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Designing Smart Legging for Posture Monitoring Based on Textile Sensing Networks

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ABSTRACT
Running is a highly popular form of exercise, while incorrect running posture over an extended period can lead to severe knee injuries. Smart textiles have recently demonstrated significant potential for continuous motion monitoring. This study involved the design and development of a smart legging with a resistive textile sensor network to monitor lower body motion. The study consists of three main parts. Firstly, we tested textile sensors in terms of linearity and robustness to determine the basic sensor unit that can monitor the characteristics of running postures. Next, optimal sensor placement was determined through comparison experiments, and a sensor network was proposed. Finally, based on the LSTM model with data gathered from 6 participants, we developed the smart legging system that is capable of identifying three types of improper running postures and normal postures with 99.1% accuracy. The evaluation revealed that the smart legging system had the potential to help users adjust their running postures to prevent knee injury through continuous monitoring and multi-modal feedback.

KEYWORDS
Wearable technology; textile sensor; posture monitoring; machine learning

1. Introduction

1.1. Background

Running has been the most popular exercise because of its widely known health benefits. Regular running, as aerobic exercise, may reduce risk factors for cardiovascular disease and obesity (Lee et al., 2014). However, poor running postures may lead to musculoskeletal injuries, especially in the lower limbs (Van Gent et al., 2007). Incorrect running postures may disrupt the lower limb's center of gravity, resulting in increased ground reaction forces on bones and joints of the body. For instance, excessive internal and external rotations of the knees and hip swings during running may weaken the stabilizing forces and increase pressure on the knee joints, which may cause knee injuries if it occurs over an extended period (Fredericson & Misra, 2007; Taunton et al., 2002; Van Gent et al., 2007). Therefore, continuous posture monitoring and quick correction are crucial for reducing injuries associated with running.

Recently, textile strain sensors have demonstrated their potential in the field of posture monitoring, such as estimating elbow joint angle (Liu et al., 2019) and assessing lumbar posture assessment (Vu et al., 2020). Advancements in materials and computing technologies have notably enhanced the stability and precision of textile sensors. This improvement is attributed to refined sensor preparation techniques, machine learning (ML) algorithms, and the integration of human-computer interaction (HCI). Despite these advancements, the utilization of textile strain sensors for monitoring running postures has received limited research attention. Hence, this study aims to explore the integration of textile strain sensors, deep learning algorithms, and HCI technologies to develop a smart legging wearable system capable of monitoring running postures and providing multi-modal feedback guidance during running.

1.2. Challenges and motivation

From the analysis of existing literature, we identified three key challenges in employing textile strain sensors to develop a smart legging system that aims at monitoring lower limbs' movement and classifying improper running postures. The first challenge is determining the configuration and arrangement of textile strain sensors within a legging to ensure accurate monitoring outcomes. The placement, orientation, and quantity of sensors can significantly impact the accuracy of a body motion tracking system (Tavassolian et al., 2020). And these factors about sensor placement depend on the features of the monitored body motion and the involved joints. Therefore, specific methods are often required to determine the placement of textile sensors in the development of sensorized wearable garments. For instance, the study by Tognetti et al. (2005) adopted a heuristic approach that involved positioning sample sensors around the joints of the upper limb, observing the data measurements during the execution of natural movements, and ultimately determining the sensor placements that could produce most meaningful outputs regarding movement reconstruction.

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In the study by Gholami et al. (2019), the authors utilized a grid of markers and six motion capture cameras to analyze the strains on the garment for finding the best sensor placement for hip joint angle estimation. In this study, to address this challenge, we first explored the performance of the fabric sensing material to determine the configuration of the basic sensor unit. Then we developed a prototype to test the data outputs from different combinations of multiple sensor locations. Based on the results, we determined the ultimate sensor network that could effectively collect enough information to infer the essential features concerning the running posture.

The second challenge of designing a smart legging system is identifying what types of improper running postures should be monitored. Patellofemoral Pain Symptoms (PFPS) and Iliotibial band syndrome (ITBS) are the two most prevalent running-related injuries (Ferber et al., 2009; Taunton et al., 2002). And PFPS affects approximately 13% of runners. The research by Besier et al. (2001) about intensive lower limb movement analysis has revealed that internal and external rotation of the knee joint were the primary postures that caused knee injuries during running. During running, the movement of the hip joint also plays a crucial role in maintaining proper alignment of the lower limb and the stability of the knee. Pelvic rotation in the frontal plane may place extra stress on the knee joint and cause its instability (Willson et al., 2008). Hence, in this study, we focused on the monitoring of three improper running postures that mostly cause knee injuries: internal and external rotation of the knee, and hip joint instability, as shown in Figure 1.

The third challenge in developing the smart legging system is how to translate the outcomes from the posture classification algorithms into effective feedback for end-users, making them aware of their running posture and adjust the incorrect posture timely. To address this challenge, the system interactivity and user experience need to be considered in the design of the smart legging system. While running, timely intervention and guidance (Van Hooren et al., 2020) upon detecting incorrect running postures not only can prevent users from running injuries, but also help them relearn the running skills and improve running performance. In the sports and fitness industry, there has been a huge potential market for interactive wearable products. In this study, beyond the exploration of textile sensors and posture classification algorithms, we also preliminarily explored the interaction and feedback design for smart legging system.

1.3. Structure of the study

In this study, we developed a comfortable smart legging system that can detect incorrect running postures and provide users with multi-modal user feedback for injury prevention. The system consists of an array of resistive textile strain sensors and a corresponding deep-learning model to recognize running postures. The system was evaluated among 6 participants who were similar in size and fitted to the smart legging prototype. The results provided new insights for the product development of sports manufacturers, and provide future development possibilities and practical references for stakeholders in smart textile and related fields. As shown in Figure 2, the study includes three stages. In each stage, we

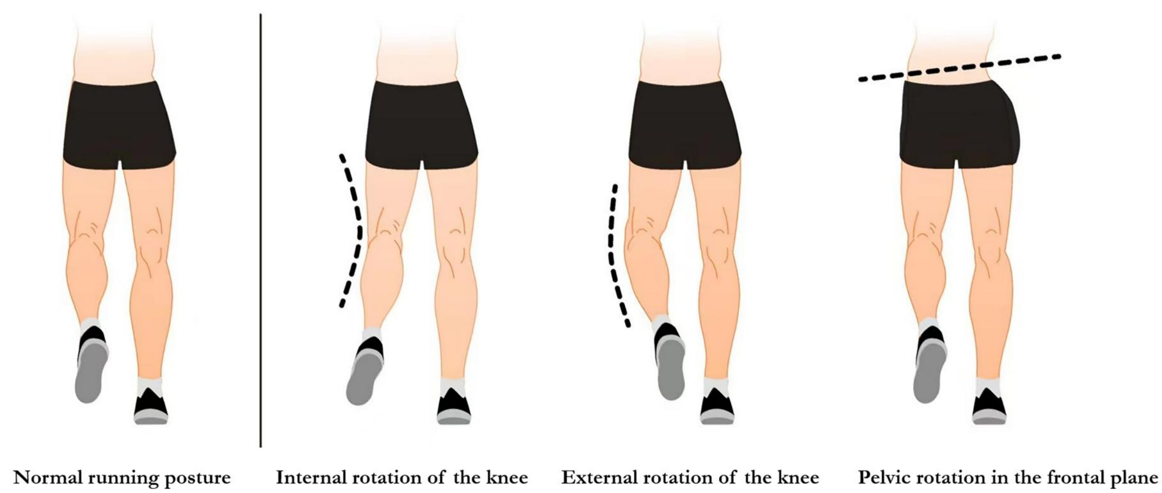

Figure 1. Illustration of three most common improper running postures.

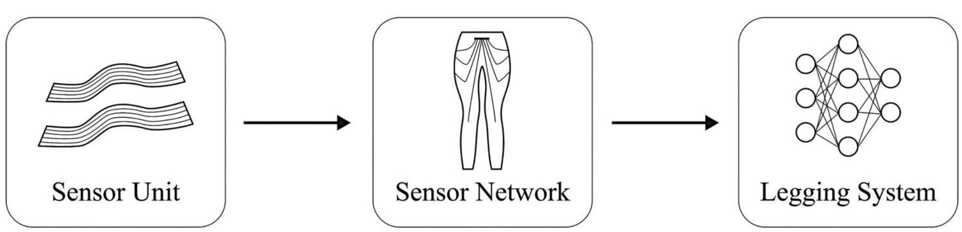

Figure 2. Three stages of the study: (1) investigation of the sensor unit, (2) design of sensor network, and (3) development of the smart legging system.

focused on one of the following research questions (RQs) corresponding to the challenges mentioned above:

- RQ1: What requirements should be included for the textile sensors?
- RQ2: How to optimize the sensor placements of the smart legging?
- RQ3: To what extent would the smart legging prototype be accurate regarding running posture classification and acceptable regarding its usability?

In the remainder of the paper, we present the findings of the first stage which investigated the textile sensor performance and the requirements for a sensor unit (to answer RQ1). We then discuss the results of the second stage which focused on the optimization of sensor placements and the design of the sensor network (to answer RQ2). Next, we present the development of the smart legging system which integrates the sensor network and corresponding deep-learning algorithms for running posture classification. And lastly, we discuss the final findings of the user study which evaluated the system regarding its usability and user experience (to answer RQ3).

2. Related work

2.1. Advances in body motion monitoring technologies

Kinematics monitoring technologies are developed to capture and analyze body motion and are extensively applied in sports analysis and rehabilitation to reduce the user's risk of exercise injuries and achieve the desired training effects (Elvitigala et al., 2019). Marker-based optical motion capture technique has been readily available for many years. And it is commonly considered the gold standard for movement monitoring due to its accurate results (Pellegrini et al., 2021; Wang et al., 2017). Recently, various markerless solutions are rapidly developed based on the combination of advanced image processing algorithms and image capturing techniques including Web camera, Kinect, and OpenPose (D'Antonio et al., 2020; Wade et al., 2022). While optical-based motion tracking systems require special set-up and high costs. They are restricted by space and the complexity of the environment, which makes them not suitable for monitoring outdoor running.

In the last decades, due to the advantages of flexibility and affordability, IMU-based (Inertial Measurement Units) wearable systems have become mainstream in sport kinematics analysis (Rana & Mittal, 2021). As the IMU sensors are compact and lightweight, they can be easily integrated into wearable garments, monitoring the various types of body motion, such as arm motion (Prayudi & Kim, 2012), upper body motion (Filippeschi et al., 2017) and lower limb motion (Hamdi et al., 2014). Nevertheless, IMU sensors have certain limitations. For instance, they typically require extra belts for mounting and are prone to displacement during long-term use (Filippeschi et al., 2017; Wang et al., 2017). Consequently, improving wearability and comfort becomes the main challenge for IMU sensors in practical applications.

In addition, various commercial strain sensors (Cha et al., 2017; Saggio et al., 2016) have been evaluated and utilized to monitor human motion and estimate human joint angles. For instance, commercial flex sensors by Flexpoint [1] and Spectra[2] have been explored for limb motion tracking (Borghetti et al., 2014). By stitching flex sensors at multiple joint positions, the wearable garment could sense flexion angles during static and kinematic motions (Abro et al., 2019). For instance, flex sensors are extensively used in various glove-based systems (Dipietro et al., 2008) to measure flexion of the joints in fingers and wrists. However, flex sensors and piezoelectric films have limitations in wearable design due to their inherent material rigidity. Their limited flexibility, softness, and durability can restrict the natural movement of the fabric and impede comfort for the wearer.

Recently, smart textiles also known as electronic textiles (e-textiles) have attracted great research interest in the wearable motion monitoring community (Shi et al., 2020; Wang et al., 2020). E-textiles incorporate electronic components within their textile structure, endowing them with the ability to fulfill both fabric and sensing functionalities. For instance, through the intertwining of carbon fiber yarns onto polyurethane fibers, the composite fiber demonstrates exceptional strain-sensing properties, including enhanced conductivity, sensitivity, and dynamic durability (Xu et al., 2023). By employing customized conductive paints composed of polyaniline and carbon nanotubes, the silk yarns can be endowed with sensing capabilities to monitor various crucial signals, including strain, temperature, and the presence of harmful gases (Ouyang et al., 2022). Due to their merits of low cost, lightweight, and flexibility, smart textiles can easily fit various human bodies to track ambulatory and daily-life human motion (Wang et al., 2020). Studies show that textile sensors have been used in various applications, such as trunk monitoring (Mokhlespour Esfahani et al., 2017), shoulder kinematics (Jin et al., 2020), knee joint monitoring (Di Tocco et al., 2021), etc.

2.2. Textile strain sensors for lower body motion monitoring

Due to their comfort and flexibility, textile strain sensors have been widely used in the fields of health, rehabilitation, and sport (Choudhry et al., 2021). Being embedded into a wearable garment, textile strain sensors could measure the wearer's body motions by the changes in the sensor's resistance, which are subsequently converted into an electrical signal for further analysis and monitoring. Textile strain sensors are often utilized to monitor joint movements and characterize specific postures of the lower extremities. For instance, by capturing activity signals from the knee, ankle, and hip joints, textile strain sensors can monitor specific lower limb movements Gholami et al. (2019); Totaro et al. (2017). Munro et al. (2008) designed a smart knee sleeve to detect the angle of knee flexion by adopting a conducting polymer. Skach et al. (2019) proposed smarty pants for posture and behavior classification based on pressure sensors. And Watson et al. (2020) succeeded in employing a conductive fabric sensor to calculate knee angles.

Beyond the calculation of knee angles, textile strain sensors can be utilized for monitoring more complex knee movements. For instance, Li et al. (2019) located 10 knitted conductive strain sensors around the knee joint, allowing for the recognition of the four gait patterns of running, walking, climbing, and descending stairs. Also, Gholami et al. (2019) developed a system that employs textile strain sensors on the pelvis, knee, and ankle to estimate the sagittal, frontal, and cross-sectional angles of multiple joints during running. A study by Tavassolian et al. (2020) developed new strain sensors by embedding rectangular loops of the stretchable conductive copper-coiled elastic thread on elastic textile. With 4 sensors on the anterior and posterior sides of the pelvic region, their setup achieved multi-axes hip angle tracking.

2.3. Running movement monitoring

Running kinematics is the key factor associated with running injury (Van Gent et al., 2007). And there is a growing body of research that focuses on recognizing and analyzing running postures (Lopez-Nava & Munoz-Melendez, 2016). Running involves a range of movements within the lower limbs, including the thigh, knee, leg, or foot (Folland et al., 2017); therefore, running monitoring can be realized by various wearable form-givings. For instance, to monitor kinematic changes with fatigue, 12 wireless inertial measurement units(IMUs) sensor devices are attached to the wearer's foot, legs, arms, and wrist to capture the full body movement throughout the runs (Strohrmann et al., 2012). Being connected with two IMU sensors attached to the wearers' arms and legs, smartwatch APPs could recognize the changes in running movement (Seuter et al., 2020). Nevertheless, such systems relying on the placement of multiple sensors on the user's body may be too obtrusive for day-to-day wear.

To improve the runner's comfort and system practicality, a variety of shoe-based and insoles-based monitoring systems have been designed. For instance, Bamberg et al. (2008) developed a GaitShoe system by integrating multiple types of sensors including FSR, piezoelectric sensors, and bend sensors to achieve complicated gait analysis. By the integration of multiple force-sensitive resistors (FSR), ab insole was enabled to detect the force distribution on the runner's foot (Mat Dris et al., 2020) and to recognize foot pronation and supination (Domínguez-Morales et al., 2019), the patterns of heel acceleration and plantar pressure for characterizing postures (Sazonov et al., 2011). A recent study (Elstub et al., 2022) developed a smart shoe system by combining an inertial measurement unit (IMU) and pressure insole with a trained algorithm to estimate tibial bone force in running. Due to the location of sensors, shoe-based wearable systems are mostly effective in detecting foot position and plantar pressure for running gait analysis, while detecting specific improper running posture that involves the rotation of the knee and hip joint instability can be challenging. This study aims to address this challenge.

Given that injuries related to running can arise due to numerous factors of running gait, continuous multi-axis kinematic monitoring of the lower extremities becomes a crucial method in the analysis of running posture and gait. This method requires the acquisition of movement data from multiple points on the body. In terms of implementation, IMU sensors remain the predominant sensor type incorporated in most wearable systems of running gait analysis (Mason et al., 2023). However, in long-term monitoring, most IMU-based multi-sensor systems show significant limitations including being prone to displacement, afflicting with drift, challenging to align IMU's coordinate system to the physiological bone coordinate system Gholami et al. (2019), and inadequate comfort. To address this challenge, in this study, we embedded multiple soft textile strain sensors into a running legging to improve wearability and comfort, and we further developed deep learning models to process multi-channel motion data, achieving high accuracy for the classification of targeted running postures.

3. Stage one: Exploration of the sensor unit

In the first stage, we focused on the exploration of the fabric sensing material to clarify the requirements for the sensor unit in the scenario of running posture monitoring. The ideal fabric sensor should meet the following requirements: (1) the sensor data exhibits a linear relationship with strain over the strain range of the actual application, (2) the maximum strain range can monitor the large-scale dynamic movement, and (3) the sensor data could remain robust, reliable, and consistent in repeated multiple stretches. Before we made the selection and configuration of the sensor unit, we first studied the deformation and strain range of the fabric around the knees, the major joint supporting running.

3.1. Study of the fabric deformation around the movable joint

When individuals wear sports leggings, the fabric closely adheres to the skin of their lower limbs and undergoes deformation with the body's movement. Previous studies (Choi & Hong, 2015; Luo et al., 2017) suggested that the knees are the main areas of skin deformation during wide-ranging lower limb movements. Therefore, this study focused on the strain range of the fabric around the knee joints. During running, the fabric around knee joints will be stretched and recovered repeatedly. To decide the maximum strain range required for the fabric sensor in running movement, it is supposed to find the maximum value within which the fabric can be stretched as much as possible and can still return to its original state and retain the original resistance characteristics of the sensor.

In this study, we performed a stretching movement simulation experiment to examine the required maximum strain range. Compared to normal running, the stretch exercise may induce larger fabric deformation, potentially leading to

Figure 3. Stain range measurement experiment.

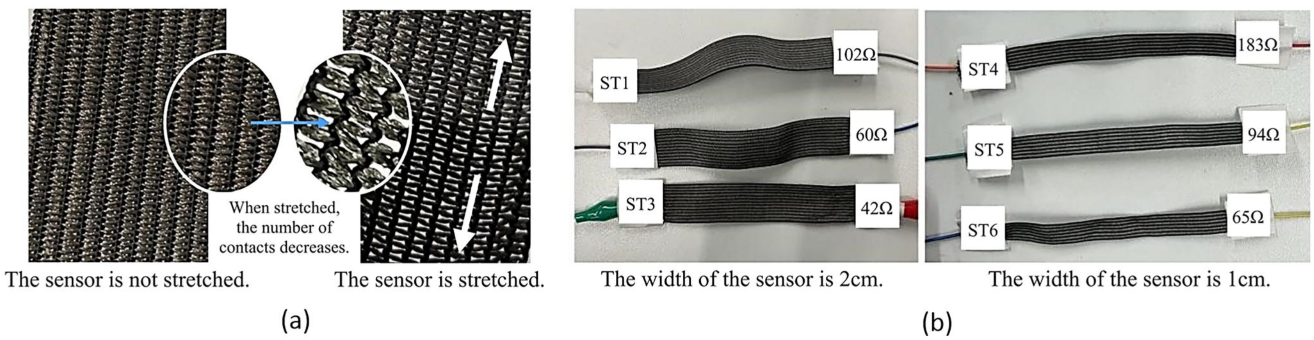

Figure 4. (a) Schematic diagram of the principle of conductive fabric sensor (b) examples of the sensor samples, with the original resistance in 10 cm length.

the fabric sensor's failure to restore its original characteristics. As shown in Figure 3, on each lower limb, we selected four marker points (P1–P4) that were symmetrically positioned along the central axis of the leg and knee joint. The initial distances (D1, D2, D3) between each pair of adjacent points on an unworn legging were set at 5 cm. This enabled the measurement of the fabric's deformation at three lengths (5 cm, 10 cm, and 15 cm). Specifically, we estimated the deformation of the 10 cm fabric by averaging the sum of D1 and D2 and the sum of D2 and D3. We observed the deformation of the 15 cm fabric by summing the values of D1, D2, and D3. The D1, D2, and D3 were measured with a tape ruler while the participant remained "stationary" and "stretched the outer thigh" respectively. In each condition, we measured D1, D2, and D3 three times for both the left and right lower limbs. The average of these six measurements was then calculated as the final value.

Next, we calculated the minimum and maximum deformation ratio of the fabric in different lengths (5 cm, 10 cm, and 15 cm). By comparing the length of fabric measured in the stationary condition to its original length, we calculated the minimum deformation ratio of the fabric in the running exercise. Similarly, we calculated the maximum deformation ratio by comparing the fabric length with "stretching the outer thigh" to its original length. The results showed that the three fabric lengths displayed a similar minimum deformation ratio at approximately 10%. The maximum deformation ratio varies across fabric lengths: namely 80% for 5 cm, 70% for 10 cm, and 63% for 15 cm.

3.2. Sensor performance testing with different configurations

In this study, we selected conductive elastic webbing (Taike, Suzhou, CN; Braided structure with conductive silver fiber, polyester, and latex silk) as the basic sensing fabric due to its adequate performance regarding the linearity, stability, and strain range requirement. Its elasticity is guaranteed by its fabric structure and latex filaments. Figure 4(a) shows the working principle of the conductive fabric sensor. When being stretched, the contact points between the silver fibers decrease, causing an increase in the resistance of the fabric. When the sensor is not stretched, the fabric has a densely woven fabric structure with maximal contact points. The conductive elastic webbing could have different intrinsic resistance based on its proportion of silver fibers and could be customized in different widths and lengths. Therefore, determining the configuration for the sensor unit becomes the first crucial step in building a smart legging system.

To determine the suitable configuration of conductive elastic webbing for monitoring running posture, we compared a group of fabric sensor samples that differ in three properties: intrinsic resistance, widths, and lengths, as shown in Figure 4(b). Six sensor samples of different intrinsic

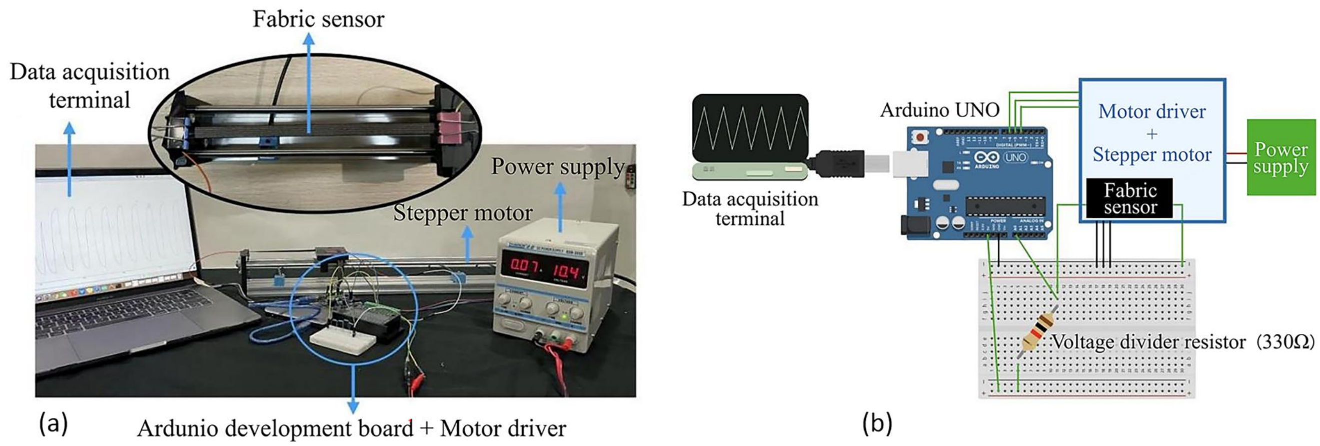

Figure 5. (a) Sensor tensile testing platform; (b) diagram of testing platform.

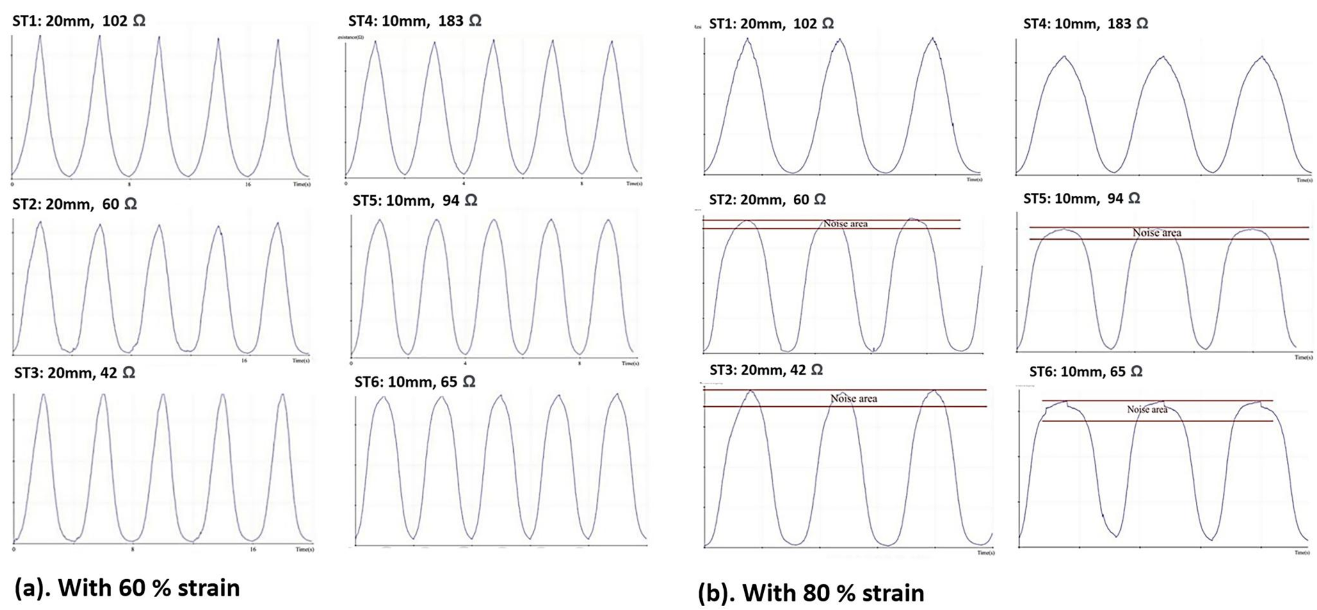

Figure 6. Test results for various sensor samples under 60% and 80% strain.

resistance and widths (10 mm, 20 mm, and 35 mm) were examined. The test focused on two aspects of sensor performance: linearity and recoverability. Firstly, regarding linearity, resistance value versus strain should remain linear with good repeatable stability during body movements. Secondly, considering large deformations caused by stretching during running, the fabric sensor is required to recover to its original state after being applied to the maximum strain. As shown in Figure 5, a tensile resistance test platform has been built with a stepper motor and an Arduino development board. Each sensor sample was attached to a slider that could move reciprocally within the specified distance range. The sensor samples were stretched with two maximum strains (60% and 80%). The stretching speed was set at 120 mm/min and the tensile tests were repeated in 20 cycles.

Figure 6 shows the recorded resistance changes of the sensor samples under 60% and 80% strains. Most of the samples had better linearity and sensitivity within the 60% strain. In particular, the samples with lower intrinsic resistance (ST2, ST3, ST5, ST6) displayed more noise when reaching approximately 80% strain. In comparison, the fabric sensor samples ST1 (width = 20mm) and ST4 (width = 10mm) show better linearity and sensitivity within 60% of the strain (as shown in Figure 6(a)) and also better stability with less noise when close to 80% strain (Figure 6(b)). In further comparison, ST4 (width = 10mm) had better stability performance than ST1 (width = 20mm). For instance, when reaching the maximum strain at 80%, ST1 showed a slight deformation (see Figure 7). Therefore, 10 mm ST4 was finally selected for further performance tests to specify the parameters of the sensor unit.

After determining the intrinsic resistance and width, we further explored the suitable length for the sensor unit. Three 10 mm wide sensor samples with different lengths (sample 1: 100 mm length; sample 2: 150 mm length; sample 3: 200 mm length) were evaluated in the repeated tensile test with 20 cycles. The stretching speed was set at 120 mm/min. As shown in Figure 8, sample 2 (150 mm length) showed better linear changes in resistance within the strain range of

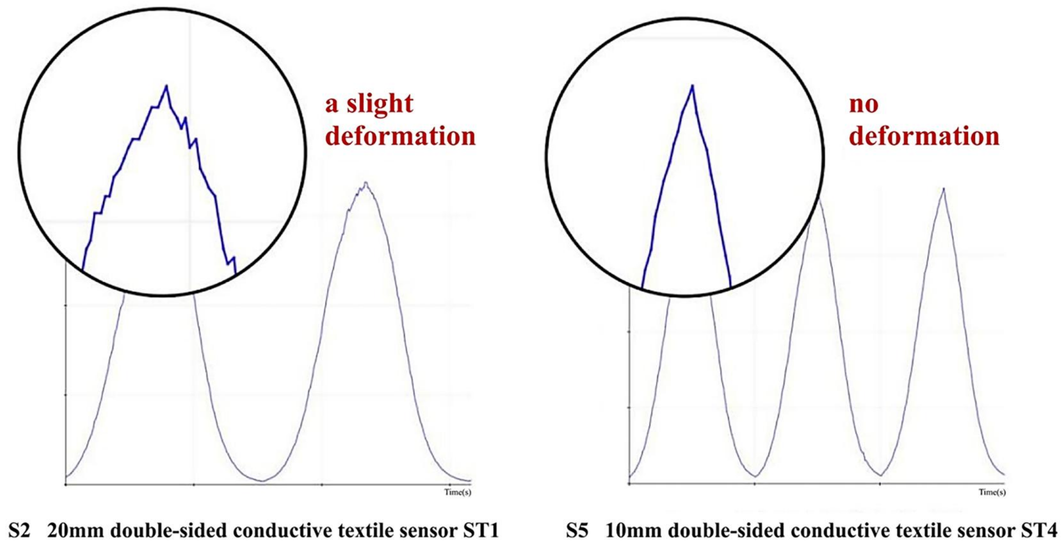

Figure 7. Close-up of sensor output at 80% strain.

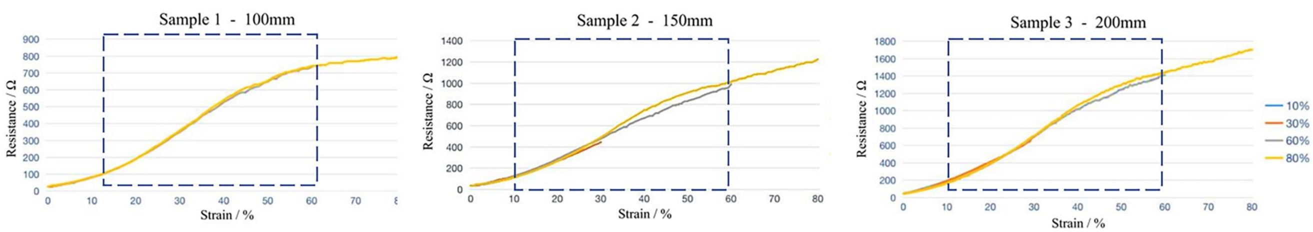

Figure 8. Variation curve of resistance value with sensor strain.

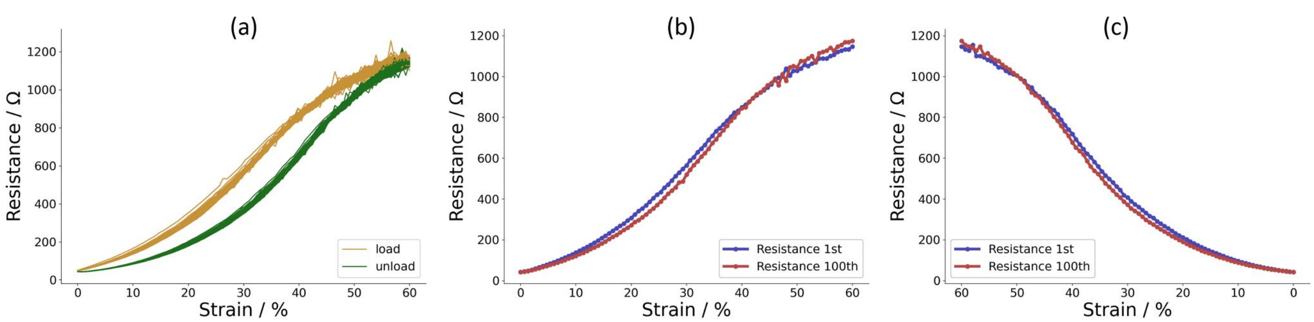

Figure 9. (a) Hysteresis of strain sensor sample 2; (b) results of repeated tensile tests in stretching state; (c) results of repeated tensile tests in relaxing state.

10–60% (see grey curves). A linear analysis was also performed to compare the coefficient of determination (R^2). With a 60% maximum strain, sample 2 has the best sensor linearity ($R^2 = 0.995$) compared to sample 1 ($R^2 = 0.987$) and sample 3 ($R^2 = 0.989$). The linear characteristic of sample 2 shows a gauge factor (GF $= \Delta R/R_0\varepsilon$ where ΔR is the variation of the sensor resistance, R_0 is the original sensor resistance, and ε is the applied strain) of about 23.24. A high GF value is a positive factor for strain gauge realization, and the GF value of our sample 2 from ST4 demonstrates relative advantages compared to conventional textile strain sensors Liang et al. (2019).

To further validate the performance of sensor sample 2, we assessed its hysteresis and repeatability. Hysteresis holds significant importance for strain sensors, given its adverse impact on sensor durability (Schmool & Markó, 2018). Figure 9(a) illustrates the hysteresis curve in the stretching-relaxing cycles, the maximum hysteresis is 24.85%, which is also comparable to typical textile strain sensors Liang et al. (2019). For the evaluation of repeatability, the sample underwent 100 cycles of stretch using the tensile testing platform, with a stretching speed of 22.5 mm/s. The resistance value of the sample was measured both before and after 100 cycles. As demonstrated in Figure 9(b,c), the mean discrepancy between loading and unloading is 26.04Ω and 20.26Ω, while the peak difference is 61.42Ω and 46.27Ω, respectively. The results indicated the sample showed consistent sensitivities and sensing ranges.

In summary, in this stage of exploration of sensing materials, we first studied the fabric deformation around the movable joint during running and determined the main strain range for the fabric of different lengths. We then evaluated the sensor performance within the targeted range (10%–60%) regarding its linearity and stability at different configurations. Finally, we tested the hysteresis and repeatability of the selected sample to validate the performance. These results informed our decisions on the fabric sensor unit, a double-sided conductive elastic webbing with a 10 mm width and 150 mm length. In the next stage, we further explore building the sensor network with the sensor units for recognizing more complex postures.

4. Stage two: sensor network design and prototype implementation

4.1. Identification of sensor nodes locations

In this stage, we focused on designing a sensor network that could monitor the deformation of multiple fabric sensor units distributed across the lower limbs, as shown in Figure 10. The data collected by the sensor network aims to (1) identify running movements; (2) classify different running postures, such as the correct running posture and the poor postures that are prone to knee injuries. We conducted a comprehensive study and analysis of the movement characteristics of the human lower limb during running. Specifically, we examined the primary muscle groups engaged in running, as well as the muscle areas activated during instances of poor posture leading to knee injuries. Based on our research, we identified six key deployment areas for sensors: the posterior waist, hip, back of the thigh, lateral crotch (centered around the greater trochanter), outer thigh, and the anterior aspect of the knee joint. The inner thigh areas were not selected as the sensor placement area, considering that these areas are prone to friction during actual running movements, which may affect the sensor performance.

Figure 11 shows 10 sensor nodes located on a single side of the lower limb. In the anterior region of the knee, with the patella at the center (red dot at the knee joint

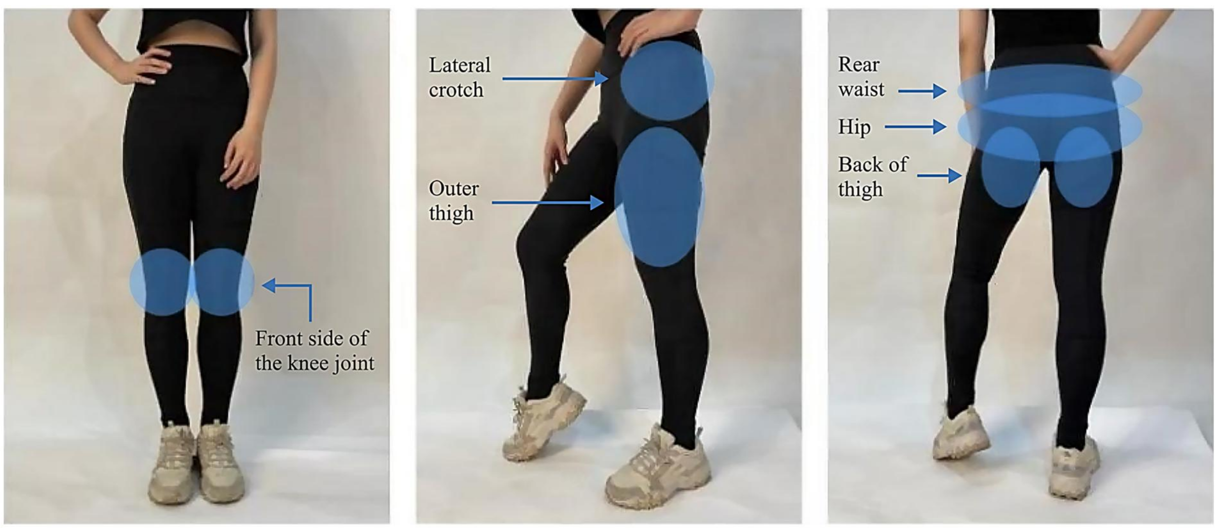

Figure 10. Main areas for sensor locations.

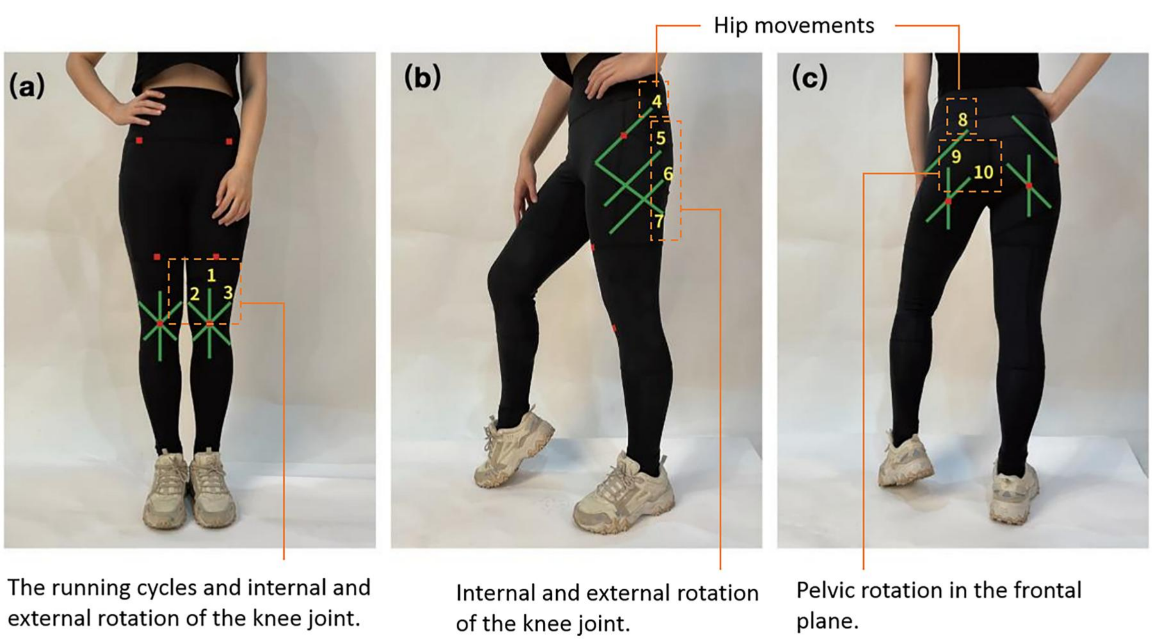

Figure 11. The deployment of sensor nodes on main Active muscle areas.

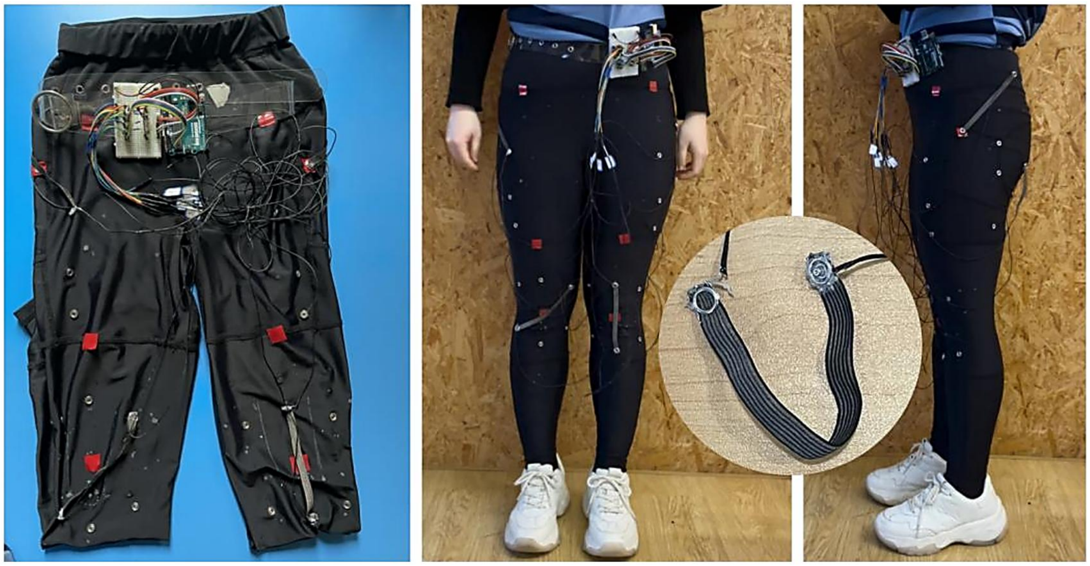

Figure 12. Testing legging prototype.

in Figure 11(a)), the sensor nodes 1, 2, and 3 are located along a line inclined at 45° vertically, left and right. During running, the knee joint is flexed and extended periodically, so nodes 1, 2, and 3 are expected to monitor whether the knee is internally or externally rotated and characterize the running cycles. At the lateral crotch and lateral thigh area, sensor node 4 is positioned at an angle of 45° from the center of the greater trochanter (red dot in Figure 11(b)). At the upper outer thigh, the positions along the line inclined at 45° on the left and right are used as sensor nodes 5, 6, and 7. They are expected to be sensitive to the internal and external rotation of the knee joint. In the posterior lumbar and buttock areas and the posterior thigh area, the lower end point of the sensor is the greater trochanter, and a position along an inclination of 45° is selected as the sensor node 8, together with sensor node 4, they are capable of monitor hip movements. Lastly, the midpoint of the dividing line between the buttocks and the posterior thighs is selected as the canter (red dot in Figure 11(c)), and the sensor nodes 9 and 10 are positioned at a vertical and 45° inclination to monitor the pelvic rotation in the frontal plane.

4.2. Comparison experiments for sensor network

To further optimize the number and location of sensor nodes that could efficiently classify the target motions with lower cost and more comfort, we conducted comparison experiments to observe the data from sensor nodes under different simulated running activities. To do so, we developed a testing legging prototype (see Figure 12) which enabled us to place the fabric sensors at multiple positions and test the results of different combinations. This prototype system served as the platform for exploring different sensor node configurations. The legging prototype was made of polyester material with a similar tension coefficient to the fabric sensor, to give a better fit and reduce interference by the clothing itself. We have pre-set snap buttons at the alternative sensor nodes for sensor installation and removal. In this prototype, the snap buttons were sewn on both ends of the fabric sensor to connect to the Arduino board which captures the resistance change of each tensile textile sensor.

4.3. Final sensor network

The experiment used a multi-channel data monitoring method to compare the effectiveness of the different sensor nodes in characterizing running movement. The sensor outputs are shown in Figure 13. In summary, among sensor nodes 1, 2, and 3, when characterizing the running cycle and the internal and external rotation of the knee joint, the sensor at node 1 shows the most significant resistance; between sensor nodes 4 and 8, when characterizing the crotch swing, the sensor at node 4 shows the most significant resistance changes; among sensor nodes, 5, 6 and 7, when characterizing the internal and external rotation of the knee joint, node 6 shows the most significant changes in the resistance of the sensor; between sensor nodes 9 and 10, when characterizing the pelvic rotation, the resistance of the sensor changes to a similar extent, but when characterizing the running cycle, the resistance of the sensor changes more significantly at node 9. Therefore, based on this observation, among ten sensor nodes, the location of nodes 1, 4, 6, and 9 were finally selected for the deployment of the sensor network on a single side of the lower limb. The smart legging system adopted a sensor network with eight sensors which are distributed symmetrically on the left and right lower limbs to monitor the target running postures. Figure 14 demonstrates the layout of the eight sensors on the smart legging with front and back views.

5. Stage three: Smart tight system development

The final stage is to build a smart legging system with the selected sensor network. The system architecture is shown in Figure 15. This system consists of three parts: (1) the data sensing part consists of multiple fabric sensors to

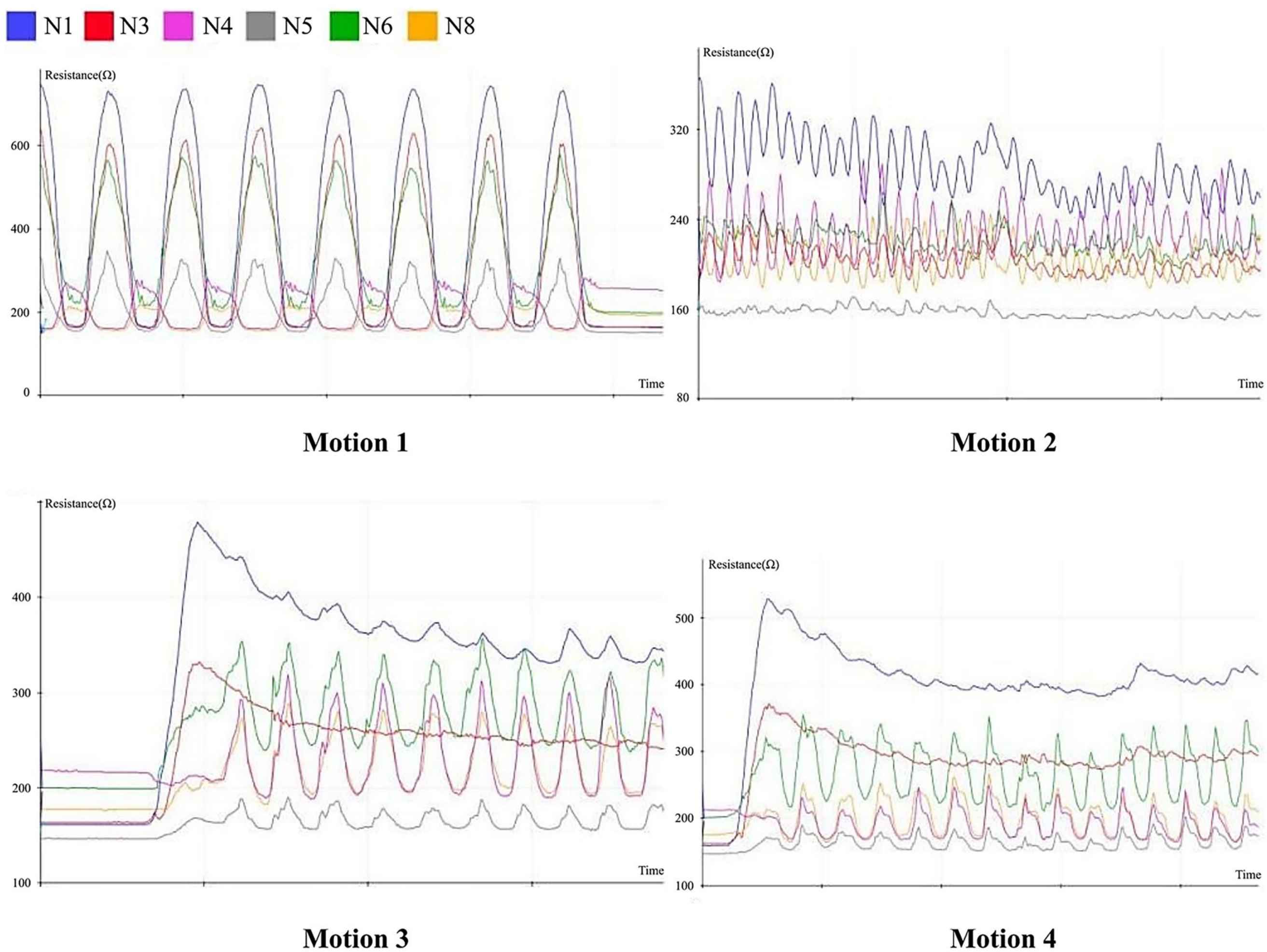

Figure 13. Sensor output from the multiple sensor nodes.

Figure 14. The layout of the 8 sensors on the smart legging with front and back views.

collect posture information as a system input; (2) the data processing part which includes a posture classification model that could classify running postures based on real-time multiple channels data from the sensor network; (3) the information output part which could provide the end-users multi-modal feedback.

In the development of the smart legging system, we take into account various factors, including posture recognition accuracy, wearability, comfort, and aesthetics. Specifically, We adopted the anchored pants to guarantee the fabric is skin-fitted and reduce the relative movement between the fabric and the body. The legging is made of stretchy and

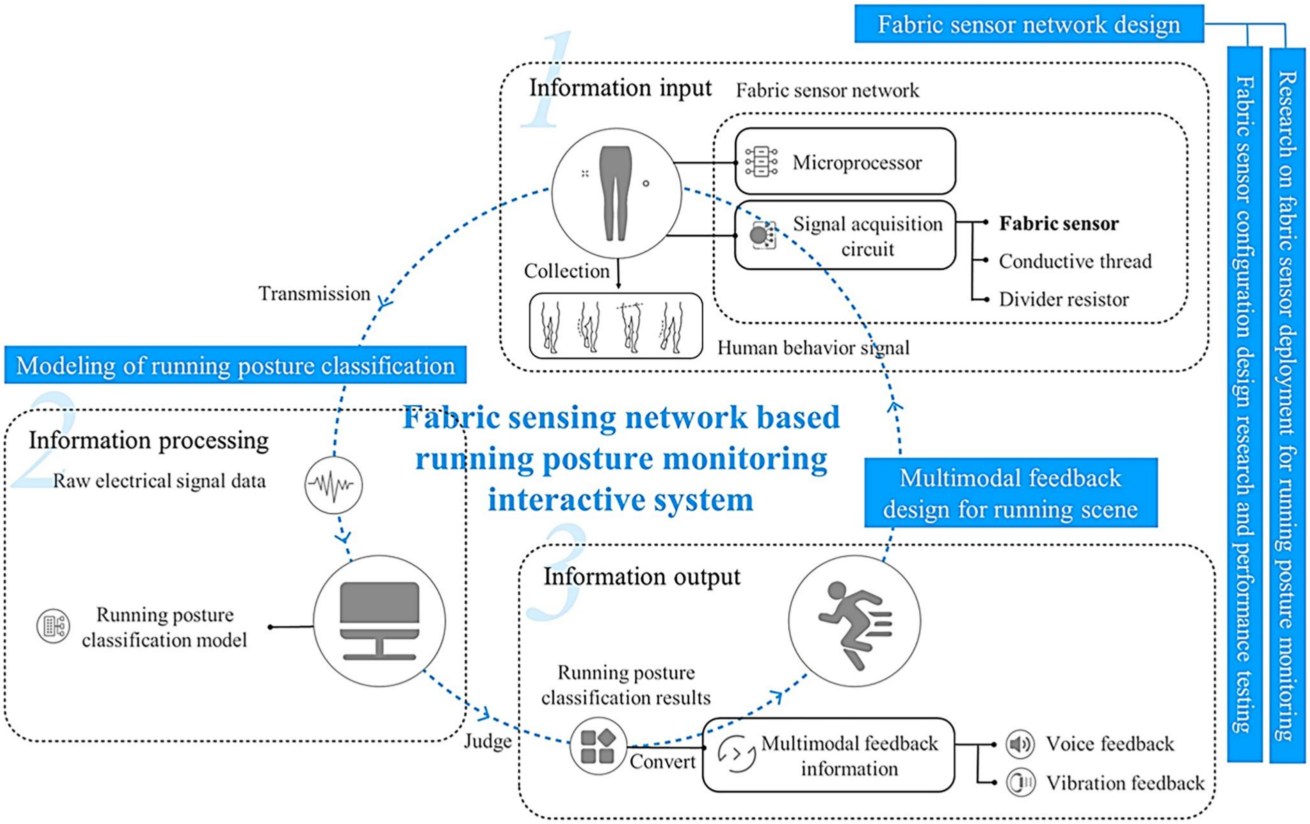

Figure 15. System architecture.

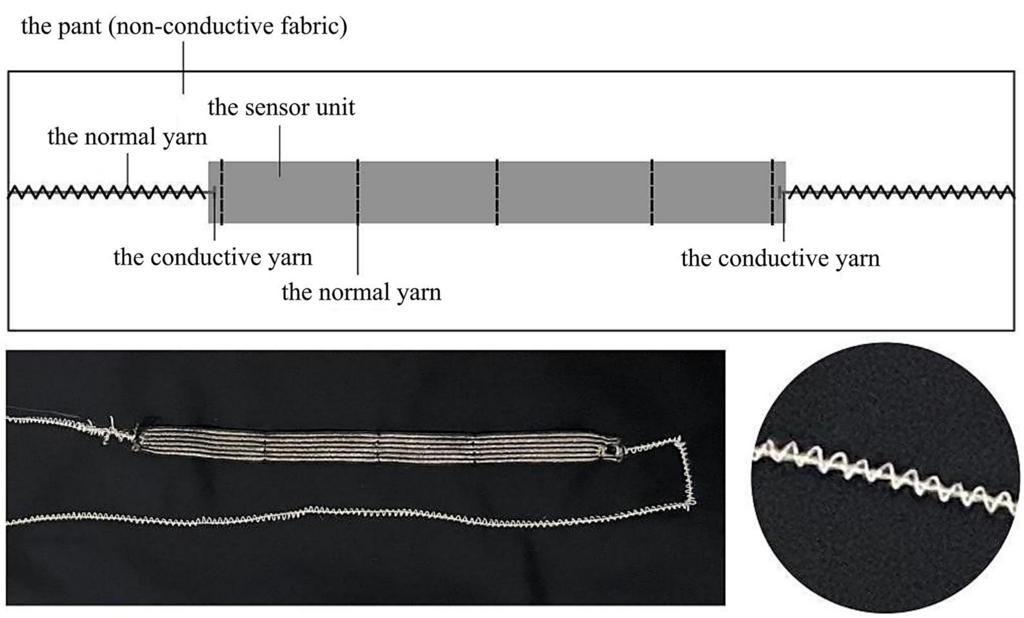

Figure 16. The sensor unit is Sewed to the legging fabric and connected to seeeduin board by the conductive yarns.

comfortable quick-drying fabric, with an empire waist and stirrup design. We used the Seeeduino XIAO development board as the signal processor because it has rich analog interfaces to connect to eight sensor units. Also, its small size (23.5 mm × 17.5 mm) and lightweight (9 g) have little effect on physical movement. The sensor unit has been connected to the Seeeduino XIAO board by conductive yarns at both ends, and we used normal yarns with flat stitches to fix the sensor unit on the legging fabric (see Figure 16).

5.1. Smart legging prototype

Additionally, the resistance ratio of the sensor resistance to the transmission line plays a crucial role in determining the sensitivity of the voltage readings. Therefore, we dedicated some effort to ensuring their appropriate values. In an unstretched relaxed state, the resistivity values for the sensor and the conductive lines are 1830 Ω/m and 100 Ω/m, respectively. Each sensor unit consists of a 150 mm fabric sensor with two 200 mm zigzag conductive lines attached at both ends. In this case, the resistance ratio of the sensor to conductive lines in one unit is approximately 6.9. In order to guarantee that the sensor's resistance variations induce substantial voltage changes, we have included 100 Ω resistors in each circuit. As the stretchability and durability of the conductive yarn threads may affect the system's reliability, in the early stage of prototyping, we conducted a manual stretching test that demonstrated the threads could stretch up to 150%, and thus ensured they could accommodate the most range of knee movement. Moreover, we designed a zigzag path for the conductive leads, which further improved their durability.

5.2. Running posture classification model

Human activity recognition is a typical multi-classification task that involves the collection of sensor data, algorithm selection, and model building. In recent years, deep learning-based algorithms for activity recognition have been developed and have emerged as the dominant approach for classification. Typical deep learning models Mu and Zeng (2019) include convolutional neural networks (CNN), Multilayer Perception (MLP), recurrent neural networks (RNN), long short-term memory networks (LSTM), and etc. Given the dynamic and intricate nature of human running, which encompasses uncertain states and continuous changes, traditional CNNs or MLPs are reckoned to be inadequate in handling the complexity of this task, especially long-time distance features recognition Mu and Zeng (2019); Yin et al. (2017). While RNN models can handle time-sequential data, they are prone to the issues of vanishing or exploding gradients Shewalkar et al. (2019). In contrast, LSTM models exhibit superior performance in handling time-sequential data, rendering them better suited for the purpose of running pose classification in this study. Therefore, we propose utilizing the LSTM neural network to achieve the task of running pose classification in this study. Figure 17 shows our procedure for building a deep-learning-based running posture classification model.

5.2.1. Data collection

Six young females aged from 22 to 27 (M = 26, SD = 1.79) participated in the study. All participants have a good habit of running for more than 3 years, regularly running more than 3 times per week. In the smart legging system, the sensors are sewn to follow the location of the joints and muscles in the lower limbs of the body. The body circumference of the wearers will influence the initial value of the sensor resistance at each node. To ensure a certain degree of consistency in the areas monitored by the sensor network on the legging prototype, the recruited participants have similar lower limb body measurements (height 162.17 ± 1.83 cm, weight 55.83 ± 2.56 kg, thigh circumference at the root 56.67 ± 3.33 cm, mid-thigh circumference 51 ± 3.74, knee circumference 36.33 ± 1.86, hip height 73.17 ± 3.71, and knee height 47.33 ± 1.5).

The study was carried out in a lab where the treadmill was placed on a stage and a laptop on the desk next to the stage. Before the data collection sessions, the participant watched a tutorial video and did a trial running session at a speed of 6 km/h to get familiar with the experiment set-up and specified running activities. The study consists of 5 sessions of data collection. In the first session, the participant kept still for 30 s during which the system recorded the initial resistance value of all sensor nodes in the sensor network. Then, the participants completed the following four running sessions on a treadmill: running with good posture; running with a simulated improper posture of internal rotation of the knee; running with a simulated improper posture of external rotation of the knee; running with a simulated improper posture of hip joint instability. Each running session lasted about 2 min on average, during which the prototype sensor data and video recording were stored when their movement has been stabilized. There was a 10 min break between each session.

5.2.2. Data processing

After collecting the experimental data from a cohort of 6 participants, we first pre-processed the dataset of each running session. Based on video observation, we selected a data segment of 30 s during which the participant maintained consistent running postures. To eliminate potential noise and baseline drift, each data segment was then calibrated by subtracting the average of the initial sensor values measured when the participant stood still. Thus, each calibrated dataset has the same length of 30 s and contains 8 channels of time-sequential data from the fabric sensor network recorded at a sampling rate of 259 Hz. The calibrated data were subsequently used to train and test the running postures classification model using the artificial neural network LSTM (Long short-term memory).

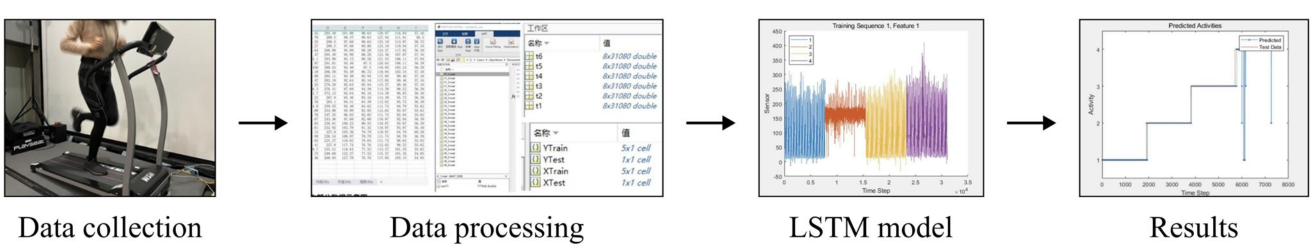

Figure 17. The procedure of building the running posture classification model.

5.2.3. Running posture recognition

Though intra-subject models are reckoned to be more accurate, they require extra training data of fresh users, which is less economical and feasible for potential large-scale applications. Thus, we applied inter-subject model training and testing in this study to verify the possibility of wider application by developing a few standard models for different groups. 5 out of the 6 sets, which are respectively collected from different subjects, served as the training sets, while the remaining one (chosen randomly) is used as the test set. We used MATLAB (2018) to prepare and train the model. In order to train a machine learning model for classifying time-sequential data collected from the smart legging, we used an LSTM network as the core of our machine learning model, which excels at handling sequence data Mu and Zeng (2019); Yin et al. (2017), namely the runner's time-sequential data representing running posture. In this study, the LSTM network accepts a sequential input with 8 channels (the dimension of sensor network data) and finally predicts users' running posture. Specifically, a bidirectional LSTM layer with 200 hidden units is used to receive the input first. And The sequence from the last processing step is then fed to a full-connection layer with 4 units, finally followed by a softmax layer and a classification layer.

As shown in Figure 18, the results demonstrate the model's feasibility in recognizing the two predominant categories of improper running postures, namely, internal and external rotation of the knees. Regarding the running activities with the improper posture of internal and external knee rotations, the classification model exhibits a high level of accuracy, achieving a prediction accuracy of approximately 99.1%. However, in case of the running activities with hip joint instability, the prediction accuracy needs further improvement.

5.3. Feedback design

According to Wang et al. (2017), the most commonly-used feedback modalities in wearable systems are visual, auditory, and haptic feedback. During running, the runner's visual perception channel will be limited. Therefore, the feedback design in our system focused on using a combination of vibrotactile and auditory modalities for real-time eye-free feedback display. Specifically, the system is designed to provide users with posture feedback and guidance tips to prevent their bad running posture that may cause knee injury.

Auditory feedback takes the form of verbal guidance. The level of detail in the verbal guidance is adapted to novice or experienced users. For novice runners who are new to the smart legging system, the feedback uses more explanatory prompts with details about how to adjust their current posture to the correct posture. For instance, When the poor running posture of pelvic rotation is detected during the running, the novice user will receive the verbal feedback "*Please pay attention to your hip area, engage your core muscles, stay stable, and avoid any unnecessary movement.*". When users have entered the stage of mastering the skill of adjusting running posture, the verbal feedback should be concise and require less time. Therefore, the feedback prompts normally consist of 3–4 words, which reduces the system's use of the user's attention. In the same condition, for experienced users, the feedback takes the form of a short reminder: "*Attention, hip area!*". In addition, the auditory feedback utilizes a gentle voice which is more approachable and may stimulate users to respond more positively. The play of audio feedback is directly triggered by the model classification results. In MATLAB, the pre-recorded audio files are associated with specific classification labels and type of user (novice or experienced), so that when a targeted improper running posture is detected, the corresponding audio file is played by MATLAB function *audioplayer*. As shown in Figure 19, via the Bluetooth sport earphones, the user could promptly receive relevant verbal guidance during running activities.

In this study, we utilized two smart wristbands providing users with vibrotactile feedback. Based on the previous study Karuei et al. (2011), when walking on a treadmill without

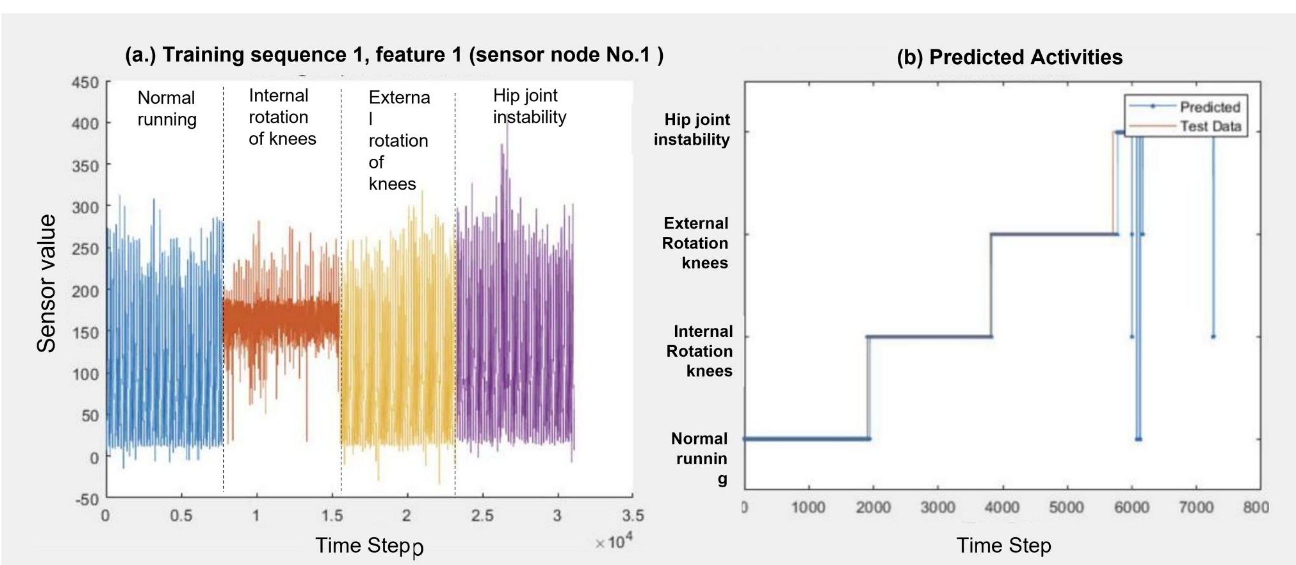

Figure 18. The prediction results of the classification model.

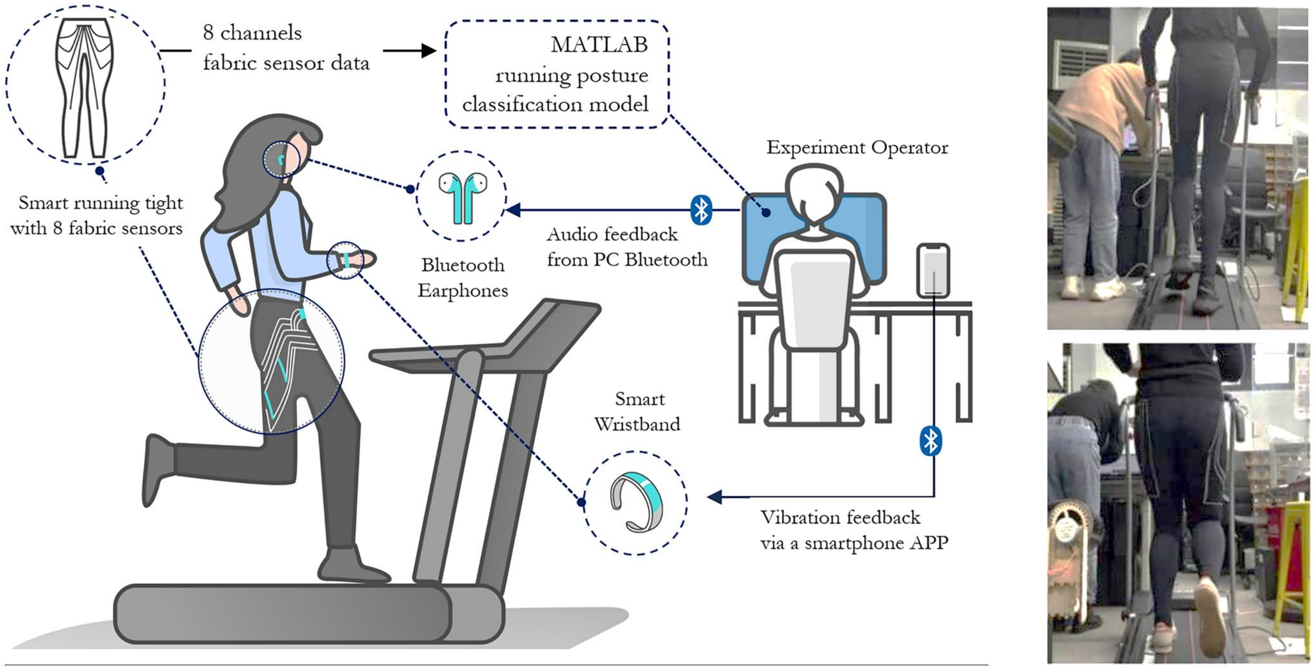

Figure 19. Usability evaluation study set-up and the system audio and vibration feedback design.

visual cues, the vibration feedback at the wrist could be perceived most effectively. In contrast, the vibration feedback at the thigh location is less effective and less desirable user experience. Therefore, we used two sport wristbands conveying vibrotactile feedback via a variety of vibration patterns including continuous long vibrations, rapid short frequency continuous vibrations, and switching between left and right vibrations. In this study, the implementation of vibration feedback was achieved through the adoption of the Wizard of Oz approach Dow et al. (2005). Two wristbands were coupled with a smartphone via Bluetooth connection and controlled by a mobile APP. Based on the real-time classification results from Matlab, the experiment operator sent the APP commands to the wristbands, triggering the corresponding vibration patterns, see Figure 19.

6. Usability evaluations

The evaluation aimed to confirm the feasibility of the application of the conductive sensing network for motion monitoring and verify the performance of the smart legging system in terms of system usability and user experience. In addition, through the evaluation, we also identified the advantages and shortcomings of the current solution in terms of rationality, novelty, and user satisfaction. These results informed the next step for optimization and iteration of the smart legging system.

6.1. Participants

Due to the size restrictions of the legging prototype, the six participants with similar physiques (height 162 ± 2cm, weight 55 ± 3kg) who joined stage three were invited for system evaluation. Two of them were novice runners, two were amateur runners with 1–2 years of experience and the remaining two were experienced runners with more than two years of experience.

6.2. Procedures and measurements

Initially, the participants are instructed to wear the smart legging system and acquaint themselves with the surroundings. Before the running session, the participants were asked to stand still on the treadmill for 30 s during which the initial sensor data were collected and averaged for the resistance calibration. Then, in the follow-up 10-min running session, the participants were asked to perform the four kinds of running postures that were supposed to be recognized in the system. Specifically, the eight fabric sensors in the smart legging system collected the user's running motion data, and the LSTM network-based machine learning model further analyzed these multiple-channel data and classified the running posture. And finally, based on the classification results, the system provided users with the corresponding posture feedback in real time.

After the running test, the participants filled out the User Experience Questionnaire (UEQ) Schrepp et al. (2017), which measures six key dimensions of user experience: attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. The System Usability Scale(SUS) Lewis and Sauro (2009) was also used to evaluate the system's usability. Finally, we interviewed each participant about their opinion and suggestions about the smart legging system regarding the aspects of wearability, comfort, usability, and reliability.

6.3. Results

Compared to the benchmark value at 68 Sauro (2011), the mean SUS score for the smart legging system is 80.42 (SD = 4.59), indicating a commendable level of usability.

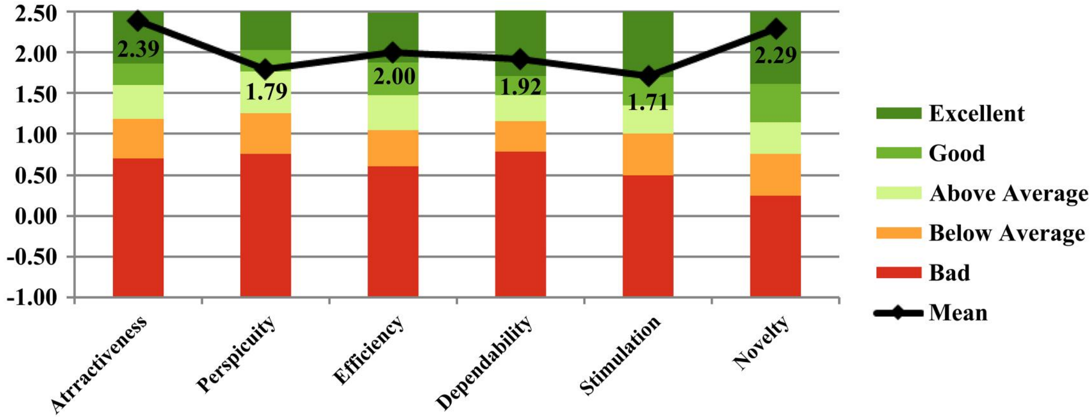

Figure 20. The UEQ benchmark, Showing the scores for each subscale and their meaning.

Figure 20 shows the average scores of each scale of UEQ. According to Schrepp et al. (2014), our system was rated as "Excellent" in all dimensions except for "Perspicuity". Specifically, the users gave high ratings to the dimensions of "Attractiveness" and "Novelty". The good ratings in the dimensions of "Efficiency", "Dependability", and "Stimulation" indicated that the users were satisfied with the innovation of the wearable solution and the system's ability to achieve its aim of alerting to incorrect running postures. In the dimension of "Perspicuity", the users' rating result was also benchmarked as "good" but scored lower than other dimensions. This was mainly because of the complexity of the tactile vibration feedback design and the lack of intuitive visual guidance in the initial phase.

Regarding the qualitative data, we analyzed the transcriptions of the interview recordings by using the content analysis method. We found that all participants showed a positive attitude regarding the wearability and appearance of the system. The lightness and no need for extra bulky equipment made the smart tight system suitable for outdoor running. For instance, one participant mentioned that *"there is no major difference (between smart tight system) with ordinary leggings, and I can wear them comfortably during doing exercise or running."* The participants also expressed high demand for the personalized appearance of the smart tight system. Secondly, from the perspective of ease of use, they mentioned that a *clear interaction process* allowed them to understand the working of the system without extra effort. Thirdly, the feedback design of the system was generally considered acceptable, *"without taking too much attention away from the running process."* However, two participants showed concerns about the system's reliability, as when a relative sensor displacement occurs during running, it may reduce the accuracy of posture recognition and system feedback. Participants also made suggestions for our future iterations, for example, addressing washability in our next step.

7. Discussion and future work

This research aims to develop a smart legging system to help runners learn and keep correct running postures. In the three-staged study, we first evaluated material performance and clarified the requirements of the single textile sensor unit. And then we explored and optimized the placement of multiple sensor units and finalized the sensor network. Next, based on the sensor network, we developed corresponding machine-learning algorithms for running posture classification. The smart legging prototype was evaluated regarding its usability and user experience.

7.1. About sensor

Although new fabric materials are constantly researched Alam et al. (2022); Lu et al. (2023), how to apply the sensing materials into an everyday garment is still a common challenge in wearable design. The different goals of human motion monitoring have specific requirements for fabric sensors regarding their strain range, sensitivity, and robustness. Therefore, before applying the sensor, understanding the features of the human movements to be monitored and further clarifying the sensor requirements are crucial. To explore the strain range of the fabric sensor around the knee joint, we performed manual measurements of the fabric deformation between marker points using a tape ruler while the participant was in a stationary position and stretching the outer thigh. While our current approach has proven effective, we recommend that future studies consider leveraging photogrammetry and Digital Image Correlation (DIC) techniques Barrios-Muriel et al. (2017); Blenkinsopp (2015) for achieving more precise strain analysis of the fabric sensor during actual gait movements.

To determine the configurations of a single sensor unit for optimal performance, we then conducted a comparative test of the material of different widths, lengths, and configuration parameters. Based on the sensing performance within the targeted strain range during running, we finally selected the double-sided conductive elastic webbing with a 10 mm width and 150 mm length as the sensor unit. The advantages of the selected fabric sensor unit are its high linearity over a wide strain range, softness, comfort, and naturalness. It has the potential to be used in other textile-based motion monitoring studies. The limitation of this fabric sensor is that it currently needs to be integrated into the garment carrier by sewing, which requires a certain amount of workmanship. Another limitation of our system is associated with the relatively low resistance value of the textile strain sensor. Strain sensors with low resistance tend to produce lower output voltages, which make them susceptible to noise from the readout circuitry. Besides, low resistance sensors also require a circuit to amplify and process their low output signals, which could consume more power. In future work, we propose investigating textile sensing materials with higher resistive values, a step that promises to enhance both robustness and the overall performance of the wearable garment in everyday scenarios.

7.2. Sensor network

For monitoring complex movements and classifying different postures, we need a sensor network with multiple sensors covering movement characteristics. Therefore, in this study, we examined different sensor locations that are most sensitive to the target postures. One limitation of this study is that we had only chosen the participants with one type of body dimension. In the future, we plan to investigate the performance of the current sensor network with various groups with diverse body parameters. Moreover, personalized models have been demonstrated to exhibit higher accuracy in previous studies Esfahani and Nussbaum (2018); Gholami et al. (2018, 2019). Therefore, developing an efficient method for collecting personalized data from new users holds significant potential for future research. Currently, the sensor network is built for monitoring 4 target running postures. Future studies may explore the possibility of extending or optimizing the sensor network to monitor more body postures in physical exercises. To achieve this, alternative types of sensors like IMU can be merged into the system Li et al. (2018); Lorussi et al. (2018); Ru et al. (2023); Watson et al. (2020); Zhu and Shi (2016) and enable it to recognize the moving direction and detect fall for example.

Although this study focused on monitoring lower body movements for recognizing improper running postures, upper body movements and foot postures also play a vital role in maintaining balance, stability, and overall running efficiency. Therefore, in future work, to achieve a more comprehensive running posture monitoring and performance analysis, we suggest further extending the system's capabilities by incorporating sensors distributed on the upper body and foot. Specifically, by integrating fabric stain sensors and IMU sensors within the upper body wearable garment to monitor the shoulder position, arm swing, and torso alignment, the future system could provide insights into the runner's alignment, balance, stability, and core engagement. By incorporating force-sensitive resistors (FSR) and pressure sensors within the running shoe or insole, the future system could perform gait analysis of foot posture during running, including foot pronation and supination patterns, heel acceleration, and plantar pressure Bamberg et al. (2008); Elstub et al. (2022); Mat Dris et al. (2020). The feasibility of full-body distributed sensors for tracking full-body motion has been explored in previous studies Kim et al. (2019); Roetenberg et al. (2009). However, determination of optimal locations of textile sensors and the design of comfortable wearable forms for running monitoring are challenging and complex tasks, we would encourage future work to apply textile sensor network simulation, using the analysis of skin deformation during target posture and certain constraints to generate the layout network.

7.3. System design and evaluation

The motivation of this study is to develop an interactive wearable smart legging system by combining fabric sensors and machine learning algorithms to monitor lower limbs' movement, classify improper running postures, and provide users with real-time feedback. Our three-stage approach started with the exploration of the characteristics of fabric sensing material and the configuration of the sensor unit. Based on the user experiment, we further developed a multi-sensor network for data collection. Lastly, the corresponding ML algorithms were developed to analyze multiple-channel sensor signals for posture recognition. The system still has many aspects that can be improved in future work. For instance, the smart legging prototype can be personalized and tailored to the individual's unique body shape, size, and biomechanics, not only ensuring a better fit and comfort but also supporting sensors in precise locations to measure data accurately. While this study focused on the classification of three primary improper running postures using solely lower limb movement data, as discussed above, we suggest the sensor network be extended both in quantity and variety, for instance including IMU and textile sensors distributed on the upper body and FSR sensors on the insole. Accordingly, a smart running shirt and a smart running shoe can be designed to comprehend the current smart legging system, as a running analysis kit.

In general, developing a smart garment system requires interdisciplinary collaboration. To achieve precise algorithms for angle estimation, gait analysis, and running performance evaluation, collaborative efforts with experts in sports medicine and data sciences are essential. This collaboration will ensure the availability of accurate training data and the development of reliable machine-learning models. Besides, to address the interactivity of the system for providing users with effective and user-friendly feedback, more collaboration with HCI designers is also needed. In our future work, we will further collaborate with user researchers and user experience designers to refine our design of haptic and auditory feedback regarding the modality, time, and frequency. Regarding evaluation, our study is limited to a small user population and a short period of time. In the future, we will then design and conduct a long-term study with a diversity of target users, to investigate the usefulness, effectiveness, and resilience of our system. Additionally, although the conductive material we used is sweat-resistant, due to the short test time, no heavy sweating occurred and the effect of sweat on the sensing unit needs to be further investigated.

8. Conclusion

In conclusion, this study demonstrates the potential of fabric resistive strain sensors in developing a smart legging system for monitoring lower body motion during running. The study presents a comprehensive examination of the textile sensors in terms of linearity and reliability to determine the suitable sensor unit. The proposed sensor network with eight sensors was developed for capturing the characteristics of running postures. The LSTM machine learning model was developed to analyze the multiple channels sensor data and further classify three improper running postures and normal postures with a high accuracy rate of 99.1%. The evaluation of the smart legging system showed its potential in preventing knee injuries by providing continuous monitoring and real-time feedback to help users adjust their running postures. Overall, this study presents a promising approach to using smart textiles for motion monitoring in sports and fitness applications.

Notes

1. Flexpoint TM, https://flexpoint.com/
2. Spectra Symbol, https://www.jameco.com/Jameco/Products/ProdDS/150551.pdf.

Disclosure statement

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