Wireless Sensing Technology Empowers Fall Protection for the Elderly

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Abstract. Amid contemporary challenges in social security, the issue of falls among the elderly has emerged as a key concern, drawing widespread attention and urgently requiring innovative solutions. At the same time, the field of wireless sensing technology is experiencing rapid development, demonstrating broad prospects for application across various domains. This study, entitled "Wireless Sensing Empowering Fall Prevention and Protection for the Elderly," aims to explore the intersection of these two critical areas, utilizing cutting-edge wireless sensing technology to address the pressing issue of falls among older adults. By analyzing and synthesizing recent research data on the application of wireless sensing in fall detection and prevention, this study underscores the immense potential and necessity of developing and implementing wireless sensing technology in elderly care.The research also highlights the advantages of wireless sensing over traditional fall prevention methods, including its non-intrusive nature, continuous monitoring capabilities, and potential for seamless integration with existing healthcare systems.

Keywords: social security; wireless sensing technology; CSI.

1. Introduction

1.1. Research Background and Objectives

In today’s society, safety issues are becoming increasingly prominent in public awareness. Recent data indicate that the global aging process is accelerating, with the incidence rate of accidental falls among people over 75 steadily rising. Each year, about 30% of this group experience falls [1], with 10% resulting in serious injuries, and the mortality rate due to lack of timely assistance is as high as 50% [2]. Traditional technologies, such as those based on vision, sensors, infrared, and sound, are all easily affected by environmental interference and are not highly accurate. In recent years, the rapid development of wireless communication technologies has given rise to wireless sensing technology, which can operate in complex environments and brings new opportunities for human safety detection.

The main purpose of this paper is to systematically review the research achievements of wireless sensing technology in the field of elderly fall detection, compare the strengths and weaknesses of wireless versus sensor technologies, analyze the challenges faced in complex scenarios, summarize the current status and future trends in this field, and provide a comprehensive technical overview and cutting-edge perspective for related research, thus promoting the practical application of these technologies.

1.2. Structure and Scope of the Paper

This article focuses on the application of wireless sensing technology in elderly protection. It begins by elaborating on the research background and objectives. Then, by listing the behavioral characteristics of the elderly when they fall, it sets the stage for the subsequent discussion on the advantages and disadvantages of wireless sensing technology and the bottlenecks that need to be overcome in the future. Through theoretical analysis, it concludes that traditional sensor sensing technology is not applicable. It then analyzes the basic principles and respective advantages and disadvantages of mainstream wireless sensing technologies. It further examines the existing challenges from both technical and practical application perspectives. Finally, it looks ahead to the research directions in the field of elderly protection empowered by wireless sensing technology in the future.

2. Theoretical Basis of Wireless Sensing for Elderly Fall Detection

2.1. Analysis of Characteristics of Falling Behavior in the Elderly

According to statistics, the behavioral characteristics of the elderly when they fall can be divided into four categories. The first category is the warning signs before a fall, which include high-risk actions such as sitting down or standing up, as well as falls caused by failed compensation—for example, when reaching out to grab a support object, muscle weakness or delayed reactions can result in a fall. The second category involves the motions that occur during the fall itself. Falling forward usually results from unsteady walking or losing control during actions like bending over. The third category is closely related to the environment, such as places indoors that are prone to falls like kitchens and bathrooms, as well as hazardous outdoor areas like slippery roads on rainy or snowy days, or regions near rivers and lakes. The fourth category pertains to individual differences. For instance, compared to healthy elderly individuals, those with chronic illnesses like Parkinson's disease or those with depression are more likely to fall [3]. There are also differences between elderly men and women; according to a 2022 survey by Deborah A. Jehu, in a 12-month study period, the average number of falls for men was 2.80 ± 6.86 times, significantly higher than the 1.25 ± 2.63 times for women [4]. Recent survey results show that among incidents of falls in the elderly, environmental factors account for 50%, physical condition for 33%, activity status for 7.9%, and unknown causes for 9.1%.

2.2. Theoretical Principles of Wireless Sensing Technology

According to the current mainstream research on human infinite perception technology, it can be mainly divided into two categories. One is the human behavior perception technology based on RSS (Received Signal Strength), where the data required is obtained by measuring the level of signal power received by the wireless signal receiving end. It is usually used to evaluate the degree of signal coverage, connection level, and possible interference of the wireless network. The other is the human behavior perception technology based on CSI (Channel State Information), which involves separating data specifically related to human movement from the original CSI. In an environment characterized by dynamic movement, the propagation path of wireless signals constantly changes. According to the principle of wave superposition, the superposition of wireless signals can lead to constructive interference (amplitude positive superposition of the same phase) or destructive interference (amplitude mutual cancellation of opposite phases). Therefore, in this dynamic setting, the CSI data curve shows significant waveform fluctuations.

3. The Application of Mainstream Wireless Sensing Technologies in Fall Monitoring

3.1. Sensor Sensing Technology

Mainstream sensor detection technologies can be categorized into three types: the first is wearable sensor technology; the second is audio-based sensor technology; and the third is sensor technology based on video surveillance capture.

3.1.1 The judjments of sensor technology

First, wearable sensor technology, which gained significant popularity in previous years, fails to achieve real-time monitoring due to factors such as user discomfort from near-body wear and insufficient timely charging, based on feedback in recent years. Second, audio-based sensor technology operates on the principle of detecting falls through the sound of a fall. However, in noisy environments, it cannot accurately distinguish between noise and the sound of a fall, resulting in persistently high false alarm rates. Third, video surveillance-based sensor technology captures images of elderly falls via cameras and similar devices. Nevertheless, it is susceptible to interference from lighting conditions and obstructions, and the high cost of camera equipment hinders its widespread adoption. Therefore, wireless sensing technology is precisely a technology that should be developed in response to the needs of the times.

3.2. Wi-Fi sensing technology

This includes RSS (Received Signal Strength) body movement sensing technology and based on CSI (Channel State Information) body movement sensing technology [5].

3.2.1 RSS Technology

The basic principle is to assume there are an anchor points in a scene, and the RSS measurement of the signal emitted by the target node received at each anchor node is a function of the distance between them, specifically expressed by the following log-normal shadow fading model [6].

$$P_i = P_o - 10\beta \log_{10} \frac{d_i(x_i, y_i)}{d_o} + m_i \quad (1)$$

Here, P_i is the RSS measurement collected by the i-th anchor node, and P0 is the signal power at the reference distance d_o .

As early as 2014, Gu with his team conducted experiments on elderly fall detection based on RSS. They collected RSS data from Wi-Fi signals and then calculated the variance of each set of samples. By applying a fusion algorithm based on K-nearest neighbors and decision trees, they were able to classify indoor human activities such as resting, walking, sitting, and standing, achieving an average accuracy of about 73.3% **[7]**. However, in typical indoor environments and confined outdoor spaces, the propagation of Wi-Fi signals is easily obstructed. Under such circumstances, the level of RSS attenuation is not positively correlated with measurement distance, which affects detection accuracy. In these cases, Channel State Information (CSI) offers a certain degree of multipath resolution, making it possible to monitor small changes in signals along line-of-sight or non-line-of-sight paths.

This helps improve sensing sensitivity.

3.2.2 CSI Technology

First, let's introduce the propagation characteristics of WiFi signals [8].

1. Free-space propagation model: The transmission of wireless signals follows an attenuation model where the electromagnetic wave acts as the distance function. Assume the distance between the transmitter and the receiver is, and the signal power at the receiver (denoted as Prd) is

$$P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2 L} \quad (2)$$

2. Logarithmic Path Loss Model: The large-scale fading characteristics of the channel follow a log-normal distribution. The received signal strength exhibits an approximately linear relationship with the logarithmic distance.

$$PL(d) = PL(d_o) + 10n\lg\left(\frac{d}{d_o}\right) + X_\sigma \quad (3)$$

3. Attenuation factor model: Through numerous experiments, an attenuation factor model based on logarithmic path loss was developed.

$$PL(d) = PL(d_o) + 20\lg\left(\frac{d}{d_o}\right) + \alpha d + FAF \quad (4)$$

Next, let’s introduce several existing CSI-based fall action recognition methods [8].

(1) Decision Trees. This is a relatively simple recursive algorithm.

(2) Random Forest. This technique illustrates the learning process through random sampling and promotes the effective use of samples. Therefore, after improvements, it can be used for methods to recognize fall actions [9].

(3) K-Nearest Neighbors (KNN). When a large number of samples are selected, the computational complexity of the KNN method increases significantly, which brings challenges to its application in fall detection methods.

(4) Support Vector Machine (SVM). The core concept behind using SVM for classification is to determine the optimal separating hyperplane as the decision boundary, which divides the feature space and maximizes the distance between different types of samples and the decision boundary.

(5) Convolutional Neural Networks (CNN). The identification of human fall actions is achieved by applying convolutional neural network methods.This paper takes the 2021 study that used support vector machines as the classification algorithm as an example [10], with its decision function as follows:

$$predict_{label} = \mathrm{sgn}(\sum_{i=1}^{n} w_i K(x_i, x) + b) \tag{5}$$

4. Discussion

4.1. Existing Challenges

4.1.1 Technical challenges

In indoor or outdoor confined environments, various obstacles such as trees and furniture make wireless signal propagation very complex. In scenarios involving multiple people, their movement can distort the wireless signal characteristics, complicating the accurate detection of falls. Such distortions may lead to misinterpreting the actions of others as a fall by a relevant elderly person, or make it impossible to detect actual fall events. Therefore, a multiple-input multiple-output (MIMO) approach can be used, as it provides better transmission performance and higher spectral resolution, which was demonstrated in Marco Cominelli’s 2023 study [11].

4.2.2 Obstacles in practical application

Regarding device deployment and costs, the widespread use of traditional wearable devices imposes economic and usability burdens on the elderly, as the maintenance, data transmission, and storage of these devices incur additional costs. While Wi-Fi sensing technology utilizes existing networks, it requires high-performance channel state information (CSI) acquisition devices, which are costly and thus limit widespread adoption. In solutions involving the integration of multiple technologies, the collaborative deployment of various devices requires solving hardware compatibility and network adaptation issues, further increasing deployment costs and hindering feasibility in ordinary households and small care institutions. Moreover, most elderly people do not understand the principles of new wireless sensing technologies, which can lead to mistrust and discomfort, further impeding the promotion of these technologies.

4.2. Prospects for Future Research

4.2.1 The trend of multi-technology integration

In the future, it will be possible to adopt cross-fusion of several CSI-based fall detection approaches. A single device could employ two or more methods simultaneously for monitoring. For example, integrating the decision tree method with the K-nearest neighbors (KNN) approach [12] can greatly enhance the accuracy of monitoring systems and reduce false alarms or missed alarms. Other wireless sensing technologies, such as millimeter-wave radar, can also be integrated. By leveraging the high-precision capabilities of millimeter-wave radar for monitoring human posture and distance, the system can compensate for Wi-Fi sensing’s limitations in complex environments. This would enable the construction of a multi-technology collaborative, complementarily advantageous fall detection system, improving both detection accuracy and robustness.

4.2.2 Intelligent and personalized monitoring solutions

In terms of wireless sensing for elderly fall prevention, AI can be utilized to train monitoring devices across various environments and different types of elderly falls. This enables the monitoring system to autonomously learn and adapt to the fall characteristics of seniors in different environments and circumstances, thereby enhancing monitoring accuracy.

5. Conclusion

This study finds that wireless sensing technology stands at the forefront of the revolution in elderly fall prevention, providing unparalleled potential for transformation in this crucial field. This paper demonstrates the outstanding features of Wi-Fi sensing's RSS and CSI technologies. Although challenges such as environmental interference, device deployment costs, privacy issues, and acceptance by the elderly persist, the integration of multiple technologies, as well as advancements in intelligent and personalized solutions, are paving the way to overcome these obstacles. Persistent efforts are needed to tackle technical problems, refine application mechanisms, and accelerate the maturity of wireless sensing technology in elderly fall prevention. By doing so, a safer, more convenient, and people-centered elderly care system can be built, effectively addressing the urgent health and safety challenges posed by an aging society. Now is the time to take action—the benefits are too important to ignore.

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