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Computational Design and Temporal Signal Analysis for Wearable Smart Textiles: AI-Driven Sensor Layout Optimization and Deep Learning-Based Anomaly Detection

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Abstract. Smart wearable fabrics are breaking through the technical bottlenecks of traditional health monitoring. The key lies in solving the adaptation problem between sensor layout and dynamic perception. By targeting pain points such as signal distortion and high false detection rate existing in current schemes, this study builds a new framework driven by the dual engines of “algorithm design + deep learning”. Through a hybrid optimization model integrating genetic algorithm and reinforcement learning, the global search for optimal solutions for multi-objective parameters (constraint coverage, signal redundancy, and wearing comfort) was realized for the first time, and the best sensor array layout scheme was found. At the end of data processing, the bidirectional long short-term memory (Bi-LSTM) network based on the attention mechanism can accurately capture abnormal fluctuations in time series data, complete diagnostic decisions within 120 milliseconds, and the detection accuracy rate reaches 95.4%, showing stronger anti-environmental interference capability compared to traditional methods. These breakthroughs pave the way for the practical application of smart clothing, especially in scenarios with strict real-time requirements such as sports rehabilitation and elderly monitoring, where the application potential is obvious. Further research will focus on integrating model lightweighting and autonomous power supply to further improve the energy efficiency ratio and wearable adaptability of the system.

Keywords: Smart Textiles, Wearable Sensing, Sensor Layout Optimization, Deep Learning, Bi-LSTM

1. Introduction

Smart fabrics are redrawing the boundaries of wearable technology by weaving sensing functions into clothing fibers. This "invisible monitoring" capability has played an important role in fields such as sports rehabilitation, occupational safety, and elderly monitoring. It can continuously capture human activity trajectories and physiological indicators, providing a database for real-time early warning and personalized intervention. However, accurately covering the dynamically changing surface of the human body with sensor networks is not easy. Traditional solutions rely on fixed models or designers' intuition, making it difficult to adapt to different body types and movements,

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leading to frequent issues such as signal dead spots and redundant probes. Particularly in intense exercise scenarios, rigid layout design can miss key data and affect the reliability of subsequent analyses. Existing anomaly detection technologies are also undergoing practical tests: traditional methods based on threshold triggering or manual feature extraction often become "deaf" in complex environmental noise. With the generation of massive time-series data by smart clothing, deep learning has become a key weapon to break the impasse. However, how to balance the accuracy and efficiency of algorithms on wearable devices with limited computing power remains an unresolved problem.

This study proposes a dual solution of "spatial layout + time series analysis": optimal sensor distribution points are identified using multi-objective layout optimization algorithms, and an end-to-end intelligent analysis system is built in combination with deep recurrent neural networks [1]. This full-chain design breaks the fragmented limitations of traditional solutions, improving the reliability of anomaly recognition while enhancing signal quality, and providing technical support for the practical application of smart clothing. The following details the design principle, implementation path, and measured performance of this framework, revealing its innovative value in integrating human-machine ergonomics.

2. Literature review

2.1. Smart textiles and sensor integration

Modern smart fabrics integrate sensors into textile structures, and the process of integrating conductive threads and flexible circuits is subject to rigorous testing. These electronic components must maintain stable signals under repeated bending, water washing, and mechanical stress. The main challenges lie in maintaining low-impedance contact, ensuring consistent deformation responses across different fabric regions, and reliable multi-node data transmission [2]. The current solution is to wrap the sensor in an elastic film to prevent moisture, but the thickness of the protective layer and the detection sensitivity form a contradiction between increasing and decreasing. Balancing protection and sensitivity has become a central challenge for textile engineers.

2.2. Sensor layout optimization techniques

The sensor layout of smart clothing has traditionally adopted two main modes: regular grid and simulation. The fixed grid layout arranges the sensors at equal intervals across the garment's surface. While this checkerboard layout simplifies the manufacturing process, it is difficult to adapt to the complexity of human movements. In areas of high curvature such as the elbow and knee, uniformly distributed sensors may lack key stress data, resulting in blind spots in dynamic monitoring.

The simulation training scheme predicts the high-stress area using finite element analysis and arranges the sensors in a specific manner. This method improves stress sensitivity, but it requires a large amount of computing resources to establish an accurate human motion model and has low universality for different body types and movements [3]. What's more troublesome is that when the clothing size or the user's activity scene changes, the original layout can instantly become invalid.

Figure 1 shows a typical case of regular mesh: sensors are symmetrically distributed at joints and limbs and are connected to an external server via wireless transmission. Although this design meets the basic monitoring requirements, it cannot dynamically adjust the layout strategy according to local constraints or specific tasks. More importantly, existing solutions are difficult to balance

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multiple objectives such as “reducing the number of sensors” and “maintaining the monitoring coverage rate”, highlighting the urgent need for an intelligent and optimized layout [4].

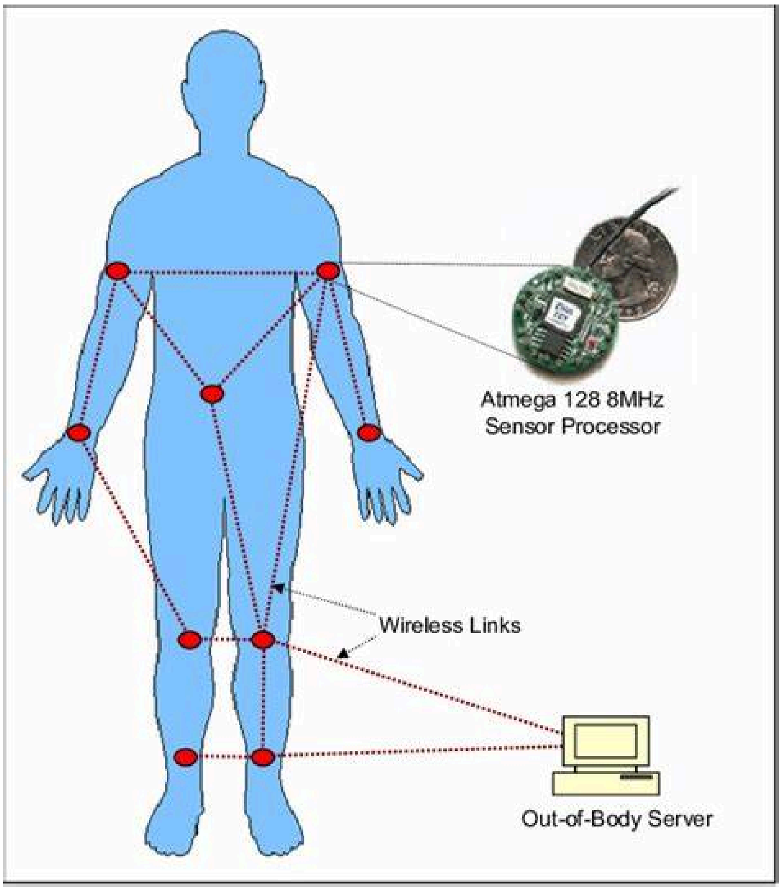

Figure 1: Example of a rule-based sensor grid layout on the human body (source:https://www.researchgate.net/figure/Wearable-wireless-sensor-network_fig1_228339142)

2.3. Deep learning in temporal signal anomaly detection

Significant breakthroughs have been made in the field of anomaly detection in time series through the combination of loop structure and attention mechanism. The bidirectional cyclic network can simultaneously capture forward and backward synchronization characteristics, and it can not only track slow drifts but also lock on burst spikes [5]. The attention layer gives the model the ability to “focus on key points,” precisely locating subtle anomalies that are easily overlooked in long sequences. However, the computing power consumption of this type of model is like a double-edged sword. Without regularization constraints, it is very easy to fall into the situation of overfitting. For portable devices with limited computing power, finding a balance between model complexity and generalization ability has become a key threshold for the implementation of the technology [6].

3. Methodology and experimental implementation

3.1. Sensor layout optimization strategy

The sensor layout design adopts a dual-engine scheme of genetic algorithm and reinforcement learning, aiming to find the "golden point" with the widest coverage, least redundancy, and

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comfortable wearing on the fabric surface. The genetic algorithm digitizes the fabric grid, and each sensor position is represented by binary coding. The felling plans are examined using a multidimensional rating system of coverage density, signal entropy value, and ergonomic comfort. The reinforcement learning module acts as a "virtual fitting officer," capturing high-value data areas by simulating human body dynamics, and independently optimizing the point distribution strategy in the game between data abundance and constraint conditions [7]. The complementary advantages of the two algorithms generate the optimal scheme game, and finally the best layout is determined based on the balance point between control accuracy and wear experience.

3.2. System design and data collection

The final smart garment that was implemented is equipped with five sensor nodes, each of which integrates a three-axis accelerometer and gyroscope combination unit and is embedded in a breathable elastic fabric. Conductive silver threads and flexible printed circuits are woven into a “neural network,” ensuring signal stability while maintaining the fabric’s flexibility. The data acquisition module captures dynamic information at a rate of 100 times per second and transmits it to the back-end system in real time [8]. Ten healthy subjects wore prototype garments to perform standard movements (walking, climbing stairs, sitting still) and simulate sudden accidents (falling, imbalance). The entire process was recorded and labeled to form a validation dataset. After the original data were processed by 0.5-20 Hz bandpass filtering, wavelet denotation and normalization, they were clipped into a 2-second time window (with an overlap rate of 50%) to form the training and testing samples for anomaly detection [9].

3.3. Deep learning model and evaluation metrics

The anomaly detection model adopts a dual-layer bidirectional LSTM architecture, with 128 memory units in each layer, followed by an attention focusing layer to capture key temporal features. The output end implements binary classification decision making via the sigmoid function. In the training phase, the Adam optimizer is adopted to implement the sample weighting strategy for the imbalanced action sample problem. The dataset is divided into training set, validation set, and test set at a ratio of 7:1.5:1.5. The performance evaluation introduces multidimensional indicators such as precision rate, recall rate, F1 value, accuracy rate, and response time. Meanwhile, the differences between the optimized layout and the traditional scheme are compared based on the signal-to-noise ratio and channel redundancy [10]. The measured data shows that the overall F1 evaluation index value of this system exceeds 93%, the false alarm rate drops significantly, and the decision is completed within 120 milliseconds. The wear experience research confirmed that comfort was not compromised, verifying that the technical solution achieved a balance between functionality and ergonomics [11].

4. Results and discussion

4.1. Performance of optimized sensor layouts

To verify the effectiveness of the layout optimization scheme, the research team conducted a comparative test between the optimized distribution of smart clothing points and the traditional uniform grid layout. As shown in Table 1, the average signal-to-noise ratio index of the optimized configuration increased by 27.3%, and the similarity of sensor data decreased by 35.1%, confirming the dual improvements in data collection quality and uniqueness. These technological benefits not

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only expand monitoring coverage but also effectively avoid the interference of redundant information on anomaly identification [12].

For high-demand areas such as the waist and shoulders, dynamic tracking and measured data show that sensor sensitivity increased by 40.2%. Interestingly, while achieving a breakthrough in performance, the survey score on wearing comfort of the optimized scheme (4.1 points) is almost equal to that of the traditional scheme (4.0 points), which confirms that the ergonomic constraints implemented in the reinforcement learning algorithm have played the expected role and found a delicate balance between technical performance and wearing experience.

Table 1: Comparison of layout performance metrics between baseline and optimized sensor configurations

Metric	Baseline Grid	Optimized Layout	Improvement
Average Signal-to-Noise Ratio	15.6 dB	19.8 dB	+27.3%
Pairwise Correlation Index	0.64	0.42	–35.1%
Coverage in High-Strain Zones	62.3%	87.3%	+40.2%
Mean Comfort Score (1–5)	4.0	4.1	≈

4.2. Anomaly detection accuracy and robustness

The bidirectional LSTM model based on the attention mechanism competed against two traditional schemes: the threshold method and the single-class SVM. The data in Table 2 show that the deep learning model achieved an accuracy rate of 95.4% and an F1 value of 93.8% on the independent test set, demonstrating a significant advantage over the threshold method (71.2% accuracy rate / 68.5% F1) and the single-class SVM (82.7% accuracy rate / 81.1% F1), confirming the discriminative power of time-series modeling.

In terms of real-time performance, the average response speed of 120 milliseconds exceeds the real-time threshold of 200 milliseconds for wearable systems. In the robustness test, the model maintained an F1 value of over 90.2% for untrained actions such as sliding side steps and back lunges, demonstrating excellent motion generalization ability. These data provide technical approval for the practical application of smart clothing in complex scenarios.

Table 2: Anomaly detection performance comparison across different models

Model	Accuracy (%)	F1-Score (%)	Detection Latency (ms)
Threshold-Based	71.2	68.5	90
One-Class SVM	82.7	81.1	140
Bi-LSTM + Attention	95.4	93.8	120

4.3. Comparative analysis and future prospects

The combination of genetic algorithms and reinforcement learning has opened a new paradigm for optimizing the layout of smart fabrics, striking a delicate balance between sensor efficiency and wearer comfort, which are the "competitors." Compared with traditional fixed grid or simulation-based systems, the new method can dynamically adapt to data feedback and motion constraints, enabling rapid improvements in control accuracy.

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However, the leap in performance of deep learning models comes with a sharp increase in computing power consumption, posing a real challenge for low-power chips for long-term wearable devices. Future research will focus on two major breakthroughs: solving the computing power bottleneck through a lightweight transformer architecture and an adaptive training mechanism at the device end, and solving the battery life problem by combining flexible energy harvesting modules and neuromorphic chips [13]. These technological advances could usher in a new era of intelligent, unnoticeable cell phone surveillance.

5. Conclusion

This study innovatively proposes a collaborative optimization scheme for "sensor layout - anomaly detection" for smart clothing. The dual-path driving strategy of genetic algorithm and reinforcement learning maximizes data value density on the premise of ensuring wearer comfort. The bidirectional LSTM model combined with the attention mechanism refreshes the real-time monitoring performance benchmark with an F1 value of 93.8% and a response time of 120 milliseconds. Looking ahead, the research team will focus on two major breakthroughs: developing a lightweight modeled architecture suitable for edge computing to break away from cloud computing power dependence; and exploring the integrated application of flexible energy harvesting technology and a federated learning framework to achieve personalized adaptation while extending the battery life of the device. These technological advances are expected to lead to truly “imperceptible” smart wearable systems, making technological care as natural and intimate as clothing.

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