Application of a 24 GHz FMCW Automotive Radar for Urban Target Classification

Shahar Villeval[1], Igal Bilik[1]
[1]Smart Sensing and Vision Systems Group
General Motors Advanced Technical Center
Herzliya, Israel
igal.bilik@gm.com, shahar.villeval@gm.com

Sevgi Zübeyde Gürbüz[2,3]
[2]TOBB University of Economics and Technology
Department of Electrical and Electronics Engineering
[3]TUBITAK Space Technologies Research Center
Ankara, Turkey
szgurbuz@etu.edu.tr

***Abstract*—Pedestrian safety is one of the major tasks of automotive radars. Pedestrian detection in practical urban scenarios is challenging task due to the strong vertical and horizontal multipath phenomena from the asphalt roads and surrounding buildings, proximity to other obstacles with high-radar cross section, and high probability of blockage by other targets. This work addresses the problem of joint pedestrian detection and classification in a practical urban environment by a 24 GHz FMCW automotive radar. The urban RF environment consisting of the asphalt road, vehicles and pedestrian was simulated. Micro-Doppler analysis was used to discriminate between pedestrians, vehicles, and animals. A variety of human activities, including mixed motion sequences were tested in target classification simulations.**

I. Introduction

Pedestrian detection using a variety of on-board sensors has recently become an important active safety research topic in the automotive industry. Cameras are one of main sensors that are currently used in pedestrian safety systems. However, camera-based solutions are limited in complex lighting and weather conditions and thus the radar-based solution can be advantageous. Therefore, reliable radar-based pedestrian detection is critical for robust active safety features.

Pedestrian detection in practical urban scenarios using automotive radar is a challenging due to the large amount of multipath reflections from asphalt roads and surrounding buildings, close proximity to targets with a high radar cross section (RCS) such a vehicles, and high probability of blockage by other targets. Thus, pedestrian detection in practical urban environments is compromised by a low signal-to-clutter ratio (SCR), and moreover by structure relating especially to the presence an immense amount of asphalt roads. The presence of this road clutter further challenges the pedestrian classification task.

Prior work in human modeling and gait analysis has shown that kinematic models [1,2] can be used to increase signal-to-noise (SNR) at the detector output [3,4] as well as to provide a basis for target identification and classification [5], enabling the discrimination between humans, animals, and vehicles [6,7]. A majority of these works involve micro-Doppler-based target classification, with a focus on the scenarios where the target is directly walking towards the radar, in low-noise environments. Moreover, human classification is typically focused on activity recognition – the discrimination between different types of human activity and very few works address the automatic classification of humans from animals. These works primarily focus on the visual differences between human and animal micro-Doppler [10].

This work proposes a more realistic analysis of urban target classification in practical urban scenarios characterized by clutter generated by an automotive environment simulator. Moreover, the impact of a variety of pedestrian motions is analyzed in the context of discriminating between three classes or urban targets: pedestrian, animal, and vehicle.

II. Urban Clutter Modeling and Simulation

The highly cluttered environment in typical urban scenarios compromises the performance of near-ground mounted automotive radars. Motion of the host vehicle results in the Doppler spread of the static clutter and therefore challenges the separation of the relevant moving automotive targets such as pedestrians and vehicles from the static clutter. Therefore, any appealing performance of the automotive radar needs to be evaluated in the presence of a practical automotive environment. Specifically, the performance of the proposed target classification approach needs to be evaluated considering radar echoes from automotive targets being contaminated by the automotive clutter. This section summarizes the simulation of the realistic automotive clutter.

The road is the largest entity of the automotive environment that induces the strongest radar echo. Reflections from the road pose a special challenge due to the fact that they occupy a wide range of range-azimuth cells.

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Unlike other environment objects such as building on the side of the road or bridges from above, the road echoes may not be removed by antenna design since they originate in the same directions as the targets. In this work, a road was represented by a parametric model characterized by the following four parameters: width, length, curvature and reflectivity. The radar echo returned from the road surface is represented by the superposition of K radar echoes from the K point-like reflectors.

The reflectors are spread uniformly in both axes on a horizontal surface at a pre-defined spatial resolution dy (Figure 1). The distance dy between the point scatterers is set to be less than half of the carrier's wavelength λ. For each scatterer the range r_k and azimuth and elevation angles, θ_k and φ_k, of scatterer k are calculated with respect to the radar transmitter. The attenuation α_k and the accumulated phase ϕ_k of the radar echo are obtained according to the range between the reflector and the receiver via the conventional radar equation. The propagation delay τ_k is simulated by inserting delay samples according to the reflector's range.

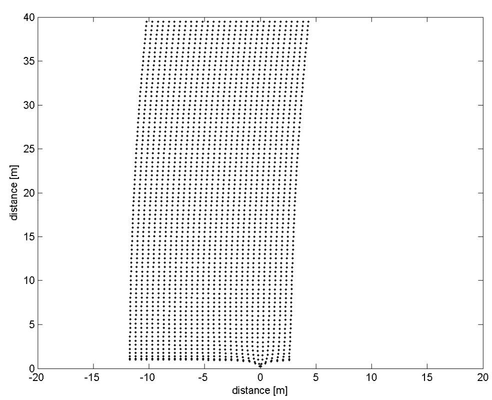

Figure 1. Bird's eye view of a road represented with point-size reflectors.

This work considers continuous wave linear frequency modulated (CW-LFM) automotive radar with the following transmitted waveform,

$$s(t) = \cos(2\pi\beta t^2)\cos(2\pi f_c t), \tag{1}$$

where β is a frequency change rate and f_c is a carrier frequency. The received radar echo from element k is of the form

$$r_k(t) = \alpha_k \cos(2\pi\beta(t-\tau_k)^2 - \phi_k)\cos(2\pi f_c(t-\tau_k) - \phi_k) \tag{2}$$

where $\tau_k = \frac{2r_k}{c}$, $\phi_k = \frac{4\pi f_c r_k}{c}$, $k = 1,\dots,K$

and c is the speed of light. The radar echo from the whole road surface is the sum of echoes from the different particles,

$$r(t) = \sum_{k=1}^{K} r_k(t) \tag{3}$$

III. Urban Target Micro-Doppler Simulation

In this work, three classes of targets are considered: pedestrians, animals, and vehicles. Each target is modeled by representing the overall target response as the superposition of responses from a finite number of point targets located at various places on the target. The time-varying position of these point targets can be computed using either kinematic models or motion capture data. Motion capture data (MOCAP) possesses two important advantages over data generated from kinematic models: 1) simulated signatures for any desired motion can be generated, and 2) the data generated matches much more closely to real data than the kinematic data. The primary disadvantage of MOCAP data, however, is that you are limited by the characteristics of the motion capture data provided in databases. Thus, there is no flexibility in selecting test subjects, motion trajectories, or even the type of motion to be captured. While kinematic data can supply an unlimited number of simulations, MOCAP data is limited by the number of entries supplied by the database.

One method for overcoming at least some of the disadvantages of MOCAP data is to simulate micro-Doppler signatures using the Kinect sensor [11]. Unlike most commercially available MOCAP systems, the Kinect sensor is low-cost and capable of being set-up in any laboratory environment. With the aide of a treadmill, human spectrograms were simulated for a variety of activities, including walking, running, leaping, boxing, and random motion. In this work, the walking, running and random data sets were included as representative human activities in an urban environment. Spectrograms for each of these activities is shown in Figures 2-4.

A limitation of the Kinect-based system, however, is that it is not able as of yet to be able to collect data for animals, or low height human activities, such as crawling. Thus, animal spectrograms were generated from animation of a simple skeletal model in which the legs oscillate back and forth in a complementary fashion, while the translational torso motion is slowly perturbed with a sinusoid. An example spectrogram for a dog running toward the radar is shown in Figure 5.

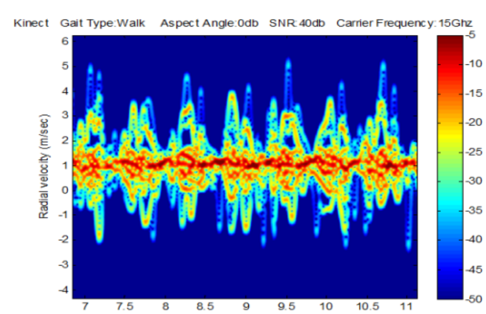

Figure 2. Kinect-based spectrogram for a human walking at 4 km/hr [11].

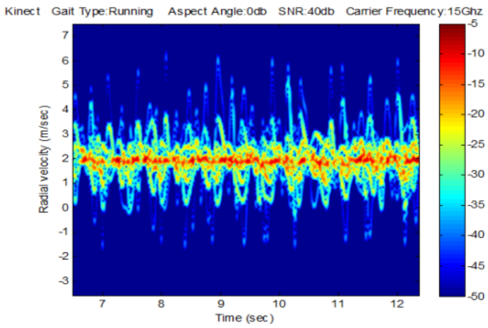

Figure 3. Kinect-based spectrogram for a human running at 7 km/hr [11].

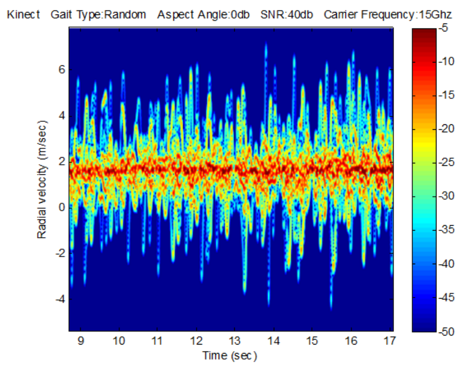

Figure 4. Kinect-based spectrogram for random human activity at 3 km/hr [11].

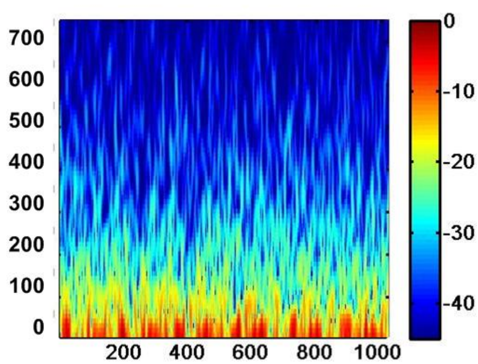

Figure 5. Dog spectrogram based on kinematic animation of a skeletal model.

In general, the signature of vehicles also exhibits fluctuations in micro-Doppler due to the rotation of the wheels. Especially in vehicles such as tractors and tanks, where the wheels or treads are highly visible, this micro-Doppler component is quite apparent [12]. However, measured data from typical automobiles show that the micro-Doppler component from the wheels is quite small in comparison to the overall Doppler from gross motion [13].

Thus, micro-Doppler signature from a car is very closely approximated by a straight line, and well approximated by a single point target. For example, consider the signature of a vehicle at 100 m distance moving directly towards the radar

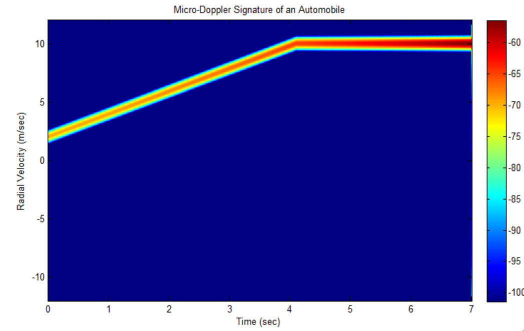

Figure 6. Spectrogram for a vehicle initially accelerating at 2 m/s^2 before moving at a constant speed of 10 m/s.

at an initial speed of 2 m/s, accelerating at a rate of 2 m/s^2 before continuing at a constant speed of 10 m/s. The simulated micro-Doppler signature for such a target is shown in Figure 6.

IV. Simulation Results

Urban target data was classified using a support vector machine (SVM) and k-nearest neighbor (kNN) classifier based upon the values of two features: the bandwidth and mean of torso oscillations. Half of the data was used for training and the remaining half for testing.

Classification performance was first evaluated using long dwell time data (several seconds of data). At a signal-to-clutter (SCR) ratio of -40 dB, the confusion matricies for classification of human, animals, and vehicles are given in Tables 1-4. A total of 131 measured spectrograms were utilized: 22 walking samples, 19 running samples, 28 random motion samples, 32 vehicle samples, and 40 dog samples.

Table 1. Classification between humans and vehicles at SCR = -40 dB using SVM.

	Humans	**Vehicles**
Humans	% 100	% 0
Vehicles	% 0	% 100

Table 2. Classification between humans and non-humans at SCR = -40 dB using SVM.

	Human	**Non-Human**
Human	% 100	% 0
Non-Human	% 13.88	% 86.11

Table 3. Classification between humans and dogs at SCR = -40 dB using SVM.

	Humans	**Dogs**
Humans	% 89.8	% 10.81
Dogs	% 20	% 80

The classification performance improves to %100 when the SCR is -20 dB. For the confusion matrix given in Table 4, a total of 107 samples were used: 26 walking, 19 running, 32 vehicle, and 40 dog samples.

Table 4. Classification between humans, dogs, and vehicles at SCR = -20dB using kNN.

	Humans	Dogs	Vehicles
Humans	% 100	% 0	% 0
Dogs	% 0	% 100	% 0
Vehicles	% 0	% 0	% 100

The success of these classification algorithms shows that generalized human activities can be recognized as belonging to humans, although under low SCR animal and human classification is sometimes confused.

V. CONCLUSION

The results presented in the paper represent preliminary work as part of a wider study and human detection and classification with automotive radars. In future work, a broader range of classification algorithms, such as Gaussian mixture models, and feature selection methods will be considered. Most importantly, the problem of classification with data of extremely short durations will be examined using a wider feature set.

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