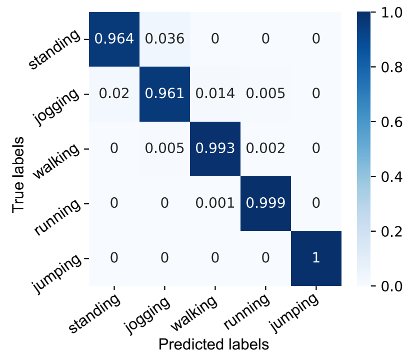

Figure 6: Confusion matrix on the test dataset of activity monitoring on five activities.

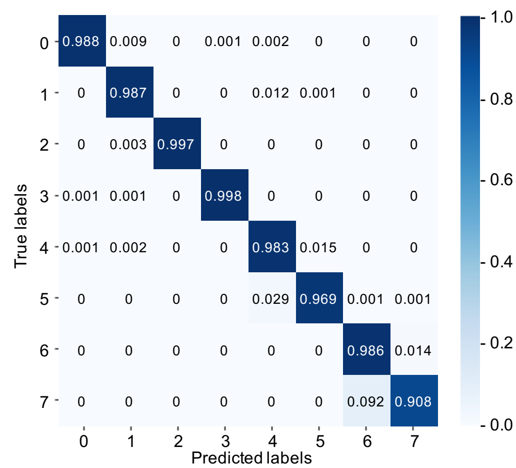

Figure 7: Confusion matrix on the test dataset of individual identification on eight users.

a deep learning model, Residual Dense-BiLSTM, for multichannel floor-based gait recognition. Our method offers many favorable properties compared to current gait recognition systems, including low-cost, easy-to-fabricate, lightweight, and decent durability. Experimental results demonstrate that it performs well at recognizing different users' activities and personal identities as they walk through the system, with an average accuracy of over 98% and 97%, separately. The TENG-based gait sensor system is capable of real-time gait recognition and is suitable for mass manufacturing as well as large-scale deployment. Combined with the proposed deep learning algorithm, our approach has a broad range of applications for human activity recognition, individual identification, and personal health care.

ACKNOWLEDGMENTS

This work was supported in part by National Natural Science Foundation under Grant No. 52007019.

REFERENCES

[1] Leticia M. Avellar, Arnaldo G. Leal-Junior, Camilo A. R. Diaz, Carlos Marques, and Anselmo Frizera. 2019. POF Smart Carpet: A Multiplexed Polymer Optical Fiber-Embedded Smart Carpet for Gait Analysis. *Sensors (Basel, Switzerland)* 19, 15 (2019), 3356. https://doi.org/10.3390/s19153356

[2] Paul J. Bennett and Lynette R. Duplock. 1993. Pressure distribution beneath the human foot. *Journal of the American Podiatric Medical Association* 83, 12 (1993), 674–678.

[3] Wenbo Ding, Changsheng Wu, Yunlong Zi, Haiyang Zou, Jiyu Wang, Jia Cheng, Aurelia C. Wang, and Zhong Lin Wang. 2018. Self-powered wireless optical transmission of mechanical agitation signals. *Nano Energy* 47 (2018), 566–572. https://doi.org/10.1016/j.nanoen.2018.03.044

[4] Feng-Ru Fan, Zhong-Qun Tian, and Zhong Lin Wang. 2012. Flexible triboelectric generator. *Nano Energy* 1, 2 (2012), 328–334. https://doi.org/10.1016/j.nanoen.2012.01.004

[5] Barry R. Greene, Denise McGrath, Ross O'Neill, Karol J. O'Donovan, Adrian Burns, and Brian Caulfield. 2010. An adaptive gyroscope-based algorithm for temporal gait analysis. *Medical & Biological Engineering & Computing* 48, 12 (2010), 1251–1260. https://doi.org/10.1007/s11517-010-0692-0

[6] Klaus Greff, Rupesh K. Srivastava, Jan Koutnik, Bas R. Steunebrink, and Jurgen Schmidhuber. 2017. LSTM: A Search Space Odyssey. *IEEE Transactions on Neural Networks and Learning Systems* 28, 10 (2017), 2222–2232. https://doi.org/10.1109/tnnls.2016.2582924

[7] Thomas Kleinberger, Martin Becker, Eric Ras, Andreas Holzinger, and Paul Müller. 2007. Ambient intelligence in assisted living: enable elderly people to handle future interfaces. In *International conference on universal access in human-computer interaction*. Springer, 103–112.

[8] Jiarong Li, Changsheng Wu, Ishara Dharmasena, Xiaoyue Ni, Zihan Wang, Haixu Shen, Shao-Lun Huang, and Wenbo Ding. 2020. Triboelectric nanogenerators enabled internet of things: A survey. *Intelligent and Converged Networks* 1, 2 (2020), 115–141. https://doi.org/10.23919/icn.2020.0008

[9] Daniel Minoli, Kazem Sohraby, and Benedict Occhiogrosso. 2017. IoT Considerations, Requirements, and Architectures for Smart Buildings—Energy Optimization and Next-Generation Building Management Systems. *IEEE Internet of Things Journal* 4, 1 (2017), 269–283. https://doi.org/10.1109/jiot.2017.2647881

[10] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, and Luca Antiga. 2019. Pytorch: An imperative style, high-performance deep learning library. *arXiv preprint arXiv:1912.01703* (2019).

[11] Mike Schuster and Kuldip K. Paliwal. 1997. Bidirectional recurrent neural networks. *IEEE Transactions on Signal Processing* 45, 11 (1997), 2673–2681. https://doi.org/10.1109/78.650093

[12] Erik Stone and Marjorie Skubic. 2011. Evaluation of an inexpensive depth camera for in-home gait assessment. *Journal of Ambient Intelligence and Smart Environments* 3, 4 (2011), 349–361. https://doi.org/10.3233/ais-2011-0124

[13] Peihong Wang, Ruiyuan Liu, Wenbo Ding, Peng Zhang, Lun Pan, Guozhang Dai, Haiyang Zou, Kai Dong, Cheng Xu, and Zhong Lin Wang. 2018. Complementary Electromagnetic-Triboelectric Active Sensor for Detecting Multiple Mechanical Triggering. *Advanced Functional Materials* 28, 11 (2018), 1705808. https://doi.org/10.1002/adfm.201705808

[14] Zihan Wang, Jiarong Li, Yuchao Jin, Jiyu Wang, Fang Yang, Gang Li, Xiaoyue Ni, and Wenbo Ding. 2021. Sensing beyond itself: Multi-functional use of ubiquitous signals towards wearable applications. *Digital Signal Processing* 116 (2021), 103091. https://doi.org/10.1016/j.dsp.2021.103091

[15] Changsheng Wu, Wenbo Ding, Ruiyuan Liu, Jiyu Wang, Aurelia C. Wang, Jie Wang, Shengming Li, Yunlong Zi, and Zhong Lin Wang. 2018. Keystroke dynamics enabled authentication and identification using triboelectric nanogenerator array. *Materials Today* 21, 3 (2018), 216–222. https://doi.org/10.1016/j.mattod.2018.01.006

[16] Zhiyi Wu, Wenbo Ding, Yejing Dai, Kai Dong, Changsheng Wu, Lei Zhang, Zhiming Lin, Jia Cheng, and Zhong Lin Wang. 2018. Self-Powered Multifunctional Motion Sensor Enabled by Magnetic-Regulated Triboelectric Nanogenerator. *ACS Nano* 12, 6 (2018), 5726–5733. https://doi.org/10.1021/acsnano.8b01589

[17] Cheng Xu, Duo Chai, Jie He, Xiaotong Zhang, and Shihong Duan. 2019. InnoHAR: A deep neural network for complex human activity recognition. *Ieee Access* 7 (2019), 9893–9902.

[18] Jin Zhang, Fuxiang Wu, Bo Wei, Qieshi Zhang, Hui Huang, Syed W. Shah, and Jun Cheng. 2021. Data Augmentation and Dense-LSTM for Human Activity Recognition Using WiFi Signal. *IEEE Internet of Things Journal* 8, 6 (2021), 4628–4641. https://doi.org/10.1109/jiot.2020.3026732

[19] Yu Zhao, Rennong Yang, Guillaume Chevalier, Ximeng Xu, and Zhenxing Zhang. 2018. Deep Residual Bidir-LSTM for Human Activity Recognition Using Wearable Sensors. *Mathematical Problems in Engineering* 2018 (2018), 1–13. https://doi.org/10.1155/2018/7316954