# **ToF Sensor-Based Fall Detection for Elderly Care <sup>+</sup>**

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+Presented at the 11th International Electronic Conference on Sensors and Applications (ECSA-11), 26–28 November 2024.

### Introduction

Falls among the elderly are a major public health concern, with many elderly people experiencing falls each year resulting in serious injuries. This highlights the importance of prompt fall detection. While wearable devices are widely used, contactless detection solutions have become increasingly popular.

3D Time-of-Flight (ToF) sensors provide an effective solution for real-time monitoring of spatial positioning and posture changes. As shown in Figure 1, through an 8x8 lowresolution ToF sensor, a standing person appears as a vertical rectangular pattern, while a fallen person appears as a horizontal pattern. However, low-resolution ToF sensors struggle to distinguish between actual falls and intentional horizontal postures. This paper presents a new approach to address this issue and reduce false-positive rates.



Figure 1. Posture detection using an 8x8 multi-zone ToF sensor.

### Methods

The proposed system utilizes a ceiling-mounted Multi-zone Time-of-Flight (ToF) sensor configured to monitor human motion and posture within an enclosed space (e.g., bathroom) while preserving privacy. The sensor's positioning enables comprehensive spatial monitoring. Upon detecting human presence, the system initiates a continuous rolling measurement buffer, e.g., 20-second. Concurrent with this temporal recording, the system actively monitors for potential fall events by identifying person-sized objects at floor level. When such an object is detected, the system activates a sophisticated fall confirmation process. The complete system workflow is illustrated in Figure 2.



Figure 2. Workflow of the fall detection system.



Figure 3. Feature extraction for each identified stage.

The system first extracts head position data from the recorded measurements to generate a comprehensive trajectory. The complete trajectory is then divided into several distinct stages based on head height variations, e.g., 5 stages. This segmentation enables detailed analysis of the falling motion's characteristics at different phases. For each identified stage, the system calculates three key biomechanical features, as illustrated in Figure 3, including the vertical velocity of the head, the horizontal displacement of the head and the cross-sectional occupation of the body. These parameters were selected based on their high correlation with human postural dynamics and activity patterns.

# **Conclusions**

This paper presents a novel fall detection system utilizing low-resolution ToF sensors and a retrospective confirmation approach.

Our experimental results demonstrate exceptional accuracy (98.41%) in distinguishing between genuine falls and intentional lying-down events, addressing a critical challenge in elderly care monitoring systems.

The proposed method's key innovation lies in its retrospective analysis of fall trajectories and posture data, enabling more reliable detection compared to traditional velocity-based approaches. This is particularly valuable for detecting gradual falls common among elderly individuals.

While the current implementation shows robust performance, future research should address environmental variables such as room configurations.

#### **Results and Discussions**

The system achieved the following performance metrics:

- Overall accuracy: 98.41%
- Error rate: 1.59%

The achieved accuracy of 98.41% was obtained after parameter optimization, with key adjustments mainly including feature weighting modifications.

 Increased weights for vertical velocity in stages 4 and 5.

 Enhanced emphasis on horizontal cross-sectional occupation patterns

Based on our architecture, we developed an integrated monitoring solution in the form of a panel lamp with a ToF sensor integrated, illustrated in Figure 6.



Figure 6. (a) A panel lamp integrated with a ToF Sensor; (b) An application scenario of the panel lamp with the ToF sensor.

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## **Author Contributions**

Conceptualization, G. Wei and G. Wang; methodology, Y.W., S.L., J.Q. and G. Wei; software, Y.W. and J.Q.; validation, Y.W. and J.Q.; writingoriginal draft preparation, Y.W.; writing—review and editing, Y.W. and G. Wei; supervision, G. Wang; Project administration, G. Wang. All authors have read and agreed to the published version of the manuscript.

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