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A Textile-based Wearable Electromyography Sensing System with Bluetooth Low Energy Internet-of-Things Gateway for Baseball Pitching Analysis

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With the rapid miniaturization of physiological sensing components and the widespread adoption of wearable devices, long-term physiological monitoring has become increasingly feasible in daily life and sports applications. In this study, we initially analyzed data from a conductive-fabric-based electromyography (EMG)-like sensing sleeve. The developed sleeve employs textile electrodes to emulate surface EMG sensing and integrates six sensing channels, with a small amount of water applied to enhance electrode conductivity. Compared with conventional adhesive EMG systems, the textile-based sleeve is easy to wear and effectively mitigates electrode displacement during high-speed baseball pitching motions. Experiments on three representative movements demonstrate that the proposed sleeve reliably captures muscle activity, instilling confidence in its practical use for sports training and biomechanics analysis.

1. Introduction

Baseball pitching and batting increasingly rely on quantitative sensing for objective motion assessment and training feedback. Wearable inertial sensors capture high-speed pitching kinematics under dynamic conditions,(1) while biomechanics studies link pitching mechanics to injury risk and long-term performance outcomes.(2) Noninvasive electromyography (EMG) complements kinematic sensing by characterizing muscle activation and fatigue-related behavior through signal processing and machine learning.(3) However, adhesive EMG electrodes remain susceptible to displacement during high-intensity pitching, often requiring additional fixation that reduces usability;(4) textile-based flexible EMG interfaces therefore provide a practical alternative with improved comfort and mechanical stability while supporting dense muscle signal acquisition.(5)

Internet of Things (IoT)-enabled wearable systems have advanced continuous monitoring through low-power communication, distributed sensing, and scalable data aggregation. Prior

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work has demonstrated activity recognition with lightweight wearable sensing configurations,(6) deep-learning-enhanced IoT frameworks for healthcare-oriented monitoring,(7) and end-to-end wearable IoT designs integrating sensing and analytics in smart environments.(8) Recent studies have further explored smartphone-based sensing platforms for real-time monitoring(9) and multimodal fusion in IoT systems to enhance robustness in complex recognition tasks.(10) In the baseball domain, IoT-integrated smart gloves equipped with pressure and motion sensors have been developed to characterize batting swing mechanics and correlate handgrip strength with hitting performance.(11)

Building on these directions, in this work, we target the practical gap between stable EMG acquisition during ballistic arm motions and IoT-grade multi-device synchronization in sports training. We design a conductive-fabric EMG-like sensing sleeve that enhances stability during dynamic movements and reliably captures muscle potentials from major upper- and forearm muscle groups. The sleeve streams data via Bluetooth low energy (BLE) to an IoT gateway that supports synchronized acquisition across multiple BLE sports sensors. The system is validated for inclined board lifting, baseball pitching, and the first eight forms of Yang-style Tai Chi, covering representative motion-speed and activation-intensity conditions. In addition, the gateway enables the real-time integration of EMG-like signals, bat grip force measurements, and smart baseball kinematic data, providing a unified sensing pipeline for realistic baseball training environments.

2. Conductive-fabric-based EMG-like Sensing Sleeve

In this study, a wearable EMG-like sensing sleeve based on conductive textiles is developed. The sleeve follows the sensing principle of miniaturized surface EMG and provides six sensing channels. Each channel comprises a pair of rectangular conductive-fabric electrodes measuring 4×1 cm² and a square ground electrode measuring 2.3×2.3 cm². Each conductive-fabric electrode adopts a three-layer construction: an outer conductive textile layer that interfaces with the BLE module through the snap-button terminals, an inner moisture-retaining textile layer that forms the active skin-contact pad, and an insulating textile layer that surrounds the moisture-retaining pad on the same face as the conductive layer to confine the active sensing area; a small amount of water is applied to the moisture-retaining layer prior to wear to lower the electrode-skin impedance. The electrode layout and placement on the sleeve are shown in Figs. 1(a)–1(c), where the inner-surface electrode patches and the ground location are highlighted. Muscle-related voltage variations are transmitted to a receiving device or gateway through a BLE transceiver module, as shown in Figs. 1(d) and 1(e); the sleeve and module are connected via snap-button terminals that provide fixed channel mapping (ch1–ch6) and a dedicated ground contact for repeatable measurements. The BLE transceiver module is electrically and mechanically interfaced to the sleeve via matched snap-button terminals and elongated elastic conductive textile traces [Fig. 2(a)]. For pitching measurements, the module is mounted on the inner or outer side of the right shoulder [Fig. 2(b)] to avoid restricting arm extension or altering the natural throwing motion. The BLE transceiver module weighs approximately 180 g (including the enclosure and battery) and is fixed to the shoulder via the elastic textile sleeve [Fig. 2(b)]. Mechanical isolation between the module and the sensing electrodes is achieved by

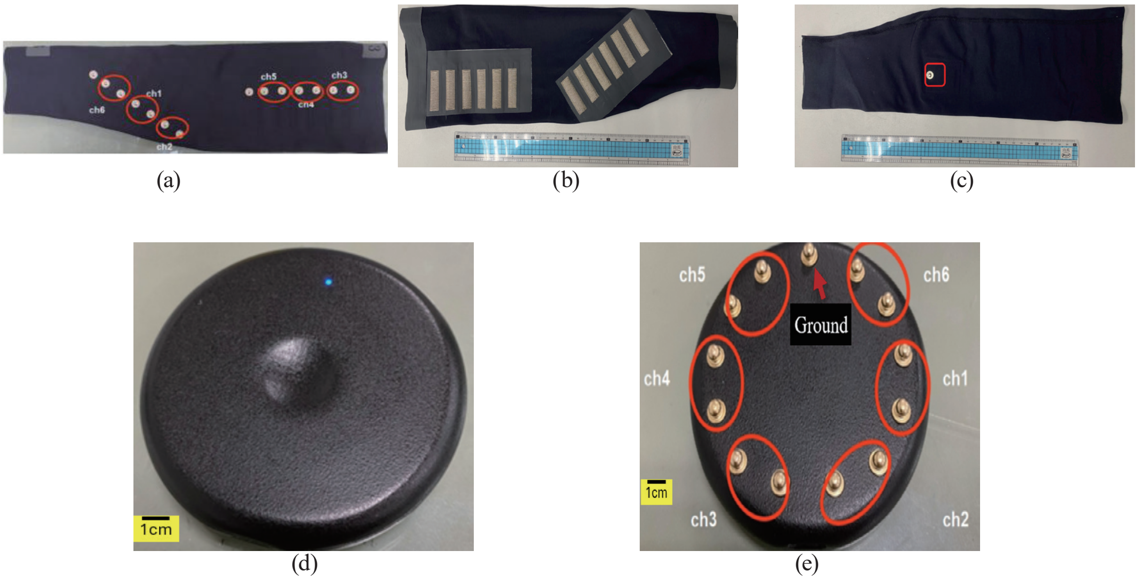
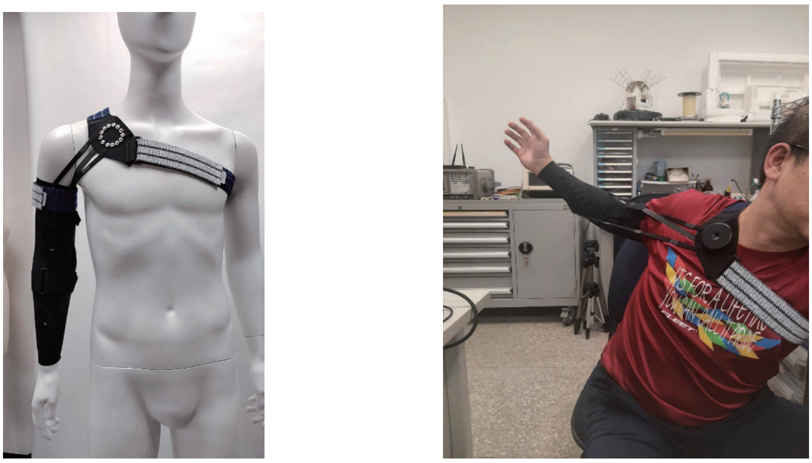


Fig. 1. (Color online) Developed EMG sensing sleeve and BLE transmission module: (a) snap-button connection points for six sensing channels (front view), (b) conductive textile sensing electrodes for six channels (inner surface), (c) ground electrode location, (d) front view of BLE module, and (e) rear view showing snap-button contacts for six channels.



(a) (b)

Fig. 2. (Color online) Designed sleeve and transmission module worn on the arm: (a) wearing method and (b) simulated pitching stretching.

keeping the sleeve tightly fitted to the upper and lower arms while connecting the module via loose conductive textile strips with sufficient slack to accommodate the full range of pitching motion; this prevents the module from pulling on the sensing electrodes during ballistic movement. Residual motion fluctuations introduced by arm flexion under high-intensity movement are further attenuated by the moving average (MA) filter described in Sec. 4. Because the textile electrodes provide a larger contact area than commercial miniaturized EMG electrodes, the recorded signals represent superimposed responses from multiple muscles and tendons rather than single-muscle activity. On the basis of the arm muscles' positions, Channels

3, 4, and 5 capture the superimposed variation of the biceps brachii at the lower, middle, and upper portions of the upper arm, respectively, during pitching. In contrast, Channels 1, 2, and 6 collectively capture the superimposed activity of the palmaris longus, pronator teres, and brachioradialis muscles on the forearm.

3. Sensing Data Gateway

Real-time pitching practice often involves multiple sensing devices; therefore, a BLE-based gateway is developed to support scalable, synchronized acquisition across heterogeneous sensors. BLE is used for low-latency device-to-device communication, while Wi-Fi provides external connectivity via access points. The gateway is implemented in Python 3.x and runs on an Intel NUC7JY (Celeron J4005, 2.7 GHz, 8 GB of RAM) with Lubuntu to ensure stable operation under limited computing resources.[12] The graphical interface (Fig. 3) provides a device list, logging controls, and scan/connect/stop functions. Real-time streams are displayed in per-device tabs (e.g., sleeve and smart bat), with status and runtime messages shown in a dedicated message panel. Upon scanning, the gateway discovers nearby BLE devices and filters them by complete local name against a registered list; once connected, it reads, visualizes, and optionally logs sensor data, and the stop command terminates data collection for all active BLE links.

4. Experimental Results

The conductive-fabric-electrode sleeve is a wearable sensing device designed for sports that involve extensive arm motion. Compared with commercial EMG systems, the sleeve provides

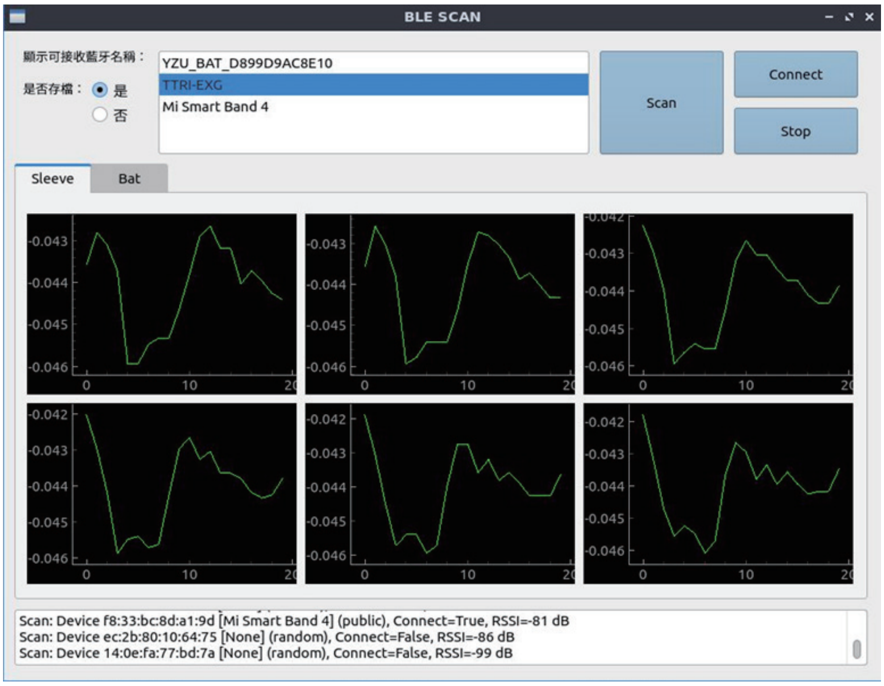


Fig. 3. (Color online) Graphical interface of channel device.

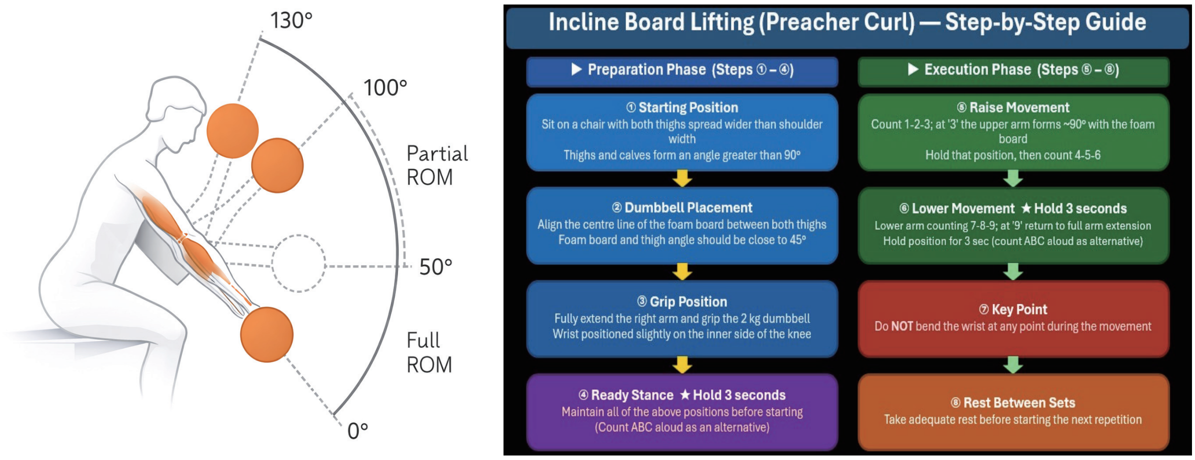
improved wearing stability and ease of fixation during arm-intensive activities. However, owing to the electrical conductivity characteristics of textile electrodes, a relatively larger electrode area is required to achieve sufficient sensitivity to voltage variations. As a result, the proposed sleeve does not isolate the electrical activity of individual muscles as effectively as commercial EMG systems with miniaturized metallic electrodes. Instead, it captures superimposed electrical responses from multiple muscles involved in each movement. For baseball pitching and other arm-dominant sports, such as Taekwondo and martial arts, conductive-fabric-based sensing sleeves remain a practical and meaningful solution for measuring and analyzing muscle activity.

In this study, arm-related sports movements are categorized according to two factors: arm motion speed and muscle activation intensity. As summarized in Table 1, three movement types are defined. Baseball pitching and Taekwondo are classified as Type I movements, characterized by rapid motion and high muscle activation. Resistance-based muscle training movements, such as inclined board lifting, are classified as Type II, which exhibit slower motion but strong muscle activation. Movements involving rapid arm motion with low muscle activation intensity are not included owing to the lack of representative sports. Type III movements include health-oriented activities, such as Yang-style Tai Chi, that emphasize guided, controlled motion patterns. These three movement types are selected for experimental evaluation, and sleeve-based voltage signals are collected for each category.

First, the Type II Incline Plate Curl (Preacher Curl) movement shown in Fig. 4(a) is used to calibrate the sensing data using the raw sleeve sensor voltage signals, as shown in Fig. 4(b). The raw sleeve voltage signals shown in Fig. 5(a) exhibit three repeated lifting cycles with a gradual downward shift in baseline voltage over time. The observed voltage variation is approximately 8 mV. Raw EMG-like signals are sampled at 1,024 Hz. The raw signals are pre-processed with an MA filter to attenuate high-frequency noise and motion artifacts, then segmented into 1 s sliding windows with 0.25 s overlap between adjacent windows. The MA-filtered, sliding-window waveforms provide both the continuous temporal profile of muscle activity displayed in Figs. 5(b), 6(b), and 7, and the basis for the per-window power spectral density (PSD) used in the fatigue feature analysis introduced later in this section. After processing, the signals from all six channels are presented in Fig. 5(b). Channels 3 and 4, located on the upper arm, exhibit pronounced variations corresponding to the activation of the biceps brachii. Channel 2, located on the forearm, shows observable variations associated with the activation of the brachioradialis and palmaris longus muscles, relative to Channels 1 and 6. Across the three lifting cycles, the measured waveforms clearly reflect arm positions near 130 and 0°, and the lifting motion between these angles occurs at a nearly uniform speed. Among the six channels, Channel 2 shows slightly larger voltage variations, which can be attributed to minor fabric wrinkling near the inner elbow joint during arm movement.

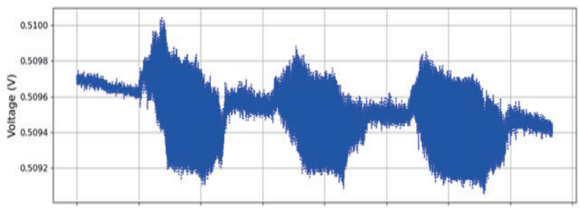
Table 1
Classification of forearm movements.

Forearm muscle usage intensity	Variation speed	
	Fast	Slow
Strong	Type I	Type II
Weak	—	Type III

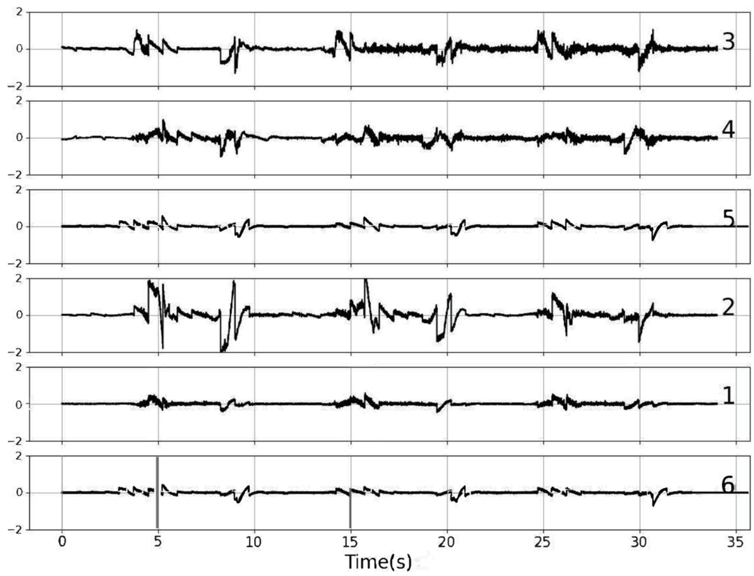


(a) (b)

Fig. 4. (Color online) Schematic and procedure of incline curl exercise: (a) schematic figure and (b) details of the procedure.



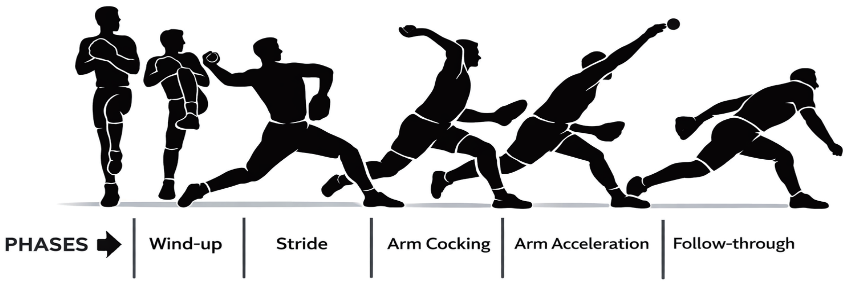
(a)



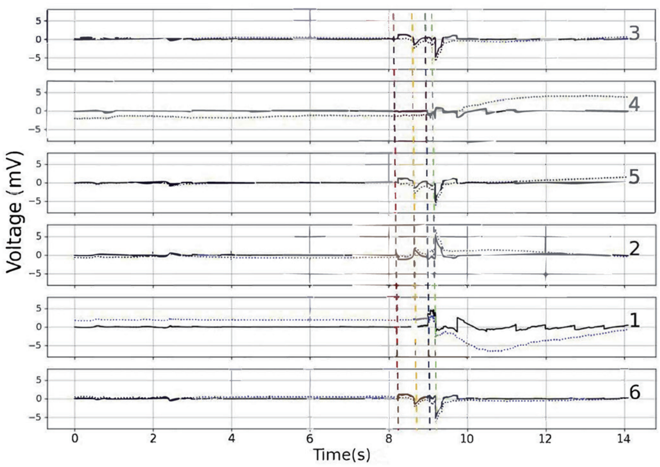
(b)

Fig. 5. (Color online) Sleeve-based measurements collected during the Preacher Curl exercise: (a) raw sensor signal and (b) measurement signals from three incline-curl repetitions.

The Type I pitching motion can be broadly divided into six phases, namely, wind-up, stride, arm cocking, arm acceleration, arm deceleration, and follow-through [Fig. 6(a)].[13] Pitching data were collected from a nonprofessional subject; although phase boundaries were not always distinct, key events, such as ball release, remained identifiable in the sleeve signals. The subject held a static posture for 5 s after the start cue, executed a pitch, and then maintained the follow-through for another 5 s. In Fig. 6(b), four colored dashed lines mark the key phase transitions of the pitch, and each transition time is identified directly from the corresponding EMG-like voltage changes across the six channels. Specifically, the first dashed line at approximately 8.2 s marks the start of the throwing motion; the second dashed line at approximately 8.6 s marks the entry into the wind-up phase of Fig. 6(a). The third dashed line at approximately 9.0 s corresponds to the onset of the stride phase, when the arm begins to open and the fourth dashed line at approximately 9.3 s marks the ball-release instant of Fig. 6(a). At the channel level, the upper-arm Channels 3 and 5, and the forearm Channel 6 begin to vary at approximately 8.2 s, marking motion onset. Pronounced changes appear at about 8.6 s in Channels 3 and 5 (upper arm) and Channels 2 and 6 (forearm), consistent with the wind-up. Clear responses emerge around 9.0 s in Channels 4 and 1, indicating the start of the stride, and a simultaneous surge across all channels occurs near 9.3 s, corresponding to release. The subsequent signal decay



(a)



(b)

Fig. 6. (Color online) Sleeve sensor signals during pitching motion: (a) phases of pitching motion and (b) sleeve sensor signals.

reflects relaxation during follow-through. Overall, the sleeve captures phase-relevant timing and integrated upper- and forearm responses; further electrode miniaturization may enable more localized muscle assessment.

The conductive-fabric sleeve is suitable for both slow, high-activation movements (e.g., lifting an inclined board) and fast, high-activation movements (e.g., pitching and Chen-style Tai Chi). It was further evaluated on Type III movements with slow arm motion and lower activation intensity, specifically the first eight forms of the 37-form Yang-style Tai Chi sequence (total duration ≈70 s). As shown in Fig. 7, these motions are smooth and continuous, and only the upper-arm Channel 4 exhibits a prominent voltage variation, suggesting the dominant involvement of the mid-bicep region. Peaks near 45 s in forearm Channels 2 and 6 are attributed to transient fabric deformation caused by brief sleeve folding. These results indicate that meaningful electrical activity can be captured even under low-intensity arm motions. Because Yang-style Tai Chi relies more on lower-limb engagement, future work may extend the textile sensing concept to lower-limb garments.

For static contractions, localized fatigue is commonly characterized by median frequency (MF) and mean power frequency (MPF), where a downward shift of the MPF centroid across time segments is treated as a fatigue marker.(14,15) For dynamic motions such as pitching, centroid shift alone is insufficient, particularly when large electrodes yield superimposed muscle responses. Therefore, MPF distributions were analyzed using data from a semi-professional pitcher who performed nine pitches, with signals from Channels 4 (A) and 3 (B) on the upper arm and Channels 6 (C) and 1 (D) on the forearm. In Fig. 8, Sensor C shows a markedly lower spectral amplitude and an unstable centroid. For Sensor A, centroid values exceed 100 Hz intermittently across the three pitch blocks, indicating that centroid variation does not provide a consistent fatigue indicator. In contrast, the spectral envelope area differs visibly between blocks [e.g., Fig. 8(a) versus Fig. 8(c)]. Accordingly, three features are defined: frequency width (FW) at a 3 dB drop from the peak envelope, spectral weight center (WC), and total power (TP) from the

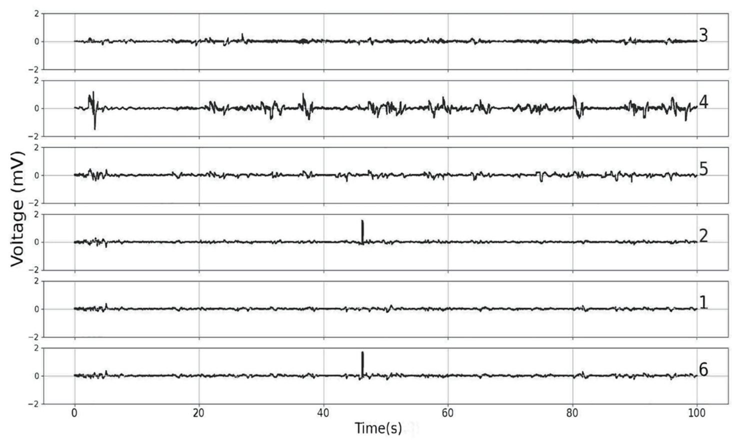
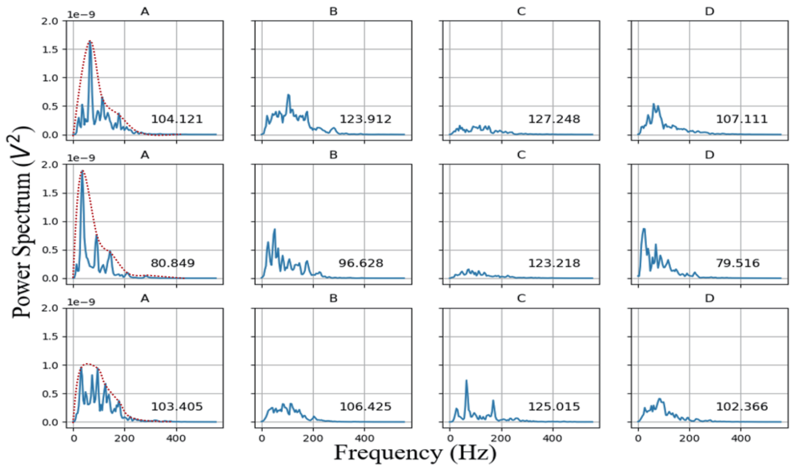
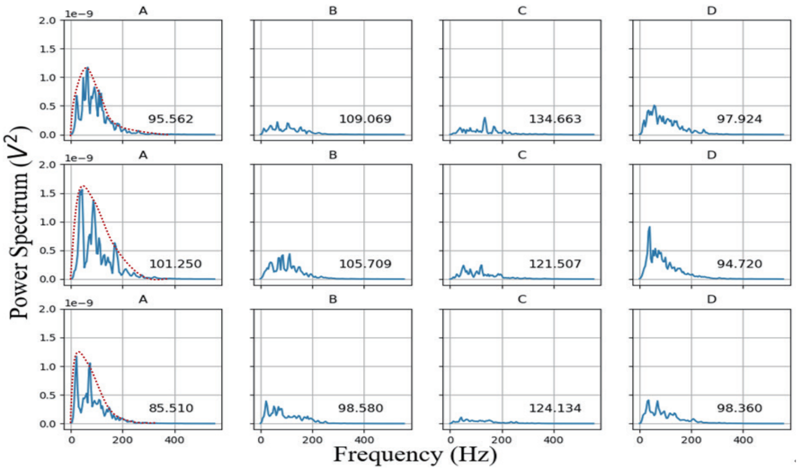


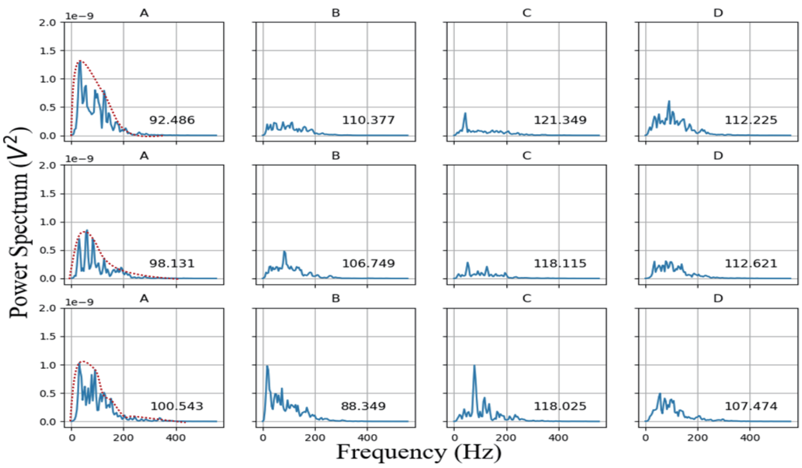
Fig. 7. Sleeve sensor signals corresponding to the first eight movements of the 37-form Yang-style Tai Chi.



(a)



(b)



(c)

Fig. 8. (Color online) Average EMG power distribution of the pitching motion (the numbers shown indicate the centroid frequency): (a) Trials 1–3, (b) Trials 4–6, and (c) Trials 7–9.

envelope area. FW, WC, and TP, when combined, better differentiate trial-to-trial changes in muscle condition, and larger-scale validation is required.

5. Conclusions

In this paper, we initially analyzed data from a conductive-fabric-based EMG-like sensing sleeve using three representative movements exhibiting distinct characteristics. The proposed system improves wearability and sensing stability during dynamic movements compared with conventional EMG solutions. Although the large electrode area limits single-muscle selectivity, preliminary spectral analysis suggests the potential to assess muscle fatigue when multiple features are jointly considered. Future work will focus on large-scale validation, electrode miniaturization, and advanced data analytics to further enhance the applicability of textile-based EMG systems in real-world sports training.

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