WARE-Care: a novel RF-based system to assess and prevent falling

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Introduction

Many falls in nursing facilities are not reported during night when older adults are alone. It can lead to reduced quality of life, increased fear of falling and restriction of activities, decreased ability to function, and increased risk of injuries or death. We propose WARE-Care: mmWave based fall Assessment and pRevEntion, as a non-intrusive system to work during the night to collect and assess older adults' falling data. WARE-Care will provide an accurate measurement of movement and be compact and easy to set up. The system is safe, private, and user-friendly for nursing facility applications. The system is of strong interest to the nursing centers, including the local Handmaker Jewish Services For Aging center.

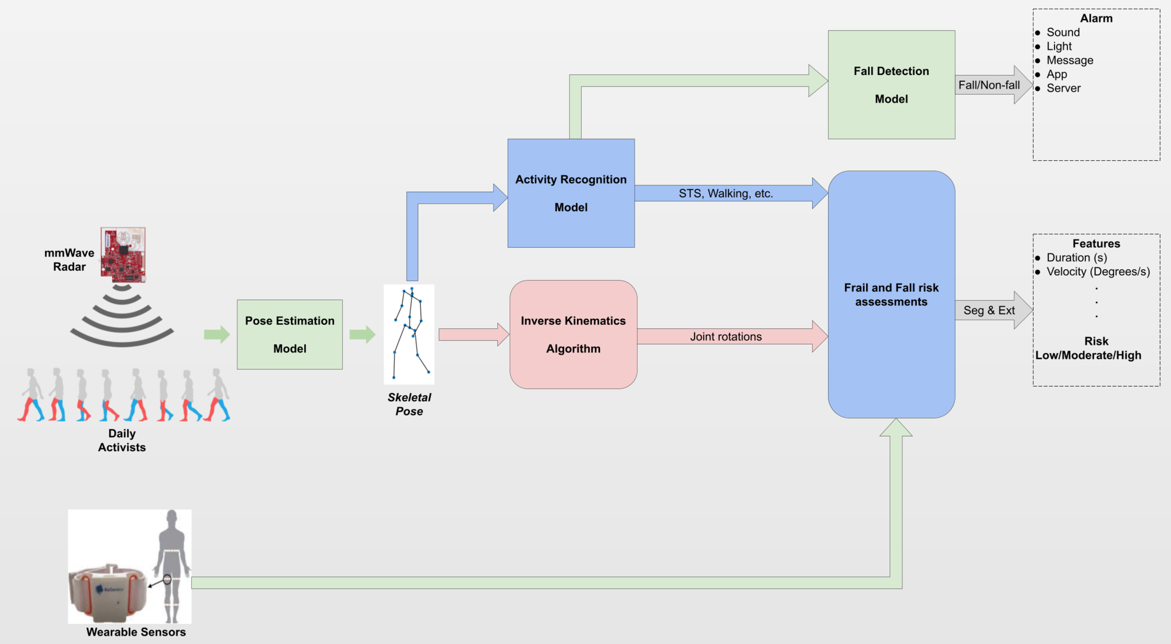


Figure 1. Ware-Care Project Pipeline

The WARE-Care system, shown in Figure 1, is novel and unique and is based on the developments in mmWave radar combined with advanced machine learning techniques. The new field of mmWave radar opens opportunities for elders monitoring with significant advantages that complement existing visual and body-worn sensors. mmWave radar operates in all lighting conditions and generates a point cloud that can be used to accurately create a skeleton while respecting privacy, e.g. no detailed facial information will be collected. The non-touch, non-obtrusive sensor can be preferred to battery limited and potentially irritating body worn sensors during sleeping hours for elders. We first build and verify the proposed system in different rooms including a typical bedroom in the nursing home. We then apply new neural-network based methods to recover accurate skeleton movement and detect abnormal behavior of people regardless of age, sex, weight, or height. An architecture view of our model is shown in Figure 2.

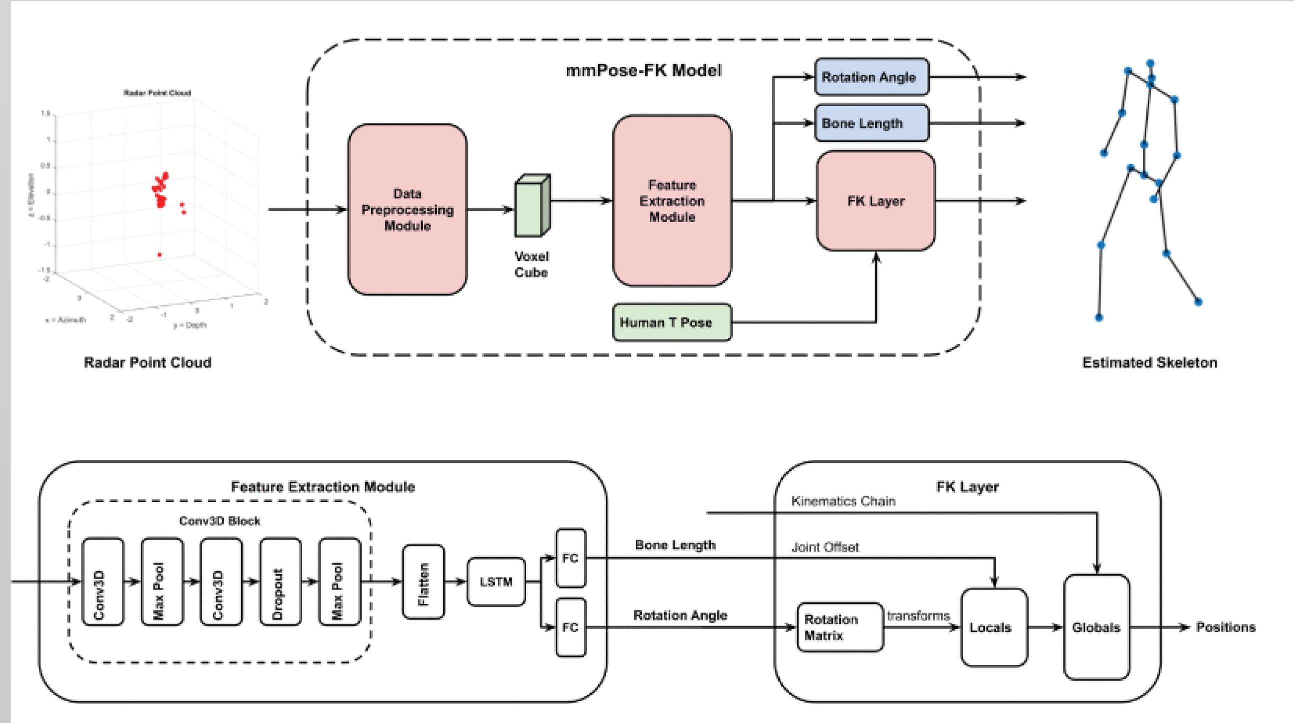


Figure 2. mmPose-FK Architecture

We recruited a group of healthy adults (18 or older) for setting up and training the proposed system. The model is further validated on a targeted older group (65 and older) and be compared with wearable motion sensors. An interdisciplinary team has been assembled to develop and perform initial clinical validation of this novel system.

Methodology and Data Collection

Our experiments utilize the IWR6843ISK-ODS mmWave radar from Texas Instruments (TIs) and the Microsoft Azure Kinect to generate GT joint positions. We designed a 3-D-printed bracket to hold the radar and Kinect together. We employ the built-in body-tracking feature from Kinect to obtain the positions of 25 joints, which serve as our GT. However, we only utilize the 17 key joints as depicted in Figure 3. Wearable sensors were also placed on participants' body to provide comparative data. Specifically, five LEGSys Bio-Sensics sensors were positioned on the left and right shins, left and right thighs, and the waist. These sensors were synchronized with the LEGSys App via Bluetooth for real-time data acquisition. The wearable sensors are shown in Figure 4.

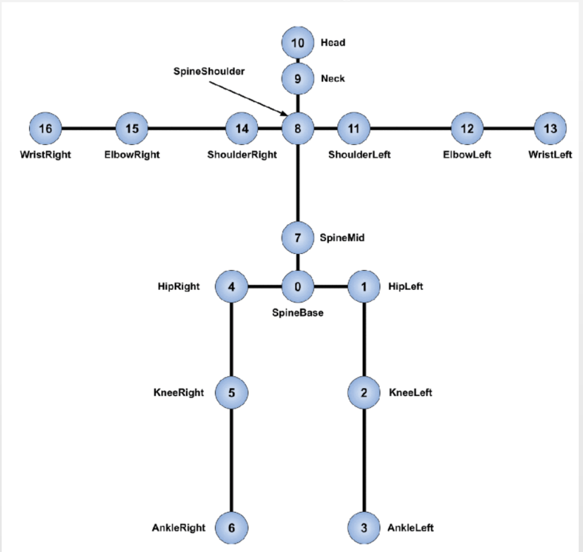


Figure 3. T-Pose Joints

Figure 4. LEGSys Bio-Sensics Sensors

Data collection Tasks:

- **Balance:** Maintain four static stances for 10 s each without external support.
- **Timed Up & Go (TUG):** From a seated start, stand, walk straight to the floor marker, turn, walk back, and sit. 10 trials.
- **Sit to Stand (STS):** From a seated start, repeatedly stand and sit for 1 min without using the arms for support.
- **Gait (Free Walk):** Walk freely within the marked area for 10 min.
- **Upper Extremity Function (UEF):** Rapid elbow flexion–extension of the dominant arm for 30 s.

Additional Data (Younger Adults):

- Simulated bedroom—no walking aid device: 15 min of unstructured activities.
- Simulated bedroom—with assistive device: 10 min of unstructured activities.
- Simulated bed falls—no assistive device: 5 trials onto a protective mat.
- Simulated bed falls—with assistive device: 2 trials onto a protective mat.

Data collection was carried out in multiple environments, including research laboratories at the University of Arizona such as the Electrical and Computer Engineering (ECE) Lab and the Health Sciences Sensor Lab, and also in two retirement communities, Hacienda and La Posada, where data were collected from older adult participants, as shown in Figure 5.

Figure 5. The experimental setup

Results

Frail and Fall Risk Assessments

We perform joint angle rotations calculation using Inverse Kinematics (IK), and automatic signal segmentation, extract feature for each activities, for example, Sit-to-Stand (STS), Gait, Timed Up & Go (TUG), Upper Extremity Functional (UEF) and Balance. Features calculated from these activities are used to classify individuals into low, moderate, or high fall risk categories. Figure 6 shows the features we extracted.

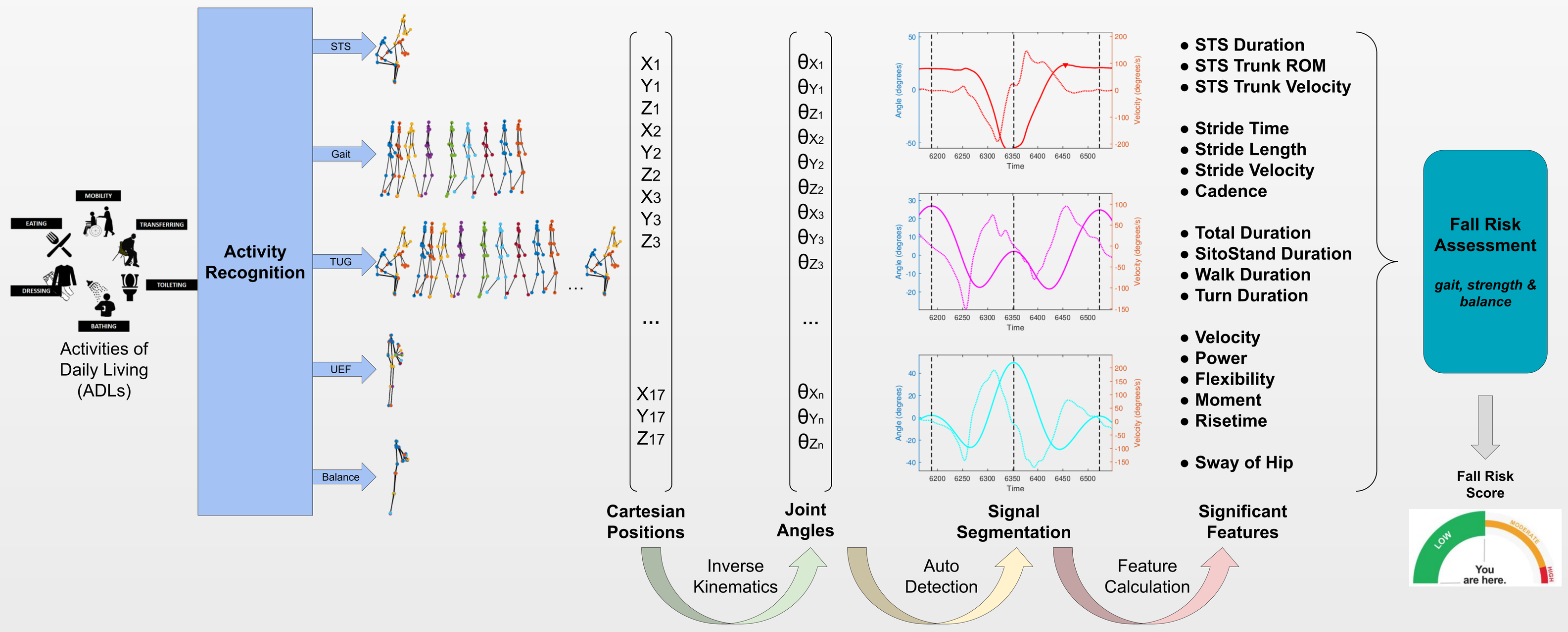
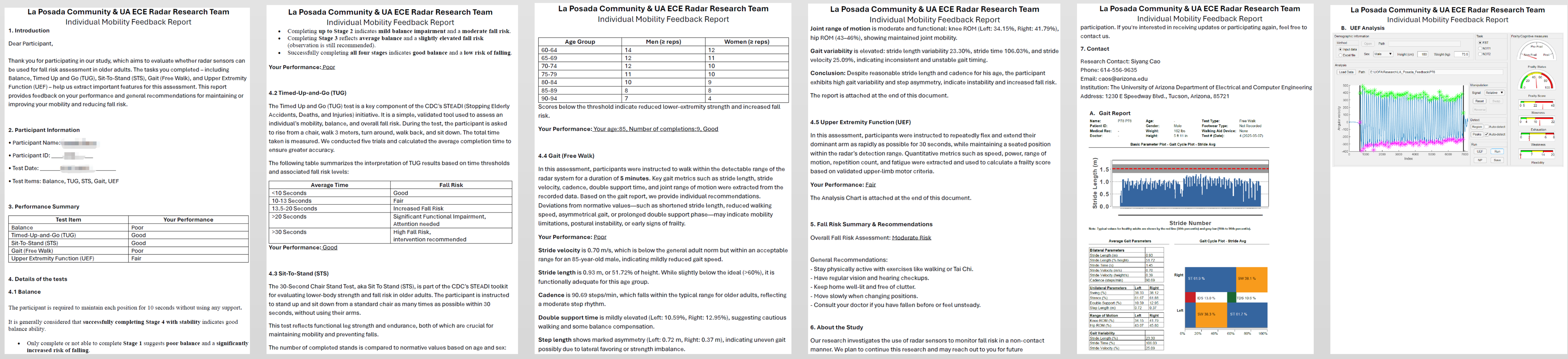


Figure 6. Main Feature extracted from ADLs

We perform statistical analysis and provide older adult participants with individualized feedback reports. This report summarizes each participant's performance and offers advice to improve balance and strength exercises. Below is an example.



Fall Detection

Based on the 17 joints' skeleton predicted by the pose estimation model, we developed an interpretable fall detection model named mmFall-Ex. It contains multiple Spatial-Temporal Graph Convolutional Networks (STGCN) layers, automatically learning both the spatial and temporal patterns from human body skeletons. Besides, mmFall-Ex seeks to explain a fall output in terms of the input skeleton by calculating the backward gradients. The generated gradient heatmap encoded information of falling type and possible body parts impacted. We can further project the attributes onto the skeletons and record them as videos for better interpretation by humans. Figure 7 shows this model.

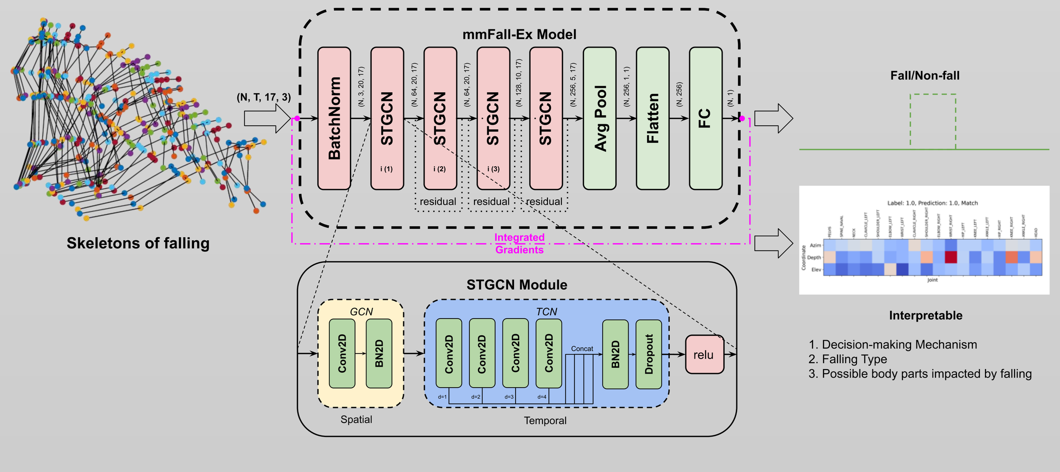


Figure 7. mmFall-Ex Architecture

Figure 8 shows our current detection and false alarm rates with trend lines. Our goal for fall detection is to achieve a false alarm rate of once per week, which currently still has a big gap. We analyzed the influence of dataset size.

To more accurately estimate the size of the dataset needed to achieve our desired outcomes, such as a target detection rate of ≥99.5% and a false alarm rate of ≤ once a week (0.006 N. / Hs), we find the S values corresponding to target rates using inverses functions.

To achieve the goal of false alarm rate, we need at lease 500 hours of ADL data to evaluate.

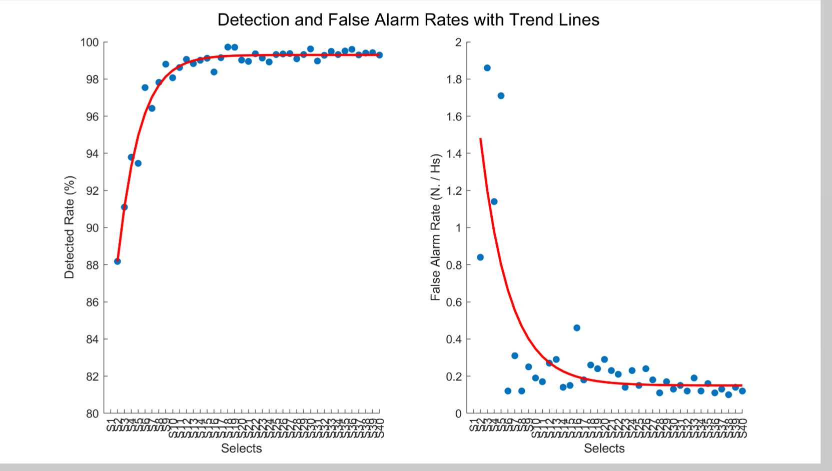


Figure 8. Detection and False Alarm Rates