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Fall Detection using Doppler Radar and Classifier Fusion

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Abstract—**Falling is a common health problem for elders. It is reported that more than one third of seniors 65 and older fall each year in the United States. We develop a dual Doppler radar system for fall detection. The radar system generates a specific Doppler signature for each human activity which is then categorized by a set of classifiers as fall or non-fall. However, different classifiers may produce different decisions for the same signature. In this paper, we propose a fusion methodology based on the Choquet integral that combines partial decision information from each sensor and each classifier to form a final fall/non-fall decision. We employ Mel-frequency cepstral coefficients (MFCC) to represent the Doppler signatures of various human activities such as walking, bending down, and falling. Then we use three different classifiers, kNN, SVM and Bayes, to detect falls based on the extracted MFCC features. Each partial decision from a classifier is represented as a confidence. We apply our fusion method to a dataset that consists in 450 activity samples (109 falls and 341 non-falls).**

I. INTRODUCTION

FALLS are the leading causes of accidental death in population over age 65 in the US [1]. The fall caused death rate among elders has been increasing during the past decade [2]. In the mean time, studies [3, 4] showed that delay in the medical intervention after a fall is negatively correlated to the survival prognosis. A possible solution for reducing the intervention time is to detect fall automatically and then promptly report the fall to the related medical personnel.

Many fall detection methods have been described in the literature [5-13]. There are two main types of fall monitoring devices: wearable and non-wearable. The simplest wearable device is a "Push-button", which can be manually activated in a fall case. Accelerometer-based wearable devices detect falls by measuring the applied acceleration along the vertical axis [5]. The wearable devices are inexpensive but they have two main drawbacks: they cannot be activated when a loss of consciousness occurs after a fall and they may not be worn at all times [6] (e.g. during nightly bathroom visits). Among the non-wearable devices, we mention floor vibration sensors [7], video cameras [8], infrared cameras [9], smart carpets [10] and microphone arrays [11-13]. All these methods are currently under development and show promising results. The main challenge of a fall detection system is to have as few false alarms as possible while detecting all the falls. Thus, it is necessary to develop multiple fall detection modalities together with multiple classification methods for each sensor and then fuse them using a sensor fusion framework.

Various studies have shown that radar sensors can be employed for human activities recognition [14]. Six features are extracted from a de-noised radar spectrogram and used to classify different human activities [15]. Human operators that listen to the Doppler audio output from the surveillance radar are able to detect and identify certain targets. The Doppler signatures are represented by mel-frequency cepstral coefficients features and a Gaussian Mixture Model (GMM) is used to classify activities with 88% accuracy [16]. Our previous work shows the feasibility of using gait velocity and stride duration to estimate the fall risk [17]. In [18] we proposed the idea of an automatic fall detection system that employs a Doppler range control radar (RCR). RCR uses the Doppler principle to estimate the relative velocities of the targets within the detection range. It is reasonable to investigate fall recognition based on the Doppler signature since a human fall comprises a series of human body part movements.

Fuzzy integral has been previously employed for information fusion and pattern classification [19-21]. A least square error methodology was proposed for training fuzzy measures for Choquet integral based on quadratic programming and a heuristic gradient-descent algorithm [20].

In this paper we present an application of classifier fusion methodology that aims at improving the fall detection rate while reducing the false alarm rate. It involves two RCR sensors and three classifiers (kNN, Bayes and SVM).

This paper is organized as follows: In section II, we describe the framework of our fall detection system and the available datasets. In section III, we describe the detection algorithms and its implementation. In section IV, we present and analyze the experimental results. The conclusions are given in section V.

II. SYSTEM ARCHITECTURE

Our fall detection system consists of two RCRs placed on the floor close to two adjacent corners of a room. We used a

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computer to record both RCRs Doppler signatures of various fall and non-fall events produced in the middle of the room by a trained actor [17, 18]. For each event, a two second radar signal signature was extracted as described in III.C. Then, we represented each activity signature using 6 Mel-frequency cepstral coefficients (MFCCs). The resulting feature vector was *k*=6x174=1044 long. We used three different algorithms, k-nearest neighbor (kNN), support vector machine (SVM) and naïve Bayes, to classify each activity signature as fall/non-fall. Each classifier generates a fall confidence, $Conf_i \in [0, 1]$. We evaluate each classifier using a receiver-operator characteristic (ROC) curve obtained by thresholding the fall confidence at different levels. We then compare the performance of individual classifiers and RCRs with the one obtained by Choquet integral fusion.

Our dataset has 450 samples, including 109 falls and 341 non falls. Two RCRs are recoding data at the same time. Our fall detection system has *N* sensors and *L* types of parallel-acting classifier that are trained on *M* samples. MFCC features of the i^{th} sample are denoted by $S_i = [S_{i1}, S_{i2}, ..., S_{ik}]$, where *i*=1,…, M is the sample index and *k* is the dimension of the feature vector. We used a "leave one out" testing methodology, i.e. in the i^{th} iteration, the i^{th} sample S_i is left for testing and the other *M*-1 samples are used for training. The entire methodology is shown in Fig. 1. For our case, *M*, *N* and *L* are 450, 2 and 3, respectively. The number of information sources that are fused is $N \times L$=6.

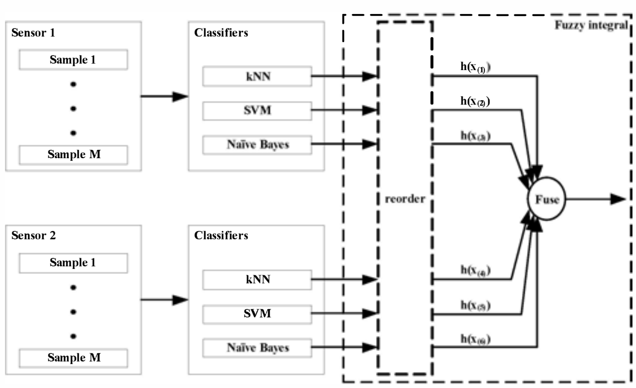


Fig. 1. The diagram of a fall detection system with fuzzy integral fusion

III. Algorithm Description

A. Fuzzy integration

Choquet fuzzy integral has been widely used in multiple source fusion cases [21]. Fuzzy measure is a representation of uncertainty. This is different from the assignment of membership grades in fuzzy sets. Membership grade represent the degree of membership in a particular set with unsharp boundaries for a value, which is assigned to each element of the universal set. Fuzzy measure represents the degree of evidence or belief that a particular element belongs to this set value by assigning a value to each crisp set of the universal set. Let $X = \{x_1, x_2, ..., x_n\}$ be any finite set and $\lambda > -1$. **Sugeno λ measure** is defined by the function *g*: $2^X \to [0,1]$ which has the following properties:

(1) $g(\Phi) = 0$ and $g(X) = 1$;

(2)if $A, B \subseteq X$ with $A \cap B \subseteq \Phi$, then

$$g(A \cup B) = g(A) + g(B) + \lambda g(A) g(B). \quad (1)$$

A set function satisfying the above conditions is a fuzzy measure. **Fuzzy density** can be defined by $g^i = g(\{x_i\})$.

The value of λ satisfies

$$\lambda + 1 = \prod_{i=1}^{n} (1 + \lambda g^i), \quad (2)$$

where $\lambda \neq 0$ and $\lambda > -1$.

To specify a Sugeno λ measure on a set *X* with *n* elements only requires *n* different densities, thus the number of free parameters is reduced from $2^n - 2$ to *n*.

Fuzzy Choquet integral can be used to fuse *n* different information sources from a discrete fuzzy set *X*. Let *h* be a function from *X* to [0,1]. Let $\{x_{(1)}, x_{(2)}, ..., x_{(n)}\}$ represent the reordering of the set *X* such that $h(x_{(1)}) \geq h(x_{(2)}) \geq ... \geq h(x_{(n)})$. Hence, the Choquet integral of *h* with respect to a fuzzy measure g on set *X* is defined by

$$\int_C hog = \sum_{i=1}^{n} h(x_{(i)}) [g(^{\alpha_i}H) - g(^{\alpha_{i-1}}H)], \quad (3)$$

where $^{\alpha_i}H = \{x_{(1)}, ..., x_{(i)}\}$ and $g(^{\alpha_0}H) = 0$.

Another general form of equation (1) is

$$g(\{^{\alpha_i}H\}) = g^i + g(\{^{\alpha_{i-1}}H\}) + \lambda g^i g(\{^{\alpha_{i-1}}H\}). \quad (4)$$

B. Learning the fuzzy measure

A gradient descent method is used to learn the fuzzy measure. Minimum square error is considered for a two-class classification problem. The cost function is defined as

$$E^2 = \frac{1}{2} \sum_{w \in C_1} (\int_C hog(h_w) - T_{C_1})^2 + \frac{1}{2} \sum_{w \in C_2} (\int_C hog(h_w) - T_{C_2})^2, \quad (5)$$

where T_{C_i} is the desired output for *i*th class and $\int_C hog(h_w)$ are minimized under constraints.

By taking a partial derivative with respect to each of the density g^j, we get

$$\frac{\partial E^2}{\partial g^j} = \sum_{w \in C_1} (\int_C hog(h_w) - T_{C_1}) \frac{\partial}{\partial g^j} \int_C hog(h_w) + \sum_{w \in C_2} (\int_C hog(h_w) - T_{C_2}) \frac{\partial}{\partial g^j} \int_C hog(h_w). \quad (6)$$

Gradient of the discrete Choquet integral with respect to Sugeno λ measure can be obtained by differentiating equation (3).

The partial derivative of (4) with respective to g^j is

$$\frac{\partial g(\{^{\alpha_i}H\})}{\partial g^j} = \frac{\partial g_{(i)}}{\partial g^j} + \frac{\partial g(\{^{\alpha_{i-1}}H\})}{\partial g^j} + \frac{\partial \lambda}{\partial g^j} g_{(i)} g(\{^{\alpha_{i-1}}H\}) + \lambda \frac{\partial g_{(i)}}{\partial g^j} g(\{^{\alpha_{i-1}}H\}) + \lambda g_{(i)} \frac{\partial g(\{^{\alpha_{i-1}}H\})}{\partial g^j}, \quad (7)$$

where $\partial\lambda/(\partial g^j)$ is deducted in [21] by

$$\frac{\partial \lambda}{\partial g^j} = \frac{\lambda^2 + \lambda}{1 + \lambda g^j [1 - (1+\lambda)\sum_{i=1}^{n}(\frac{g^j}{1+g^j\lambda})]}. \quad (8)$$

C. Algorithm

The flowchart of the algorithm is shown in Fig. 2.

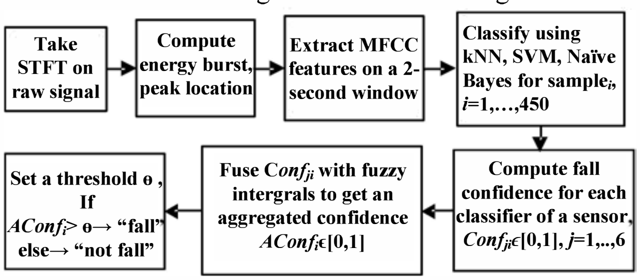


Fig. 2. The flowchart of fall detection algorithm

The major algorithm steps are as follows:

Step1: Compute the spectrogram with short time Fourier transform STFT(f, t) of the raw radar signal.

Step2: Compute the energy burst $EB(t)$ assuming a human torso motion frequency range of [25 Hz, 50 Hz], $EB(t) = \sum_{f=25Hz}^{50Hz} STFT(f,t)$, and its peak location t_{peak}.

Step3: Extract MFCC features from the raw radar signal with a 2-second window, which includes the peak location t_{peak} of the energy burst curve.

Step4: Classify the extracted MFCC features from each sample by three classifiers, kNN, SVM, Bayes, respectively.

Step5: The outputs of the classification result generate six groups of fall confidences $Conf_{ji} \in [0,1]$. Considering the difference among classifier, fall confidence for kNN, NB is obtained by

$Conf_{kNN/NB} = normalized((Dist_{fall} - Dist_{nonfall}) / Dist_{fall})$,

where $Dist_{fall}$ is the distance to the nearest fall from current testing sample, and $Dist_{nonfall}$ is the distance to the nearest non fall from current sample. For SVM, the probability for the current classification result is taken as the confidence.

Step6: Fuse $Conf_{ji}$ by Choquet fuzzy integral with learning fuzzy measure to obtained the aggregated $Conf_i$.

Step6.0: Random initialize the fuzzy densities: g^j , j=1,…6. Calculate the corresponding λ by equation (2).

Step6.1: Compute the fuzzy integral with equation (3).

Step6.2: Calculate $\partial E^2/(\partial g^j)$ by equations (4), (6) - (8) with $T_{C_1} = 1$ (fall) and $T_{C_2} = 0$ (non fall).

Step6.3: Update fuzzy density by $g^j_{new} = g^j_{old} + \alpha \partial E^2/(\partial g^j)$, α is the learning rate.

Step6.4: Calculate the total fuzzy density error from two continuous steps with $\sum_{j=1}^{6} | g^j_{new} - g^j_{old} | < \xi$. ξ is the calculation accuracy for fuzzy measure.

Step6.5: The iteration stops when the termination condition $\sum_{j=1}^{6} | g^j_{new} - g^j_{old} | < \xi$ is met or the maximum iteration step is achieved and step 6 is exited with the current fuzzy integral as the aggregated fall confidences $Conf_i$. Otherwise, go to the step 6.1 and continue the learning.

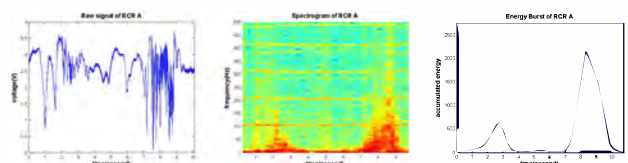
Step7: Threshold the aggregated fall confidences $Conf_i$, a final decision can be made and a ROC curve is drawn.

IV. Experimental Results and Analysis

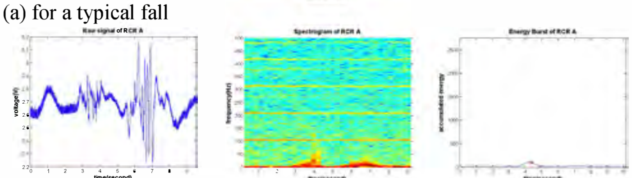
A. Radar signal and window size selection

Fig. 3 shows the raw signal, its spectrogram and the energy burst of a typical fall and false alarm for both RCRs.

Features extracted from a larger window size may cover more information. But the processing time for both feature extraction and classification will increase. There is a compromise between larger window and processing time. We chose the 2-second window size by trial and error.



(a) for a typical fall



(b) for a typical false alarm: "pick up a book from the floor"

Fig. 3. Doppler signal (speed), spectrogram and energy burst captured by RCR sensor A

B. Classification for each sensor

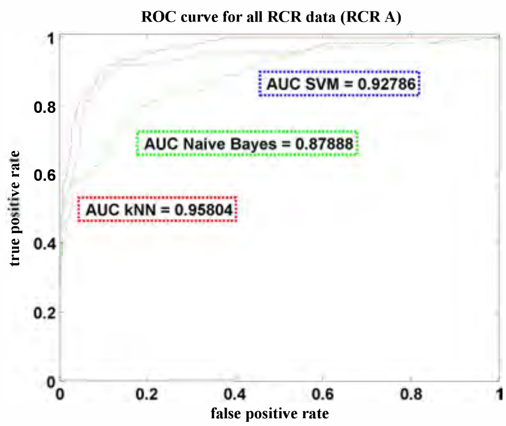
The ROC curves for each sensor and for 3 classifiers are shown in Fig. 4. We find that AUC value range is in [0.88, 0.97]. The best classifier in both cases is the kNN (k=1).

C. Fuzzy integrals with different fuzzy measure

We employed two different methods for defining the fuzzy measure: use the AUC values from each information source computed above and use the learned fuzzy measure proposed in this paper (see Fig. 5). We see that Choquet integral with the learned fuzzy measure performs better (by about 2.5%) than the one based on the AUC values. Also, the fusion result is slightly better (0.5%) that the best single classifier.

V. Conclusions

In this paper, we proposed a multiple sensor based fall detection system with Choquet Integrals for data fusion. Two Doppler radar sensors RCRs measure the relative speed of motion on a direction parallel to its emission axis. Since a human fall comprises a series of human body parts in motion, it is reasonable to investigate fall recognition based on the Doppler signature. MFCC features are used to represent the activity signatures. To further reduce the false alarm rate we employed three classifiers, kNN, SVM and Naïve Bayes. Although each standalone classifier produced reasonable results (AUC results between 0.88 and 0.97), we further increased the recognition performance using a fusion methodology based on the Choquet integral.



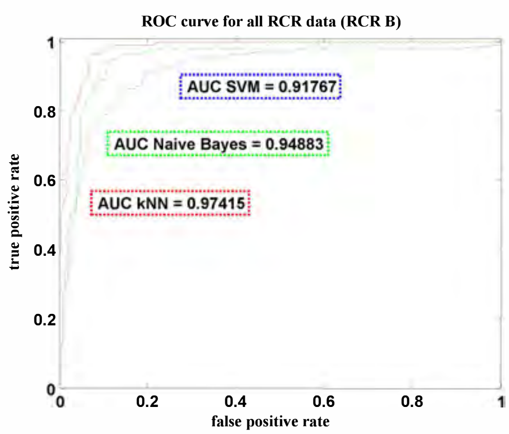


Fig. 4. RCR A and RCR B classification results with a 2-second window (red-kNN, blue-SVM, green-Navie Bayes)

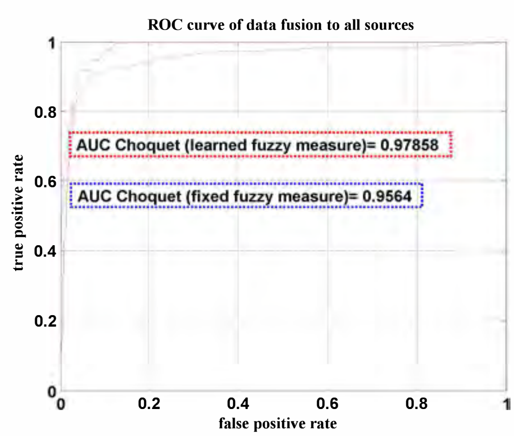


Fig. 5. Data fusion with Choquet integral (a) blue dot curve is from with fixed fuzzy measure from information sources' AUC; (b) red dash curve is with learned fuzzy measure.

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