Feature Selection for Classification of Human Micro-Doppler

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***Abstract*—Over the past decade, the human micro-Doppler signature has been a subject of intense research. In particular, much work has been done in relation to computing features for use in a variety of classification problems, such as arm swing detection, activity classification, and target identification. Although dozens of features have been proposed for these purposes, little work has examined the issue of which features are more important – i.e., have a greater impact on classification performance – than others. In this work, an information theoretic approach is applied to compute the importance ranking of features prior to classification for the specific problem of discriminating human walking from running. Results show that the ranking of features according to mutual information directly relates to classification performance using support vector machines.**

Keywords—human micro-Doppler, feature selection, classification, multistatic radar, radar network

I. Introduction

The micro-Doppler effect [1-3] refers to the frequency modulations of the received radar signal caused by the vibration or rotation of any part of the target, also known as micro-motion dynamics. For example, the rotational motion of vehicle wheels, tank treads or helicopter blades all results in radar micro-Doppler [4-7] in addition to the Doppler shift caused by translational motion of the target. Human motion, which is comprised of complex time-varying movements of the body, arms, legs, hands and feet, also result in the presence of micro-Doppler in the radar signature. Studies have shown that the human micro-Doppler signature is a unique signature, differentiable from all other micro-Doppler signatures, including those caused by four-legged animals [8-9]. In fact, the human micro-Doppler signature also exhibits variations dependent upon the activity being engaged in. Thus, in addition to target identification, micro-Doppler can also be used to detect and classify target activity as well.

Over the years, numerous features have been proposed for the purposes of classifying micro-Doppler signatures. The most commonly used time-frequency representation of micro-Doppler is the spectrogram: the short-time Fourier transform of the slow-time slice of the pulse compressed radar return signal. Most of the features proposed in the literature are directly extracted from the received signal's spectrogram. For example, Tahmoush and Silvious [8] proposed using eight different features to distinguish humans from animals: average velocity, maximum foot swing velocity, animal and human torso velocities, the period, the phase between leg and torso, foot swing time, and the range profile of the animal. Otero [9] proposed two features for human – dog discrimination, which are extracted from the cadence frequency plot, defined as the fast Fourier transform (FFT) of the spectrogram. The first feature, stride rate, is computable from the fundamental frequency of the cadence frequency plot, while the second feature, appendage-torso ratio, is given by the ratio of the torso radar cross section (RCS) to the sum of appendage RCS. Otero considered the amplitude of cadence frequency plot at the fundamental frequency and harmonics to be indicative of torso and appendage RCS, respectively. However, experiments by Andric [10] have shown the cadence frequency plot to be unreliable in the presence of multiple targets.

For classification of human activities, Kim and Ling [11-12] have proposed six different features: torso Doppler frequency, total bandwidth of the Doppler signal, offset of the total Doppler, bandwidth without micro-Dopplers, normalized standard deviation of the Doppler signal strength, and period of the limb motion. These features were successfully used to classify seven different activities: running, walking, walking without moving arms, crawling, boxing, boxing while moving forward and sitting with slight fidgeting movements. Other researchers have used features such as the distance between the upper and lower frequency envelopes of the Doppler signatures to determine if a person is walking with or without arm swing [13-14], melfrequency cepstral coefficients to discriminate falling from other human activities such as walking or bending [15], the shape of the spectrogram envelope, mean torso velocity, maximum envelope velocity, torso oscillations, limb trajectories, and ratio of torso echoes to other echoes in the spectrogram [16], and Fourier series coefficients of spectrogram envelope [17] to characterize human gait. Non-parametric features derived from subspace representations of the time-frequency distribution have also been proposed [18-20]. For example, Tivive [18] proposed a three-stage algorithm employing both fixed directional and adaptive filters that extract micro-Doppler features via learning.

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Once a certain set of features have been extracted, a number of different classification algorithms can then be applied, including, artificial neural networks [11], support vector machines (SVM) [12], principle component analysis (PCA) [19, 21], linear discriminant analysis (LDA) [19], statistics [22], distance measures [23], k-means [24], Bayesian probability theory [25], and information theory [26]. However, in terms of impact on classification performance, the *choice of which features are used is much more significant* than the specific classification algorithm applied [27].

Dozens of different features have been proposed in the literature, but given a specific classification problem, which features, and how many should be used? There are relatively few works that analyze the contribution of features towards classification performance. In Kim and Ling [12], the significance of features was determined based on classification performance achieved after processing with SVM. This work focuses on determining the importance ranking of features *prior to* classification, thereby enabling an approach for feature selection specific to the classification problem at hand. In particular, this problem is considered in the framework of information theory, an approach which has had some success when applied to feature extraction from video [28]. Application of mutual information calculations to fusion of multistatic data obtained from the radar network is also discussed.

II. Multistatic Human Micro-Doppler

In general, the signal received by a radar from is a time-delayed, frequency-shifted copy of the transmitted signal. For the purposes of this study, a pulsed Doppler radar transmitting a linear frequency modulated (LFM) or chirp signal is considered. Thus, for a point target the received radar return may be written as [29]

$$s_r(n,t) = a_t rect\left(\frac{\hat{t}-t_d}{\tau}\right)\cdot \exp\left\{j\left[-2\pi f_c + \pi\gamma\left(\hat{t}-t_d\right)^2\right]\right\}, \quad (1)$$

where the time t is defined as $t = T(n-1)+\hat{t}$ in terms of the pulse repetition interval (PRI), T, pulse number, n, and time relative to the start of each PRI, $\hat{t}$; a_t is the amplitude as given by the radar range equation; τ is the pulse width; c is the speed of light; γ is the chirp slope; f_c is the transmitted center frequency; and t_d is the round-trip time delay from antenna and target, defined in terms of the range, R, as $t_d = 2R/c$.

A. Human Radar Return

Humans are complicated targets because of the intricate motion of body parts moving along different trajectories at different speeds, which results in a micro-Doppler shift. A validated model for the radar return from a human was proposed by Van Dorp [30] based on the kinematic model of walking found by Boulic [31]. Van Dorp models the human body as being comprised of 12 point targets, located at the centroid of each body part (head, upper arms, lower arms, torso, thighs, lower legs and feet), which are modeled as either spherical or cylindrical, depending on which shape best matches. Thus, the total return from a human target may be expressed as

$$s_h(n,t) = \sum_{i=1}^{12} a_{t,i} rect\left(\frac{\hat{t}-t_{d,i}}{\tau}\right) e^{j[-2\pi f_c t_{d,i} + \pi\gamma(\hat{t}-t_{d,i})^2]}, \quad (2)$$

where $a_{t,i}$ and $t_{d,i}$ are the amplitude and time delay of the return of each body part.

The received return from the human target, stored as a slow-time, fast-time data matrix, is then pulse compressed so that the peak occurs at the target's range bin. Taking a slice across slow-time at the range bin of the peak output,

$$x_p[n] = \sum_{i=1}^{12} a_{t,i}\tau e^{-j\frac{4\pi f_c}{c}R_{d,i}}, \quad (3)$$

where $R_{d,i}$ is the range from the antenna to the center of each body part. The short-time Fourier transform of overlapping time segments of this slow-time slice yields the spectrogram of the human return, which comprises the starting point for the data processing accomplished in this work.

B. Video Motion Capture Data

Many researchers use the human walking model developed by Boulic to compute the time-varying range of each body part, $R_{d,i}$, that is required by (3) to generate simulated human radar data. However, the spectrogram generated by the Boulic model is quite "clean" in comparison that derived from measured radar data, yielding easier obtainable, more accurate feature estimates and thus greater classification performance. A more realistic human spectrogram can be obtained by instead computing the time-varying ranges from motion capture data of human activities.

The Carnegie Mellon University (CMU) Motion Research Laboratory has developed a library of human motion capture data [32], which it distributes free of charge to researchers worldwide. The CMU database contains data of many different people engaged in a variety of motions, including walking, running, climbing, crawling, jumping, different sports, and composite activities, such as running – stopping – and running again. The data was collected with the aid of 41 sensos placed on the human body and was recorded by 12 infrared cameras at a frequency of 120 Hz. The database contains a total of 2605 different motion records belonging to 112 different subjects.

The difference in human spectrograms generated from motion capture data and those generated using the Boulic walking model can be seen in Figure 1. Notice how the curves in the spectrogram generated from CMU data are not as sharp or well defined as that computed from the Boulic model, thus more closely approximating real data. Moreover, simulated data generated from motion capture data is not limited to just one human activity (walking), but enables the generation of data corresponding to almost any desired activity, so long as a record exists in the database.

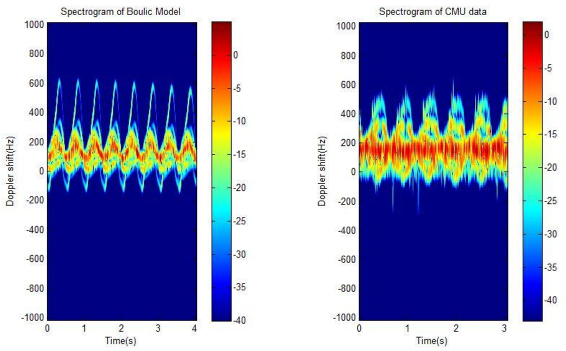


Figure 1. Human spectrograms generated from the Boulic walking model (left) and CMU motion capture data of human walking (right) [33].

C. *Multistatic Data from Radar Network*

In this work, a three-antenna radar network is considered for illustration of the proposed feature selection algorithm, as shown in Figure 2. A single human target initially located at a range of 1000 meters from the nearest network antenna is simulated for both walking and running towards the network.

Here, an important consideration is aspect angle, defined as the angle of the target motion relative to the radial path between antenna and target. The aspect angle of target motion has a great impact on the spectrogram measured and thus the quality of the features extracted for the purposes of classification. Consider the spectrograms measured from the network receivers for a human running towards the radar network at a 0° aspect angle and those for a human running tangential to the radar network at a 90° aspect angle, as shown in Figure 3.

When the aspect angle zero, the motion of the torso, arms, and legs can be distinctly seen in the spectrogram, enabling reliable estimates of features for use in classification. But when the aspect angle is 90 degrees, the amount of Doppler shift observed is significantly smaller, due to the small radial velocity component observed by the radar. Moreover, the micro-motion of the body parts has seemingly been merged or blurred together, inhibiting the extraction of relevant features that could be used to distinguish targets.

Thus, when exploiting features extracted by a radar network, it is important to take into account not just the usefulness of a given feature to discriminate between the desired activities, but also to account for differences is the quality of feature estimates, with is strongly dependent upon aspect angle, among other factors. As will be seen, information theory will be able to taken into account all factors impacting the contribution of a feature to classification performance.

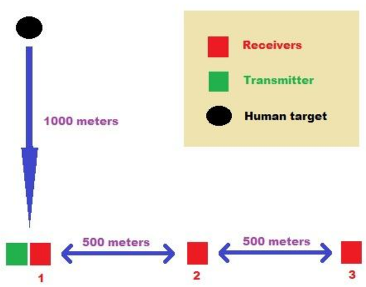
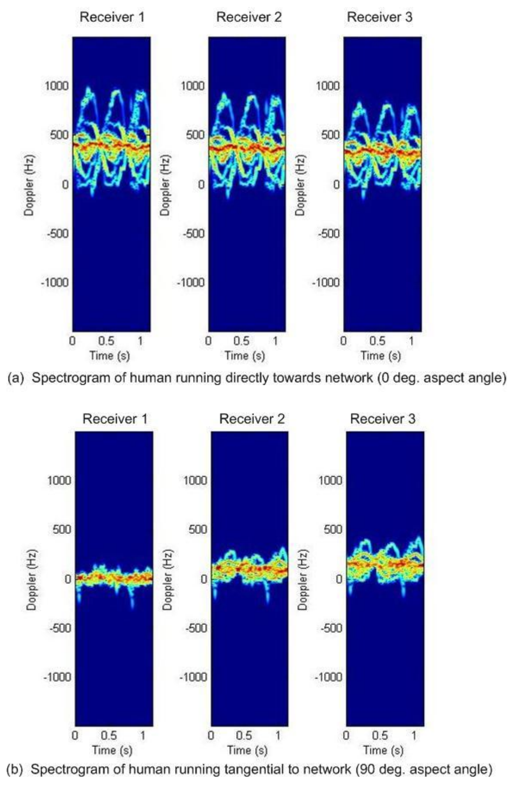


Figure 2. Radar network topology.



(a) Spectrogram of human running directly towards network (0 deg. aspect angle)

(b) Spectrogram of human running tangential to network (90 deg. aspect angle)

Figure 3.

III. Information Theoretic Approach

A. *Ranking Features According to Mutual Information*

The mutual information of two random variables is defined as the quantity that measures the amount of information contained in one random variable about the other. Hence, random variables that are independent of each other have zero mutual information, and as correlation increases mutual information increases. In the context of radar networks, mutual information can provide a quantitative basis for assessing the contribution of data collected from each sensor.

First, let us consider the monostatic case for classifying returns according to whether a human is running or walking. For illustration, let us just study two features:

1) the average torso Doppler frequency, and

2) the bandwidth of torso oscillations.

and use mutual information theory to determine their relative importance.

Define X_1 and X_2 as random variables corresponding to the average torso Doppler frequency (feature 1) and bandwidth of torso oscillations (feature 2), respectively. Let Y be a random variable taking a value of 0 when the subject is walking, and 1 when the subject is running. Then, the mutual information between X_1, X_2 and Y may be defined in two ways [34]:

$$I(X_1, X_2; Y) = I(X_1; Y) + I(X_2; Y \mid X_1) \tag{4}$$

$$I(X_1, X_2; Y) = I(X_2; Y) + I(X_1; Y \mid X_2) \tag{5}$$

where, $I(X_1,X_2;Y)$ represents the mutual information between both feature 1 and feature 2 with Y. $I(X_1;Y)$ and $I(X_2;Y)$ represent the mutual information between feature 1 and Y, and feature 2 and Y, respectively. $I(X_2;Y|X_1)$ represents the mutual information of feature 2 and Y, given feature 1. $I(X_1;Y|X_2)$ is defined similarly. Then, to determine whether feature 1 or 2 gives more information about the classification variable Y, $I(X_1;Y)$ and $I(X_2;Y)$ are compared and the feature, which results in a larger value is selected.

The mutual information for two discrete random variables X and Y can be computed as follows:

$$I(X;Y) = \sum_x \sum_y p(x,y) \cdot \log_2 \left(\frac{p(x,y)}{p(x)p(y)} \right) \tag{6}$$

where $p(x,y)$ is the joint probability mass function (PMF), $p(x)$ and $p(y)$ are the marginal PMFs of x and y, respectively.

The expressions given in (4) and (5) can be generalized to n number of features as follows [34]:

$$I(X_1, X_2, ..., X_n; Y) = \sum_{i=1}^{n} I(X_i; Y | X_{i-1}, ..., X_1) \tag{7}$$

Note that the chain rule in (7) can be written in any order over the set {1,…,n} and comparing all $I(X_i;Y)$ with each other, the most important feature among n features can be determined.

Now suppose we have M antennas, each of which extracts N features from the measured spectrogram. Then, (7) may be extended for multistatic radar networks as follows:

$$\begin{aligned} I(X_{11}, ..., X_{1n}, ..., X_{m1}, ..., X_{mn}; Y) \\ = \sum_{j=1}^{m} \sum_{i=1}^{n} I(X_{ji}; Y | X_{j,i-1}, ..., X_{j,1}) \end{aligned} \tag{8}$$

where $I(X_{ji};Y)$ represents the mutual information of the i^{th} feature of the j^{th} antenna and the classification variable, Y.

B. Simulation Results for 3-Antenna Network

Simulation results are presented for the three-antenna radar network, shown in Figure 3, observing a single human engaging in one of two possible motions: 1) walking, and 2) running. Each motion is simulated for four different people (small man, large man, small woman, large woman), target motions ranging between 0° and 90° aspect angles relative to the radar, and target speeds ranging between 0.1 m/s and 2.2 m/, yielding a total of 8008 simulations over the variable parameter space. From the spectrogram generated in each simulation, feature 1 and feature 2 are estimated and ordered according to mutual information.

The mutual information for a given feature is computed by compiling a histogram of feature values for when the subject is running and walking. It is assumed that it is equally likely for the person to be walking as running. Thus, p(y=0) = p(y=1) = 0.5. As the histograms for the two motions are found separately, the histograms represent conditional probabilities, from which the desired joint and marginal distributions may be computed for both features ($i = 1,2$) as follows:

$$\begin{aligned} p(x_i, y=0) &= p(x_i | y=0) p(y=0) \\ &= 0.5 p(x_i | y=0) \end{aligned} \tag{9}$$

$$\begin{aligned} p(x_i, y=1) &= p(x_i | y=1) p(y=1) \\ &= 0.5 p(x_i | y=1) \end{aligned} \tag{10}$$

$$p(x_i) = \sum_{y=0}^{1} p(x_i, y) \tag{13}$$

In the case of a radar network, the total number of histograms generated is equal to the number of features times the number of antennas times the number of classes. In this example, we extracted two features from three antennas to classify two different motions, so the total number of histograms generated is 2 x 3 x 2 = 12 histograms. For illustration, consider the histograms computed for Receiver 1, as shown in Figures 4 and 5.

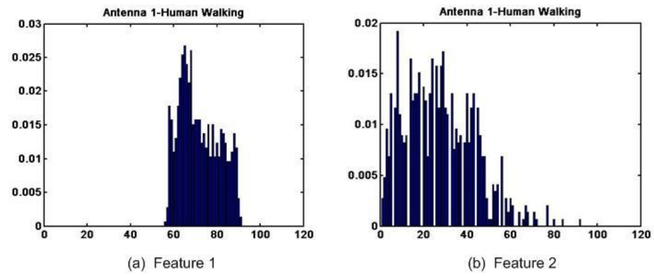


Figure 4. Marginal PMF for feature 1 and feature 2 when subject is walking.

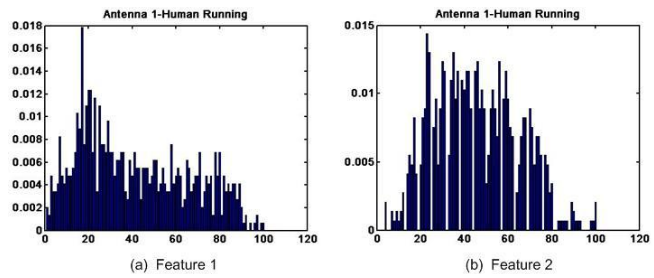


Figure 5. Marginal PMF for feature 1 and feature 2 when subject is running.

Using these data, (8) may be used to compute the mutual information of each feature and each antenna, as tabulated in Table 1. From these calculations, a number of important observations can be made. Firstly, for all antennas, the mutual information values of feature 2 are significantly lower than that of feature 1, indicating that feature 1 is a much more useful feature in regards to discriminating walking from running. This result makes physical sense, as feature 1, the average Doppler shift of the torso is directly related to target velocity. A main discriminator between walking and running is indeed velocity.

Secondly, antenna 3 overall possess higher mutual information values for both features, indicating that antenna 3, when processed individually, will yield better classification performance. This is consistent with expectations, since the target motion vector sweeps between 0° to 90° the angle seen by antenna 3 changes between +/- 45°, yielding spectograms of sufficient quality to obtain reasonable feature estimates in most cases – hence, the higher the mutual information values.

Table 1. Mutual Information for Each Feature Extracted from Three Antenna Multistatic Radar

	Mutual Information		
	Antenna 1	**Antenna 2**	**Antenna 3**
Feature 1	0.5192	0.7124	0.8945
Feature 2	0.2218	0.2955	0.3156

IV. CONCLUSION

This paper presents an information theoretic approach for finding the importance ranking of features extracted for the purpose of classifying human micro-Doppler in radar sensor networks. Results show that the mutual information of features can be used to learn which features are more important to successful classification prior to the application of any classification algorithm.

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