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Research on Indoor Activity Trajectory Monitoring Model for Elderly Living Alone Based on CNN-LSTM

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Abstract:

This paper presents an innovative neural network model, integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM), designed to longitudinally monitor and predict the health status of elderly individuals living alone. In the model architecture, CNN is tasked with extracting spatiotemporal features related to behavioral patterns and health from daily activity trajectory maps, while LSTM leverages these feature sequences to learn the normal behavioral patterns of the elderly, handling long-term dependencies in time-series data. This dual approach not only enables the identification of immediate anomalies but also forecasts potential health issues, such as Alzheimer's disease. By defining exceptional behavior tags and encoding them as supervised learning objectives, the model achieves effective prediction of abnormal states among the elderly, providing a more comprehensive and proactive solution for their healthcare monitoring.

Keywords — **CNN-LSTM model; trajectory map analysis; abnormal state recognition.**

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I. INTRODUCTION

The aging trend in China is intensifying, bringing with it a series of social challenges and placing higher demands on the social service system, especially in terms of care and security for elderly individuals living alone. Due to the lack of immediate family care, they face numerous safety risks. Therefore, intelligent monitoring systems have gradually become a popular research direction to address the health risks of elderly individuals living alone. Feng et al. proposed a method based on the 3σ criterion to extract the threshold for the length of stay, detecting abnormal states by determining whether the elderly's stay time in indoor spaces exceeds the threshold. Yang et al. proposed a behavior recognition method based on trajectory segmentation and template matching, constructing user behavior models, indoor key point models, and behavior time models to provide a foundation for trajectory analysis. Such research, based on location information, has achieved positive results in real-time monitoring and abnormal behavior recognition. However, these results mostly contribute to short-term, immediate abnormal behavior detection, with insufficient exploration of the long-term trends in the elderly's health status and their correlation with daily activity patterns.

This paper proposes a new neural network model for abnormal state monitoring, combining Convolutional Neural Networks (CNN) and Long Short-Term Memory networks (LSTM), to achieve long-term tracking and monitoring of the indoor activity trajectories of elderly individuals living alone. By leveraging CNN's efficient visual understanding and LSTM's deep sequence learning capabilities, it provides a more intelligent and proactive solution for the care of elderly individuals living alone.

II. TRAJECTORY MAPPING

Currently, mature indoor positioning technology can continuously and accurately capture an individual's location information within a confined space. To optimize the data for CNN model analysis, this paper proposes the following three preprocessing steps.

A. Time Scale Integration

Aggregate data on a daily basis to construct a 24-hour periodic trajectory map. This strategy not only facilitates long-term monitoring of the evolution of behavioral patterns in elderly individuals living alone but also provides CNN with a time-continuous and reasonably spanned analysis unit. In this way, the model can transcend short-term fluctuations and deeply explore long-term behavioral habits and health trends.

B. Activity Pattern Recognition

Divide the indoor space into functional areas, such as bedrooms and kitchens, assigning unique identifiers to each area. This encodes the trajectory data, enabling the CNN model to more specifically learn activity patterns within different areas and extract corresponding features. This region-sensitive processing enhances the model's accuracy in recognizing the daily behavioral patterns of the elderly.

C. Sampling Frequency Adaptation

The sampling frequency of location information is key to constructing the trajectory map, determining the shape and information content of the graph. As shown in Figure 1, too low a sampling rate results in sparse trajectory lines, with diverse shapes and lack of regularity; if the sampling frequency is too high, the trajectory lines become too dense, and the daily trajectory maps tend to be similar, losing the dynamic differences in behavioral changes. Both scenarios are detrimental to CNN's accurate extraction of behavioral features and learning of the elderly's behavioral patterns, affecting monitoring effectiveness.

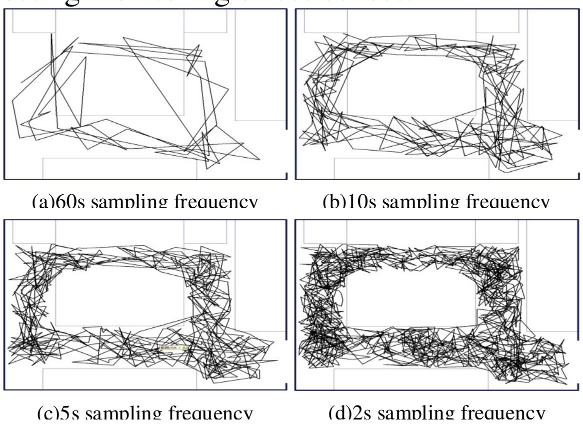

Fig. 1 Relationship between trajectory density, shape, and time scale

Through the above preprocessing steps, we not only ensure the quality and analytical effectiveness of the trajectory maps but also lay the foundation for the CNN-LSTM model-based tracking and health status monitoring of indoor activity trajectories of elderly individuals living alone.

III. MODEL CONSTRUCTION

A. Trajectory Feature Extraction

The goal of this model is to use CNN's powerful image recognition and feature extraction capabilities to deeply analyze the daily activity trajectory maps of elderly individuals living alone, capturing subtle clues that reveal their behavioral habits and potential health status. These refined features, aggregated on a daily basis, form the valuable raw material for the subsequent LSTM model to learn behavioral patterns and make forward-looking judgments on abnormal states.

In defining trajectory features, this paper divides them into two core dimensions: trajectory density Di and activity hotspot distribution Hi. Trajectory density comprehensively considers the coverage range Di_scope and the density of trajectory lines Di_count, quantifying the breadth and activity level of the elderly's movements. Activity hotspot distribution Hi identifies and quantifies key activity areas Hi_nLocation and their importance Hi_nWeight, constructing a comprehensive hotspot map that reflects the elderly's preferred areas and behavioral intensity within the indoor space.

To better extract trajectory features, this paper designs a multi-level CNN architecture, adopting the following key design strategies:

1)Hierarchical Convolutional Layers: By configuring multi-level convolutional layers with different-sized kernels, CNN can flexibly capture diverse features in the trajectory maps — from microscopic local action details, such as frequently trodden paths, to macroscopic overall activity patterns, such as the aggregation of activity areas during specific periods.

2)Strategic Pooling Layers: Implementing max pooling or average pooling strategies aims to reduce dimensionality while maintaining the integrity of important features, enhancing the model's tolerance for slight positional changes in the trajectory maps. This step ensures that the model can focus on higher-level feature structures, such as the invariant features of activity patterns.

3)*Cross-Date Feature Integration:* Innovatively introducing a feature fusion mechanism, the model inputs trajectory maps from several consecutive days into CNN, enhancing the model's sensitivity and understanding of behavioral pattern evolution through feature superposition and comparison over time. This provides a new perspective for identifying long-term behavioral trends and health status changes.

B. Behavioral Pattern Learning

LSTM demonstrates exceptional performance in handling time-series data, particularly in capturing long-term dependencies, thanks to its unique memory gate mechanism. Due to the stability of the indoor environment, the daily life patterns of the elderly exhibit significant regularity over time, which can be reflected in their activity trajectories, i.e., the feature sequences output by the CNN model. For the behavioral trajectory feature sequences obtained from the CNN model, this paper proposes a multi-layer hidden LSTM network, as shown in Figure 2, aiming to deeply explore and simulate the intrinsic patterns and potential anomalies in the daily activities of elderly individuals living alone.

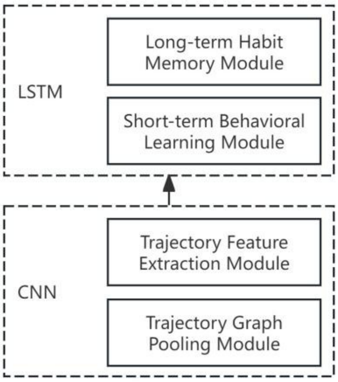

Fig. 2 CNN-LSTM-based Behavior Monitoring Model

1)Multi-Layer LSTM Structure Design: Construct a model containing multiple LSTM units, with each layer responsible for capturing complex dependencies between behavioral features at different time scales. The lower-level LSTM primarily learns short-term behavioral patterns, while the upper-level LSTM focuses on identifying and modeling long-term behavioral trends. This hierarchical design enables the model to more effectively learn and remember long-term and short-term patterns in behavioral sequences.

2)Feature Sequence Input and Target Label Matching: Input the daily behavioral feature sequences extracted by CNN into the LSTM model, with each day corresponding to a feature vector. Simultaneously, match each feature vector with corresponding target labels based on annotations by behavioral experts or known normal behavioral patterns to perform supervised learning. This pairing ensures that the LSTM model can learn feature patterns representing normal behavior.

3)Attention Mechanism Integration: To enhance the LSTM model's focus on key time points or behavioral features, we consider integrating an attention mechanism into the model. This mechanism allows the model to dynamically assign different weights to different feature vectors when processing the entire sequence, thereby focusing more on features crucial for behavioral pattern recognition, improving prediction accuracy and model interpretability.

C. Model Training and Prediction

During the model training and prediction stages, we strictly select continuous and undisturbed normal activity periods as the training basis. We uniformly adopt a time resolution of one day to ensure the continuity and standardization of model training. This choice of time scale not only promotes the LSTM network's sequential learning of daily behavioral patterns but also provides a stable learning benchmark, enabling the model to accurately capture and predict the behavioral patterns and habit changes of the elderly across different time periods.

In defining "abnormality," we adopt a more detailed and comprehensive perspective. Abnormal states are not limited to significant increases or decreases in activity levels or irregular movement paths but also include, but are not limited to, the following key dimensions:

1)Reduced Activity Range: Long-term observation of a significant reduction in the elderly's activity area may indicate declining mobility or health issues.

2)Decreased Activity Density: A reduction in the point density of daily activity trajectories reflects a decrease in the elderly's activity enthusiasm, potentially related to declining physical strength or emotional changes.

3)Increased Repetitive Behavior: Frequent repetition of the same path or lingering in specific areas may be early signs of memory decline or disorientation.

4)Activity Hotspot Shift: Sudden changes in previously high-frequency activity areas, unexplained by normal life adjustments or environmental changes, suggest abnormal changes in behavioral patterns.

5)Unreasonable Activity Distribution Across Areas: The proportion of time spent in specific areas does not match daily life needs, such as prolonged absence from the kitchen or bathroom, potentially indicating a decline in self-care ability.

For these abnormal behaviors, we design a detailed labeling system, such as "activity restriction" and "behavioral pattern deviation," as supervised learning targets for model training. By encoding these labels, we guide the CNN-LSTM model to learn the boundary between normal and abnormal behavioral patterns, enabling it to accurately identify potential health risks or changes in living conditions during the prediction phase.

IV. CONCLUSIONS

In summary, this study constructs a CNN-LSTM-based neural network model to achieve deep learning and analysis of indoor activity trajectories of elderly individuals living alone, aiming to provide an effective means for long-term tracking and prediction of their health status. Through fine preprocessing of trajectory data and CNN feature extraction, combined with LSTM's ability to learn temporal behavioral patterns, the model not only identifies daily behavioral patterns but also has the potential to predict abnormal states. Future work can further optimize model parameters to improve the accuracy of anomaly detection and explore the integration with other physiological monitoring data to build a more comprehensive intelligent monitoring system, actively responding to the needs of an aging society and safeguarding the safety and health of elderly individuals living alone.

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