A Real-Time Human Activity Recognition for In-Home Health Monitoring Applications

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Summary

This study presents a real-time Human Activity Recognition (HAR) system utilizing Wi-Fi Channel State Information (CSI). By integrating the CSI ratio phase and magnitude, the system achieves a highly efficient workflow, processing 50 seconds of data in 1.2 seconds. Tests in two in-home scenarios demonstrated recognition accuracy exceeding 94%, confirming its practicality for home monitoring.

Introduction

In recent years, HAR has gained significant attention in smart home applications. CSI-based sensing offers privacy protection, cost-effectiveness and wide coverage. However, most existing CSI-based HAR systems require complex signal processing, limiting their real-time capability which is crucial for timely monitoring and intervention. To address these challenges, we propose an efficient signal processing workflow that enables real-time HAR capabilities.

Methods

The dataset [1] was collected using the Linux 802.11n CSI Tool [2], operating on a 2.4 GHz network with a sampling rate of 250 Hz. Data collection was conducted in a discussion room, with 6.2 meters in length and 4.2 meters in width. Within this experimental setting, we recorded two stationary activities, four small activities, tremor, and walking. The total duration of all activities amounted to 8,000 seconds.

Our signal processing workflow (Figure 1) first extracted two base signals: ratio phase and ratio magnitude [3]. Subsequently, the algorithm selected the antenna pair with the strongest Received Signal Strength Indicator (RSSI) and applied two filters. Finally, through normalization, CLAHE image enhancement, and feature combination, we transform these features into images with 30×30 pixels.

Two CNN architectures were designed for grayscale single-feature images and RGB multi-feature images. Both models consisted of convolutional layers for feature extraction followed by fully connected layers for final classification. The dataset was split into 60% for training, 20% for validation, and 20% for testing, and we performed 5-fold cross-validation to ensure the robustness of training results.

To validate our proposed workflow, we conducted two case studies. The first case study involved a 50-second activity recognition experiment, where participants performed different activities from our dataset at 10-second intervals. The second case study focused on the Timed Up and Go (TUG) test, which comprised standing up, walking, turning, and sitting down movements.

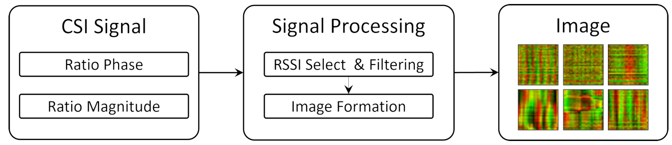

Figure 1: Signal processing workflow

Results and Discussion

Our experimental results demonstrated the effectiveness of our proposed approach. As shown in Table 1, The combination of ratio phase and ratio magnitude achieved results with 94% accuracy, showing a 7% improvement over single-feature approaches. This can be attributed to how different features captured different aspects of the activities.

For the 50-second activity recognition experiment, we recorded video as ground truth to document participant movements. We conducted ten experimental trials, analyzing a total duration of 500 seconds. The system misclassification occurring in 30 seconds of the total duration, achieving an accuracy of 94%.

In the TUG test evaluation, we performed four experimental trials over a total duration of 280 seconds. The system maintained consistent performance with misclassification limited to 15 seconds, resulting in an accuracy of 94.6%.

Conclusions

We successfully developed an efficient signal processing workflow capable of real-time sensing for CSI-based human activity recognition, validated through two case studies. This technology shows promising potential for applications in healthcare monitoring and smart home elderly care. Future research will focus on reducing the required amount of training data through few-shot learning approaches and data augmentation techniques, making the system more practical for rapid deployment.

References

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Table 1: Accuracy of Single and Combined Features (RP: ratio phase, RM: ratio magnitude, LP: linear phase).

Feature	RP	RM	LP [4]	RP+RM	RP+LP	RM+LP	All
Accuracy (%)	87.6 ± 1.2	85.0 ± 2.3	74.9 ± 1.5	**94.1 ± 0.9**	91.3 ± 1.4	92.7 ± 1.8	93.3 ± 1.0