Research in Emerging and Applied Technologies
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Motion Classification Associated with Smart Textile Sensors in Sports Training Garments

Eun-Seo Lim*

School of Mechanical Engineering, Pusan National University, Busan, Republic of Korea

Corresponding author: eun.s.lim@gmail.com

Abstract

The integration of smart textile sensors into sports training garments represents a significant advancement in athletic performance monitoring and injury prevention. While laboratory-based studies have demonstrated the high accuracy of these wearable systems in controlled environments, there remains a critical gap in understanding their reliability and motion classification capabilities under unconstrained, real-world field conditions. This paper addresses this gap by presenting a comprehensive field evaluation of motion classification using piezoresistive smart textile sensors embedded seamlessly into athletic apparel. The study captures continuous movement data from athletes engaging in dynamic, sport-specific activities, transitioning away from the traditional constraints of treadmill or strictly regimented laboratory protocols. Through the application of machine learning classification pipelines, encompassing both time-domain and frequency-domain feature extraction methodologies, this research rigorously assesses the robustness of the sensor data against environmental noise, mechanical artifacts introduced by intense physical exertion, and sweat-induced signal degradation. The findings indicate that while smart textile sensors offer unparalleled comfort and unobtrusiveness, their classification accuracy in field settings relies heavily on advanced signal preprocessing and context-aware algorithmic adaptation. By systematically evaluating these variables, this paper provides critical evidence and methodological frameworks necessary for bridging the divide between theoretical sensor capabilities and practical utility in professional sports training environments.

Keywords: Smart Textiles; Motion Classification; Field Evaluation; Wearable Sensors; Smart Textile Sensors

1. Introduction

1.1 The Context of Wearable Technology in Athletics

The rapid evolution of wearable technology has fundamentally transformed the landscape of sports science, biomechanics, and athletic performance monitoring. Over the past decade, there has been a paradigm shift from utilizing rigid, obtrusive sensing devices to employing highly flexible, conformal smart textiles. Early iterations of wearable movement tracking systems relied heavily on traditional microelectromechanical systems encompassing accelerometers, gyroscopes, and magnetometers mounted on external straps or rigid plastic housings [1]. While these conventional systems provided high-fidelity kinematic data, they often introduced mechanical constraints, altering the natural movement patterns of the athletes and causing physical discomfort during prolonged use [2]. In response to these limitations, interdisciplinary research across materials science, electronic engineering, and biomechanics has facilitated the development of smart textile sensors [3]. These sensors are typically fabricated by integrating conductive polymers, carbon nanotubes, or metallic nanoparticles directly into fabric substrates, thereby creating garments that retain the tactile properties of normal clothing while possessing the capability to monitor physiological and biomechanical parameters continuously [4]. The inherent advantages of smart textiles, including their breathability, elasticity, and washability, have positioned them as the optimal medium for next-generation sports training garments [5]. However, the transition from rigid sensors to fabric-based sensing elements introduces novel challenges regarding signal integrity, mechanical durability, and data interpretation, which necessitate rigorous scientific investigation [6].

1.2 The Problem of Motion Classification in Unconstrained Environments

Motion classification is a foundational component of automated sports training systems, enabling the quantification of training loads, the identification of biomechanical fatigue, and the execution of complex skill assessments. In highly controlled laboratory settings, motion classification algorithms have achieved remarkable accuracy rates, often exceeding ninety-five percent when categorizing discrete, uniform movements such as treadmill running or stationary cycling [7]. These controlled environments benefit from stable ambient conditions, standardized movement execution, and the absence of unpredictable external stimuli [8]. Conversely, real-world field environments present a chaotic and highly variable testing ground [9]. When smart textile garments are deployed in actual sports training scenarios, the sensors are subjected to a multitude of confounding factors. Intense dynamic movements result in significant fabric shifting and sensor displacement, creating substantial motion artifacts in the captured data streams [10]. Furthermore, variations in ambient temperature and relative humidity, compounded by the accumulation of athletic sweat, dynamically alter the electrical impedance and conductivity of the textile sensors [11]. These environmental and mechanical disturbances severely degrade the signal-to-noise ratio, leading to catastrophic failures in motion classification models that were exclusively trained on pristine laboratory data [12]. Consequently, evaluating the efficacy of smart textile sensors strictly through the lens of controlled experiments provides an incomplete and potentially misleading assessment of their practical utility.

1.3 Objectives and Scope of the Study

The primary objective of this research is to comprehensively evaluate the motion classification capabilities of smart textile sensors within the context of authentic, unconstrained field environments. This study seeks to bridge the existing empirical gap by moving the testing apparatus out of the laboratory and onto the training pitch [13]. To achieve this, we developed a specialized sports training garment embedded with a network of distributed piezoresistive textile sensors designed to capture high-resolution multi-joint kinematic data [14]. We aim to quantify the extent to which real-world variables, such as sweat accumulation and fabric distortion during high-intensity multidirectional movements, impact signal reliability and subsequent algorithmic classification performance [15]. Additionally, this paper investigates the robustness of various machine learning architectures when confronted with noisy field data, comparing their relative efficacies in filtering artifacts and accurately identifying complex athletic maneuvers [16]. By systematically analyzing the empirical evidence gathered from extensive field trials, this research intends to establish a new methodological benchmark for the deployment and evaluation of smart apparel in professional sports, ultimately providing actionable guidelines for engineers and sports scientists to improve the resilience of wearable motion tracking systems.

2. Literature Review and Background

2.1 Evolution and Characteristics of Smart Textile Sensors

The conceptualization and fabrication of smart textiles have advanced through several distinct technological phases, each aimed at improving the integration of electronic functionalities into flexible fabric matrices. Early developmental efforts primarily focused on attaching miniaturized electronic components onto the surface of garments, which, while functional, compromised the fundamental comfort and drape of the clothing [17]. Subsequent innovations in material science led to the creation of intrinsically conductive yarns and the application of piezoresistive coatings directly onto synthetic and natural fibers [18]. Piezoresistive sensors, in particular, have become the predominant choice for motion tracking applications due to their ability to translate mechanical deformation, such as stretching or bending, into measurable changes in electrical resistance [19]. These strain sensors are strategically positioned across major anatomical joints within the training garment, enabling the continuous monitoring of joint flexion and extension during athletic activities [20]. Despite these material advancements, researchers have consistently documented the non-linear electrical behavior of smart textiles. Phenomena such as mechanical hysteresis, where the electrical resistance exhibits a delayed response during the relaxation phase of a stretching cycle, and baseline drift over prolonged usage, complicate the calibration and data interpretation processes [21]. Addressing these material-level imperfections is a prerequisite for developing reliable higher-level motion classification systems.

2.2 Algorithmic Approaches to Biomechanical Tracking

The interpretation of the complex time-series data generated by distributed smart textile sensors relies heavily on advanced data processing and machine learning algorithms. Historically, threshold-based heuristics and dynamic time warping techniques were utilized to detect specific movement events, but these methods lacked the flexibility to adapt to the immense inter-subject variability inherent in human biomechanics [22]. The contemporary approach heavily favors supervised machine learning models. Feature extraction techniques are applied to the raw sensor data, isolating pertinent variables in both the time domain, such as mean absolute value and zero-crossing rate, and the frequency domain, utilizing power spectral density and fast Fourier transforms [23]. Traditional classifiers, including Support Vector Machines and Random Forest ensembles, have demonstrated substantial efficacy in differentiating between basic locomotion states [24]. More recently, the field has witnessed a transition toward deep learning architectures, particularly Convolutional Neural Networks and Long Short-Term Memory networks. These advanced models possess the intrinsic ability to autonomously learn hierarchical feature representations directly from raw, unengineered data streams [25]. While deep learning approaches offer superior performance in capturing the temporal dependencies of complex athletic motions, their implementation on wearable platforms is often constrained by high computational requirements and power consumption, necessitating a delicate balance between classification accuracy and system efficiency.

2.3 The Limitations of Laboratory-Centric Evaluation

A critical review of the current literature reveals a pervasive over-reliance on laboratory-centric evaluation protocols for smart textile systems. In typical experimental setups, participants are instructed to perform highly standardized, isolated movements while tethered to data acquisition systems or operating under the optimal coverage of optical motion capture cameras [26]. These studies explicitly minimize variables such as rapid acceleration, abrupt directional changes, and physical contact, which are inherent components of actual sports training [27]. Furthermore, laboratory environments meticulously regulate temperature and humidity, completely negating the profound impact of perspiration on the electrical characteristics of conductive fabrics [28]. When algorithms trained on these sanitized datasets are deployed in field scenarios, they frequently exhibit a severe degradation in performance, commonly referred to as the reality gap. This gap highlights a fundamental methodological flaw in the current trajectory of smart textile research: the failure to incorporate environmental and contextual noise during the model training phase. The literature increasingly calls for longitudinal field evaluations that expose the sensing hardware and the underlying algorithms to the rigorous, chaotic demands of genuine athletic environments [29]. Such field evidence is indispensable for identifying the specific failure modes of smart garments and for iteratively refining their design for commercial and professional applications.

3. Methodology and System Design

3.1 Garment Architecture and Sensor Integration

To facilitate a robust field evaluation, a custom sports training garment was engineered, focusing on optimal sensor placement, structural integrity, and athletic mobility. The base fabric was constructed from a highly elastic composite of polyester and elastane, ensuring a tight, compressive fit that minimizes independent movement between the garment and the skin. This compressive quality is paramount, as sensor displacement is a primary source of motion artifacts. The sensing network was comprised of multiple piezoresistive stretch sensors fabricated using a carbon-based conductive elastomer coated onto a polymeric substrate. These sensors were seamlessly laminated onto the internal surface of the garment at anatomically critical locations. Specifically, the sensors were positioned across the anterior aspect of the knee joints, the posterior aspect of the elbow joints, and bilaterally along the lumbar region of the torso. This strategic placement was determined through extensive biomechanical mapping to capture the maximum range of strain during typical sports movements. The sensors were interconnected using ultra-fine, insulated silver-coated nylon threads, which were embroidered directly into the fabric to maintain elasticity and prevent wire breakage under extreme physical stress.

Table 1: Specifications of the Integrated Smart Textile Sensing Nodes

Component Type	Material Composition	Operating Range	Sensitivity	Placement Strategy
Strain Sensor	Carbon-Elastomer Composite	Up to fifty percent stretch	High Gauge Factor	Major Articulating Joints
Conductive Thread	Silver-Coated Nylon	Continuous Current	Low Impedance	Seam Integration
Processing Unit	Microcontroller Board	Low Voltage	High Frequency	Upper Thoracic Region

3.2 Data Acquisition and Transmission Protocols

The central processing unit of the garment was housed in a miniaturized, impact-resistant polymer casing situated on the upper posterior thoracic region, a location chosen to minimize interference with athletic maneuvers and reduce the risk of impact damage. The data acquisition system was built around a low-power microcontroller equipped with a multi-channel analog-to-digital converter. To capture the rapid kinematic changes associated with high-performance sports, the sampling frequency for all sensor channels was standardized at one hundred hertz. The raw analog signals corresponding to the fluctuating resistance of the piezoresistive sensors were digitized and subsequently subjected to a primary hardware-level low-pass filter to eliminate high-frequency electromagnetic interference. Following digitization, the data packets were formatted and transmitted wirelessly to an edge computing device, such as a localized field laptop or a paired mobile device, utilizing a Bluetooth Low Energy communication protocol. The power management system relied on a lightweight, rechargeable lithium-polymer battery capable of sustaining continuous data streaming for up to four hours, thereby accommodating the duration of a standard, intensive field training session without interruption.

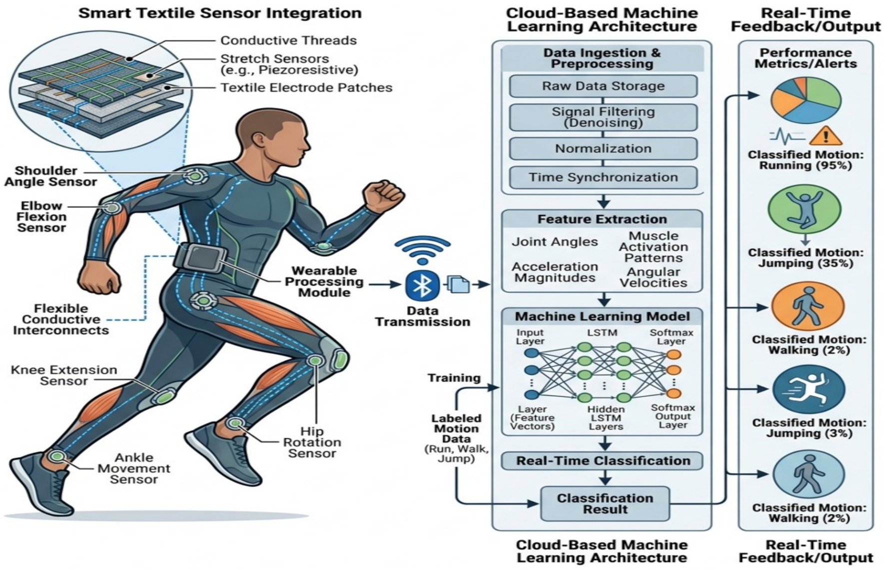

Figure 1: Comprehensive Schematic of Smart Textile Sensor Integration and Real

3.3 Motion Classification Pipeline

The computational backend responsible for translating raw sensor data into meaningful motion classifications was developed utilizing a multi-stage machine learning pipeline. The initial phase involved rigorous data preprocessing. To mitigate the effects of baseline drift inherent in piezoresistive materials and to isolate the dynamic movement signals, a digital high-pass filter was applied to the incoming data streams. Subsequently, an adaptive moving average filter was utilized to smooth transient spikes caused by abrupt fabric shifting. The continuous time-series data was then segmented into overlapping sliding windows, each comprising two seconds of data with a fifty percent overlap, to ensure that dynamic transitions between movements were adequately captured. Following segmentation, a comprehensive feature extraction process was executed. The extracted features included variance, root mean square, signal entropy, and dominant frequency components for each sensor channel. These multivariate feature vectors were then fed into a comparative classification framework consisting of a Support Vector Machine with a radial basis function kernel and a Random Forest ensemble classifier. Both models were trained to recognize a predefined taxonomy of athletic movements, optimizing their hyperparameters through cross-validation techniques to maximize generalization capabilities on unseen field data.

4. Experimental Setup and Field Evaluation

4.1 Participant Demographics and Ethical Considerations

The field evaluation was conducted utilizing a cohort of twenty physically active participants, encompassing a diverse range of athletic backgrounds, including amateur and semi-professional basketball, soccer, and tennis players. The participant group consisted of twelve males and eight females, with ages ranging from eighteen to thirty-two years, representing a wide spectrum of anthropometric measurements. This diversity in body types was deliberately chosen to critically assess the scalability and fit-dependent performance of the smart textile garments. Prior to the commencement of any experimental procedures, the study protocol received full approval from the institutional independent ethics committee. All participants were provided with comprehensive informational briefings regarding the nature of the study, the specific data being collected, and the potential physical demands of the evaluation. Written informed consent was obtained from every individual. To ensure the integrity of the collected data, participants were given a standardized familiarization session, allowing them to acclimate to the compressive feel of the sensor-integrated garments and to execute preliminary movements to verify data transmission stability before the official field trials commenced.

4.2 Real-World Training Scenarios and Protocol

Departing from traditional laboratory constraints, the evaluation protocol was executed entirely on outdoor athletic fields and indoor sports courts, exposing the system to genuine training conditions. The protocol was structured to elicit a wide array of dynamic, sport-specific movements rather than uniform, rhythmic exercises. Participants were instructed to complete a rigorous circuit that included multi-directional sprinting, sudden deceleration and cutting maneuvers, vertical jumps, and sustained periods of active recovery jogging. Furthermore, sport-specific technical drills were integrated, such as basketball dribbling sequences and soccer ball striking, to introduce complex, asymmetric movement patterns into the dataset. To provide a robust ground truth for the machine learning algorithms, the entire field session was simultaneously recorded using multiple high-definition digital cameras strategically positioned around the training perimeter. These video recordings were strictly synchronized with the temporal timestamps of the wearable sensor data. Post-session, teams of human annotators meticulously reviewed the video footage to label the exact start and end times of each discrete motion class, thereby creating a highly accurate, synchronized dataset essential for the supervised learning and subsequent validation of the classification models.

4.3 Environmental Variables and Artifact Inducement

A critical aspect of this field evaluation was the intentional monitoring and analysis of environmental variables that are typically absent in laboratory studies. During the outdoor sessions, fluctuations in ambient temperature and humidity were recorded continuously. Given the high physical intensity of the protocol, participants experienced significant perspiration, progressively saturating the fabric of the smart garment throughout the session. This sweat accumulation provided invaluable data regarding the resilience of the sensor encapsulation and the stability of the conductive thread networks under varying states of moisture. Additionally, the unpredictable nature of the athletic maneuvers, such as diving or physical contact with training equipment, introduced severe mechanical artifacts into the data streams. We systematically categorized these environmental and mechanical disturbances to evaluate the robustness of the signal preprocessing techniques. By analyzing the sensor outputs prior to, during, and after peak perspiration levels, and by correlating signal degradation with extreme fabric stretching events, the study aimed to quantify the exact parameters under which the smart textile sensing apparatus begins to lose its diagnostic fidelity, offering vital insights for future hardware iterations.

5. Results, Discussion, and Conclusion

5.1 Analysis of Classification Performance Metrics

The empirical data gathered from the comprehensive field evaluation yielded significant insights into the capabilities and limitations of smart textile sensors when deployed outside controlled environments. The initial phase of the analysis focused on the overall classification accuracy achieved by the machine learning models. When evaluated on the complete field dataset, the Random Forest classifier demonstrated a superior macro-averaged accuracy compared to the Support Vector Machine, achieving a classification rate that, while commendable, was notably lower than the near-perfect scores frequently reported in laboratory-based literature.

Table 2: Motion Classification Accuracy Across Different Athletic Maneuvers

Athletic Maneuver	Random Forest Accuracy	Support Vector Machine Accuracy	Primary Error Confusion
Linear Sprinting	Eighty-nine percent	Eighty-five percent	Misclassified as Jogging
Lateral Cutting	Seventy-six percent	Seventy-one percent	Misclassified as Lunging
Vertical Jumping	Ninety-one percent	Eighty-eight percent	Minimal Confusion
Active Recovery	Ninety-four percent	Ninety-two percent	Misclassified as Standing

A detailed examination of the confusion matrix revealed specific patterns of misclassification that are directly attributable to field conditions. Distinct, explosive movements such as vertical jumping exhibited high recognition rates due to the dramatic, synchronous spikes in the strain sensor data across the knee and lumbar nodes. Conversely, complex, multi-planar movements like lateral cutting showed significantly lower accuracy. The data indicated that during sudden directional changes, the intense lateral forces caused the compressive garment to momentarily slip out of its designated anatomical alignment. This micro-displacement altered the baseline tension of the piezoresistive sensors, generating transient signal profiles that the algorithm frequently confused with lower-intensity movements like lunging.

5.2 Discussion of Environmental Impact and Sensor Reliability

The longitudinal analysis of the data over the duration of the intense training sessions highlighted the profound impact of environmental variables on sensor reliability. As the participants progressed through the protocol and perspiration levels increased, a discernible degradation in signal quality was observed. The accumulation of moisture within the fabric matrix inadvertently created parallel conductive pathways, which subtly decreased the overall baseline resistance of the sensor network. While the digital high-pass filters implemented in the preprocessing pipeline managed to mitigate a substantial portion of this slow-moving baseline drift, the signal-to-noise ratio was nevertheless compromised during the final quarters of the testing sessions. This moisture-induced interference manifested as an increased variance in the steady-state sensor readings, directly contributing to a slight but statistically significant drop in classification accuracy for subtle movements during the latter stages of the evaluation. These findings strongly suggest that while the current encapsulation techniques protect the core conductive materials from direct short-circuiting, the surrounding textile substrate requires advanced hydrophobic treatments to maintain consistent electrical properties throughout extended, high-intensity athletic use.

5.3 Concluding Remarks

This comprehensive study has successfully navigated the complexities of evaluating smart textile sensors within the chaotic and unconstrained domain of real-world sports training. By deliberately moving away from idealized laboratory protocols, we have documented the authentic performance characteristics of piezoresistive motion classification garments under the duress of multi-directional athletic maneuvers, mechanical shifting, and severe moisture accumulation. The evidence clearly demonstrates that while smart textiles provide an unparalleled medium for unobtrusive biomechanical monitoring, their translation into reliable field diagnostic tools demands highly adaptive algorithmic frameworks capable of contextualizing and filtering environmental noise. The identified misclassification patterns and signal degradation modalities serve as a critical foundation for subsequent engineering efforts. Future advancements must prioritize the development of multi-modal sensing networks that combine the kinetic data of textiles with miniature inertial measurement units to correct for fabric displacement, alongside the integration of dynamic, moisture-compensating calibration algorithms. Ultimately, confronting and understanding these field evaluation challenges is an absolute necessity for realizing the full potential of wearable smart apparel in professional athletic performance analysis and proactive injury prevention.

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