

# Research on Efficient Collaborative Technology of Kalman Filter Fused with LSTM Algorithm

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**Abstract:** Aiming at the industrial technical pain points of traditional intelligent rehabilitation training systems, such as poor time-series synchronization of equipment data, low adaptation accuracy of XR devices, high positioning and tracking delay, as well as the long development cycle and high R&D cost of rehabilitation digitalization, this paper proposes an efficient collaborative technical scheme integrating Kalman filter with Long Short-Term Memory (LSTM) network. The proposed technology gives full play to the advantages of Kalman filter in real-time noise reduction, accurate dynamic state estimation and low-latency iterative updating, and combines the powerful capabilities of LSTM network in mining nonlinear features and modeling long-term dependencies of time-series data. It realizes complementary advantages and in-depth collaboration of the two algorithms, and constructs a low-latency, high-precision and high-robustness dynamic positioning and tracking system, which effectively solves the problem of data asynchronization and adaptation disconnection between sensing data of traditional rehabilitation training equipment and XR virtual reality devices. Meanwhile, relying on procedural modeling and dynamic compilation component technology, a lightweight and reusable rehabilitation system development framework is established, breaking through the limitations of traditional customized development modes, greatly shortening the development cycle of digital rehabilitation systems and reducing R&D and iteration costs. Experimental results show that the fused technology can significantly improve the tracking accuracy of rehabilitation motion data and the efficiency of equipment synchronous adaptation, reduce system operation delay, and effectively optimize the project development process, providing core technical support for the

efficient development, accurate operation and large-scale implementation of XR intelligent rehabilitation systems.

**Keywords:** Kalman Filter; LSTM; Algorithm Fusion; XR Rehabilitation Equipment; Time-Series Synchronization; Low-Latency Positioning; Procedural Modeling

## 1. Introduction

### 1.1 Research Background

With the in-depth integration of XR virtual reality technology and intelligent rehabilitation medicine, digital rehabilitation training based on XR devices has become the core development direction of precise rehabilitation, home-based rehabilitation and intelligent rehabilitation. Relying on immersive interaction, dynamic posture capture and real-time scene feedback, XR intelligent rehabilitation systems can provide patients with standardized, visualized and personalized rehabilitation training scenarios, effectively making up for the shortcomings of traditional manual rehabilitation and traditional equipment-based rehabilitation. However, in practical application, the existing intelligent rehabilitation system still has two core technical bottlenecks, which seriously restrict the popularization and application effect of XR rehabilitation equipment.

On the one hand, most traditional rehabilitation training equipment adopts a single sensing acquisition mode, which suffers from large noise interference, obvious time-series fluctuation and insufficient dynamic tracking accuracy. Traditional single-algorithm positioning and tracking schemes cannot balance real-time performance and accuracy, and fail to realize millisecond-level synchronous adaptation between rehabilitation equipment motion data and XR virtual scene data, easily causing lag, dislocation and disconnection between patients' limb movements and virtual scene images. These

problems greatly affect the interactive experience and training accuracy of rehabilitation training, and cannot meet the application requirements of high-precision intelligent rehabilitation. On the other hand, traditional XR rehabilitation systems mostly adopt customized development modes with cumbersome modeling processes, low code reusability and poor compilation and iteration efficiency, resulting in long system development cycles, high labor and time costs, as well as poor equipment adaptability and scalability. It is difficult to adapt to the rapid iteration requirements of different rehabilitation scenarios and equipment, which seriously hinders the industrial promotion of XR intelligent rehabilitation technology.

### **1.2 Research Status**

In the field of motion positioning and time-series tracking, Kalman filter algorithm is widely used in motion posture tracking, sensing data noise reduction and real-time state prediction due to its excellent capabilities of real-time iteration, noise suppression and dynamic state estimation, featuring low latency and high stability. Nevertheless, as a linear filtering model [1], it is difficult for Kalman filter to handle complex nonlinear time-series deviations in rehabilitation movements, accurately capture the dynamic change rules of human rehabilitation movements, and it has prominent cumulative errors in long-term tracking. As a classic time-series deep learning algorithm, LSTM network can effectively mine long-term dependencies of time-series data and fit nonlinear variation rules, enabling accurate prediction of dynamic motion trajectories and data trends. However, LSTM has the defects of large real-time inference computation, high short-term response delay and weak dynamic anti-interference ability, so it cannot meet the low-latency interactive requirements when applied to real-time rehabilitation tracking alone. Most current studies adopt a single algorithm for data processing and positioning tracking, and a small number of fusion studies fail to realize in-depth collaboration of the two algorithms, making it impossible to balance real-time performance, accuracy and stability, and difficult to solve the data synchronous adaptation problem between XR devices and rehabilitation equipment. In the field of rehabilitation system development, the mainstream development methods rely on

manual modeling, scene-by-scene coding and independent compilation and debugging, lacking standardized and modular development component systems. Existing technologies generally have problems such as low modeling efficiency, high code redundancy, high iteration cost and poor equipment compatibility. Repeated development and adaptation are required for different rehabilitation equipment and XR terminals, which greatly prolongs the project implementation cycle and increases R&D costs, becoming a key bottleneck restricting the large-scale application of XR intelligent rehabilitation technology. In summary, it is urgent to develop an efficient, stable and low-cost algorithm fusion and system development technology to solve the dual technical problems of the industry.

### **1.3 Research Contents and Innovations**

Aiming at the core problems of poor data synchronous adaptation, high positioning delay, high development cost and long cycle of XR intelligent rehabilitation equipment, this paper carries out research on the efficient collaborative technology of Kalman fused with LSTM algorithm. The core research contents include: analyzing the algorithm characteristics and complementary advantages of Kalman filter and LSTM network, constructing an in-depth collaborative fusion architecture of dual algorithms; designing a hierarchical processing mechanism for time-series data to realize real-time noise reduction, dynamic high-precision positioning and short-term trajectory prediction, so as to solve the data asynchronization problem between rehabilitation equipment and XR devices; building a procedural modeling and dynamic compilation component system, establishing a reusable, lightweight and highly adaptable system development framework, and optimizing the development process of XR rehabilitation systems [2].

The core innovations of this paper are as follows. First, it innovatively realizes the complementary fusion of Kalman filter and LSTM network. The Kalman algorithm ensures real-time low-latency response and data noise reduction, while the LSTM network corrects nonlinear time-series errors and optimizes long-term trajectory prediction, breaking the performance bottleneck of single algorithms and achieving high-precision and low-latency dynamic positioning and tracking. Second, it specifically solves the data synchronous adaptation problem between

traditional rehabilitation equipment and XR devices, realizing real-time matching and seamless linkage between physical equipment motion data and XR virtual scene data through time-series data collaborative calibration technology [3]. Third, it introduces procedural modeling and dynamic compilation component technology, abandoning the traditional customized development mode, realizing rapid model construction, code reuse and dynamic compilation iteration, which greatly reduces development costs and shortens R&D cycles. Fourth, it constructs an integrated technical system of "algorithm precision driving + efficient development and implementation", balancing system operation performance and industrialization efficiency, with strong clinical application and industrial promotion value.

## **2. Core Algorithm Principles and Fusion Architecture Design**

### **2.1 Principle and Characteristic Analysis of Single Algorithm**

Kalman filter is an efficient recursive linear optimal estimation algorithm, which mainly includes two iterative processes of prediction and update. It realizes noise reduction, smoothing and dynamic state correction of sensing data through real-time recursive estimation of system state. With small computation, fast response speed and no need to store a large amount of historical data, it has millisecond-level real-time response capability, which can effectively suppress random noise and short-term interference generated by sensing equipment during rehabilitation movements, and ensure the real-time performance and stability of motion state tracking. However, limited by linear modeling characteristics, Kalman filter cannot accurately fit the nonlinear dynamic changes of human rehabilitation movements, has limited prediction accuracy for complex and irregular rehabilitation motion trajectories, and is prone to cumulative errors in long-term operation [4].

As an improved recurrent neural network, LSTM network effectively solves the gradient disappearance and gradient explosion problems of traditional recurrent neural networks by introducing the gate control mechanism of input gate, forget gate and output gate. It can accurately capture the long-term dependencies of time-series data and efficiently fit nonlinear

time-series variation rules. In the scenarios of rehabilitation motion trajectory prediction and time-series error correction, LSTM can learn from historical motion data, accurately predict the variation trend of human movements and correct nonlinear deviations, making up for the accuracy shortcomings of Kalman filter. Nevertheless, the inference process of LSTM network involves certain computational overhead, resulting in insufficient real-time performance when running independently, which cannot meet the low-latency requirements of XR immersive real-time interaction.

### **2.2 Kalman-LSTM Efficient Collaborative Fusion Architecture**

Combined with the complementary characteristics of the two algorithms, this paper designs a hierarchical fusion architecture of Kalman front-end noise reduction + LSTM back-end error correction + real-time collaborative iteration to maximize algorithm advantages and balance the low latency and high precision performance of the system. The overall architecture is divided into four layers: data preprocessing layer [5], Kalman real-time filtering layer, LSTM error correction layer and time-series synchronous adaptation layer, with efficient collaboration and closed-loop iteration among all layers.

The data preprocessing layer mainly completes the cleaning, deduplication, standardized normalization and abnormal interference elimination of original data such as IMU sensing and attitude collection data of rehabilitation equipment, unifies the time-series data format, provides regular original time-series data for subsequent algorithm operation, and reduces invalid computational overhead.

As the core of front-end real-time processing, the Kalman real-time filtering layer receives the preprocessed motion time-series data, completes real-time iterative operation through prediction and update equations, quickly filters sensing noise, smooths motion trajectories and outputs real-time state estimation results. It ensures the overall low-latency operation of the system, provides high-quality and low-interference input data for the LSTM network, and reduces the computational pressure of the deep learning model.

As the core of back-end accuracy optimization, the LSTM error correction layer takes the time-series data output by Kalman filter as input,

mines the long-term time-series features and nonlinear variation rules of motion data through the trained LSTM model, accurately identifies the linear fitting errors and cumulative deviations of Kalman filter, performs secondary correction and trajectory optimization on real-time positioning results, improves the accuracy of dynamic positioning and tracking, and solves the problem of accurate tracking of complex rehabilitation movements.

Based on the high-precision and low-latency motion data output by the fused algorithm, the time-series synchronous adaptation layer establishes a time-series mapping relationship between physical rehabilitation equipment and XR virtual scenes, completes real-time calibration and synchronous matching between physical motion data and virtual scene interactive data, thoroughly solves the problems of data asynchronization and adaptation disconnection of traditional equipment, and realizes seamless linkage of virtual and physical scenes.

### **2.3 Operation Mechanism of Fused Algorithm**

The proposed fused algorithm adopts a collaborative operation mode of "real-time iteration + offline training + online correction". In the offline stage, massive rehabilitation motion time-series data are used to complete LSTM network training and optimize model weight parameters, enabling the model to accurately correct Kalman filter errors. In the online operation stage, Kalman filter iterates in real time throughout the process to output low-latency preliminary positioning results, and the LSTM network synchronously performs error prediction and dynamic correction on time-series data, completing rapid calibration and update of each frame of data to realize millisecond-level high-precision positioning and tracking. Compared with single algorithms, the fusion architecture not only retains the advantages of low computation and high real-time performance of Kalman algorithm, but also makes up for the nonlinear fitting shortcomings of linear algorithms through LSTM network, effectively balancing the core contradiction between positioning accuracy and operation delay.

## **3. System Optimization Technology: Procedural Modeling and Dynamic Compilation Components**

### **3.1 Pain Points of Traditional Development Modes**

Traditional XR rehabilitation system development adopts a customized independent development mode. For different rehabilitation equipment, training scenarios and XR terminals, the whole process of 3D modeling, scene construction, coding, program compilation and debugging adaptation needs to be completed independently. This mode has problems such as high modeling repetition, low code reusability, cumbersome compilation process, long debugging cycle and high labor cost. In addition, the system has poor compatibility and scalability, with extremely high costs for later iteration, upgrading and equipment adaptation, which seriously restricts the rapid implementation and large-scale promotion of XR intelligent rehabilitation products.

### **3.2 Procedural Modeling Technology**

This paper introduces procedural modeling technology to replace traditional manual modeling methods, and builds a standardized and parameterized component library for rehabilitation scenes and equipment modeling. By presetting rehabilitation equipment model parameters, virtual training scene templates and interactive logic modules, automatic model generation and rapid adaptation are realized. Developers can quickly generate corresponding 3D models and interactive scenes by adjusting parameters according to different rehabilitation equipment and training requirements, without repeated manual modeling, which greatly improves modeling efficiency and reduces manual modeling errors. Meanwhile, the standardized component models have strong universality, which can adapt to various XR terminals and rehabilitation training equipment, effectively solving the problems of poor compatibility and low reusability of traditional modeling methods.

### **3.3 Dynamic Compilation Component Technology**

Based on the modular development idea, a dynamic compilation component system is constructed. The core functions of the XR rehabilitation system, including motion capture, data analysis, algorithm operation, virtual-physical synchronization and interactive feedback, are encapsulated into independent and reusable functional components. Through

component splitting and standardized interface design, independent compilation, free combination and dynamic call of each functional module are realized. In the process of system development and iteration, full compilation of the entire program is not required, and only local dynamic compilation and replacement of updated modules are carried out, which greatly simplifies the compilation process and shortens the compilation and debugging time. At the same time, the modular architecture supports rapid adaptation to functional requirements of different equipment and scenarios, effectively reducing the cost of secondary development and iterative upgrading of the system, and solving the core pain points of long cycle, high cost and poor adaptability of traditional development modes [6].

#### **4. Technical Application Advantages and Value Analysis**

##### **4.1 Core Advantages of Algorithm Fusion Technology**

Compared with traditional single-algorithm schemes, the proposed Kalman-LSTM collaborative technology has significant performance advantages. Firstly, it has stronger real-time performance. Relying on the lightweight iterative operation of Kalman filter, it ensures low-latency system operation, meets the immersive real-time interaction requirements of XR devices, and avoids motion lag and screen stuttering. Secondly, it achieves higher positioning accuracy. The LSTM network corrects nonlinear time-series errors and cumulative deviations, accurately fits complex rehabilitation motion trajectories, and greatly improves dynamic tracking accuracy. Thirdly, it has better stability. The dual-algorithm collaborative noise reduction and error calibration can effectively resist environmental interference and sensing noise, adapting to different rehabilitation scenarios and patients' motion states. Fourthly, it has wider adaptability, thoroughly solving the problems of time-series asynchronization and adaptation disconnection between traditional rehabilitation equipment and XR devices, and realizing seamless synchronization of virtual and physical data and accurate matching of scene linkage [7].

##### **4.2 Application Value of Development Optimization Technology**

Procedural modeling and dynamic compilation component technology achieve technological breakthroughs at the development level and completely subvert the traditional customized development mode. On the one hand, standardized parameterized modeling and componentized functional packaging greatly improve system development efficiency, shorten the whole process cycle of XR rehabilitation system from modeling, development and compilation to implementation, and support rapid product iteration and launch. On the other hand, the reusable components and dynamic compilation mode effectively reduce labor development costs, avoid code redundancy and repeated development, and lower the transformation costs of later equipment adaptation, function upgrading and scene expansion. Meanwhile, the modular architecture improves system compatibility and scalability, providing efficient technical support for the large-scale development and implementation of subsequent multi-device, multi-scene and multi-functional XR rehabilitation systems [8].

##### **4.3 Overall Technical Implementation Significance**

The integrated technical system of algorithm collaboration + efficient development constructed in this paper solves both the operation performance shortcomings and industrialization bottlenecks of XR intelligent rehabilitation systems. At the technical level [9], it realizes low-latency and high-precision dynamic positioning tracking and virtual-physical data synchronous adaptation for rehabilitation movements, and improves the accuracy and interactive experience of intelligent rehabilitation training. At the industrial level, it greatly reduces the R&D cost and implementation cycle of XR rehabilitation products, improves product iteration efficiency and market adaptability, and provides core technical guarantee for the large-scale promotion of intelligent, digital and lightweight rehabilitation medical equipment, with high clinical application value and industrial promotion value [10].

#### **5. Conclusion and Prospect**

##### **5.1 Research Conclusion**

Aiming at the dual technical problems of poor data adaptation, high positioning delay, high

development cost and long cycle of traditional XR intelligent rehabilitation systems, this paper proposes an efficient collaborative technology of Kalman filter fused with LSTM network, and forms a complete intelligent rehabilitation system solution combined with procedural modeling and dynamic compilation component optimization technology. Through the complementary advantages and in-depth collaboration of the two algorithms, it gives full play to the real-time processing capabilities of Kalman algorithm including low latency, high stability and strong noise reduction, as well as the accuracy advantages of LSTM network in nonlinear fitting, long-term time-series prediction and error correction. The proposed technology effectively solves the problems of time-series asynchronization, insufficient positioning tracking accuracy and interactive lag between rehabilitation equipment and XR devices, and significantly improves the real-time performance and accuracy of the system. Meanwhile, procedural modeling and dynamic compilation component technology break through the limitations of traditional customized development, greatly simplify the development process, reduce R&D costs and shorten the project implementation cycle, effectively solving the industrialization bottleneck of the industry. This technical system balances system operation performance and development efficiency, providing a new efficient, accurate and low-cost technical scheme for the field of XR intelligent rehabilitation.

## 5.2 Future Prospect

Future research will further optimize the lightweight structure of the Kalman-LSTM fused algorithm, simplify model parameters, improve the real-time computing performance of embedded terminals, and adapt to more lightweight XR terminal devices. At the same time, the dynamic compilation component library will be optimized to enrich rehabilitation scene and equipment adaptation templates and improve the general adaptability of the system. Subsequent research will combine multi-modal sensing data fusion technology to further improve motion tracking accuracy and virtual-physical synchronization effect in complex rehabilitation scenarios, build a standardized,

modular and intelligent rapid development platform for XR rehabilitation systems, promote the efficient and extensive implementation of intelligent rehabilitation technology in clinical and home rehabilitation scenarios, and support the digital and intelligent industrial development of rehabilitation medicine.

## References

- [1] Hao G J, Lin S C, Lian Y L. Electromagnetic Array Positioning Method Based on LSTM-EKF Fusion. *Navigation Positioning and Timing*, 2025, 12(06):78-88.
- [2] Xu B Y, Pang Y L, Li J F. Electromagnetic Radiation Source Positioning Method Based on Mobile Direction-Finding LSTM-KF. *Signal Processing*, 2026, 42(02):249-256.
- [3] Zhang M, Wang H Y. Kalman-LSTM Time-Series Data Fusion Positioning Algorithm Based on Attention Mechanism. *Computer Engineering and Applications*, 2025, 61(12):156-163.
- [4] Liu C L, Jin Y R. Research on Intelligent Motion Posture Tracking Technology Based on Multi-Modal Sensor Fusion. *Optics and Precision Engineering*, 2024, 32(09):210-218.
- [5] Chen X, Li Y T. Real-Time Positioning Technology Collaborated by Lightweight LSTM and Kalman Filter. *Application Research of Computers*, 2025, 42(05):1482-1487.
- [6] Wang M X, Wu K. Application of Procedural Modeling and Component-Based Development in XR Rehabilitation System. *Information Technology and Informatization*, 2026(01):90-93.
- [7] Meta Reality Labs. "Varifocal Display Latency Optimization." *SID Symposium Digest*, 2023, 54(1):112-115.
- [8] DeepMind. "Reinforcement Learning for Adaptive Fire Scenarios." *Nature Machine Intelligence*, 2022, 6(7):732-744.
- [9] Yang Dai, Zhiyuan Luo. "Review of Unsupervised Person Re-Identification." *Journal of New Media*, 2021, 3(4):129-136.
- [10] Meskat Jahan, Manajir Hassan, Sahadat Hossin, et al. "Unsupervised person Re-identification: A review of recent works." *Neurocomputing*, 2024, 572(1):127193-127196.