E-textile Sleeve with Graphene Strain Sensors for Arm Gesture Classification of Mid-Air Interactions

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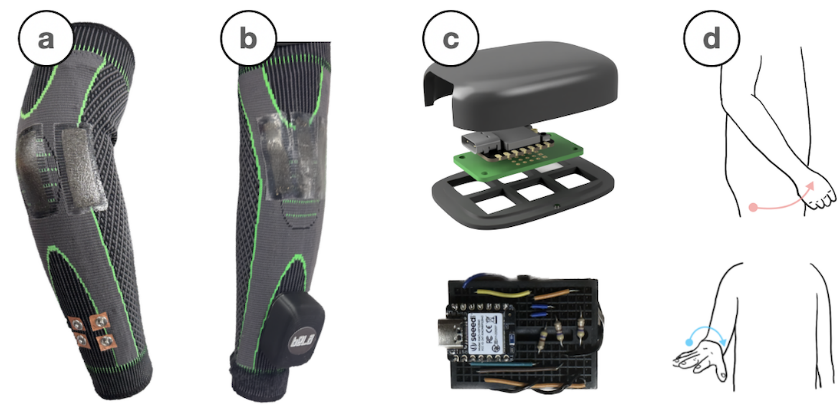

Figure 1: Overview of the wearable: (a-b) photos of the sleeve; (c) data processing unit; and (d) examples of two arm gestures.

ABSTRACT

Arm gestures play a pivotal role in facilitating natural mid-air interactions. While computer vision techniques aim to detect these gestures, they encounter obstacles like obfuscation and lighting conditions. Alternatively, wearable devices have leveraged interactive textiles to recognize arm gestures. However, these methods predominantly emphasize textile deformation-based interactions, like twisting or grasping the sleeve, rather than tracking the natural body movement.This study bridges this gap by introducing an e-textile sleeve system that integrates multiple ultra-sensitive graphene e-textile strain sensors in an arrangement that captures bending and twisting along with an inertia measurement unit into a sports sleeve. This paper documents a comprehensive overview of the sensor design, fabrication process, seamless interconnection method, and detachable hardware implementation that allows for reconfiguring the processing unit to other body parts. A user study with ten participants demonstrated that the system could classify six different fundamental arm gestures with over 90% accuracy.

CCS CONCEPTS

• **Human-centered computing → Interaction devices**.

KEYWORDS

E-textiles, Gestural Interaction, Wearable devices

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1 INTRODUCTION

Over recent years, numerous studies have emerged focusing on embedding sensors into various types of garments for sensing gesture-related interactive activity [1, 21, 26, 27, 38]. Unlike computer vision technology, which can be limited by factors such as low-light conditions or obstructions in the camera's field of view, e-textile sensors present a more versatile solution as they can be deployed across various scenarios with minimal environmental constraints, providing a robust and adaptable alternative for gesture recognition and interactive applications [19, 34]. Moreover, compared to inertia measurement units (IMU), a sensor commonly used for commercial smartphones and watches, textile-embedded sensors could provide more comprehensive body coverage. Current IMU-related research usually necessitates the use of multiple IMUs at various wearing points to achieve an efficient posture-tracking [18]; this usually results in wearing multiple extra devices and somewhat diverges from a vision of seamless integration into our daily lives.

Previous work sensing gestures through interactive garments primarily use pressure-sensing methods such as touch, twisting and gripping directly on the e-textile as input [7, 22, 23, 27, 39, 41]. These studies endeavour to devise a brand-new suite of custom-made gestures for the garment. Computer vision methodologies instead tend to detect natural body or joint movements, such as elbow bending, hand swiping and scrolling [20, 24, 33, 34]. Some researchers leverage multiple IMUs to monitor arm or hand gestures [29, 40], but it is evident that e-textiles can be more adequately leveraged, perhaps in tandem with IMU sensing.

As illustrated in Figure 1, this paper introduces a system-level design of an e-textile sleeve that can sense arm gestures. It incorporates a network of three ultra-sensitive graphene strain sensors at the elbow area of a commercial sport sleeve. In conjunction with a six-axis internal measurement unit (IMU), the sleeve can recognize the following arm gestures: 30° and 90° elbow bending, pronation, supination, lateral rotation, and medial rotation. These arm gestures are inspired by previous research [5, 8, 34], as these gestures are the fundamental features in common interactive scenarios.

The main contributions of this research are:

- A novel e-textile sensing system that seamlessly integrates highly flexible graphene strain sensors which can detect rotational and bending gestures.
- The graphene strain sensors offer unique sensing capabilities when compared to an IMU sensor capturing the same gesture, demonstrating that the two sensing subsystems are complementary to each other for mid-air arm gestural recognition tasks.

After reviewing relevant existing work, this paper presents the design and fabrication of an arm sleeve that captures arm movements via three graphene-based strain sensors and a six degrees-of-freedom IMU. A user study is then conducted to evaluate gesture classification of the signals generated by the arm sleeve. The paper closes with a discussion of the results, limitations of the arm sleeve, and how these findings could be applied to future research.

2 BACKGROUND

2.1 Facilitating Mid-Air Gesture Input

Mid-air interaction is a unique approach to human-computer interaction (HCI). Users utilise touch-free gestures to engage with displays or devices outside their immediate reach [35]. There are many aspects of research and application for mid-air interaction in recent years; for example, Mathieu et al. [20] suggests mid-air pointing techniques on ultra-high resolution wall-sized displays; Arun and Joseph developed a finger-based 3D gesture set for the menu selection [12]. Contrary to conventional research methods, Rafael et al. [34] introduce a novel elbow-anchored technique for mid-air input on smart TVs, focusing specifically on casual postures. They contend that users' interactions in relaxed settings are not accurately depicted in traditional lab environments. This argument aligns with Dustin et al. [5] who notes that when the user sits causally, the resulting fixed elbow postures can yield significantly different results from camera predictions, as forearm gestures may become tangential to the camera's viewpoint.

This limitation of arm-related gesture recognition aligns with the current research on hand gestures, where computer vision-based methods are still heavily affected by the environment setting and condition; interference such as lighting and obstacle can still lead to errors in gesture identification [2]. However, unlike the current hand gesture research, which has compact wearable sensors or data glove design that shows promise for accurate, non-intrusive hand modelling, there is limited research on how hardware or textile design can support recognising arm gestures. Thus, this paper aims to address this gap and utilize multiple sensors similar to the previous hand gesture research [25, 30] to deliver a novel methodology that facilitates the mid-air arm gesture input.

2.2 Gesture Design

The recognition of arm and hand gestures constitutes a vast field of research, with its pertinence and application changing considerably depending on the user context [2]. In these settings, the gestures used for interaction can vary substantially [8, 20, 34]. One central aim of this research is to pinpoint the basic arm gestures that can smoothly interact with the sleeve prototype, thereby enabling smooth and instinctive communication with the user. This effort is essential for improving the user experience and guaranteeing the successful operation of the prototype.

Prior studies focusing on the design of mid-air interactions have extensively evaluated users' frequency of arm gestures while interacting with smart displays. The findings from these studies indicate that medial and lateral rotations of the forearm are among the most used gestures when movements are annotated in a horizontal direction. On the other hand, for vertical directionality, flexion and extension at the shoulder or elbow positions are typically invoked. Interestingly, across a wide array of postures, the flexion and extension of the elbow are consistently observed, highlighting their prevalence in user interactions [34]. This outcome is corroborated by a multitude of studies and applications that are related to mid-air arm gesture research [6, 7, 17]. Notably, TickTockRay [9] and Armura [8] provided valuable insights into using extra gestures for input - wrist pronation and supination. These two inputs can be employed for decision-making functions, including selecting options such as 'yes' or 'no', grabbing items in a game, or executing a click action during website browsing. Such decision-making functions can complement the navigating function (up and down, left and right) provided by elbow-related movement.

2.3 Enabling a More Diverse Wearable Interaction

Researchers have explored various methods for embedding sensors onto forearm sleeves to capture gesture inputs. Parzer et al. [22] designed the Smart Sleeve, capable of using real-time sleeve surface and deformation to detect gestures, augmenting interaction with twirling, Twisting, folding, pushing, and stretching techniques. Stefan and Alexandra [27] developed a forearm gesture sleeve serving as an extended touchpad for smartwatch input; their results indicate superior performance of touch input on the sleeve compared to the smartwatch. These instances highlight the feasibility of using sleeve-based e-textile garments for practical applications, although they generally concentrate on a specific device and location. Addressing this gap, Yu et al. [41] proposed a reconfigurable scarf-like sensor for multipurpose measurement, which, however, appears less accurate in surface and deformation gesture detection compared to the Smart Sleeve. This might be due to the sensor requiring slight stretching for optimal readings, resulting in potentially less clean or responsive results.

Two opportunities emerge from the current sleeve-based wearables. First, the recognition of more diverse gestures: due to most research focusing on pressure-related gesture inputs requiring active user interaction with textiles, this study explores the potential of e-textile strain sensors detecting natural arm movements. Secondly, enhancing the inclusiveness of e-textile sensors, which can be achieved by integrating e-textile with existing products like smartwatches [27], assembling the e-textile sensors with another unit such as a power source or signal processing unit [37] or making it reconfigurable to be worn across different part of the body [10]. This research aims to amalgamate previous research opportunities by designing a detachable hardware sensor board with an embedded IMU; it also serves as the processing unit when connected to the e-textile sensors. This allows for configuring wearable devices across different body parts while simultaneously creating a scenario for mutual assistance between the e-textile strain sensor and devices equipped with an IMU. This approach is inspired by Rushil et al.'s [10] research on designing detachable smartwatches. They successfully re-engineered the smartwatch attachment mechanism, enabling different form morphing and enhancing the overall interaction experience.

2.4 Existing E-textile Strain Sensors and Applications

Several studies have explored the use of e-textile strain sensors on arms for two-dimensional joint angle measurement [4, 16]. Their accuracy is often compromised by complex fabrication processes and limited connection methods. For strain sensors, no universally accepted method exists for connecting textiles to fabrics. Some approaches involve coating the textile with a conductive material [28], while others attach a pre-cut commercial textile sensor to the garment using thermal bonding [14].

Other example applications for e-textile strain sensors include [15] which combines the bonding method with the commercial silver-plated fabric to explore the relatedness of sensor placement to the body's movement under the dancing scenario. Ryu et al. [25] introduced a wearable device crafted from dry-spun carbon nanotube (CNT) fibres grown on a flexible Ecoflex substrate. Stretching these CNT fibres decreases their conductive pathways, enabling them to act as sensitive strain sensors. While there isn't a strict protocol for choosing from the array of e-textile sensors, several fundamental factors have emerged based on previous studies [14, 42] that warrant consideration:

- **Sensing Range:** This is the relationship between the change in electrical resistance and the mechanical strain.
- **Gauge Factor:** A ratio quantifying the relative change in electrical resistance due to mechanical strain.
- **Cyclic Stability:** This gauge how the sensor holds up under repeated strain.
- **Linearity:** This assesses the relationship between changes in resistance and factors such as bending angle, twisting angle, and pressure.
- **Durability:** This is measured through UV ageing and washability tests to evaluate the sensor's resilience over time and under different environmental conditions.

With all these selection specifications in mind, previous research suggests that a silver-plated yarn sensor outperforms other commercial sensors regarding sensitivity and linearity [13]. It can also be easily bonded to the garment fabric using TPU and a heat press, an ideal material for the initial testing. Zhou et al. [42] introduced a graphene composite sensor that can be embedded onto the garment through film coating. The research shows the sensor has excellent sensitivity (GF = 498), a wide sensing range from 0% - 293% and outstanding reliability (5% deviation after 10000 cycles of stretching under a 5% strain. This graphene sensor's excellent performance matched this research requirement for human elbow-related motion tracking and was therefore chosen for prototyping the sleeve.

3 SLEEVE DESIGN AND FABRICATION

To address the need for a wearable system to facilitate mid-air gestural control, an e-textile sleeve was designed and fabricated. This section outlines the gestures selected for the sleeve, the circuit design, and the fabrication process for the wearable system along with the graphene-based sensors. It then briefly presents the physical prototype refinements made after a pilot user study along with the data pre-processing applied to the signals generated by the signals.

3.1 Gesture Selection

To facilitate mid-air gestures, the first step was to identify the gestures being captured as that informs the engineering of the wearable system. Six fundamental gestures were selected for interaction needs under a wide range of usage scenarios based on the background gesture design research presented in section 2.2. Figure 2 shows the graphical representation of the gestures: (a) and (b) refer to elbow extension and flexion, which could contribute to scrolling up and down in the navigating function; (c) and (d) refers to the lateral and medial rotation that might serve as the left and

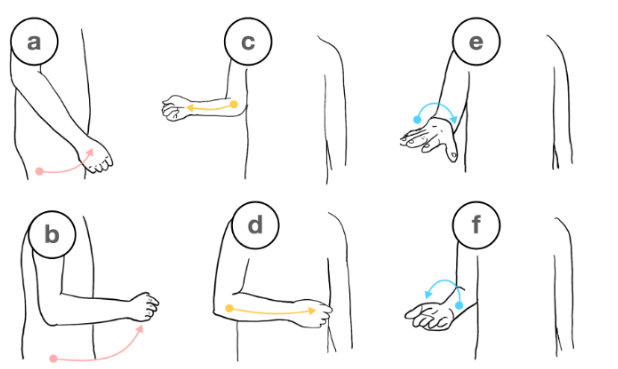

Figure 2: Six fundamental gestures selected: (a) elbow bending 30 degrees; (b) elbow bending 90 degrees; (c) lateral rotation; (d) medial rotation; (e) pronation; (f) supination.

right movement in navigation; and lastly, (e) and (f) refer to the above decision-making functionality described by [8, 9].

3.2 Circuit Design

The graphene sensing mechanism is similar to many other e-textile strain sensors in that a change in resistance in response to mechanical deformations such as stretching, bending or pressure is measured [32, 36]. The notable difference in the graphene sensing mechanism when compared to metalized fabrics is that the stretching of the fabric pulls apart the conductive graphene network causing an increase in resistance under strain, as opposed to a decrease in resistance as seen in metalized fabrics.

A potential divider circuit was used to connect the graphene sensors to an Arduino-compatible microcontroller, a Seeeed Studio XIAO nRF52840 Sense. The voltage values of the potential divider were captured at a sampling rate of 100 Hz.

3.3 Fabrication Process

Enokibori and Mase [4] explored using one large e-textile strain sensor to predict the elbow joint angle. However, one sensor could only provide limited 2-dimensional arm gesture reorganisation. To explore using multiple e-textile strain sensors placed on the arm to sense 3-dimensional gestures, this research thus started by using the commercial sensor to rapidly test the effectiveness of the sensor location to the arm gestures. Based on literature, the individual sensor is constructed using 2 cm for the width [15, 43], and the length is selected to be 6 cm, which is twice the calculated elbow radius and can well cover the sensing region.

To quickly evaluate sensor placement, three TPU bonded sensors made from metalized knit fabric (Shieldex Technik-tex P180B) were fabricated and placed on the arm sleeve. Three rough locations were selected: one sensor was placed in the middle of the elbow to sense the bending gestures, and two other sensors were 1.5 cm on each side to assist with left and right rotational gestures. The sensor placement was shown to be effective at capturing varying signals according to the gesture and so the graphene sensors were fabricated on an identical sleeve at the same location.

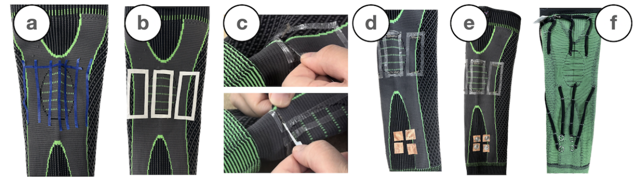

Figure 3: Fabrication process: (a-b) Using textile tape and TPU to frame where graphene will be added; (c) Sewing elastic wire to the top and bottom the sensor location; (d-e)Attaching a snap onto conductive textile for a more stable signal connection; (f) The sleeve turned inside-out to show the conductive elastic isolated in a tubular yarn.

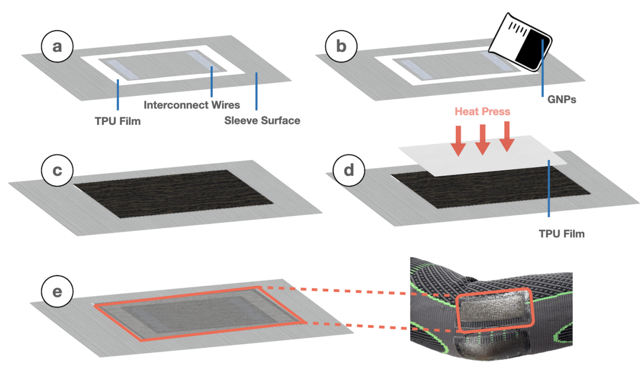

Figure 4: Applying GNPS onto the sleev: (a) Starting from setting up the sleeve on a flat desk; (b-c) and using a film applicator to distribute the GNPs evenly; (d) Then, another piece of laser-cut TPU film was used to cover the top of the GNPs and apply an even heat press from the top; (e) Wait until the unit cools down to room temperate and remove the wax paper from the TPU.

The exact sensor locations were marked using textile tape and a TPU frame. A commercial silver fibre elastic wire was hand sewn to form a stable connection between the top and bottom of the sensor and metallic snaps press fit over conductive woven textile (Shieldex Kassel) bonded onto the sleeve created the connections between the sensors and the external processing board. Figure 3 shows each step of the fabrication process before the graphene is applied.

The graphene nanoplatelets (GNPs) used for high-fidelity prototyping are manufactured based on past research work by Zhou et al. [43]. Figure 4 shows the process of integrating the GNPs onto the sleeve. The GNPs were first evenly applied into the region marked by TPU film using a film applicator, and an extra layer of the TPU was then bonded to the sleeves and GNPs through heat pressing, forming an encapsulation for the sensor.

All of the non-textile electronic components were integrated into a small board housed within a 3D-printed case attached via snaps. Figure 5 shows the finished sleeve.

Figure 5: Finished sleeve: (a) photo of the sleeve; (b) top and bottom view of the circuit board and snap sockets; (c) photo of the sleeve with circuit board attached; (d) render of the casing; (e) Final prototype appearance with sensor number label, 1-3 represent the graphene sensors, 4 represent the IMU and processing unit location

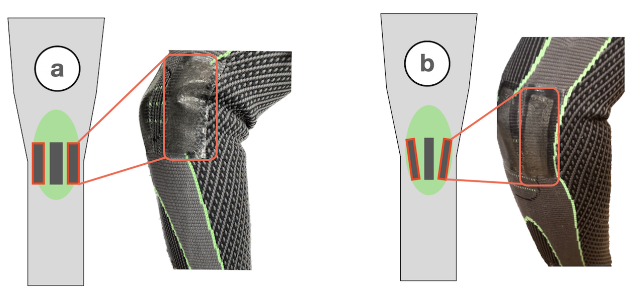

Figure 6: Prototype refinement. (a)The initial sensor dimension is 2 cm x 6 cm. (b)The refined sensor dimension is 1.5 cm x 6 cm and has a curved arrangement to better fit the elbow movement.

3.4 Sensor Refinement

For a pilot study, two right-handed participants were recruited to perform the six identified gestures. The sensors' preliminary performance was assessed by observing the deformation of the sensor visually and comparing such deformation to signal variation during each gesture. A sensor design defect became apparent after observing the user performing medial and lateral arm rotations. As illustrated in Figure 6, the initial sensor dimension and arrangement led to folding of the two side sensors when the arm was bent, which could generate noise in the signal and potentially reduce the sensor's durability. The prototype was initially designed according to dimensions from previous research [15], which focused on sensing body movement rather than arm movement, thus leading to a relatively larger initial sensor dimension for this study. This insight prompted a redesign of the sensor dimension and arrangement. The sensor width was reduced from 2 cm to 1.5 cm and placed in a curved arrangement.

3.5 Data Pre-Processing

Using the data collected from the two participants of the pilot user study, a signal processing tool chain was established to pre-process the data generated by the three strain sensors and IMU. First the graphene sensor signals were converted from the sample voltage to a resistance value and then normalised against the resistance value of the sensor under no strain.

Then all nine sensor signals (the IMU and strain sensors) were low pass filtered to remove high-frequency noise that could originate from the sensor, processing unit, or the user's movement.

Spectral analysis of the captured signals showed that noise was introduced around 2 Hz. A first order Butterworth filter with a cutoff frequency of 2.5 Hz was chosen. It was found to strike an effective balance between noise reduction and preserving crucial signal information, as shown in Figure 7.

4 EVALUATION OF ARM GESTURE RECOGNITION

In order to evaluate the performance of the arm sleeve a gesture classification study was designed to examine the sleeve system's ability to recognise the six gestures shown in Figure 2. Users were invited to wear the sleeve and repeatedly perform the different gestures as shown in a video demonstration. The core questions being asked by this study are:

- Does the sensing system produce sufficiently differentiated signals for each gesture that they could be algorithmically classified?
- What are the classification performance differences between the strain sensors, IMU, and combination of both sensor types?

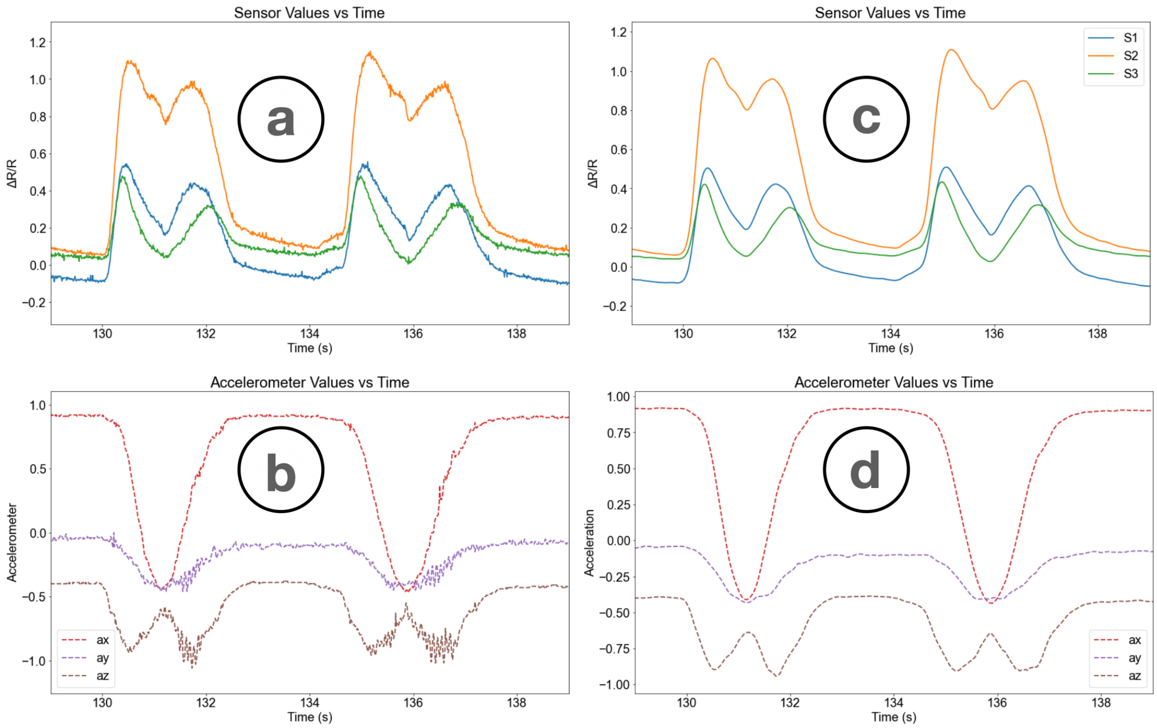

Figure 7: Sensor signals of two arm bending activities before (a - b) and after (c - d) applying low-pass filter.

4.1 Procedure

Before the commencement of the study, participants gave their informed consent[1] for the use of their data in the gesture classification analysis. Ten right-handed participants took part. After a short briefing and demonstration, the participant put on the sleeve prototype and performed the six gestures following video guidance displayed on the monitor. They repeated each gesture ten times; the time duration for each gesture being 4.5 seconds with a five-second rest interval to facilitate data segmentation.

The collected data was segmented and labelled with the corresponding gesture. The data set consisted of 100 samples for each gesture and 600 labelled samples in total. The final data set was stratified and randomly split into a training data-set (80%) and a test data set (20%). Each sample contained nine channels: three from the graphene sensors, each representing one sensor's change in resistance; and six from the IMU, representing the linear and angular acceleration measurements.

A deep learning model integrating both a convolution neural network (CNN) and LSTM (Long Short - Term Memory) was selected for the classification. The model's architecture was originally developed for classifying time-series data for hand gesture recognition [3]. The CNN layers are used to automatically and adaptively learn spatial hierarchies of features from the time series data, and the LSTM layers are used to learn temporal dependencies from the features obtained by the CNN. The architecture initially includes a TimeDistributed wrapper that allows for CNN application at each time step of the input sequences. The CNN component comprises two Conv1D layers, each accompanied by a BatchNormalization layer and a MaxPooling1D layer. Activation functions, 'tanh' and 'relu', are utilized for enhanced non-linearity after certain layers. A Dropout layer, set at a rate of approximately 21%, is employed to mitigate overfitting. The CNN output is flattened to feed into two LSTM layers designed to capture temporal dependencies. Each LSTM layer is complemented with a Dropout layer for overfitting prevention. Subsequent to the LSTM layers, a fully connected (FC) layer with 'tanh' activation is employed. Model training is performed using the Adam optimizer with a learning rate of 1e-4, and a categorical cross-entropy loss function. Model performance is monitored based on validation accuracy throughout training. The model is trained for 200 - 600 epochs (depending on the convergence of training accuracy), with a batch size of 64.

4.1.1 Extended Single User Dataset. Previous studies discovered classification results tested within the same user have a consistent 10% increase in accuracy than across users [41]. To see if this was repeated with the arm sleeve, a small extension to this study was conducted. The same procedure was used as above, but with only a single participant. They were asked to perform each gesture 20 times with the data fed into the same classification algorithm under the same settings as above.

[1] University ethics approval for this study was granted by [redacted for review]

4.2 Results

To evaluate if the sensors were generating recognisably different signals for each gesture, the signals were plotted and visually inspected. Figures 8 and 9 are only four of the gestures, but all gestures generated visual patterns that were highly correlated with the gesture and repeated across users. Figures 8 and 9 demonstrate the robust directional awareness of Sensor 1 and Sensor 3, which are positioned on the sides of the elbow. When the user executes a reversed gesture, the signal's peak correspondingly reverses, with the degree of reversal relating to the magnitude of the movement. Notably, medial and lateral rotations show more pronounced reversals in resistance change compared to pronation and supination.

Five-fold cross validation was used to evaluate the performance of the machine learning model. When using data from graphene sensors only, the system can achieve an accuracy of 90.7% (SD: 0.028). When using IMU data alone the system can achieve a higher accuracy of 94.1% (SD: 0.013). However, the highest accuracy is achieved with when using both sensor types are included the model with an accuracy of 96.1% (SD: 0.0085).

The confusion matrices for each model are shown in Figure 10. The graphene sensors excel at the bending gestures, which the IMU is relatively weaker at correctly classifying. The graphene sensors struggled more at correctly classifying the lateral and pronation gestures, which the IMU could classify without any error. Both sensor types misclassified the medial gesture the most.

When combining both sensor types the accuracy of the deeper bend, lateral, supination, and pronation gestures all were either equal or improved upon the individual performance of a single gesture type. The more shallow bend gesture was best classified with the graphene sensors only and the medial gesture performed best with the IMU only.

4.2.1 Extended Single User Dataset. The classification results shows the graphene sensors' accuracy of a single user with more sample gestures increased greatly over the model of 10 users with half the number of gestures per user. It achieved an 98.4% accuracy (SD = 0.022). The IMU results remain at an accuracy of 94.2% (SD: 0.035). When using both sensor's data the system can achieve 97.9% accuracy (SD: 0.026).

The confusion matrix result are shown in Figure 11. There was some consistency with the larger, mixed user data set. The graphene sensors alone were the best at classifying the more shallow bending and were worse at distinguishing lateral and pronation gestures. Both individual sensors were relatively poor at classifying medial gestures. When combined, only the more shallow bending was misclassified.

5 DISCUSSION

Through simple inspection of the data and also more rigorous analysis using machine learning, the wearable sensing system can clearly produce sufficiently differentiated signals for each gesture whether considering only a single sensor type on the wearable or combining the output of both the three graphene strain sensors and the IMU. However, a more nuanced discussion is needed to examine the performance of each sensor type and their combination.

The graphene strain sensors showed excellent performance in predicting bending activities achieving high or perfect accuracy for bending 30° and 90°. It has relatively lower accuracy regarding wrist movement (pronation and supination). The IMU showed a reversed performance result, with perfect accuracy in rotational activities (lateral rotation and pronation), and a lower accuracy in predicting the level of bending. When merged, the accuracy is more balanced in predicting across all gestures as well as increased overall accuracy, with the exception of the 30° bend which performs equal or worse with combined sensors than with either individual type.

There are two potential factors that may be influencing these results. The first one is that each user's gesture amplitude differs, making it challenging to achieve consistency during the data collection process. The second, and more crucial factor, is that the size of the user's arm and the subsequent fit of the sleeve significantly influences the scale of the signal shape, since the user who provided the training data for the model also supplied the test data. When looking at the signals produced by users with very different arm circumferences, the signals have similar shapes but different scales as the sensors are under different initial state (the user with a larger arm will pre-stretch the sensor), which could potentially lead to less accurate classification result. The graphene sensors are not linear across their entire working range [43], so shifting the sensing range used could greatly impact the generated signal. The extended user dataset supports the theory that arm size variance will affect classification accuracy.

These results highlight some successful features introduced by this design. The first is through the design of sensor placement, the graphene strain sensors can be harnessed to capture more nuanced three dimensional movements beyond the large-scale rotation generated by body joints. Secondly, mixed sensing modalities can complement each other to provide more accurate classification of richer gestures. Further research would be needed to verify if the high-sensitivity of the graphene sensors is necessary to capture these movements or if sensors constructed from commercially available conductive textiles could perform similarly, as well as whether the advantage of mixed sensing modalities can be enhanced.

The study here is limited to a fix set of gestures performed in a lab setting. Its performance in a more ecologically valid context needs to be addressed in future work to more fully assess its potential.

5.1 Fabrication Durability

The sleeve prototype with strain sensor was tested rigorously throughout the two studies above. The testing period is approximately three weeks, involving over 1200 stretching and rotation practices, yet no significant change in sensor signal occurred. The interconnection within the sleeve prototype remained stable after all the tests. Such a result demonstrates the system's excellent durability.

5.2 Wearing Experience

All of the connections are fully embedded inside the sleeve, and the electronic hardware is placed on the outside of the sleeve (similar to the position of wearing a smartwatch), it was observed in the experiment that the users' freedom of motion was not affected. Users generally commented that the comfort of wearing it felt the same as wearing a sports sleeve. Although more detailed tests, such

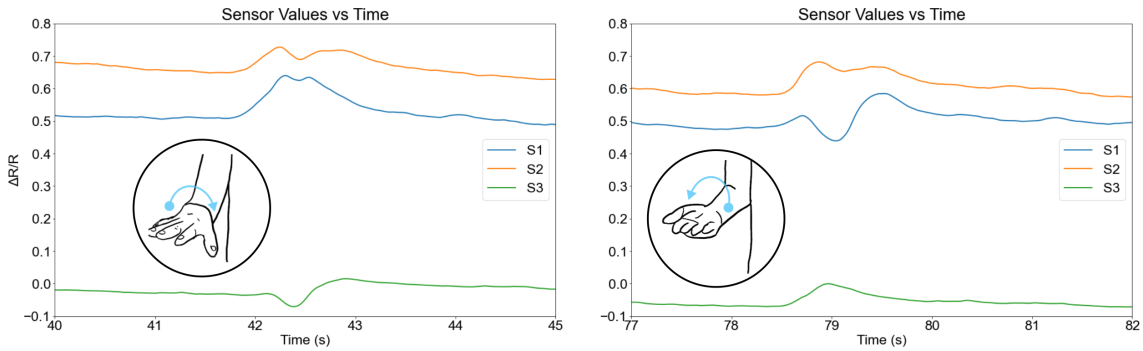

Figure 8: Time series of sensor data for pronation and supination.

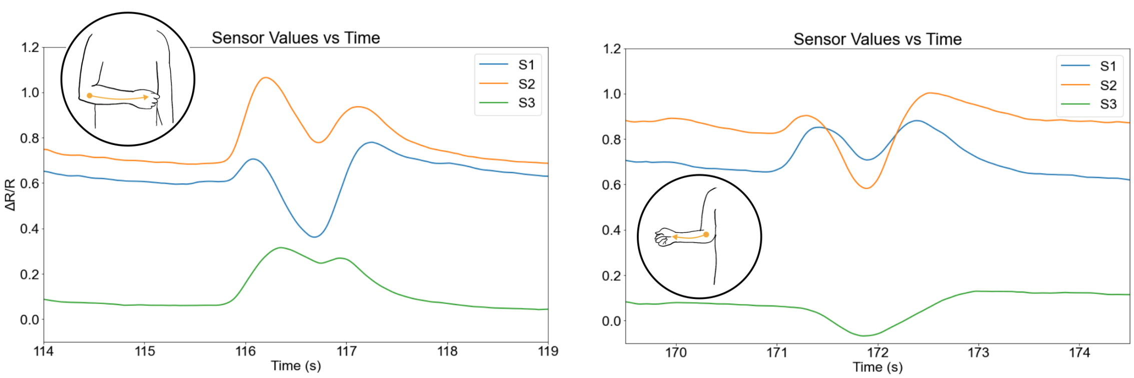

Figure 9: Time series of sensor data for medial and lateral rotation.

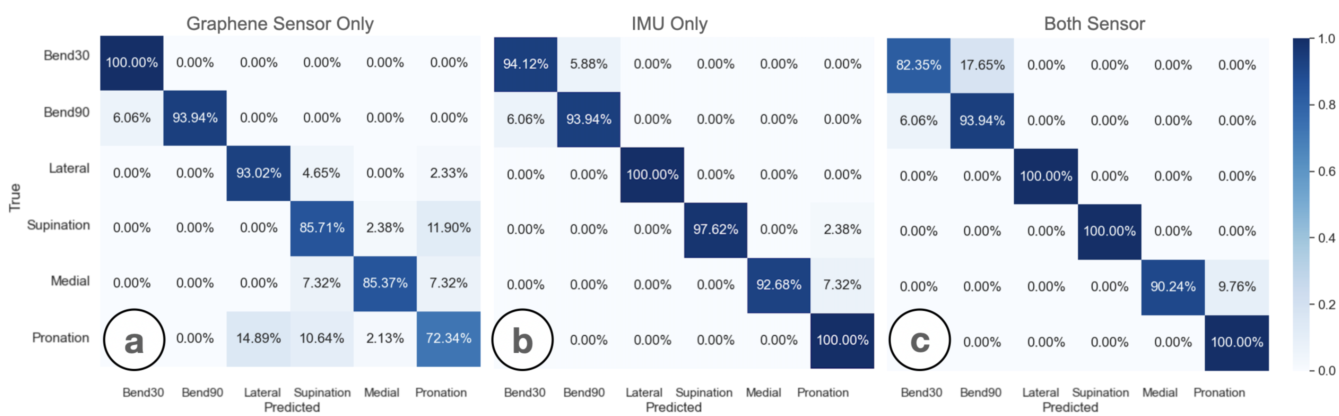

Figure 10: Confusion matrices of the classification of six guestures performed by 10 users: (a) graphene textile sensors only, (b) IMU data only, (c) combination of both sensor types.

as wear time, were not conducted, preliminary experimental results have proven that the design can offer a comfortable wearing experience. This is significant as the wearability of prototype systems can hinder data capture whether due to wearer discomfort or breakage of the device when donning and doffing [31]. There were no issues encountered in our user study, demonstrating the success of our sensor integration.

5.3 System Design

This paper assesses the potential of integrating data from an IMU with graphene strain sensors, yielding a enhancement in gesture recognition capabilities. Nonetheless, the present system lacks feedback mechanisms for the user. In view of future product-level development, further refinements could include the incorporation of actuators such as a haptic motor and a speaker to enrich the user

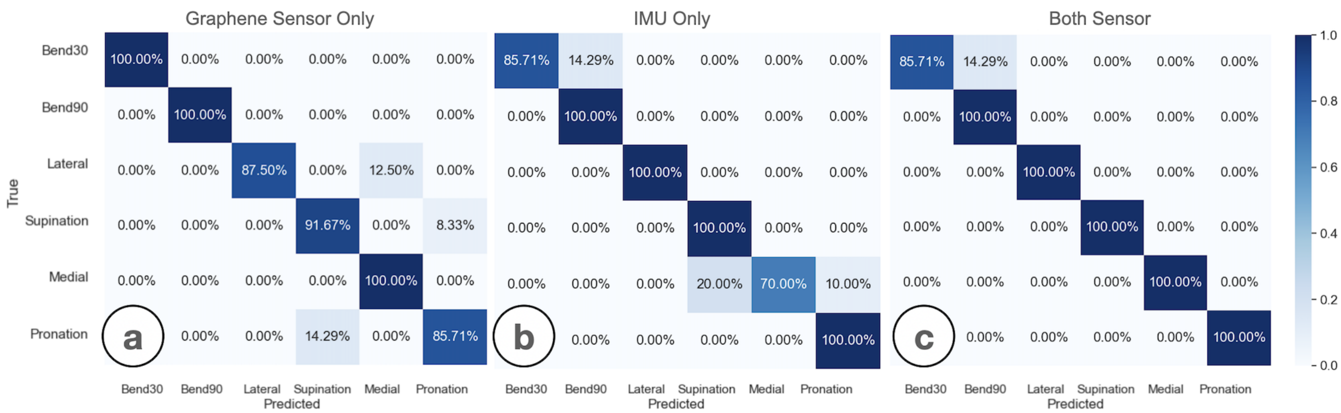

Figure 11: Confusion matrices of single participant classification result performing six gestures: (a) graphene textile sensors only, (b) IMU data only, (c) combination of both sensor types.

interaction journey, making it more tangible and interactive. For example, OmniFiber, an fibre based actuator [11] when combined with the printed graphene strain sensor fabrication presented here could be one method for integrating haptic feedback with gesture recognition.

5.4 Customizing Hardware and Interconnections

Existing research posits that e-textile sensors generally exhibit superior performance when they conform to the body and are slightly stretched [15, 22, 41, 42]. Consequently, unlike traditional hardware products that can adopt a one-size-fits-all approach, e-textile hardware should follow the paradigm of common apparel products, offering either different sizes to accommodate varying body dimensions or customisation options for individual users. The current prototype lacks such features, but future research should explore a broader range of fitting garment options for different arm sizes and investigate strategies to modularise the components, allowing users to select the level of configuration that best suits their needs.

6 CONCLUSION

This paper presented an e-textile sleeve designed for arm gesture recognition of mid-air interactions, with graphene strain sensors seamlessly integrated into a commercial sports sleeve. The design also incorporates a detachable processing unit, enabling the e-textile sensor to deliver at optimal performance while allowing for reconfiguration of the hardware to other body parts, accommodating a broader range of user scenarios. The sensing system is able to clearly classify between six gestures, highlighting the potential of mixing multiple strain sensors and IMUs into e-textile garments. This research aims to contribute to future interactive systems in which the human body is a natural extension of the system. In such a system, one's forearm and the related gestures can serve as tools to interact with the surrounding devices and environment, free from the constraints of specific spaces or fields of view.

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