Knowledge Exploitation for Human Micro-Doppler Classification

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***Abstract*—Micro-Doppler radar signatures have great potential for classifying pedestrians and animals, as well as their motion pattern, in a variety of surveillance applications. Due to the many degrees of freedom involved, real data need to be complemented with accurate simulated radar data to be able to successfully design and test radar signal processing algorithms. In many cases, the ability to collect real data is limited by monetary and practical considerations, whereas in a simulated environment, any desired scenario may be generated. Motion capture (MOCAP) has been used in several works to simulate the human micro-Doppler signature measured by radar; however, validation of the approach has only been done based on visual comparisons of micro-Doppler signatures. This work validates and, more importantly, extends the exploitation of MOCAP data not just to simulate micro-Doppler signatures but also to use the simulated signatures as a source of *a priori* knowledge to improve the classification performance of real radar data, particularly in the case when the total amount of data is small.**

***Index Terms*—Classification, human micro-Doppler, knowledge-based signal processing, motion capture (MOCAP).**

I. Introduction

THE detection, recognition, and classification of human targets and their activities is a topic of great interest that has many critical applications, such as search and rescue, intelligent environments, border control, and security, to name just a few. Human recognition and classification are typically accomplished based on discerning differences in the radar micro-Doppler signature for different targets and activities. Micro-Doppler refers to the additional frequency modulations observed about the central Doppler frequency, which are caused not by the gross translational motion of the target but by vibrations or rotations of parts of the target [1]. For example, the rotation of a helicopter blade, vehicle wheels, and tank tracks, as well as the periodic motion of the limbs of animals and humans all result in visually distinguishable micro-Doppler signatures. These can then be exploited for *automatic target recognition* and activity classification.

However, the development and testing of classification algorithms requires data reflecting the wide variety of potential target characteristics. This includes animals whose signatures are easily confused with those of humans, such as dogs, donkeys, cows, and sheep, as well as humans of varying size, build, and gait that are engaging in different activities at varying angles, ranges, and velocities. Experimentally generating a database of this size is both costly and impractical; therefore, much research, as well as the development of commercial systems involving classification of a human micro-Doppler signature, has utilized methods for simulating micro-Doppler signatures.

There are two main approaches to simulating human micro-Doppler signatures: kinematic modeling and motion capture (MOCAP). The radar return from a human target is generally possible to represent as the superposition of the returns from point targets located at varying locations on the human body [2], [3]. Simulating these returns requires knowledge of the time-varying positions of each of these point targets, which can be derived either from kinematic models or from MOCAP data. Some of the kinematic models that have been utilized in micro-Doppler research studies are quite simplistic, consisting of just a sinusoidal model of torso motion [4] or animation of just three parts, i.e., the torso and the legs, with a basic sinusoidal function [5]. The most comprehensive and ubiquitous kinematic model is the Boulic walking model [6], which uses a combination of equations and charts to describe the time-varying motion of 17 points on the human body. It has been successfully used in a number of human micro-Doppler studies, e.g., [7]–[9].

The primary disadvantage of kinematic modeling, however, is that there are no models covering the entire range of human or animal activity; thus, only special cases can be simulated. MOCAP data, on the other hand, are derived from observations of alternative sensors, such as video or infrared sensors. Typically, a finite number of points on the human body are marked, and their time-varying positions to the sensor are computed using skeleton-tracking software. These measurements are then used to simulate the distance measurements that would have

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been made had the subject been observed by radar. MOCAP-based data thus enable the simulation of any desired sequence of motion for any subject, including animals, while also incorporating the individual variations of a subject. Since its introduction by Ram and Ling [10] in 2008, MOCAP data have been used for a variety of radar micro-Doppler studies, including analysis of the effect of walls [11], [12], the ground [13], [14], polarization, and operating frequency [14] on the human micro-Doppler signature. MOCAP techniques have also been successfully applied to generate radar micro-Doppler signatures for animals [15]. Indeed, several works have subsequently utilized MOCAP-based simulated micro-Doppler as a basis for studying the extraction of features relevant to gait analysis [16] and classification [17]–[20]. However, validation of the approach has primarily been done by a simple visual comparison with measured micro-Doppler signatures [21]–[24].

In fact, most classification algorithms depend upon the accurate extraction of a set of features from the available data to achieve high performance. For features derived from simulated data to yield representative classification results on measured data, the statistical properties of the features extracted from simulated data should be comparable to those extracted from real data. Otherwise, the classification results obtained from simulated data could be misleading and unrepresentative of the actual classifier performance.

Beyond validation of simulated data, however, the main goal of this letter is to show that simulations derived from MOCAP data are indeed accurate enough representations to be exploited as a source of *a priori* knowledge suitable for improving micro-Doppler classification performance. More specifically, this work proposes a novel application of simulated MOCAP data as a source of training data for real radar systems, particularly in the case when the amount of measured data is small.

With this aim, in Section II, first, the radar system used to collect measured micro-Doppler signatures is described. Then, in Section III, different methods to simulate human micro-Doppler signatures are discussed, whereas in Section IV, the features extracted from MOCAP data are compared with those of measured data. Finally, in Section V, a novel approach to exploit simulated micro-Doppler signatures as *a priori* knowledge for first training classifiers before testing on measured data is presented along with classification results.

II. Experimental Measurements of Human Micro-Doppler Signatures

The experimental radar measurements used in this letter were captured using a SIRS 77 TD radar, developed by SAAB AB. It is a *frequency-modulated continuous-wave* radar with linear frequency-modulated sweeps using the carrier frequency 77 GHz. The received signal is mixed with the transmitted signal, and only the low-bandwidth-difference signal needs to be digitized. This simplifies the hardware design. Pulse compression (converting to ranges) is done using a *fast Fourier transform*. The range resolution is approximately 1 m. Doppler filtering utilizes the phase shift between different sweeps, similar to what is done in pulsed radars. In the used radar modes, the unambiguous radial velocity was ensured to be enough for a moving human.

The measurements were conducted on moving persons in Sweden in the summer of 2009, on a day with favorable dry weather. The experiments were performed on fairly flat ground covered with short grass, at a place where there were no buildings to disturb the measurements. The radar was pointing approximately horizontally. Three different adults (one woman and two men, of average build and weight) performed the activities moving either radially toward or away from the radar (aspect angle $0^\circ/180^\circ$). Five different activities were performed: running, jogging, walking, creeping, and crawling.

After the acquisition, the data were pulse compressed, followed by an ideal high-pass filter to remove clutter, and finally converted into a micro-Doppler signature by using a *short-time Fourier transform* with a Hamming window. The micro-Doppler spectra from the measurements have previously been studied and analyzed in [25].

III. Human Micro-Doppler Signatures

The micro-Doppler signature for any human activity is the result of a complex combination of the time-varying motion of each point on the human body. Suppose the entire human body is divided into K parts, which are, in turn, modeled by point targets. Then, the entire human return, i.e., s_h, can be written as the sum of returns from each individual point target [26], i.e.,

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

Here, τ is the pulsewidth, c is the speed of light, γ is the chirp slope, and f_c is the transmitted center frequency. The total time elapsed, i.e., t, can be written in terms of the *pulse repetition interval* (PRI), i.e., T; the fast-time $\hat{t}$, which denotes the time as measured from the start of each PRI; and transmitted pulse number (slow-time), n, as $t = T(n-1) + \hat{t}$. The time delay $t_{d,i}$ is measured in terms of the total elapsed time t and is defined as the round-trip travel time between the antenna and the ith body part. Thus, the time delay is related to the target range, i.e., R, as $t_d = 2R/c$. This way, the received return may be viewed as a 2-D signal that is a function of fast-time and slow-time. The amplitude, i.e., $a_{t,i}$, is defined for each point target from the range equation as

$$a_{t,i} = \frac{G\lambda\sqrt{P_t \sigma_i}}{(4\pi)^{\frac{3}{2}} R_i^2 \sqrt{L_s}\sqrt{L_a}} \quad (2)$$

where G is the antenna gain, λ is the wavelength, P_t is the transmitted power, σ_i is the *radar cross section* (RCS) for the ith body part, L_s represents system losses, and L_a is the atmospheric loss. Although this expression includes range- or geometry-dependent factors, such as the antenna gain and atmospheric losses, this work assumes that such factors are constant for each body part. The RCS is modeled according to the approximate shape of the body parts, i.e., a sphere for the head and ellipsoids for the remaining parts. Thus, grouping all factors except for the range, i.e., R_i, and RCS, i.e., σ_i, of the ith body part into a constant, i.e., A, the amplitude may be expressed as $a_{t,i} = A\sigma_i/R_i^2$.

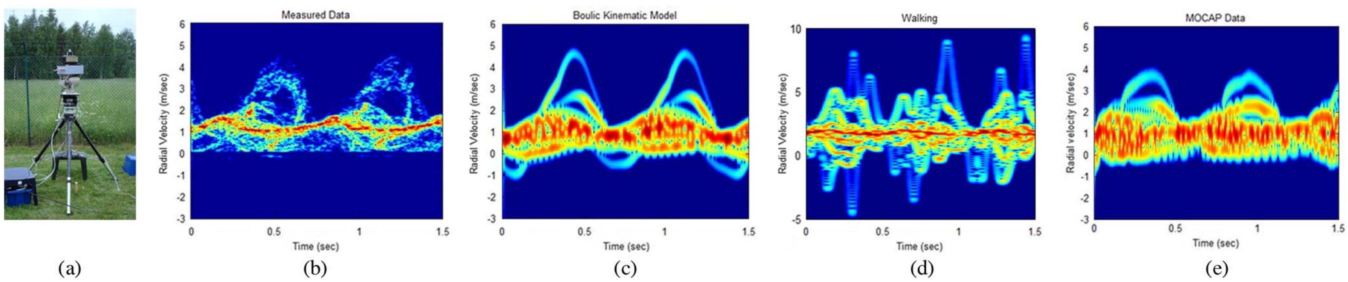


Fig. 1. (a) SIRS 77 TD radar used to collect micro-Doppler measurements and sample walking spectrograms as obtained from (b) measured SIRS 77 TD radar data, (c) the Boulic kinematic model, (d) Kinect data, and (e) the MOCAP database.

A. *Kinematic-Model-Based Signature Simulation*

In the literature, several different kinematic models have been used to simulate micro-Doppler. The simplest kinematic model [27] considers just the oscillation of the torso, which is represented by a sinusoidal function. Slightly expanding upon the torso model, the lower-body model [4] comprises three points, i.e., the torso and two legs, where each leg is animated similarly to a swinging pendulum. The spectrograms of both these models have some similarity to real data, but important components of the micro-Doppler signature are absent.

The most widely used model is the Boulic walking model, which is based on the results of a detailed experimental study of gait analysis and uses a combination of equations and charts to animate 17 different points and joints on the human body. Thus, the Boulic model is not a closed-form model. All equations and charts, however, basically depend on just two physical parameters: the speed at which the person is walking and the height of the thigh from the ground (HT).

The most significant limitation of the Boulic model is that it is only valid for walking and for speeds in which the v/HT ratio is less than 2.6 Hz. Moreover, because it is based on a model, individual gait variations cannot be incorporated into the simulations. Nevertheless, the resulting micro-Doppler signatures bear a close similarity to measured data in general shape, as shown in Fig. 1(a)–(c), with the key exception that it is much more crisp and clean. The strongest return is due to the torso, which, in both signatures, appears as a strong sinusoid around the central Doppler shift that corresponds to the average radial velocity of the person. Limb motion appears as larger amplitude oscillations, the largest being that of the legs.

B. *MOCAP-Based Signature Simulation*

More realistic human spectrograms may be obtained by exploiting video human MOCAP data, from which the time-varying ranges of points on the human body can be computed. High-quality MOCAP is typically accomplished by placing infrared markers upon the human body and observing these positions with a camera. Commercial MOCAP sensor suites are available, but these are typically quite expensive (\$30 000–\$60 000). A low-cost system using the Kinect sensor has recently been developed [28], but the accuracy is less than that of commercial systems.

Databases storing MOCAP data are available [29]–[31] and have been used for micro-Doppler signature simulation. For example, the Carnegie Mellon University (CMU) Motion Research Laboratory has developed a freely distributed library of human MOCAP data [31]. It includes a wide range of activities, such as walking, running, crawling, jumping, and boxing, to name just a few. The data were collected with the aid of 41 markers 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 primary disadvantage of using MOCAP databases is that the test subjects used and test scenarios recorded are not within the control of the user. This deficiency can be remedied by using Kinect; however, the signature quality is poorer than that of the CMU Motion Capture Library, as shown in Fig. 1(d) and (e).

IV. Evaluation of Simulated Signatures

The performance of classification algorithms is highly dependent upon the features extracted from the micro-Doppler signatures. Thus, here, CMU MOCAP spectrograms are compared with measured SIRS 77 TD radar data based upon the distributions of features used for classification.

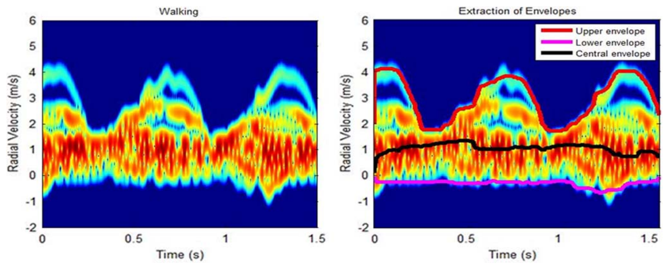
A. *Feature Extraction*

Feature extraction, which is one of the most critical steps in a classification system, is the process of computing numerical indicators (features) that will enable the discrimination of different classes of data. Moreover, feature extraction enables the classification process to progress using a small set of features rather than make computations on the much larger set of raw data. This way, the computation time of the classification process is also reduced.

Proper feature selection is important to optimize classification performance. In this letter, three features (the mean of the torso velocity, the variance of the upper envelope, and the variance of the lower envelope) [32] are extracted from micro-Doppler spectrograms. The mean of the torso velocity is a representative measurement of the translational motion of the target. The variances of the upper and lower envelopes reflect movements of arms and legs of the subject. These three features are, together, an effective set to define different human activities and can be computed from the spectrogram, as shown in Fig. 2.

The envelopes of the spectrograms are extracted using a percentile technique proposed by Van Dorp and Groen [33] in 2008. First, the element of the envelope in each column of the spectrogram data is computed. To do this, the cumulative amplitude distribution for each column is computed as follows:

$$P(v,t) = \frac{\sum\limits_{v=v_{\min}}^{v} s(v,t)}{\sum\limits_{v=v_{\min}}^{v_{\max}} s(v,t)} \tag{3}$$



(a) (b)

Fig. 2. Envelope extraction from spectrograms. (a) Original spectrogram. (b) Extracted envelopes.

TABLE I
DISTRIBUTION OF DATA TYPES

	CLASSES			
	Walking	**Running**	**Crawing**	**Creeping**
MOCAP	28	28	28	28
Measured	18	15	11	12

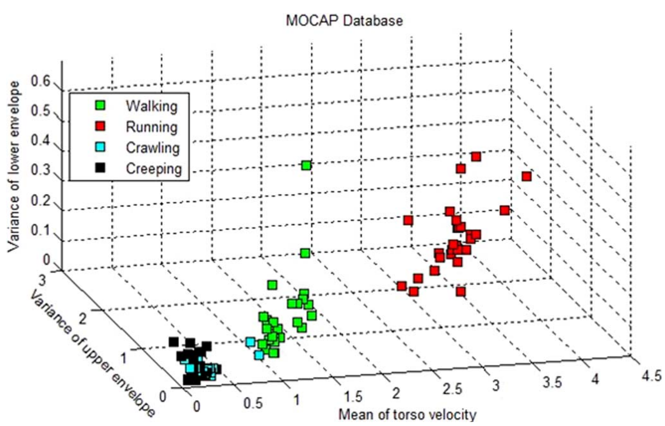


Fig. 3. Scatter graph of the features for the MOCAP database.

where v is the radial velocity, t is time, and s is the matrix storing the values for amplitude (power) of the spectrogram. For each column, the value $P(U(t), t) = 0.97$ is used to calculate the upper envelope, $P(C(t), t) = 0.5$ is used to calculate the central envelope, and $P(L(t), t) = 0.03$ is used to calculate the lower envelope. Once these three envelopes are extracted, their average value is computed, representing three different features in 3-D feature space.

B. Statistical Comparison of the Features

The three features introduced in the previous section are extracted from both measured and MOCAP data. In both databases, there are four different human motion types: walking, running, crawling, and creeping. The duration of each data file is 1.5 s, and the subjects move toward radar during the data acquisition process. Distribution of data types in these two databases is given in Table I.

To compare the distribution of features obtained from MOCAP data with that of real data, scatter graphs of features from each data set are presented in Figs. 3 and 4, respectively. In both data sets, running is clearly separable from the other classes of motion, whereas features appear to have similar values for creeping and crawling, limiting their discriminating power. Walking appears to be more easily distinguishable from MOCAP-based simulated spectrograms than would be possible from real measured data.

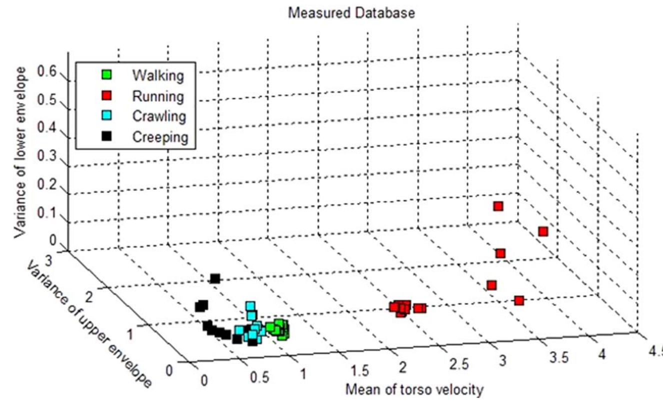


Fig. 4. Scatter graph of the features for the SIRS 77 TD radar.

Classification performance attained using a *nearest neighbor* (NN) classifier also validates the comparability of MOCAP-derived signatures with measured signatures. Using 84 MOCAP signatures for training, 25 of the remaining 28 MOCAP signatures were correctly classified, with just three crawling signatures confused with creeping. In comparison, 15 of 16 measured SIRS 77 TD radar signatures were correctly classified when 40 measured signatures were used as training.

V. SIMULATED SIGNATURES AS PRIOR KNOWLEDGE

To date, simulated micro-Doppler signatures have primarily been used just as a means to approximate real data in performance testing. In fact, simulated signatures represent prior knowledge that can be exploited to improve the classification performance of measured data. An important factor affecting performance is the amount of data used to train the classifier. Increasing the size of the training set tends to increase the rate of correct classification. However, in real operational scenarios, the total data set size may not be that large, limiting the ability to train the classifier. In this letter, this constraint is overcome by using simulated data to train measured data.

To assess the potential performance attainable by training with MOCAP data, classification of the SIRS 77 TD radar data is accomplished in two ways: 1) a subset of measured data is used to train a classifier to test the remaining measured data; and 2) MOCAP-derived signatures are used to train all measured data. With the first approach, it was found that a correct classification rate of 94% was achieved when at least 70% of the data was used for training. When MOCAP data were used to train the classifier, the highest classification performance attained was 93% when all 112 MOCAP-derived signatures were used for training (see Fig. 5). Confusion matrices corresponding to the best classification results are shown in Table II, as well as classification metrics in Table III.

VI. CONCLUSION

This letter has validated the use of MOCAP-derived simulated data through the examination of the statistical distributions of features, as well as through a comparison of classification performance. Moreover, a novel application of using simulated MOCAP data to train classifiers for testing real data has been proposed. This method can be applied using different MOCAP data sets, as well as different features and classifiers. Generally including as many different individuals as possible in the

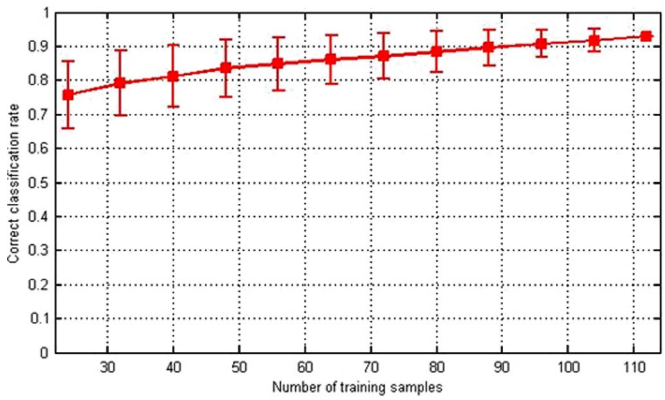


Fig. 5. Dependence of classification performance on the number of MOCAP-derived signatures used for training. Vertical bars denote the confidence interval (standard deviation) of results.

TABLE II
CLASSIFICATION PERFORMANCE OF NN ON MOCAP-BASED AND SIRS 77 TD MEASURED RADAR DATA

	Walking	Running	Crawing	Creeping
Training with SIRS 77 TD Measured Radar Data				
Walking	5	0	0	0
Running	0	4	0	0
Crawling	0	0	3	0
Creeping	0	0	1	3
Training with MOCAP-Based Simulated Data				
Walking	18	0	0	0
Running	0	15	0	0
Crawling	0	0	11	0
Creeping	0	0	4	8

TABLE III
COMPARISON OF CLASSIFICATION METRICS

	Walking	Running	Crawing	Creeping
Training with SIRS 77 TD Measured Radar Data				
Sensitivity	1	1	1	0.75
Specificity	1	1	0.92	1
Precision	1	1	0.75	1
Training with MOCAP-Based Simulated Data				
Sensitivity	1	1	1	0.67
Specificity	1	1	0.91	1
Precision	1	1	0.73	1

training set mitigates any potential losses due to different styles of gait. In summary, results show that simulated data can yield comparable results to that achieved with training on real data. This result is particularly significant for the classification of small data sets, when the amount of training data is insufficient.

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