RF-Based Fall Monitoring Using Convolutional Neural Networks

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* equal contribution
In US, about three-fourths of deaths due to falls occur in the 13% of the population age ≥65.

One in three adults over the age of 65 experiences a fall each year; 12 million seniors in the US live alone.

Falls result in $34B of direct medical costs annually.

Sources: (1) Falls in older people: epidemiology, risk factors and strategies for prevention. Age and ageing.
(2) John Hopkins Newsletters.
Current solutions

Wearables devices

- Forget to wear or charge the devices
- Recently an elderly woman got strangled with her fall detection pendant.

Non-wearable

Privacy Issues. Suffer from occlusion

Not easy to generalize to new environments.
Issues of wireless fall detection (Doppler/CSI-based)

Fails to distinguish between falls and other motion patterns

(a) Fall forward  
(b) Fall sideways  
(c) Fall while sitting in a chair  
(d) Fall when one misses a chair

(e) Sitting down on a chair  
(f) Walking  
(g) Quickly stepping forward  
(h) Opening a door
Issues of wireless fall detection (Doppler/CSI-based)

Fails to detect falls when other motion exists

Fall happens, but is overwhelmed by another walking person
Issues of wireless fall detection (Doppler/CSI-based)
Fails to generalize in new environment and people

Training set

Testing set
Aryokee

- Aryokee is highly accurate when generalizing to unseen environments and people.

- Proposed cascaded convolutional model beats previous models, such as Linear SVM, Kernel SVM and LSTM, by a large margin.

- Extensive experiment on dataset that contains more than 20 hours data: including 145 people and 57 environments
FMCW radio waves with antenna array

Traverse time → Distance
Multiple antennas → Angles
How the signals look like?

Two people are spatially separated

Fall and walking are separated
Aryokee Model Overview
Challenge: how to fuse the information from the horizontal and vertical heatmaps
Solution: CNN model with two branches applying fusion in feature space
Challenge: extreme unbalanced positive and negative samples
Solution: multi-stage detection via cascading classifiers
Challenge: duplicate detection results around a single fall
Solution: non-maximum suppression delivers single but accurate detection result.
Challenge: duplicate detection results around a single fall
Solution: non-maximum suppression delivers single but accurate detection results.
Challenge: how to continuously know the current state of the target person?
Solution: extra standup detector and state machine.

\[
\begin{align*}
\text{P(fall)} < \theta_1 & \quad \text{normal} \\
\text{P(fall)} \geq \theta_1 & \quad \text{fall} \\
\text{P(stand)} \geq \theta_2 & \\
\text{P(stand)} < \theta_2 &
\end{align*}
\]
## Evaluation (dataset)

Table 1. Dataset statistics and comparison with past work.

<table>
<thead>
<tr>
<th></th>
<th>number of falls</th>
<th>number of non-falls</th>
<th>number of fall patterns</th>
<th>number of non-fall patterns</th>
<th>number of people</th>
<th>number of environments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ours dataset</td>
<td>541</td>
<td>550,000</td>
<td>18</td>
<td>40</td>
<td>145</td>
<td>57</td>
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<tr>
<td>Palipana et al. [41]</td>
<td>326</td>
<td>744</td>
<td>4</td>
<td>8</td>
<td>3</td>
<td>5</td>
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<tr>
<td>Jokanović et al. [25]</td>
<td>117</td>
<td>291</td>
<td>4 (different angles)</td>
<td>3</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

![Non-Falls](image1.png)  
![Falls](image2.png)
Evaluation (main results)

- **Precision**: Aryokee 0.919, FallDeFi 0.760
- **Recall**: Aryokee 0.938, FallDeFi 0.700
- **F1 Score**: Aryokee 0.929, FallDeFi 0.730
Evaluation (model ablation)

The threshold is set at recall = 0.938
Evaluation (comparison with baseline models)

F1 Score Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Same People Same Environment</th>
<th>Cross People Cross Environment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Linear SVM</td>
<td>0.658</td>
<td>0.127</td>
</tr>
<tr>
<td>Kernel SVM</td>
<td>0.790</td>
<td>0.167</td>
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<tr>
<td>LSTM</td>
<td>0.864</td>
<td>0.172</td>
</tr>
<tr>
<td>Aryokee</td>
<td>0.958</td>
<td>0.929</td>
</tr>
</tbody>
</table>
Evaluation (state monitoring)
Conclusion

1. An accurate fall detection system
   a. Convolutional Nets
   b. Cascaded model
   c. NMS

2. A multi-functional design for continuous state monitoring

3. Rich empirical study
   a. vs. prior art
   b. vs. classic ML models
   c. ablation study
Thanks Q&A