Classification of Human Motion Using Radar Micro-Doppler Signatures with Hidden Markov Models

Mehmet Onur Padar
ASELSAN Inc.
Ankara, Turkey
mopadar@aselsan.com.tr

Ali Erdem Ertan
ASELSAN Inc.
Ankara, Turkey
eertan@aselsan.com.tr

Çağatay Candan
Middle East Technical University
Ankara, Turkey
ccandan@metu.edu.tr

ABSTRACT

One of the desirable features in a ground surveillance radar is to provide information about what a detected person is doing. This would give a law enforcement organization ability to detect suspicious activities remotely and act accordingly. Previously, micro-Doppler radar signatures from humans were shown to have the necessary features to make that distinction. Typically, micro-Doppler signal spectrograms are used to obtain features to classify what the person is doing. However, most of these techniques treat the spectrogram as an image, and obtain features through some image processing techniques. In this work, we propose the use of hidden Markov models as an alternative method to statistically model both instantaneous and correlated long-term variations within the micro-Doppler signal to classify a motion. In addition, we propose use of principle component analysis (PCA) as a data driven feature extraction approach that captures vital statistics of the input at a much reduced dimension. Experiments show that with the proposed methods, perfect classification of four different motions can be attained when training and testing set both contains data from same people, and 90% accuracy is obtained when training and testing set has data from different people.

Keywords: Hidden Markov Model, Micro Doppler Signature, Spectrogram, Feature Extraction, Principal Component Analysis, Human Motion Classification.

1. INTRODUCTION

Ground surveillance radars are widely used for both military purposes and civilian applications all over the world. A typical ground surveillance radar can detect a large vehicle from 60 kilometers and a pedestrian from 12 kilometers. Its ability to do surveillance under almost all weather conditions and regardless of sunlight existence makes them crucial for border protection.

When range resolution of a pulsed-Doppler radar is low, most targets detected with a ground surveillance radar can usually be considered as point targets. This is not only true on range axis but also true on Doppler axis as well. However, when detected target is a moving human and radar has high Doppler resolution, a Doppler spread is usually observed in the return signal when SNR is sufficiently large. The reason for this is different parts of the body make different motions, and these motions with different speeds result into different Doppler frequencies. Therefore, radar return signal from moving human contains multiple components with different RCS values and Doppler frequencies [1], [2], [3]. Although this spread may sometimes result in multiple detections from the same target which is not desirable from detection point of view, it can be used to classify the target and/or its motion type. The research area that deals with this phenomenon in radar applications is called micro-Doppler signal processing.

Different types of human motion result in body parts such as hand, foot and head moving differently. Therefore, different types of human motion generate different echo returns which are called as micro-Doppler signatures [4], [5]. These signatures change in time and are periodic where period depends on the speed of the target [3]. By using the characteristic features in the signatures, it is possible to classify various human motions. Youngwook uses artificial neural network in [6] and support vector machine in [7] for classification of human motions. Li chooses principal component analysis to make the discrimination between different movements of a human in [8]. Alemdaroğlu examines the human motion data and extracts the features of the echo in order to classify the different type of human movements [9].

All of these techniques treats the problem as an image classification problem, and therefore, work on the spectrograms itself for feature estimation and classification. As an alternative, one can also observe that radar return signal for human motion is in fact can be modeled as a sum of complex exponentials with constant magnitudes and time-varying frequencies as shown in Figure 1. As the time-varying frequency components have cyclic nature with period same for all complex exponentials, the observed signal also has a cyclic nature with the same period. This opens up a possibility for a modeling method that captures the characteristics of the signal in very short-time periods (i.e. instantaneous frequencies) and the time-varying nature of the signal (i.e. time varying characteristics of these frequencies). The hidden Markov model (HMM) is an excellent tool to capture both characteristics and can also be used for classification purpose.

In this study, we approach the problem in three important steps: As we are trying to capture the characteristics of instantaneous frequencies, the signal in the analysis window should be stationary (or very slowly time-varying). Therefore,

978-1-5090-0863-6/16/$31.00 ©2016 IEEE

in the first step, proper length of analysis window is investigated. This should also be an important aspect of all spectrogram based methods as the input to the FFT also should be stationary in order to prevent smearing. However, we are not aware of any study that determines the optimum window length. Second, although FFT coefficients are always used as basis of the features for micro-Doppler signature classification, there is no study, which investigates whether FFT is the most optimal transformation for human motion data that decorrelates input signal. In this study, we explore data driven transformation method that generates basis vectors that decorrelates input signal and results in coefficients more suitable for classification. Finally, HMM is used to model the time-varying characteristics of those features for four different types of human motion, namely walking, running, crawling, creeping.

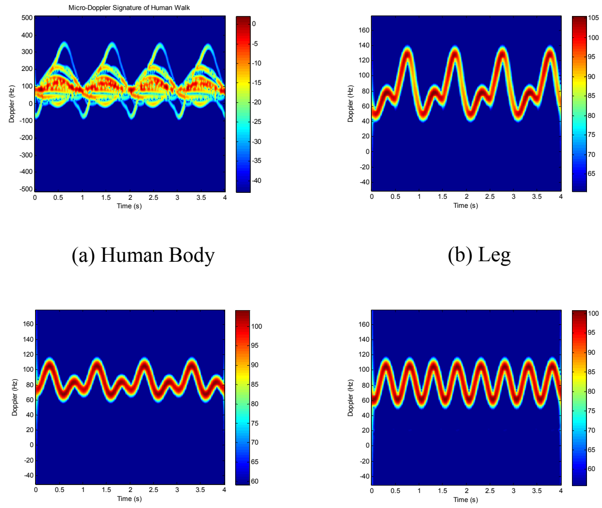
The outline of the paper is as follows: In the next section, a method to obtain optimum analysis frame length is proposed. Section 3 describes the data generation method for a pulse-Doppler ground surveillance radar. In Section 4, we presented data driven feature extraction method and classification of human motion using hidden Markov models is explained in Section 5. Finally, Section 6 presents conclusive remarks.

2. DETERMINATION OF ANALYSIS WINDOW LENGTH

As mentioned in the introduction section, the first part of this study is to determine suitable length for analysis window. The transformation techniques like FFT assume that the signal inside the analysis window is stationary. However, if the duration of the analysis window is not selected properly, there may be sharp frequency and magnitude changes within the analysis window which smears a frequency component into multiple FFT bins. However, one also would like the analysis window as long as possible as frequency resolution is inversely proportional to the length of the window; having proper frequency resolution is essential as low frequency components can properly be observed and components from multiple frequencies can be separated in the frequency domain only when frequency resolution is sufficient. Therefore, optimum analysis window length should be determined such that the signal inside the window is stationary (or time varying but does not result in any smearing) and it is as long as possible.

For this purpose, human walking simulator of Chen [1] is used to determine the best window size for human motion. To do so, the variation in the frequency from all body parts is investigated during a walking cycle: Returned signal from a human body in motion has the main frequency component around torso frequency modulated with the Doppler frequency of the whole body's movement. In addition, there are other moving and vibrating segments on the body as well during the movement. These frequency components can be seen between Figure 1(b) and Figure 1(d) which include spectrograms of body parts obtained for human walking motion by Chen's simulator [1]. Radar echo return from the body includes all these frequency components as shown in Figure 1(a) [5].

An experiment to determine the analysis window length is conducted using the human walking simulator of Chen [1].To do so, we defined two tests to examine the stationarity of the signal inside a window. First, when the frequency change within the window spans multiple FFT bins, frequency smearing is observed at the FFT output. In order to prevent this, the window length should be selected such that the change in the frequencies from all body parts should be within a single FFT bin as much as possible. Second, the change in frequency within the analysis window also affects the magnitude at the closest FFT bin. The window length should also be chosen so that the estimated magnitude of the time-varying frequency component at the closest FFT bin does not change significantly compared to magnitude of the FFT of a signal with a completely stationary frequency.



(a) Human Body (b) Leg

(c) Arm (d) Head

Figure 1. The spectrograms of human walking motion for (a) all body, (b) leg only, (c) arm only ,and (d) head only obtained by Chen's human walking simulator [1]

To satisfy the first constraint, we devised the following test: With the human walking simulator, we generated the Doppler frequency as a function of time for all body parts as shown in Figure 2. Then, for seven different window lengths ranging from 2.5 ms to 100 ms as shown in Table 1, the change in frequency within the window is measured on a frame-by-frame basis with a sliding window of one sample. This gives us the amount of change in frequency within a frame as a function of time. Then, we count percentage of the frames in which frequency change exceeds frequency resolution. The analysis window lengths that limit such change only in 5% of the entire cycle is considered to satisfy the first constraint discussed above. The results can be seen in "Max Frequency Variation" and "FFT Bin Test" columns in Table 1 for three limbs.

To verify the second constraint, the same setup is used, but this time, two signals are generated for each frame: one with the time varying frequency, and the other with a single constant frequency which is average of the frequency variation in the frame. Then, FFT of both signals are computed and the magnitude of the FFT bin closest to the time varying frequency is recorded in both of them. We consider 1 dB change insignificant, therefore analysis window lengths that limit the change by 1 dB in 90% of the frames can be considered stationary. The results can be seen in “dB Test” columns in Table 1 for three limbs. In these experiments, although only three limbs of human body are shown in Figure 2 and Table 1, we have examined all limbs on the body (shoulder, knee, elbow, hand, foot, torso, leg, arm, head, hip, neck) and concluded that the frequency change characteristics for each of these body part are always similar to one of these three limbs.

These results show that 20 ms window length always satisfies both stationarity constraints. This window length provides a frequency resolution of 50 Hz which should be sufficient to capture low frequency components and to avoid frequency smearing for the four motion types examined in this study; walking, running, creeping and crawling.

As a side note, these results also proves that radars with shorter wavelength have advantage in better obtaining micro-Doppler signatures compared to radars with longer wavelengths as the Doppler frequencies are larger which in turn allows less Doppler frequency resolution in analysis and the use of shorter windows.

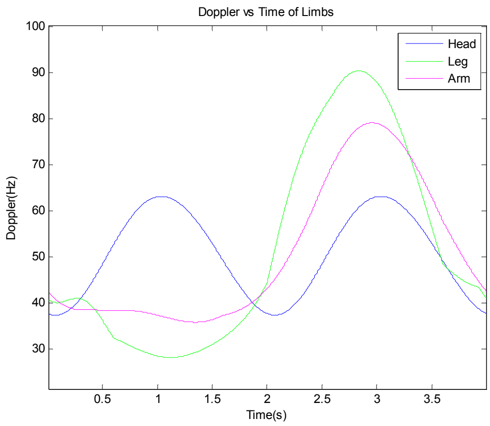


Figure 2. Doppler frequencies of head, arm and leg during walking in a single cycle

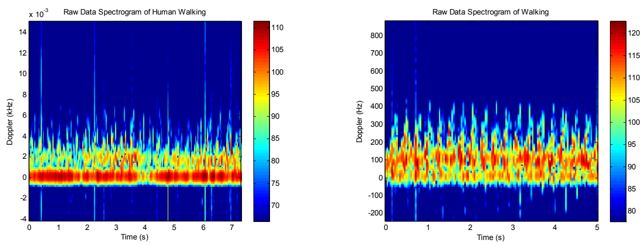
Table 1. Window size calculations

LIMB (RCS m^2)	WINDOW SIZE	MAX FREQUENCY VARIATION (Hz)	FFT BIN TEST	dB TEST
HEAD (0.0407-0.0425)	2.5 ms	0.26193	0: %100 1: %0	<1: %100 >1: %0
	5 ms	0.53761	0: %100 1: %0	<1: %100 >1: %0
	10 ms	1.0888	0: %100 1: %0	<1: %100 >1: %0
	20 ms	2.1902	0: %100 1: %0	<1: %100 >1: %0
	30 ms	3.2874	0: %100 1: %0	<1: %97 >1: %3
	45 ms	4.8991	0: %91.11 1: %8.89	<1: %91.7 >1: %8.3
	100 ms	10.7946	0: %45 1: %55	<1: %57.8 >1: %42.2
LEG (0.0128-0.3054)	2.5 ms	0.8709	0: %99.76 1: %0.14	<1: %100 >1: %0
	5 ms	1.7875	0: %99.5 1: %0.5	<1: %100 >1: %0
	10 ms	3.6206	0: %99.02 1: %0.98	<1: %100 >1: %0
	20 ms	7.257	0: %96.08 1: %3.92	<1: %100 >1: %0
	30 ms	10.7684	0: %88.24 1: %11.76	<1: %90.4 >1: %9.6
	45 ms	16.2625	0: %77.8 1: %22.2	<1: %85.9 >1: %14.1
	100 ms	31.1043	0: %35 1: %35 >1: %30	<1: %70 >1: %30
ARM (0.0078-0.1487)	2.5 ms	0.39086	0: %100 1: %0	<1: %100 >1: %0
	5 ms	0.80224	0: %100 1: %0	<1: %100 >1: %0
	10 ms	1.625	0: %100 1: %0	<1: %100 >1: %0
	20 ms	3.2687	0: %96.07 1: %3.93	<1: %97.6 >1: %2.4
	30 ms	4.9068	0: %94.11 1: %5.89	<1: %86.77 >1: %13.33
	45 ms	7.3711	0: %86.7 1: %13.3	<1: %66.9 >1: %33.1
	100 ms	16.2824	0: %35 1: %55 >1: %10	<1: %60 >1: %40

3. DATA GENERATION FOR FEATURE EXTRACTION AND CLASSIFICATION

Pulsed ground surveillance radars typically transmit a number of coherent pulses that form coherent processing interval (CPI), and then, process the received echo signal in the same range bin from all pulses with a Doppler filter bank to discriminate between stationary clutter and multiple targets with different radial velocities. In addition to solve ambiguities in range and Doppler, multiple CPI’s with different PRFs are transmitted and processed together.

Obtaining the data for micro-Doppler signal processing from such ground surveillance radar is more complicated compared to CW radar. The data required can be constructed from radar echo returns from each transmitted pulse in the range bin that contains the target. However, as the data are obtained as CPIs with different sampling rates, the signal in each CPI is first resampled to a fixed PRF (8 kHz in our tests). Original and resampled raw data spectrograms of human walking movement can be seen on Figure 3.



(a) (b)

Figure 3. Spectrogram of (a) original and (b) resampled signals

After the PRF conversion and the data from successive CPIs are concatenated, the resulting time domain signal is then filtered with a high-pass filter in order to eliminate the stationary clutter in the signal whose Doppler is around zero. Then, requested frame length of signal vectors are extracted on a frame-by-frame basis with a sliding window of one sample for data driven feature extraction and with a sliding window of 5 ms for HMM experiments as:

$$\mathbf{x_k} = [\boldsymbol{x}[(\boldsymbol{k}-\mathbf{1}) * \boldsymbol{M} + \mathbf{1}]\boldsymbol{x}[(\boldsymbol{k}-\mathbf{1}) * \boldsymbol{M} + \mathbf{2}] \cdots \boldsymbol{x}[(\boldsymbol{k}-\mathbf{1}) * \boldsymbol{M} + \boldsymbol{L}]]^{\boldsymbol{T}} .$$

where M is the length of sliding window, L is the analysis frame length, both in samples, x[n] is the high-pass filtered micro-doppler signal, and $\mathbf{x_k}$ is the kth frame. The vectors are then written into a matrix as the columns to be processed in the feature extraction and data classification sections.

The data used in these experiments are obtained by a Ku-band ground surveillance radar for walking, running, crawling and creeping motion. The database contains 50 recordings from 5 people in which three recordings are obtained for running and walking motion, and two recordings are obtained for creeping and crawling motion from every person.

4. DATA DRIVEN FEATURE EXTRACTION

As explained in the introduction section, the studies on micro-Doppler signal processing in general are based on Fourier transform and examination of the spectrogram of different motions [3], [4], and extracting features from spectrogram [7-9]. Although the use of FFT is sufficient in these studies, FFT coefficients may not be optimal to be used in HMM. As HMM requires estimation of a number of features from the input signal on a frame-by-frame basis, it is best to have features that are uncorrelated in nature. In addition, as the joint probability distribution function of features are also required in HMM, it is always best to have a feature set with as small dimension as possible so that pdf's can be estimated reliably. Unfortunately, FFT coefficients are not uncorrelated and all FFT coefficients that include the largest possible Doppler components should be preserved. For this reason, FFT coefficients do not satisfy these two desirable features.

Principal component analysis (PCA) is one of the methods that produce transformation vectors that decorrelate input. To achieve this, this transformation is defined in such a way that the first principal component has the largest possible variance, which accounts for the largest variability in the data, and each succeeding component in turn has the highest variance possible under the constraint that it is orthogonal to the preceding components. Therefore, the resulting vectors are eigenvectors of the covariance matrix with their eigenvalues corresponding to variance in the signal in that direction. Those eigenvectors also forms an orthogonal basis set.

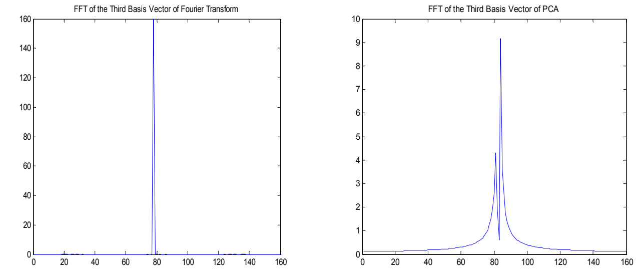
PCA is perfect fit for our purpose: it decorrelates the input measurements, and at the same time, only the first few eigenvectors with the largest eigenvalues can be used as transformation vectors to obtain the features that capture most of the variation in the signal, therefore reducing the dimension compared to input signal.

After obtaining the data matrix from training set as discussed in Section 3, the covariance matrix of the time domain signal is calculated as:

$$\mathbf{C} = \mathbf{X}\mathbf{X}^{\mathbf{H}}$$

and PCA is performed to find eigenvectors and associated eigenvalues. It is a general understanding that 95% of the total variance captured within the feature vectors is sufficient for classification purpose. Therefore, we first compute cumulative eigenvalues in which a cumulative eigenvector for an index is computed as the summation of all eigenvalues up to that index, and examine eigenvectors in the sense of energy coverage. Initially, we perform this analysis for four different types of human motion independently. For 20 ms analysis window, it can be seen on Figure 5 that while five eigenvectors cover 95% of energy for running and walking, twenty eigenvectors are needed to span 95% of energy for creeping and crawling. For this reason, the feature vectors should be extracted with 20 eigenvectors of the covariance matrix with the largest eigenvalues for 20 ms frames.

Once the number of eigenvectors to be used in feature extraction is selected, the autocorrelation matrix and its associated eigenvectors are computed using the data from all motions. Figure 4 compares one of the eigenvectors to a Fourier transform basis function using DFT of both. It can be seen that although FFT basis vectors are tuned to a single frequency, PCA basis vectors always include multiple frequency components with varying magnitudes.



(a) Example basis vector of FT (b) Example basis vector of PCA

Figure 4. Fourier transform of the basis vectors of FT and PCA

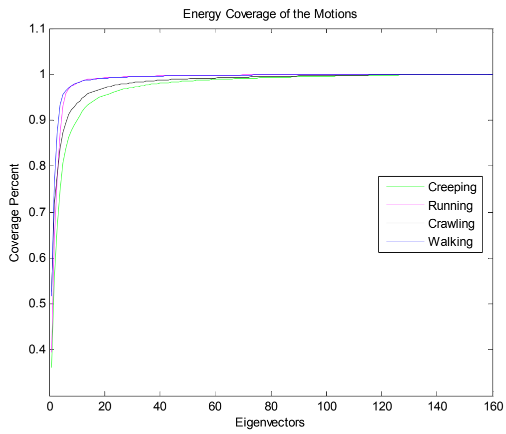


Figure 5. Energy coverage of four different motions

Once the eigenvectors are obtained for the desired frame length, the feature vectors for each frame to be used in HMM are generated by projecting input frames onto the desired numbers of eigenvectors with the largest eigenvalues as

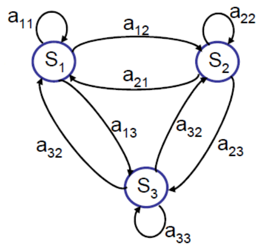
$$\hat{\mathbf{x}}_{\mathbf{k}} = \mathbf{x}_{\mathbf{k}}^{\mathbf{T}}\mathbf{E}$$

where $\mathbf{x}_k$ is the k[th] frame of input signal and $\mathbf{E}$ is the matrix whose columns are the eigenvectors.

5. CLASSIFICATION OF HUMAN MOTIONS USING HIDDEN MARKOV MODELS

Hidden Markov model is a statistical model in which the observations are assumed to be outcomes of a Markov process with hidden states [10]. In HMM, the states are not directly observable, but the observations are dependent on the states. Each state is therefore characterized by a joint probability distribution over the observation space. The model is then completed by the probabilities of state transitions from one state to the next and initial state probabilities. A three state HMM model can be seen on Figure 6.

HMMs can also be used for classification purpose: For each class, an HMM can be trained with Baum-Welch algorithm with a set of observation sequences belonging to this class. After all HMMs for all classes are trained, the class of a new observation sequence can be determined by computing maximum joint probability over all possible state sequences (efficiently with Viterbi algorithm), and selecting the model with the largest joint state sequence probability.



• Transition Parameters

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix}$$

• Initial State Probability

$$\pi_i = P[q_1 = S_i] \qquad 1 \le i \le N$$

Figure 6. A simple three state HMM structure

Time-domain micro-Doppler signal has a cyclic characteristic. This gives us the idea that it can be modeled with HMM with cyclic transitions between a number of states. In this work, we process input signal on a frame-by-frame basis with a pre-determined overlap percentage, and each frame is then transformed using a pre-determined number of the eigenvectors. The magnitudes of resulting coefficients form the observation for the frame. Once observation sequence is obtained by concatenating observations from successive frames in the entire signal, it can be used either for training of an HMM model, or can be used to identify the class that the sequence belongs to.

In this study, Murphy's HMM tool [11] is used to model the time-domain micro-Doppler signal of four different motions with HMM. These are walking, running, creeping and crawling. We devised two experiments: The first experiment use different recordings from the same people for training and testing. In the second experiment, all recordings for three people are used for training and all recordings from two different people are used for testing. The first and second experiments allow us to see the performance of the modeling for human dependent and human independent systems, respectively. In addition, different frame lengths and different number of eigenvectors used in transformation are tested. It is expected that 20 ms frames and 20 eigenvectors should work best.

A) Classification Experiment 1

In this experiment, 30 of the recordings from the five people are used as training set. The set contains 10 different recordings for walking and running and 5 different recordings for crawling and creeping. Then, an HMM is trained for each of these four classes. Tests are conducted with the remaining 20 recordings from the same five people. The experiment is repeated for four different combinations of the recordings used as training and test set.

In these tests, a four state hidden Markov model is used. As an example, the transition matrix and initial state vector for crawling HMM model after training can be seen as on Table 2. The numbers on the transition probability matrix represents the probabilities for transitions from one state to another. Initial state probability vector represents how likely a sequence begins with a particular state.

Table 2. Transition matrix and initial state vector for crawling

Crawling	Transition Probability Matrix State 1	State 2	State 3	State 4	Initial State Probability Vector
State 1	0.73	0.04	0.18	0.03	0.4
State 2	0.02	0.81	0.16	0	0.4
State 3	0.16	0.19	0.62	0.01	0
State 4	0.15	0	0.02	0.81	0.2

After generating the models for each set, each recording in the test set is converted to an observation sequence as discussed above and log likelihood of the sequence for each model is calculated. The class of the sequence is determined as model with the largest log-likelihood. The classification results for the 20 test sequence for different window lengths and different number of eigenvectors used in transformation are given in Table 3.

The results show that perfect classification can be achieved by 20 ms frame length and 20 eigenvectors used for feature extraction as expected. The classification success gets worse when the number of eigenvectors is reduced or length of analysis window is changed. When we decrease the number of eigenvectors, less of the variation in the signal which is also relevant for classification is used. On the other hand, when we increase the analysis window length, the chance of time-domain signal being non-stationary inside the window increases, and when we decrease window length, the frequency resolution suffers. Therefore, as expected, we obtained the best results with 20 eigenvectors and 20 ms analysis window length.

Table 3. Results of Classification Experiment 1

	Motion	Creeping	Crawling	Running	Walking
20ms Window 20 Eigenvectors	Creeping	20/20	0/20	0/20	0/20
	Crawling	0/20	20/20	0/20	0/20
	Running	0/20	0/20	20/20	0/20
	Walking	0/20	0/20	0/20	20/20
45ms Window 20 Eigenvectors	Creeping	18/20	2/20	0/20	0/20
	Crawling	2/20	18/20	0/20	0/20
	Running	0/20	0/20	19/20	1/20
	Walking	1/20	0/20	3/20	16/20
10ms Window 20 Eigenvectors	Creeping	15/20	3/20	0/20	2/20
	Crawling	1/20	19/20	0/20	0/20
	Running	0/20	0/20	18/20	2/20
	Walking	1/20	0/20	2/20	17/20
20ms Window 5 Eigenvectors	Creeping	14/20	4/20	0/20	2/20
	Crawling	2/20	18/20	0/20	0/20
	Running	0/20	0/20	18/20	2/20
	Walking	1/20	0/20	3/20	16/20
	Creeping	14/20	3/20	0/20	3/20

20ms Window 10 Eigenvectors	Crawling	1/20	18/20	0/20	1/20
	Running	0/20	0/20	19/20	1/20
	Walking	0/20	0/20	1/20	19/20

B) Classification Experiment 2

In this experiment, 30 of the recordings from three people are used as training set. This time, the set contains 9 different recordings for walking and running and 6 different recordings for crawling and creeping. Then, another set of HMMs are trained for the four classes. Tests are conducted with the remaining 20 recordings from two different people. The experiment is repeated for four different combinations of the people selected for training and testing set.

As in the earlier experiment, a four state hidden Markov model is used for each motion type. Classification results can be seen on Table 4. As in the first experiment, the selection of 20 eigenvectors and 20 ms analysis window length again gives the best results in comparison to other configurations because of the reasons explained earlier. However, the rate of success decreases in the second experiment when compared to the first one. This is expected as all possible variations about a motion are very hard to capture with a data only from three people. However, even with this limited training data, results show that it is still possible to capture enough variation for walking and crawling. As human dependent classification experiment results show that it is possible to classify running and creeping perfectly, we should expect that the performance for running and creeping can be improved with data from more people so that we capture the variations properly.

Table 4. Results of Classification Experiment 2

	Motion	Creeping	Crawling	Running	Walking
20ms Window 20 Eigenvectors	Creeping	12/16	3/16	0/16	1/16
	Crawling	0/16	16/16	0/16	0/16
	Running	0/24	0/24	20/24	4/24
	Walking	0/24	0/24	0/24	24/24
45ms Window 20 Eigenvectors	Creeping	8/16	4/16	0/16	4/16
	Crawling	1/16	15/16	0/16	0/16
	Running	0/24	0/24	20/24	4/24
	Walking	1/24	0/24	3/24	20/24
10ms Window 20 Eigenvectors	Creeping	1/16	8/16	0/16	7/16
	Crawling	1/16	15/16	0/16	0/16
	Running	0/24	0/24	23/24	1/24
	Walking	1/24	0/24	3/24	20/24
20ms Window 5 Eigenvectors	Creeping	0/16	8/16	0/16	8/16
	Crawling	2/16	14/16	0/16	0/16
	Running	1/24	0/24	15/24	8/24
	Walking	1/24	0/24	4/24	19/24
20ms Window 10 Eigenvectors	Creeping	9/16	3/16	0/16	4/16
	Crawling	2/16	14/16	0/16	0/16
	Running	0/24	0/24	20/24	4/24
	Walking	0/24	0/24	1/24	23/24

6. CONCLUSIONS

This study shows that typical human motions have distinguishable micro-Doppler signatures that can be utilized in the design of classifiers. This study illustrates importance of the choice of analysis window length, feature representation and the classifier in the micro-Doppler based classification problems. Different from earlier works, the set of features utilized is based on statistical analysis of the experimentally collected data. The suggested uncorrelated feature vector can be considered to contain vital statistics of the input at a much reduced dimension. The frame-to-frame variation of the mentioned vital statistics, captured by the hidden Markov model, enables us to model both instantaneous and long-term variations within each class and discriminate between various human motions with a very good success. Experiments shows that 100% accuracy can be attained for classification of four different motions when both training and testing data is obtained from same people, while 90% classification accuracy is observed when training and testing sets contain data from different people. These results are extremely encouraging and warrant for more investigation in different conditions.

REFERENCES

[1] Chen V. C., "The Micro Doppler Effect in Radar", Artech House, 2011.

[2] Chen V.C., Li F., Ho S., Wechsler H., "Microdoppler Effect in Radar Phenomenon Model and Simulation Study", EEE Transactions on Aerospace and Electronic Systems, 2006

[3] Chen V.C., "Analysis of Radar Micro-Doppler Signature with Time Frequency Transform", Proc of the Tenth IEEE Workshop on Statistical Signal ans Array Processing, 2000

[4] Thayaparan T., Abrol S., Riseborough E., Stankovic L., Lamothe D., Duff G., "Analysis of Radar Microdoppler Signatures from Experimental Helicopter and Human Data", IET Radar, Sonar & Navigation, pp. 289-299, 2007

[5] Tahmoush D., Silvious J., "Radar Micro-Doppler for Long Range Front-View Gait Recognition", IEEE 3rd International Conference on Biometrics: Theory, Applications and Systems, 2009

[6] Youngwook K., Hao L., "Human Activity Classification Based on Micro-Doppler Signatures Using an Artificial Neural Network", IEEE Antennas and Propagation Society International Symposium, 2008

[7] Youngwook K., Hao L., "Human Activity Classification Based on Micro-Doppler Signatures Using a Support Vector Machine", IEEE Transactions on Geoscience and Remote Sensing, 2009

[8] Li J., Phung S.L., Tivive F.H.C., Bouzerdoum A., "Automatic Classification of Human Motions Using Doppler Radar", The 2012 International Joint Conference on Neural Networks (IJCNN), 2012

[9] Alemdaroğlu Topuz Ö., Candan Ç, Koç S., "The Radar Application of Micro Doppler Features from Human Motions", IEEE Radar Conference, 2015

[10] Rabiner L.R., "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition", Proc. of the IEEE, v:77, issue: 2 1989

[11] Murphy K., "Hidden Markov Model (HMM) Toolbox for Matlab", https://www.cs.ubc.ca/~murphyk/Software/HMM/hmm.html, 2005