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Communications

Detection of Falls Among the Elderly by a Floor Sensor Using the Electric Near Field

Henry Rimminen, Juha Lindström, Matti Linnavuo, and Raimo Sepponen

***Abstract*—We present a new fall-detection method using a floor sensor based on near-field imaging. The test floor had a resolution of 9 × 16. The shape, size, and magnitude of the patterns are used for classification. A test including 650 events and ten people yielded a sensitivity of 91% and a specificity of 91%.**

***Index Terms*—Adaptive filters, electric field measurement, fall detection, floor sensor, pattern recognition.**

I. Introduction

Falls represent one of the greatest health risks among the elderly. In a study by Fleming and Brayne, 80% of the people that were unable to get up after a fall did not use a call system. Thirty percent of these were left lying on the floor for an hour or more [1]. Therefore, means to minimize the time spent on the floor after a fall are needed [2].

We respond to this by presenting a new method to detect falls. It uses a near-field imaging (NFI) using floor sensor and pattern recognition. The floor sensor detects the locations and patterns of people by measuring impedances with a matrix of thin electrodes under the floor [3]. The NFI floor sensor is immune to furniture shading; it is completely undetectable and requires very little computing power.

The problem with most fall detectors is that they have not been adequately tested in daily practice [2], whereas the NFI system is, in actual use, in the rooms of 60 residents in a large nursing home in Helsinki, Finland [4] and also in other nursing homes.

A. Related Work

Fall detectors worn by the user produce outstanding results [5], but the batteries must be charged frequently and some irritable patients will remove such devices [6]. The leading method in unobtrusive fall detection is computer vision [7], [8]. Sensitivity and specificity of 93% and 98% can be reached with a single camera (no unclear falls tested) [7]. The disadvantages of computer vision include its heavy demand for computing power, furniture shading, and the privacy issues caused by the visible cameras. Systems based on vibration sensors or IR sensors [9], [10] may have problems with low-impact falls or shading. Some studies using pressure-sensitive floors mention fall detection [11], [12], but performance rates are not presented. Electric field sensing has been used for tracking people [13], [14], but it has not yet been utilized for fall detection.

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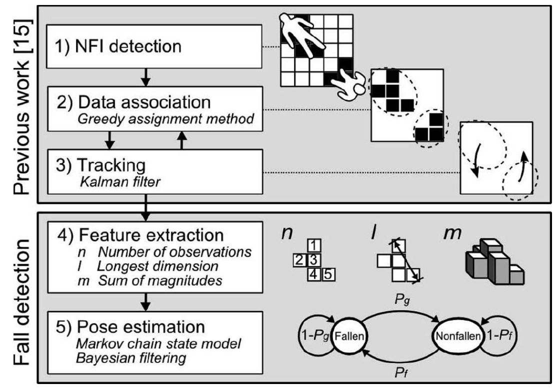

Fig. 1. Process flow of the NFI fall detector.

II. Materials and Methods

The proposed fall-detection method is described in Fig. 1. In our earlier work, we presented a method for tracking people with an NFI floor [15], as illustrated in blocks 1, 2, and 3. In this paper, the tracking system is extended with the feature-extraction and pose-estimation steps, as illustrated in blocks 4 and 5.

A. Feature Extraction

In the feature-extraction step, a collection of features is computed from the cluster of observations associated with a person. The chosen features are the number of observations (n), the longest dimension (l), and the sum of magnitudes (m) (see Fig. 1, block 4). The magnitude is a clear advantage of the NFI method, because it gives the cluster an additional dimension. To attain this with computer vision requires multiple cameras [8]. With a pressure-sensitive floor, m would equal the weight of the person, regardless of the pose. With an NFI floor, m is several times larger when a clear fallen pose is compared to a standing pose (see Fig. 2).

B. Pose Estimation

Since the features contain noise and have a significant overlap between the fallen and the nonfallen states, the pose of a person was estimated using Bayesian filtering [16] instead of the features being classified directly. The state evolution was modeled as a two-state Markov chain (see Fig. 1, block 5). P_f is the probability of falling, and P_g is the probability of getting up. The algorithm combines this prior model with information from the features and recursively computes the probability distribution of the current state, given all the features observed so far. The state-transition probabilities P_f and P_g and the probability distributions of the features in the two states were estimated from a training set.

The NFI fall detector is shown in action in Fig. 2. The features n, m, and l are shown above the NFI data. As soon as the left-hand side of the person hits the floor (frame 45), the alarm is triggered.

C. Experimental Performance Evaluation

The performance of the fall detector was evaluated using the test arrangement suggested by Noury *et al.* [17]. Sitting on a chair, lying on a bed, sliding against a wall, and coughing were removed, since the NFI floor sees only 5 cm above the floor. Kneeling on one knee was added to the nonfalls.

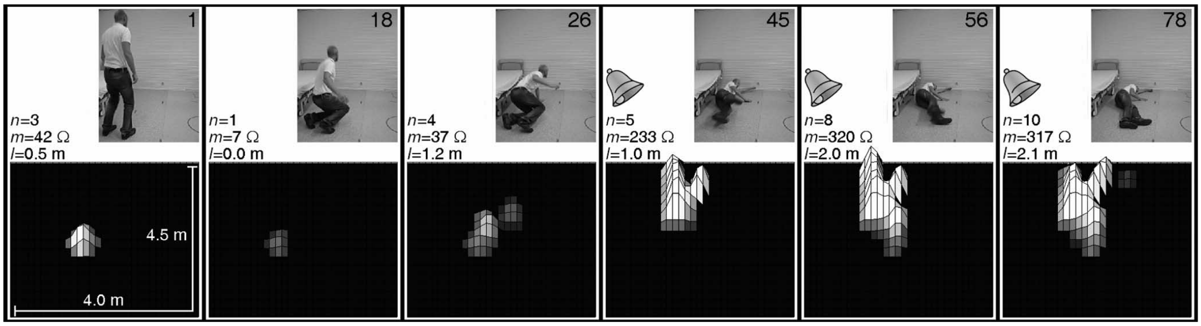

Fig. 2. Example of fall detection with the NFI floor sensor. Video (30 fps) and NFI data were recorded simultaneously. The bell indicates the fall-alarm state.

TABLE I
CONTINGENCY TABLE

Results	Fall occurred	Fall did not occur
Detected as fall	272	33
Detected as non-fall	28	317

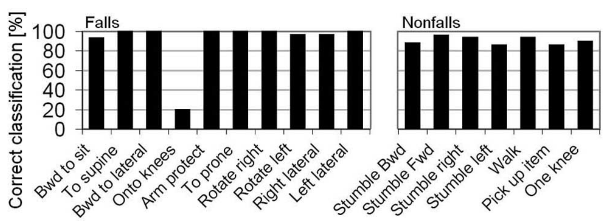

Fig. 3. Performance among event types. N for each fall type was 30 and 50 for the nonfalls.

The 19-m^2 test room was fully covered with a 9×16 matrix of sensors with a 4.5-Hz update rate. A group of ten people with even gender distribution simulated falls in random locations. The sample size of 650 should ensure statistical significance [17].

III. RESULTS

The classification results are shown in Table I. The sensitivity and specificity were 90.7% and 90.6%. Their 95% confidence intervals were 86.8%–93.7% and 87.0%–93.4%.

The performance distribution among the test events is presented in Fig. 3. The system had problems only with test subjects falling onto their knees, which produced correct classifications in only 20% of cases, as it produces a pattern very similar to a standing person.

IV. DISCUSSION AND CONCLUSION

The results suggest that the technique works well: a sensitivity and specificity of 91% and 91% were measured. The method shows a good tolerance of everyday activities. It performs moderately even if unclear falls occur (ending up sitting or on one's knees).

When multitarget tracking is successful, the fall-detection performance is valid for multiple people in the same room. Multitarget separation performance of *walking* people is discussed in our earlier work [15].

Considering that the NFI system avoids the aforementioned disadvantages of related work, and the system is in clinical use, the proposed method is a good choice for the detection of falls among the elderly.

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