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3DKnITS: Three-dimensional Digital Knitting of Intelligent Textile Sensor for Activity Recognition and Biomechanical Monitoring

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Abstract— **We present an approach to develop seamless and scalable piezo-resistive matrix-based intelligent textile using digital flat-bed and circular knitting machines. By combining and customizing functional and common yarns, we can design the aesthetics and architecture and engineer both the electrical and mechanical properties of a sensing textile. By incorporating a melting fiber, we propose a method to shape and personalize three-dimensional piezo-resistive fabric structure that can conform to the human body through thermoforming principles. It results in a robust textile structure and intimate interfacing, suppressing sensor drifts and maximizing accuracy while ensuring comfortability. This paper describes our textile design, fabrication approach, wireless hardware system, deep-learning enabled recognition methods, experimental results, and application scenarios. The digital knitting approach enables the fabrication of 2D to 3D pressure-sensitive textile interiors and wearables, including a 45 x 45 cm intelligent mat with 256 pressure-sensing pixels, and a circularly-knitted, form-fitted shoe with 96 sensing pixels across its 3D surface both with linear piezo-resistive sensitivity of 39.4 for up to 500 N load. Our personalized convolutional neural network models are able to classify 7 basic activities and exercises and 7 yoga poses in-real time with 99.6% and 98.7% accuracy respectively. Further, we demonstrate our technology for a variety of applications ranging from rehabilitation and sport science, to wearables and gaming interfaces.**

I. Introduction

Most of the current efforts in functional and electronic textiles focus on the coating, screen-printing, embedding or attachment of electronic devices on fabrics. These manual and hand-made approaches, even though they have certain values in some aspects, they restrain researchers and designers from rapid prototyping, large-scale manufacturing, and translation of electronic textiles [1-3]. Recently, advances in mechatronics, digital fabrication, and computer-aided design have revolutionized the concept of three-dimensional (3D) knitting with computerized (CNC) knitting machines. These additive manufacturing machines enable users to design and fabricate their textile patterns and structures through a specialized visual programming environment and various types of fibers and yarns. In this work, we leverage digital knitting techniques using flat-bed and circular knitting machines with thermoforming techniques to realize a set of 2 to 3D piezoresistive matrix textile mats and wearables that are able to detect multipoint pressure across their surfaces in real-time. This fabrication approach allows us to explore various parameters, including interconnect resistance, matrix resolution, pressure sensitivity, and the fabric's visual, mechanical, and electrical properties through functional and common fiber choices and knitting structures [4,5].

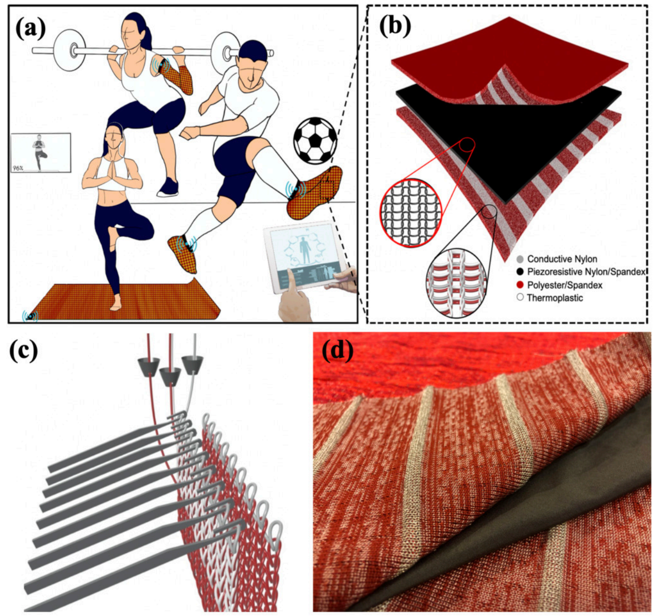

Figure 1. (a) Illustration of 3D-knitted wireless intelligent textile for sport biomechanics, including a mat for yoga posture classification, a shoe for sport biomechanics and foot-ball interactions in soccer, and a sleeve for sensing muscle contractions in weight-lifting. (b) Multi-layer structure of pressure-sensitive textiles showing all the yarns used. (c) Flat-bed knitting structure with three yarn carriers (single and twisted composite). (d) Prototype of the pressure-sensitive textile with horizontal-vertical interconnects from knitted conductive yarns and PPy-coated knitted piezoresistive textile in the middle.

We are motivated by the fact that most of our physical gestures and interactions involve contacts between different parts of our body and a surface. As we perform our daily activities such as walking, sitting, exercising or sleeping, a characteristic spatiotemporal contact and pressure pattern can be monitored and identified from sensing through the fabrics

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in our apparel or upholstery (Figure 1a). As illustrated in Figure 1b, we thus propose to a knitted piezo-resistive textile matrix for tracking and classifying activities. Monitoring biomechanical forces with high accuracy, repeatability, and comfortability through wearables or sensing surfaces is still a research and practical challenge. Our principle in personalization ensures textile wearables and structures that are robust, form-fitting and conformable and result in accurate and intimate sensing while ensuring comfortability. Moreover, it allows rapid, large-scale manufacturing of electronic textiles (Figure 1c-d) with customizable looks and functions.

A. Pressure-sensing electronic textiles

There are two common methods of pressure sensing in electronic textiles: capacitive and resistive-based. The capacitive approach consists of a spacer fabric in-between two conductive layers. Meyer *et al.* used a textile insulator in-between a bottom common electrode fabric and an embroidered array of electrodes as a top fabric for activity detection, specifically to recognize sitting postures [6]. The spacer was chosen to be squishy to improve comfortability of the pressure sensor. This method suffers from stray electromagnetic noise, requires shielding layers, and complex read-out circuits. Resistive sensing, on the other hand, leverages a piezo-resistive element in the form of yarn or fabric as a middle layer in between two conductive elements [7]. The resistance of the piezo-resistive element changes as a force is exerted due to the bridging of conductive particles. A cross-configuration of piezo-resistive sensing textile, which is a conductive top and bottom matrix lines allows a distributed 2D pressure sensing across the fabric. Several efforts also integrated piezoelectric materials in threads or textiles to detect vibration [8]. However, it does not measure pressure continuously and could only work as a dynamic pressure or impact detector.

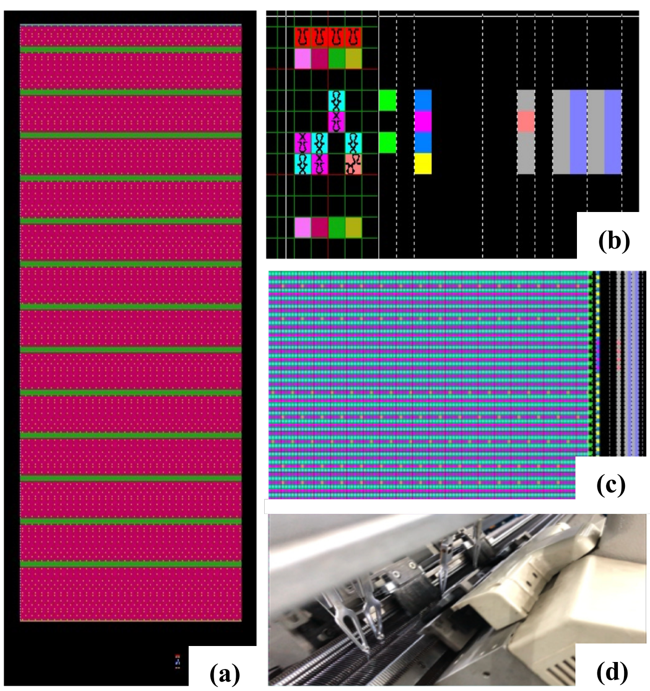

Figure 2. (a) A knitting machine program with horizontal conductive interconnects design in green blocks and common, interlocked polyester yarns in maroon and pink blocks. (b) Abstraction library that converts simple knitting program in (a) into line-by-line, machine-readable format in (c). (d) Knitting machine in action showing all the yarn carriers being moved sideways by the slider, as illustrated in Figure 1c.

B. Biomechanics, activity, and gesture monitoring with piezo-resistive textiles.

Piezo-resistivity in pressure sensing textiles have been explored in many projects, especially in the realm of human-computer interaction (HCI), sports, and medical science. In HCI, they have been used as 2D tactile inputs for musical or multimedia interface [9], as well as deformation sensor in the form of a sleeve for fabric-based gestural interaction [10]. Several researchers have also explored the use of 2D pressure sensing textile integrated as a mat, glove, or clothing for object and human activity or posture recognitions. Most of these work analyzed the subtle pressure distribution change across the fabrics throughout the activity and applied machine learning principles for feature extraction and classification [11,12]. Piezo-resistive textiles have also been widely used in rehabilitation and medical applications, such as for gait analysis [13], respiration sensing [14], pressure ulcers monitoring and prevention [15], and compression therapy [16]. Specifically, due to its breathable, soft, and comfortable nature compared to flexible pressure sensing grids, these piezo-resistive sensing textiles can also be used to augment prosthetic covers, linings, or even robotic ski. Leong *et al.* presented a 2D piezo-resistive textile that covers a prosthetic foot for a closed-loop, sensory-haptic feedback [17], while Data Glove provides a textile-based conformal pressure array for prosthetic and robotic hand applications [18].

II. Knitted Multi-layer Textile Sensor

A. Design and Development

The digital knitting programming interface consists of two grid sections (Figure 2). The left grid area is used to develop shape and patterns of the knit fabrics through a x-y color block programming, where each color and sign represent a specific knit instruction, as illustrated in Figure 2c. The right grid area defines machine parameters such as the yarn carrier number, knitting speed, and stitch tension. In addition, each color on the left grid represents different knit operations, such as knit, tuck, transfer, or skip. Since we used flat-bed knitting machine with two machine beds, most of the operations involve switching from the front to the back knit. Figure 2a shows an example of a textile pattern with 13 knitted conductive transmission lines. We first started with a low-level color block-programming that enable abstraction and simplification from a more complex, knitting machine readable instruction format. With instruction library (Figure 2b), we can then convert this low-level pattern (Figure 2a) into a line-by-line front and back knit machine instructions (Figure 2c) that can be read by the knitting machine program. The library maps each color to a specific yarn carrier or input. In this case, we used three yarn carrier: blue, magenta, and yellow for polyester, conductive, and other polyester yarns respectively. The conductive lines (dark green) are mapped into front-knit (blue with polyester yarn carrier) and back-knit (magenta with conductive yarn carrier). The final instruction consists of back-and-forth knitting patterns with different yarn carriers as instructed. Every two lines here (front and back knit) represent one loop row or course of the fabric. The machine scans through each line of instructions until the end of the file.

Three-dimensional Knitted Intelligent Textile Sensor (3DKnITS) comprises of multi-layer knit textiles fused together through intrinsically-knitted bonding or melting fibers (Figure 1b). A piezoresistive knit textile (LTT-SLPA60k, Eeonyx Corporation) is sandwiched in between two conductive knit textiles (Figure 1d). The piezo-resistive material is developed by coating polyester knit fabric with polypyrrole (PPy), which is an organic conducting polymer formed by the polymerization of pyrrole [19]. This layer exhibits the piezo-resistive effect that induces a change to its electrical property as a mechanical pressure is applied. This resistance change is constantly read by the outer transmission layers that both form a 2D conductive matrix. These layers are machine-knitted with digital flat-bed knitting machine using combination of polyester (270 denier, 2-ply), conductive (300 denier, Weiwei Line Industry), and thermoplastic polyurethane (TPU) as melting yarns (150 denier, 1-ply), as shown in Figure 1c. The outer layers are completely insulated on one side (all-polyester) and partly conductive on the other side (sequence of conductive lines in between polyester base). The knitting machine (Super-NJ 212, Matsuya) has two-layer beds and we applied interlock mechanism to blend two layers together into one textile layer (Figure 2d). This is useful, since insulating the outer layers of our knitted textile sensor will suppress any possible parasitic impedance or any shorts from the environment. By mixing polyester with melting yarns, we are also able to ensure strong adhesion between multiple layers and prevent sensor drifts from motion artifacts. As one of our final prototypes, we fabricated a piezo-resistive mat with 1 cm width of knitted conductive lines (6 loops) and 2.5 cm pitch for a total size of 45 x 45 cm with 16 x 16 knitted conductive lines.

B. *Sensor Characterization*

We performed mechanical and electrical characterization with compression and tensile testing unit (Zwick BTC-EXMACRO, Roell) and custom resistance sensing circuit (potential divider, buffer circuit, and 12-bit ADC) to study the relationship between force and resistance of the knitted textile sensors. For the compression testing, we set the Zwick's crosshead speed to 10 mm/min with 10 N preload on a piezo-resistive textile swatch with 1 x 1 cm active area, while for tensile testing, we set the crosshead speed to 10 mm/s with a 5 cm distance on 4 x 10 cm polyester-TPU textile swatches. As plotted in Figure 3a, we compared two textile sensors: with and without TPU yarns and thermoforming process. Without thermoforming, there is a non-linearity and significant hysteresis response when the sensor is compressed and relaxed as there are volume gaps and discontinuities between each layer which can cause textile and sensor drifts. We can see a large hysteresis gap of the untreated knitted sensor of around 130 % compared to an improved, reduced gap of 27 % in the case of thermoformed knitted textile sensor at 100 N force with the compromise of force-resistance sensitivity reduction from

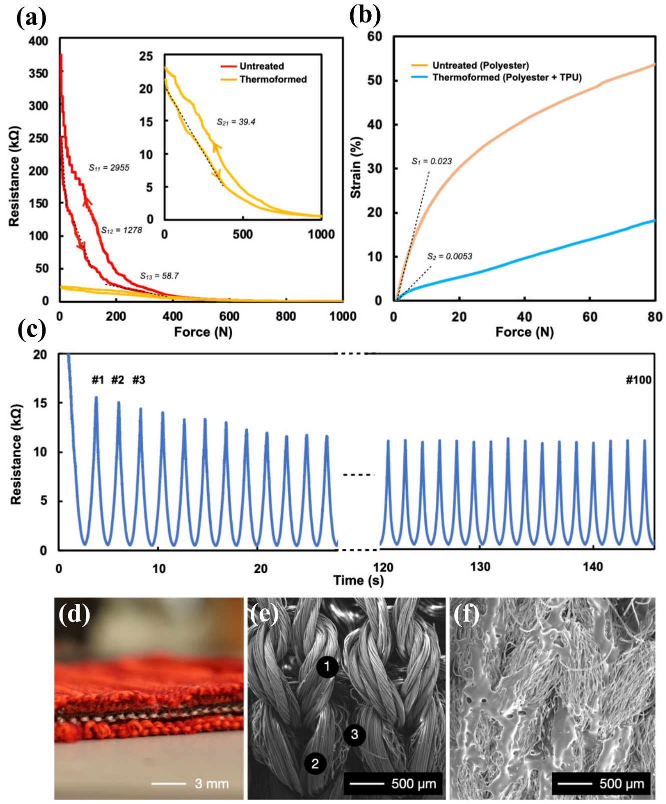

Figure 3. (a) Force *vs* resistance characterization of both the untreated and melting-yarn, thermoformed multi-layer piezoresistive knit textiles. (b) Stress-strain, tensile test showing the elasticity of both knitted textiles. (c) Cyclic repeatability test showing the robustness of thermoformed piezo-resistive knit textile). (d) Cross-section image of the thermoformed piezo-resistive textile. (e-f) SEM images of the knit structure and surface before and after thermoforming showing the strong adhesion from the melted TPU (1: silver-coated yarns, 2: polyester yarns, and 3: TPU melting fibers).

58.7 – 2955 to 39.4 below 500 N load. The thermoformed textile also demonstrates superior mechanical integrity due to strain (Figure 3b). It is much less sensitive than the untreated textile by ~1/4, making it more robust from secondary effect due to axial load. It also shows reliable performance (Figure 3c) during cyclic compression test (n = 100, crosshead speed = 30mm/min, and cyclic min/max load = 10/1000 N), showing steady response after the first 10^{th} cycle. Surface electron microscopy (SEM) images in Figure 3e-f show the yarn structures and surface texture of the knitted sensors in details before and after thermoforming.

III. Hardware Design and Architecture

Since we are working with a row-column resistive sensor matrix, we need to design a system that can scan through each line and read the entire 2D pressure points. Our system should also be robust to various sources of noise, including ghosting effects and neighboring crosstalk, which can influence the precision and accuracy of the readings. Figure 4a shows our system's final printed circuit board (PCB) design with a size of 3 x 5 cm. The circuit consists of a 16-pin multiplexer (CD74HCT4067, Texas Instrument), two 8-pin shift-registers (SN74LS595D, Texas Instrument), four 4-pin single-pole double-throw (SPDT) multiplexers (ADG734BRUZ, Analog Devices), and a potential divider with a buffer op-amp (TLV2371, Texas Instrument). The circuit enables scanning of 16 x 16 matrix lines for a total of 256 pressure sensing points. The board was designed as an extension or a shield so that the users can choose the main microcontroller and wireless communication of their choice. Using nRF5282 module with 64 MHz ARM Cortex M4F (Nordic Semiconductor), we observed scanning frequency of 15 Hz for 16 x 16 (and can reach up to 200 Hz using Teensy 3.6 with 180 MHz ARM Cortex-M4), 27 Hz for 8 x 12 matrix with wired Serial-USB, and approximately 20 Hz with wireless Bluetooth low energy (BLE) transfer.

The vertical multiplexer switches a voltage supply (3.3 V) periodically to each column, while putting the rest on high-impedance. The horizontal SPDT multiplexers with shift-registers provide a connection to the resistive sensing circuit and analog-digital converter (ADC) pin at the row of interest and grounds the rest of the row lines, switching from one line to the other in sequence (Figure 4b). This mechanism solves ghosting and crosstalk issues apparent in most resistive sensing array read-out circuits [20,21]. If we apply high-impedance to the rest of the row-column pins, as illustrated in Figure 4c, we can see the appearance of ghosting effect at the sensor point R_{12} due to the bridging connection between R_{11}, R_{21}, and R_{22}. Suppose we want to read sensor point R_{21}. In the case of switching configuration in Figure 4d and 4e, crosstalk from sensor points R_{11} + R_{22} and R_{22} respectively will influence R_{21} read-out. In our circuit configuration solution (Figure 4f), no connection exists from R_{22} or R_{12} . R_{11} will also not interfere with the potential divider circuits and ADC readings as it is connected to the ground.

IV. System Implementation and Pattern Recognition

As a sub-set of machine learning, deep learning has flourished to solve complex image processing and speech recognition challenges, as it provides an efficient way to learn high-level features from raw signals without complex feature extractions by training an end-to-end neural network [22]. In this work, we treat our spatiotemporal 2D pressure sensor data or heat-map similar to image frames. As a user balance and redirects their center of mass through their feet, they exert force on the ground. By detecting this pressure distribution of the feet through our intelligent mat, we can extract rich contextual information about our posture and activities.

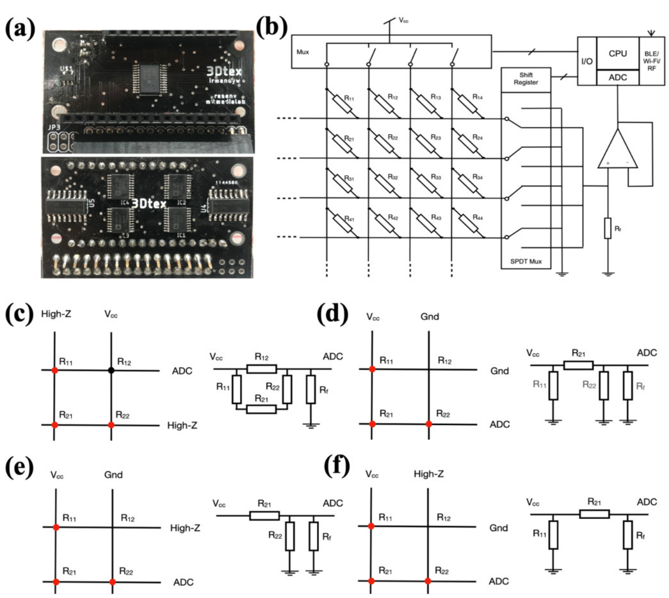

Figure 4. (a) PCB design of the robust piezoresistive matrix array circuit consisting of (b) a 16:1 multiplexer, 2 shift-registers, 4 single-pole double-throw (SPDT) muxes, and a buffer and potential-divider circuit that connects to the main micro-controller for wired-wireless control and data transfer. (c-f) Studies of influence and intervention strategies for sensor ghosting and crosstalk from neighboring nodes and multi-pressure points (R_f meaning reference resistor for potential divider).

A. Data Extraction and Processing

We performed our experimental testing on a healthy adult male volunteer with signed consent and no prior medical history of chronic disease or physical disability, in compliance with the guidelines of Institutional Review Board of Massachusetts Institute of Technology Committee on the Use of Humans as Experimental Subject (COUHES Protocol 2009000229). We gathered training data for two types of recognition: 7 common activities and exercise (Figure 5), such as standing, walking, jumping, planking, and push-ups, as well as 7 yoga poses (Figure 6), including default position, tree, eagle, tree drishti, eagle drishti, warrior three, and balancing pigeon.

The spatiotemporal pressure data were recorded and transmitted to a central processing unit. Each type of activity was performed and recorded sequentially for around one to two minutes. We collected in total of 7160 pressure data frames for common activities and exercises and 13040 data frames for yoga postures. This 22 minutes in total of training datasets were then randomized, segmented, labelled, and finally processed (80% for training, 20% for testing) in our personalized convolutional neural network (CNN) algorithm.

B. Two-Dimensional Convolutional Neural Network Model and Activity Recognition Results

CNN has been demonstrated to achieve high accuracy for human activity recognition in comparison with other methodologies such as KNN, SVM, Extra Trees, or Random Forest [23,24]. The overall architecture of our 2D CNN model is depicted in Figure 7a. We utilized layer-by-layer Sequential API of the Keras package with sci-kit learn library.

The proposed network comprises four convolutional layers Conv2D. We used nine weights on our 16 to 32 filters to evolve a pixel into a weighted average of itself and its eight neighbors for each convolutional layer. The network picks up valuable features as these weights are processed over the whole image. The Max-Pooling layers select the highest value from scanning the four neighboring pixels and reduce the image size by half. Combining convolutional and pooling layers helps our network learn more high-level features of the image input. In our final classification process, we used the features in two fully-connected Dense layers based on previous output from the previous layers. Batch Normalization allows us to optimize training time while randomly setting zero weights at each hidden layer in the training sample through Dropout drives the network to learn features in a distributed manner, reducing overfitting and generalization error.

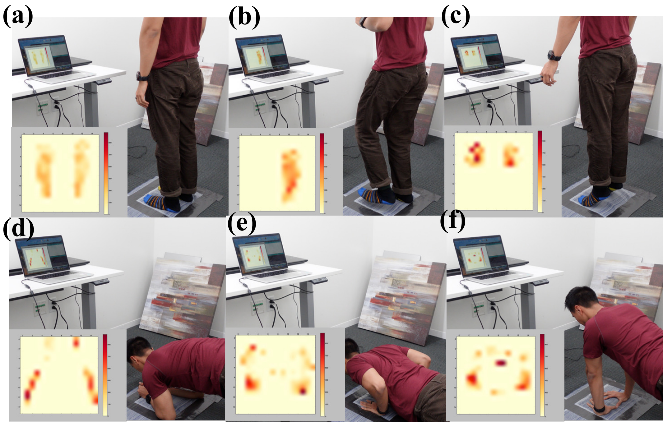

Figure 5. Pressure heat-maps of basic activities and exercise: (a) standing, (b) walking, (c) tip-toe/jumping, (d) planking, (e) normal push-up, and (f) diamond push-up.

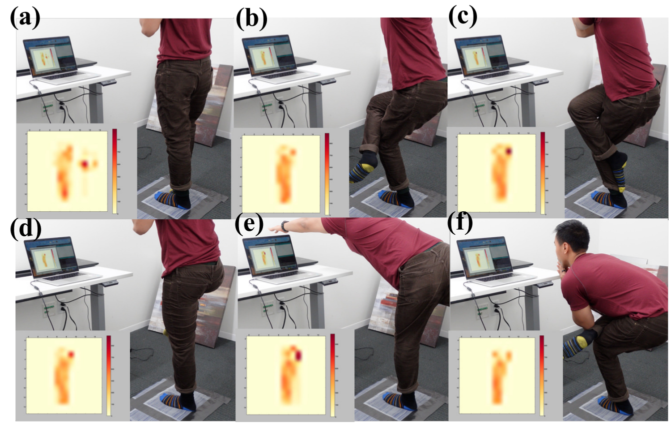

Figure 6. Pressure heat-maps of various yoga poses: (a) tree pose, (b) eagle pose, (c) eagle drishti, (d) tree drishti, (e) warrior three, and (f) balancing pigeon.

In our final CNN model, we added 2 Conv2D layers with 16 filters and ReLU activation, 2 Conv2D layers with 32 filters and ReLU activation, 4 Batch Normalization layers, 2 Max-Pooling layers, 4 Dropout layers (3 with Dropout of 0.25, 1 with Dropout of 0.5), 2 Dense layers with ReLU activation, and a final Dense layer with soft-max activation. To improve accuracy, we used 50 epochs to train the CNN model, and evaluated the accuracy using the 20% testing set. Figure 7b and 7c show the confusion matrices for both activity and yoga posture classification. The CNN models were able to classify all activities and poses with high accuracy of around 99.6 % and 98.7 %, respectively, offering great prospects for high-accuracy detection or recognition based on a deep-learning approach.

C. *Real-time Demonstration of Deep-Learning Enabled Mat for Yoga Training and Exercise Gamification*

To demonstrate practical applications of our knitted intelligent textile mat, we built a sliding window algorithm on top of our classification results to infer transient activities such as walking, running, and jumping. For instance, if we can detect the position of a left foot and a right foot on the mat, we can detect if a user is standing, walking, or running by checking for alternating left and right foot in the window of time we are looking at, or sequences of standing, tiptoe, and no activity on both feet for jumping events. As shown in Figure 7c, we used and interfaced our recognition results to control a Minecraft video game in real-time in order to gamify exercise. By showing real-time yoga pose classification results, we could also demonstrate an application to inform the user if the right balance or pose has been achieved by first feeding training data reinforced by an expert.

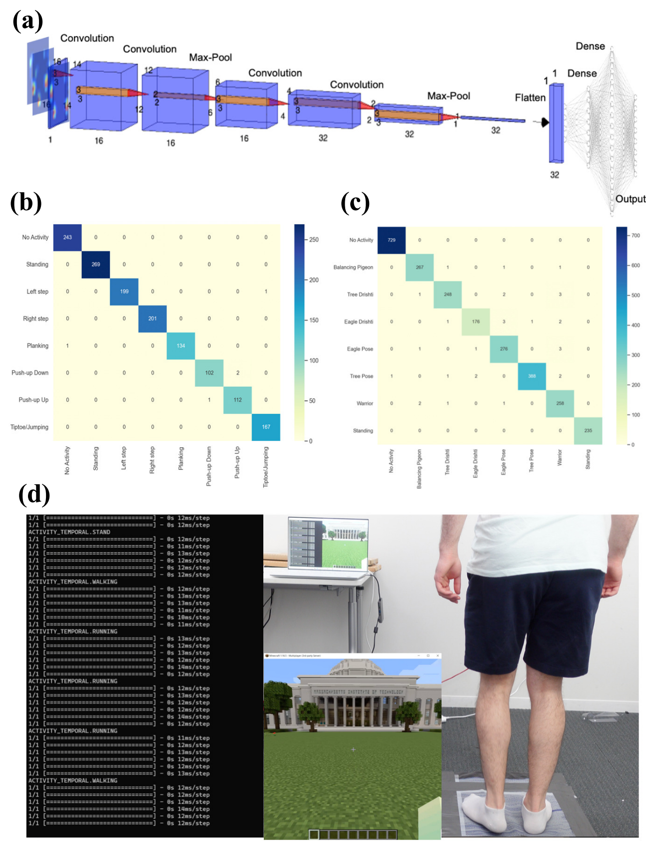

Figure 7. (a) Convolutional neural network process and parameters schematic. (b) Confusion matrix for classifying basic activities and exercises. (c) Confusion matrix for classifying yoga poses. (d) Example application of classifying movements (*i.e.* running or jumping) to control a Minecraft game.

V. 3D Knitted Sensing Shoe/Sock

A. *Design and Development*

Figure 8a illustrates the 3DKnITS fabrication and thermoforming process. To develop a tubular knit textile, we employed a digital circular knitting machine and a combination of polyester, spandex, conductive, and TPU yarns in the knitting process (Figure 8b). The machine greatly increases productivity because the relatively slow reciprocating motion of flat knit machines is replaced by a continuous and faster circular motion. The circular knitting is mostly used to make various tubular garments such as socks, shoes, sleeves, underwear or t-shirts. The result is a seamless 3DKnITS with customized orthogonal conductive stripes pattern in a tubular form-factor. In order to realize form-fitting apparel or prosthetic lining customized to the wearer, 3D-scanning of the human body could be performed to create 3D-printed models of the arms, or in the case of footwear design, we used a shoe-last that best fits the user based on the size, as demonstrated in Figure 8d-e. Figure 8f shows a full prototype of the 3DKnITS connected to the aforementioned system hardware (Figure 4a-b) for sensor read-out and wireless communication. We sewed in TPU-insulated silver-conductive threads to connect each knitted conductive line on the skinner to its corresponding pin on the PCB. There is a total of 96 (8 x 12 matrix lines) pressure-points spread across the 3D surface of the skinner, with 1 cm width of knitted conductive lines and around 2.5 to 3 cm pitch (Figure 8c).

B. Implementation and Applications

As one of the world's most practice sports, a significant research effort has been conducted to study the science behind soccer [25]. We chose to explore the functionality of our 3D knitted sensing shoe or sock in this particular sport since it involves various biomechanical movements, including gait, balance, and coordination of muscles when running, sliding, and kicking a ball, as well as positioning of the ball on the shoe to ensure the right angle and trajectory.

In our preliminary test, as shown in Figure 9a, we can see the response of three pressure sensors: two plantar pressure points at the back and front part of the foot and one dorsal pressure point at the front part of the foot. At heel strike, we can see an increase of pressure at the corresponding sensor location. As the user is ready to kick the ball before toe-off, we can see a gradual transition of pressure going to the upper from the bottom region of the foot. After toe-off, and right when the user kicks the ball, we can observe a subtle pressure response on the surface of the shoe and at the location where this foot-ball interaction occurs. We have developed a real-time 3D visualization tool to better understand the spatiotemporal pressure data as a heat-map (Figure 9b).

VI. Discussions and Conclusions

In summary, we have proposed a set of 2 to 3D knitted pressure-sensitive textiles for various applications, including activity recognition and biomechanical monitoring, using an industrial manufacturing approach of flat-bed and circular machine knitting. We have also designed a custom hardware circuit that allows accurate piezo-resistive matrix read-out while solving ghosting and crosstalk issues and eliminating the needs for sensor data post-processing. Our material choices and digital fabrication approach also enable tunable sensing resolution and customizable form-factors based on the user's needs and requirements. It results in a robust, scalable, low-cost, and sustainable interactive sensing textile with knitting and thermoforming techniques. Compared to the existing thin-film force-sensing and pressure-imaging technologies, our textile-based method is more seamless, breathable, comfortable, and intimate to the wearer, which could improve interfacial contact and accuracy of the sensing and recognition [26]. We have fabricated a prototype of 3DKnITS in the form of intelligent mat and shoe, as well as demonstrated several applications including high-accuracy, deep-learning assisted activity and posture recognition for real-time exercise and gaming interaction. Further, we proposed a smart soccer shoe that can track a player's movements and localize foot-ball interactions. Unlike

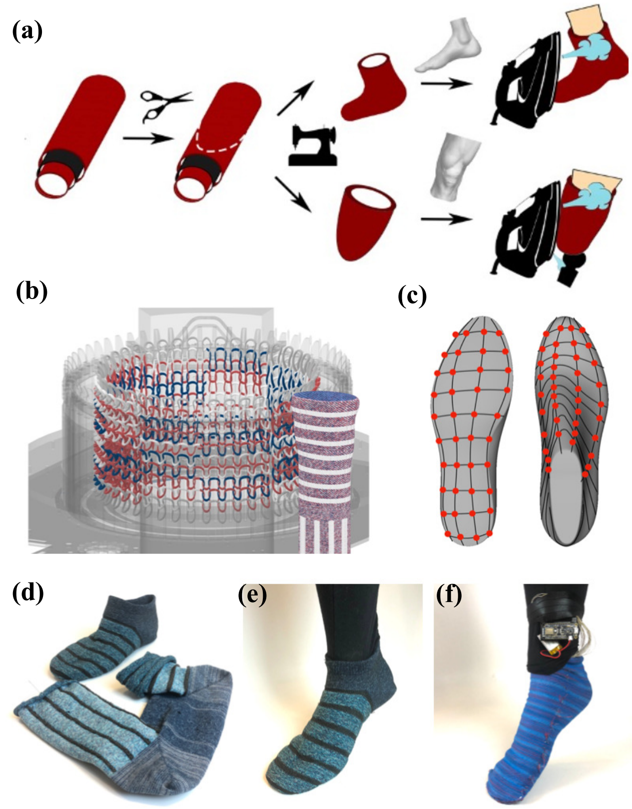

Figure 8. (a) 3D shaping and thermoforming of tubular knitted e-textiles for intelligent shoe or prosthetic lining and socket. (b) Illustration of a circular knitting machine with tubular knitted conductive textiles. (c) Pressure sensor mapping across the 3D shoe. (d-e) Knitted prototypes before and after thermoforming with shoe-last. (f) Fully-functional prototype of custom 3D-KnITS smart skinner/shoe-sock worn by the user and connected to its interface circuits with battery and wireless transmission.

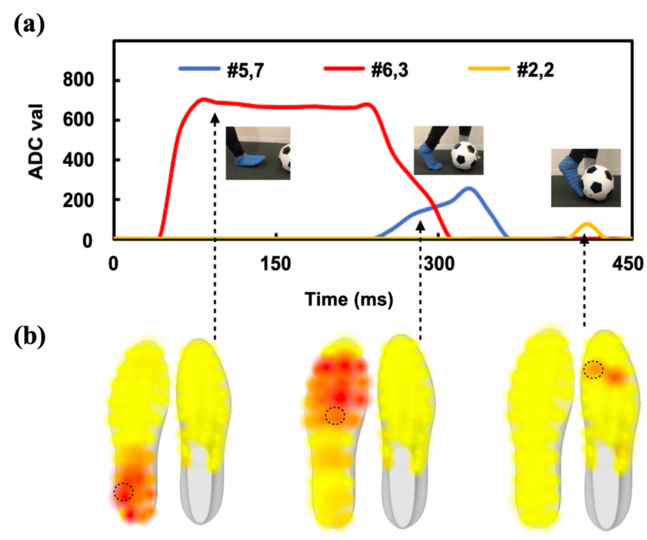

Figure 9. The smart skinner shoe for gait, biomechanics, and foot-ball interaction sensing. (a) Transient sensor data of three points (row, column: #5,7, #6,3, and #2,2) located in the shoe and (b) Plantar and dorsal pressure heat-maps of the entire 96 sensing points across the shoe before and during a kick event.

camera-based systems that potentially trigger privacy concerns regarding continuous, invasive sensing and recognition, pressure-imaging approach is less intrusive and is not sensitive to line-of-sight or lighting levels.

The prototypes and applications of 3DKnITS presented here are, however, still in its infancy. In terms of textile and hardware developments, in order to accommodate a larger-scale system, we need to modularize both the knitted textile sensor and hardware modules by applying distributed processing and networking principles [27,28]. This will enable a larger dataset that could be useful for applications such as room-scale sensing or crowd recognition. In terms of data processing and algorithms, more subjects and labels will be needed to further prove the practicality of the knitted intelligent mat on top of our user-specific models. With the current labels, several other applications such as counting and timing exercises can be incorporated into our real-time visualization and feedback. By increasing the resolution of our matrix and localizing interesting features, we could also improve accuracy and eliminate the needs to ask subjects to perform activities of interest across the entire surface of the mat when gathering training data. In our work, there are currently two separate models for common activities and yoga postures. We can also combine these two models to make the classification process and applications more universal. Involving physical therapists, orthopedics, and yoga experts for prototyping and study design, as well as data gathering will also benefit real testing, implementation, and identification of use-cases of this technology. Finally, temperature and humidity or sweat tests could also be conducted to study the effect of environmental factors the sensor properties.

The 3D knitted shoe or sock could be used to gather biomechanical and form-fitting data, which are useful not only for athletes and dancers, but also for prosthetic designers and shoemakers. The same fabrication principles can be executed to develop other types of intelligent apparel, including sleeves, gloves, or shirts. In the end, since textiles are ubiquitous in our environments, 3DKnITS process and technology can spark intelligent textile and ubiquitous computing applications spanning from activity tracking, biometrics and identification, sports and gait analysis, to robotics and HCI, creating new kinds of wearable technology and interactive environments.

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