# Feature Diverse Hierarchical Classification of Human Gait with CW Radar for Assisted Living

*Mehmet Saygın Seyfioğlu*[*], *Ahmet Serinöz*[*], *Ahmet Murat Özbayoğlu*[*], *Sevgi Zübeyde Gürbüz*[†]

[*]*TOBB University of Economics and Technology, Dept. Electrical-Electronics Eng., Ankara, Turkey*
[†]*University of Alabama, Dept. of Electrical and Computer Engineering, Tuscaloosa, AL, USA*

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## Abstract

Activity recognition and estimation of gait parameter are medically essential components of remote health monitoring systems that can improve quality of life, enable personalized treatments, acquire continual medical data to better inform doctors of the patient's well-being, reduce health costs, and ensure rapid response to medical emergencies. Discriminating between a large number of oftentimes similar activities using the radar micro-Doppler effect, however, requires extraction of features that can capture differences in nuances within the signatures. This optimal feature set varies according to the number and type of classes involved. Thus, this work proposes a novel feature diverse hierarchical classification structure, which prevents significant sources of confusion between classes. Our results show a 19% reduction in confusion between creeping and crawling and an elimination of confusion between falling and walking, yielding an overall 7.3% performance improvement above a multi-class support vector machine classifier.

## 1 Introduction

An important consequence of living in an increasingly global society is that we cannot always be near loved ones to offer constant care. Thus, there has been an increasing importance for developing remote health monitoring systems that can improve quality of live, enable personalized treatments, early diagnosis of disease, acquire continual medical data to guide doctor asssessments, and facilitate rapid response to emergencies. Although many sensors are being researched towards this application, radar-based systems have primarily focused on fall detection [1]. But, characterization of normal gait is critical not just for determining the transition from a walk to a fall [2], but also for assessing risk factors for falling [3,4], such as imbalance, lower body weakness and foot pain or injury, monitoring neurodegenerative diseases [5-7], and facilitating post-stroke walking rehabilitation [8]. Thus, the primary focus of this work is discriminating between many activities that have similar signature, such as aided and unaided walking, and indications of injury such as limping or crawling.

Continuous wave (CW) radar may be used to extract human gait information through the exploitation of the micro-Doppler effect [9]. Micro-Doppler is defined as frequency modulations caused by the rotation or vibration of parts of a target that appear centered about the main Doppler shift caused by relative translational motion. Thus, the periodic motion of the arms and limbs incurred during most human activities generates a micro-Doppler signature – joint time-frequency distribution of the radar return – that is unique to that specific motion.

Over the past 10 years there has been much research into algorithms for micro-Doppler based activity recognition [10-12], and especially fall detection [1]. However, differentiation between nuances in human gait with micro-Doppler radar has been less investigated. Amin, et. al. [3, 14] have studied in detail the differences in micro-Doppler signature between normal walking and walking using a cane. Gürbüz, et. al. [15] conducted a feasibility study for radar-based classification of elderly gait, showing results for the discrimination of walking, limping, walking with a cane, walking with a walker, and use of a wheelchair using three different systems: a 5.8 GHz wireless pulsed-Doppler radar, a 10 GHz CW radar, and a 24 GHz pulsed-Doppler radar. Results showed that the best overall performance was achieved by the 24 GHz radar at 80% correct classification with a support vector machine (SVM).

One of the most important factors on classification performance is the extraction of features that maximize the difference between different classes in a multi-dimensional feature space. The best set of features will necessarily change dependent upon the activities involved. As the number of classes increases, finding a universal feature set that distinguishes all classes becomes difficult. Thus, in this work, a feature diverse hierarchical structure is used to discriminate eleven different activities: 1) walking, 2) limping, 3) walking with a cane, 4) walking with a walker, 5) use of a wheelchair, 6) falling after tripping forward, 7) falling from chair, 8) fast sitting, 9) jogging, 10) walking with crutches and 11) crawling. At each level of the hierarchical structure, a different set of features is utilized, and the method some features are extracted is "tuned" or adapted according to the classes being considered. In this way, significant sources of confusion encountered with multi-class support vector machine (SVM) classifiers are eliminated.

This paper is structured as follows: in Section II, the experimental set-up for radar micro-Doppler measurements is given. In Section III, a detailed description of the freature diverse hierarchical classifier proposed is given, followed by classification results in Section IV.

## 2 Radar Micro-Doppler Measurements

Radar measurements for this study was conducted by programing a NI-USRP 2922 model software defined radio platform to transmit a 4 GHz continuous wave signal. The USRP-2922 has a 20 MHz bandwidth and is capable of broadcasting between frequencies of 400 MHz and 4.4 GHz. Two SAS-571 model horn antennas having 48° azimuthal beam width were used for transmit and receive. Both antennas and USRP were mounted upon a vertical panel raised 1 meter above the ground (Figure 1) and pointing directly in-line with the direction of motion for each data collect.

A total of 10 test subjects were utilized to collect a database of 842 measurements. Walking was enacted with both arms swinging in a mild fashion, while limping was done by role-playing that the left leg was injured and dragging behind the right. Two types of canes were used – a single poled cane and tripod – from which were randomly selected in the final database. Usage of a cane primarily constrains the motion of one arm; however, due to the subconscious coupling of arm motion, movement of the left arm while using a cane with the right hand is of lower amplitude than that experienced in normal walking. Movement with the aid of a walker, on the other hand, physically constrains both arms. A manual wheelchair was employed in the experiments, with test subjects turning the wheel rims with their hands to move forward. Falling was enacted by tripping on a brick and falling forward onto a mat placed on the ground.

A short-time Fourier transform (STFT), or spectrogram, is used to represent the time-frequency distribution of the return signal. Strong ground clutter returns were observed within +/- 5 Hz about 0 Hz, and the experiment was configured such that no strong multipath returns were noted in the radar signal. A 6$^{th}$ order Butterworth highpass filter was implemented to remove ground clutter returns.

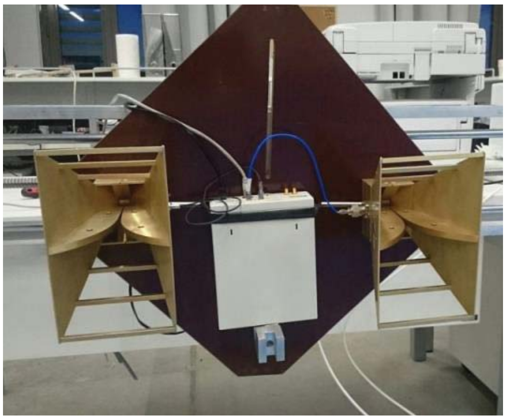

Figure 1. Panel-mounted CW radar.

## 3 Feature Diverse Hierarchial Classifier

In this work, a feature diverse hierarchical structure for classifying micro-Doppler signatures is proposed that uses a different set of tuned features at each hierarchical level to improve classification performance beyond that attainable with multi-class SVM.

### 3.1 Micro-Doppler Features

Over the years a plethora of features have been proposed for micro-Doppler classification [16]. These include but are not limited to physical features [17], speech features [18], such as mel-frequency cepstral coefficients (MFCC) and linear predictive coding (LPC) coefficients [19], Discrete Cosine Transform (DCT) coefficients [20], and Singular Value Decomposition (SVD) [21] or Principle Component Analysis (PCA) eigenvalues [22]. All together, hundreds of features may be extracted; however, use of all possible features does not guarantee the best performance due to the curse of dimensionality. A small number of appropriately selected features have been shown to yield better performance for micro-Doppler classification [23]. The selection of micro-Doppler features can be dependent upon a number of factors, such as aspect angle, signal-to-noise ratio, and observation duration (dwell time) as well as the particular classes being considered. Explicit execution of wrapper or metric-based feature selection methods, such as mutual information [23], can be used to select an optimal set of features under any operational condition – termed feature diversity, this approach was originally proposed for selection of different feature sets across multiple channels or sensors [24]. In this work, a finite sub-set of features, comprised of linear predictive coding coefficients (LPC), discrete-cosine coefficients (DCT), and cepstral coefficients were empirically selected based on experience in combination with a novel set of tunable features to enable feature diversity and, hence, utilization of different sub-sets of features across different levels in the hierarchical structure.

### 3.2 Feature Tuning

MFCC features are cepstral filters whose filterbank has been optimized for classification of human speech using the mel-frequency scale. In previous work [25], it was shown that the mel-scale was not appropriate for human micro-Doppler because the frequencies spanned by the mel-scale were not matched to the overall Doppler spread of the radar return and eliminated coefficients corresponding to negative Doppler. An alternate cepstral feature was proposed, namely, hyperbolically-warped cepstral coefficients (HWCC), which significantly improved feature discrimitivity for human micro-Doppler, and which *enable the design of filter-banks used in the extraction of features based upon the classes being considered or other situational and operational parameters*.

HWCC features are computed by first taking the FFT of the received radar return, and then passing the signal through a filterbank, afterwhich the logarithm and DCT is computed to yield the cepstral features. In HWCC, however, the filterbank is not specified using the mel-scale, but rather a hyperbolic tangent function:

$$f_{HH} = a\, tanh(f_{Hz} - b)/c \qquad (1)$$

where $a$ is the amplitude, $b$ is the shifting value of the function and $c$ is the degree of warping. Hyperbolic warping enables the filter bank to be designed to capture the greatest energy through tuning of the parameters $a$, $b$, and $c$. By changing the values of the parameters in the hyperbolic function, the frequencies spanned by the filterbank can be changed *according to the activities being classified.* HWCC features

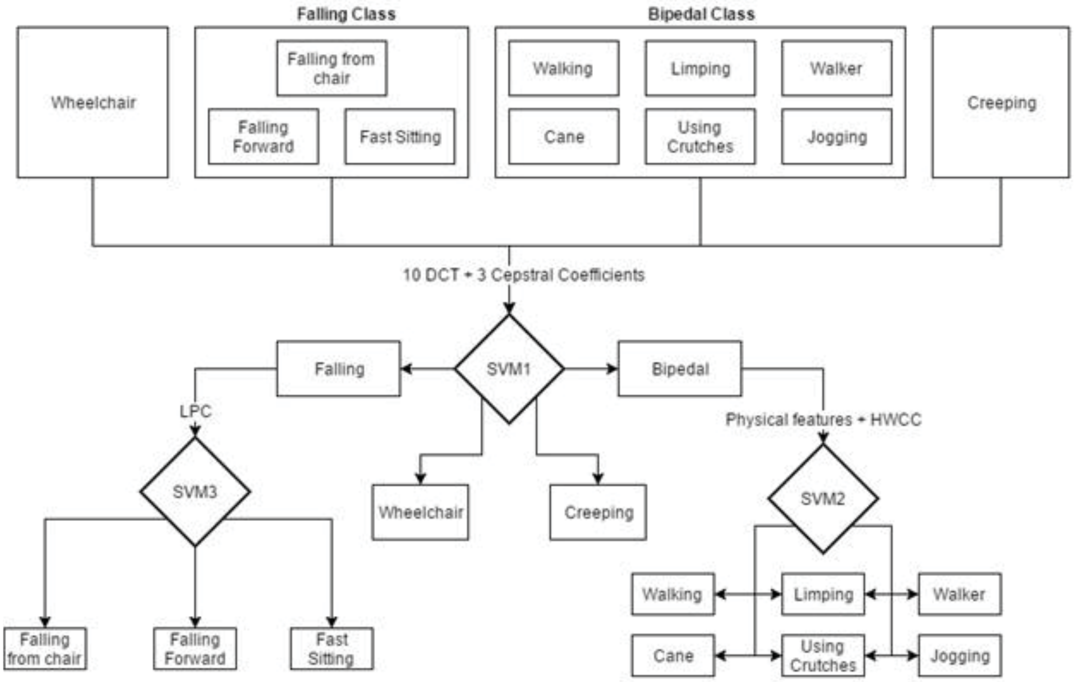


Figure 2. Block diagram of proposed feature diverse hierarchical classification structure.

computed at different nodes of the hierarchical structure can be computed differently to account for differences is the Doppler spread observed in different classes. This tuning process improves the ability of HWCC to discriminate the nuances in micro-Doppler features.

### 3.3 Hierarchical Classification Structure

In this work, a two-level hierarchical structure (Figure 2) is proposed in which first groups include similar gaits are grouped together. Walking, limping, walking with a cane, walking with a walker, using crutches and jogging are grouped into a single bipedal class, also falling from chair, falling forward and fast sitting are grouped into a single falling class. Then falling and bipedal classes are discriminated from crawling and wheelchair use. In the second level, the bipedal class and falling class are separated into its individual sub-classes.

In the first level, it was found that use of 10 DCT and 3 cepstral coefficients yielded the highest performance. In fact, the use of cepstral coefficients at this stage was observed to be absolutely essential because falling is not a periodic movement exhibits prominent energy bursts as compared to the other classes [26]. 10 manually tuned HWCC coefficients, and 13 physical features yielded the greatest performance. For the bipedal classes considered, the greatest class separation was achieved when the HWCC features were manually tuned with parameter values of $a = 400$, $b = 0$ and $c = 900$.

For classifying falling, 101 LPC coefficients were found to give the best performance. It was also seen that, even if all the features were employed to classify falling class, the classification performance did not increase noticeably.

## 4 Results

The measured data set presented in Section II was classified by first randomly selection 60% of the data to comprise the training set, with the remaining 40% utilized as a test set. A support vector machine (SVM) classifier was used to distinguish falling, wheelchair use, bipedal motion and creeping.

The training samples that correspond to the bipedal classes are then used to train the classifier in the second level. Signatures identified in the test set as bipedal activities by the first level is then used as the test set in the second level. Again, a SVM classifier is used to distinguish walking, limping, walking with a cane, walking with crutches, jogging and walking with a walker in the second level. The same approach was followed for falling class.

To increase the robustness of the classification results, this procedure is repeated 20 times and the final results obtained by taking the mean of 20 different confusion matrixes.

Performance of the proposed feature diverse hierarchical classifier is compared against the results obtained from that of multi-class SVM classification of all eleven classes. Confusion matricies for multi-class SVM and each stage of the feature diverse hierarchical classifier are shown in Tables 1 - 3. The overall classification performance of hSVM is 83.35%, which is 7.31% higher than that of multi-class SVM, which has an overall classification performance of 76.04%.

The most confusion is experienced between the classes of walker and cane. This is not unexpected because even though cane usage only explicitly constrains the swing of just one arm, subconsciously people tend to limit arm swing in the free arm when the other arm is constrained. Thus, the measured

| % | Walking | Wheelchair | Limping | Cane | Walker | Jogging | Crawling | Crutches | Sitting Fast | Falling From Chair | Falling |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Walking** | 98.04 | 0 | 0 | 0 | 0 | 0 | 1.25 | 0.71 | 0 | 0 | 0 |
| **Wheelchair** | 0 | 76.19 | 6.78 | 8.31 | 6.95 | 1.36 | 0.42 | 0 | 0 | 0 | 0 |
| **Limping** | 0 | 8.38 | 67.25 | 19.38 | 3.123 | 1.88 | 0 | 0 | 0 | 0 | 0 |
| **Cane** | 0 | 12.45 | 9.91 | 64.15 | 13.49 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Walker** | 0 | 3.82 | 6.09 | 10.82 | 79.27 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Jogging** | 1.9 | 1.09 | 3.26 | 0 | 0.22 | 93.04 | 1.30 | 0 | 0 | 0 | 0 |
| **Crawling** | 34.2 | 0 | 0 | 0 | 0 | 1.15 | 54.23 | 10.38 | 0 | 0 | 0 |
| **Crutches** | 3.68 | 0.26 | 0 | 0 | 1.05 | 0 | 0 | 95 | 0 | 0 | 0 |
| **Sitting Fast** | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 77 | 11 | 0 |
| **Falling from Chair** | 7.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1.5 | 86 | 5 |
| **Falling** | 18.75 | 1.875 | 0 | 0 | 0 | 2.5 | 0 | 0 | 6.88 | 23.75 | 46.25 |

Table 1. Confusion matrix for multi-class SVM classifier.

| % | Walking | Wheelchair | Limping | Cane | Walker | Jogging | Crawling | Crutches | Sitting Fast | Falling From Chair | Falling |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Walking** | 98.27 | 0 | 0 | 0 | 0 | 0 | 0.48 | 1.25 | 0 | 0 | 0 |
| **Wheelchair** | 0 | 84 | 3.15 | 8.16 | 3.12 | 1.23 | 0.34 | 0 | 0 | 0 | 0 |
| **Limping** | 0 | 0.39 | 76.61 | 15.88 | 3.875 | 3.25 | 0 | 0 | 0 | 0 | 0 |
| **Cane** | 0 | 2.69 | 8.77 | 72.03 | 16.42 | 0.094 | 0 | 0 | 0 | 0 | 0 |
| **Walker** | 0 | 0.18 | 7.36 | 11.91 | 80.55 | 0 | 0 | 0 | 0 | 0 | 0 |
| **Jogging** | 2.61 | 0.19 | 1.09 | 0 | 0 | 95.54 | 0.57 | 0 | 0 | 0 | 0 |
| **Crawling** | 15.16 | 1.54 | 0 | 0 | 0 | 1.2 | 78 | 4.1 | 0 | 0 | 0 |
| **Crutches** | 6.58 | 0 | 0 | 0.26 | 0 | 0.26 | 0 | 92.9 | 0 | 0 | 0 |
| **Sitting Fast** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 88.5 | 11.5 | 0 |
| **Falling from Chair** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 7.91 | 91.67 | 0.416 |
| **Falling** | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 12.5 | 28.75 | 58.75 |

Table 2. Confusion matrix for proposed feature diverse hierarchical classifier.

micro-Doppler signature of cane usage is highly similar to that of walker usage, which constrains both arms. Also falling from chair has quite similar characteristics with falling forward.

## 5 Conclusion

In this work a novel feature diverse hierarchical SVM classification strategy is proposed for the classification of elderly gaits. The filter bank of the novel hyperbolically warped cepstral features is adjusted so as to ensure maximal discrimitivity of features for bipedal gaits and at each level of the classifier an optimally selected feature set is used for classification. An overall classification result of 83.35%, which is 7.31% higher than the performance obtained with multi-class SVM. Moreover, significant sources of confusion were either reduced or eliminated, such as between walking and crawling, as well as falling and walking. Future work will focus on the use of self-organizing maps to automate determination of hierarchial structure.


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