Doppler-Resilient 802.11ad-Based Ultra-Short Range Automotive Radar

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Abstract—We present an ultra-short range automotive radar based on Prouhet-Thue-Morse modified Doppler-resilient Golay sequences embedded in the IEEE 802.11ad preamble. The proposed processing reveals detailed micro-features of common automotive objects verified through extended scattering center models of animated pedestrian, bicycle, and car targets. Numerical experiments show that our approach results in 2.5% reduction in probability of false alarm at low signal-to-noise-ratios and sidelobe suppression of 20 dB up to Doppler velocities of ±144 km/h.

Index Terms—automotive radar, Doppler resilient, Golay sequences, IEEE 802.11ad, micro-Doppler, vehicle-to-pedestrian radar

I. INTRODUCTION

During past few years, autonomous vehicles or self-driving cars have witnessed enormous development in vehicular control [1], environmental sensing [2], in-vehicle entertainment [3], efficient resource utilization [4], and inter-vehicular synchronization [5]. An ongoing challenge is automotive target detection and recognition in order to avoid road accidents and boost automotive safety. Conventional target detection techniques use sensors such as lidar [6], camera [7] and infrared/thermal detectors [8]. However, only radar offers the advantage of robust detection in adverse vision and weather conditions [4]. Currently, millimeter-wave (mmWave) automotive radars operating at 77 GHz are the preferred radar technology for target detection because they are characterized by wide bandwidths (~4-7 GHz) and, hence, very high range resolution [9][11].

A concurrent development in intelligent transportation systems is the evolution of various vehicle-to-X (V2X) communication frameworks including vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-pedestrian (V2P) paradigms [12]. The overarching objective of these frameworks is to encourage sharing of road and vehicle information for applications such as environmental sensing, collision avoidance, and pedestrian detection. In the mmWave band, the IEEE 802.11ad protocol at unlicensed 60 GHz has been identified as a potential candidate for automotive radar applications where the far-field condition between the sensor and the target is sufficiently satisfied. In practice, however, 802.11ad is unsuitable for longer ranges because significant signal attenuation at 60 GHz arising from oxygen absorption severely restricts the maximum detectable radar range [13]. Therefore, it is more useful to employ 802.11ad-based JRC for ultra-short range radars (USRs). These sensors operate below 40 m range and have garnered much interest for applications such as blind spot warning, closing vehicle detection, lane change assistance, park distance control, parking lot measurement and automatic park assistance [14].

Employing 802.11ad for USRs leads to a second problem. When the target is located within a close range of a high-resolution radar, the received signal is composed of multiple reflections from different parts of the same object [13] (Fig. 1). When the automotive target moves, these point scatterers may often exhibit micro-motions besides the gross translational motion of the dynamic body. Examples include the swinging motion of the human arms and legs and the rotation of the wheels of a car. These micro-motions give rise to micro-Doppler features captured in joint time-frequency transforms [20][21] and/or micro-range features captured in high range-resolution profiles [22]. These signatures are usually both distinctive and informative and have been used for target classification especially in the case of pedestrians [23]. This extended automotive target model is more general. But previous works on 802.11ad JRC represent targets as only point scatterers because, as we explain next, conventional 802.11ad waveform performs poorly in detecting both bulk and micro-motions.

The physical layer of IEEE 802.11ad protocol transmits control (CPHY), single carrier (SC) and orthogonal frequency-division multiplexing (OFDM) modulation frames at chip rates of 1.76 GHz and 2.64 GHz, respectively. Every single CPHY and SC PHY frame is embedded with a 2172-bit short training field (STF), a 1152-bit channel estimation field (CEF), 64-bit header, data block and a beamforming training field (omitted, for simplicity, in Fig 2). The CEF consists of two 512-point sequences $G_{512}$ and $G_{512}$ which encapsulate Golay complementary pairs [9]. These paired sequences have the property of perfect aperiodic autocorrelation which is beneficial for communication channel estimation [24] and radar remote sensing [15].

The 802.11ad-based radars proposed in [15][17] harness the zero sidelobe attribute of 802.11ad Golay pairs during the matched filtering stage of the radar receiver to estimate the target’s location in a delay-Doppler plane [25][26]. However, the perfect auto-correlation property of Golay pairs holds strictly for only static targets. When the target is moving, the Doppler phase shift in the received signal causes a deterioration in the pulse compression output leading to large non-zero side lobes [27]. This effect is accentuated for multiple moving point targets as well as a single extended target with multiple point scatterers moving at different velocities. A large body of literature exists on designing single polyphase sequences [28] as well as generalizations of complementary Golay waveforms [29] to exhibit Doppler tolerance. In particular, [27] employed Prouhet-Thue-Morse sequence [30] to design Doppler-resilient Golay complementary pairs which are free of range sidelobes at modest Doppler shifts. Such a
sequence is appropriate for detection of micro-motion signatures. In this work, we utilize the \(G_{512} \) field to construct Doppler-resilient Golay complementary sequences across multiple 802.11ad packets and show that their performance in detecting the micro-Doppler and micro-range signatures of extended automotive scatterers supersedes that of the standard 802.11ad waveform. We presented preliminary results with simplistic target models with non-fluctuating radar cross-section along constant velocity straight line trajectories in [31]. In this work, we present realistic simulation models of automotive targets accounting for size, shape, material and aspect properties along more complex trajectories involving acceleration from start, driving turns and returning to halt.

Specifically, we consider the following common targets: a small car which we model as a cluster of triangular plates with point scatterers on its body and four wheels, a bicycle that we model with cylinders and a pedestrian that we represent with ellipsoidal body parts and corresponding point scatterers. In each case, we observe nearly identical values of \(P_d\) for the standard and the modified Golay waveforms. We study the impact of the range sidelobe suppression on the radar detection performance in terms of the probability of detections \((P_d)\) and false alarms \((P_f)\) for the standard and the modified Golay waveforms. We observe nearly identical values of \(P_f\) but a significant reduction in the \(P_d\) - while using the modified Doppler resilient waveform - for low to moderate signal to noise ratios.

The paper is organized as follows. In the following section, we describe the signal model of 802.11ad-based radar and introduce our proposed Doppler-resilient link. In Section III we present Doppler radar signatures of common automotive targets at short ranges as measured by an actual radar. In Section IV we present the models of two targets for the 802.11ad-based radar. We validate our methods through numerical experiments in Section V and conclude in Section VI.

II. SIGNAL MODEL

The range and Doppler estimation methods using the SCPHY CEF field of standard 802.11ad are described in [15–17, 24]. In [16], estimation of target parameters using the CPHY frame has been proposed target movement along a complex trajectory within the maximum unambiguous range of the radar. We then retrieve the high range resolution profiles and the Doppler spectrograms from these targets using the standard and the modified Doppler resilient Golay waveforms. Our results with the modified protocol show an improvement of approximately 20 dB in the range side-lobe suppression over the standard protocol. Interestingly, these side-lobe levels are retained up to Doppler velocities of \(\pm 144\) km/hr which is well beyond the maximum target speed for urban highways. We study the impact of the range sidelobe suppression on the radar detection

A. Classical 802.11ad-based target localization

A Golay complementary pair consists of two unimodular sequences \(G_{1,N}\) and \(G_{2,N}\) both of the same length \(N\) such that the sum of their autocorrelations has a peak of \(2N\) and a side-lobe level of zero:

\[
G_{1,N}[n] \ast G_{1,N}[-n] + G_{2,N}[n] \ast G_{2,N}[-n] = 2N\delta[n].
\]

In previous studies [15–17, 24, 31], the Golay complementary pair members \(Ga_{256}\) and \(Gb_{256}\) are drawn from the CEF of the same packet (Fig. 2). When these pairs are correlated at the receiver, the pulse repetition intervals (PRIs) for both sequences in the pair differ by a delay equivalent to the transmission time of one 256-bit sequence. Such a non-uniform PRI has a bearing on Doppler estimation but was ignored in the previous studies that investigated only macro-Doppler features. In this work, to keep the PRI same among all members of the Golay pair, we propose that the complementary sequences are of length 512 and embedded in the \(G_{512}\) field of CEF alternately in two consecutive packets as shown in Fig. 3. For the \(p\)th packet, the transmit signal is the 512-bit Golay sequence in CEF:

\[
s_T[n] = G_{p,512}[n], \quad n = 0, 1, \cdots, 511,
\]

where \(G_{p,512}\) and \(G_{(p+1),512}\) are Golay complementary pairs. The discrete-time sequence \(s_T[n]\) is passed through a digital-to-analog-converter (DAC) the output of which can be represented as a weighted sum of Dirac impulses:
where \( F_c = 1.76 \) GHz = \( 1/T_c \). This signal is then amplified to impart energy \( E_s \) per symbol to the transmit signal. The amplifier output is passed through a transmit shaping filter \( h_T(t) \) to obtain

\[
x_T(t) = \sqrt{E_s} (s_T \ast h_T)(t) = \sum_{n=0}^{511} s_T[n] h_T(t - nT_c).
\]

(4)

The 802.11ad protocol specifies a spectral mask for the transmit signal to limit inter-symbol interference (ISI) [32, section 21.3.2]. We assume that \( h_T(t) \) includes a low-pass baseband filter with an equivalent amplitude characteristic of the spectral mask. A common shaping filter has a frequency response \( H_T(f) \) of the root raised cosine (RC) filter [33]. At the receiver, another RC filter \( h_R(t) \) is employed such that the net frequency response is equal to a raised cosine (RC) filter, \( H(f) = H_T(f) H_R(f) \). The RC filter is a Nyquist filter with the following time-domain property to avoid ISI:

\[
h[n] = h(nT_c) = \begin{cases} 1, & n = 0 \\ 0, & n \neq 0. \end{cases}
\]

(5)

We can formulate this as:

\[
h(t) = \sum_{k=-\infty}^{\infty} \delta(t - kT_c) = \delta(t).
\]

(6)

This property only holds for the RC, and not the RRC filter. The baseband signal is then upconverted for transmission: \( z(t) = x_T(t)e^{j2\pi f c t} \), where \( f_c \) denotes the carrier frequency. The duration of this transmitted signal is 512\( T_c = 0.5 \) ns and the number of fast time samples is therefore 512. If we assume that the data block consists of 16 Bytes and that there are no optional training fields then each packet is of \( T_p = 2 \) ms duration which corresponds to the pulse repetition interval.

Assume that the radar transmits \( P \) packets constituting one coherent processing interval (CPI) towards a direct-path extended target of \( B \) point scatterers, where a \( b \)th point is characterized by a time-varying complex reflectivity \( a_b(t) \) located at range \( r_b = c\tau_b/2 \) and Doppler \( f_{D_b} = 2c\nu_b/c = 3 \times 10^6 \) m/s is the speed of light, \( \tau_b \) is the time delay, \( v_b \) is the associated radial velocity and \( \lambda \) is the radar’s wavelength. The coefficient \( a_b \) subsumes common effects such as antenna directivity, processing gains and attenuations including path loss. Ignoring the multi-path components, the reflected received signal at the baseband, i.e., after down-conversion, is

\[
x_R(t) = \sum_{p=0}^{P-1} \sum_{b=1}^{B} a_b(t)x_T(t - \tau_b - pT_p)e^{-j2\pi f D_b t} + z(t)
\]

\[
\approx \sum_{p=0}^{P-1} \sum_{b=1}^{B} a_b(t)x_T(t - \tau_b - pT_p)e^{-j2\pi f D_b pT_p} + z(t),
\]

(7)

where \( z(t) \) is additive circular-symmetric white Gaussian noise. The last approximation follows from the fact that \( f_{D_b} \ll 1/T_p \) so that the phase rotation within one coherent processing interval (CPI) (slow time) can be approximated as a constant. Sampling the signal at \( F_c = 1/T_c \) yields \( x_R[n] = x_R(nT_c) \):

\[
x_R[n] = \sum_{p=0}^{P-1} \sum_{b=1}^{B} a_b[n]x_T(nT_c - \tau_b - pT_p)e^{-j2\pi f D_b pT_p} + z[n]
\]

\[
= \sum_{p=0}^{P-1} a_b[n]x_T(nT_c - \tau_b - pT_p)e^{-j2\pi f D_b pT_p} + z[n],
\]

(8)

where we used Nyquist filter properties [36] in the last equality.

When the sampled signal from two consecutive packets is passed through matched filters of each Golay sequence, we exploit the perfect autocorrelation property to estimate the radar channel. For instance, correlation for the \( p^{th} \) pair produces

\[
\hat{h}_b[n] = x_R[n] * G_{p,512}[-n]
\]

\[
\hat{h}_{p+1}[n] = x_R[n] * G_{p+1,512}[-n]
\]

(9)

These outputs are added to return the channel estimate

\[
\hat{h}[n] = \frac{1}{1024} \left( \hat{h}_b[n] + \hat{h}_{p+1}[n] \right)
\]

\[
\approx \frac{1}{1024} \sum_{p=1}^{P} \sum_{b=1}^{B} a_b[n]\delta(nT_c - \tau_b - pT_p)e^{-j2\pi f D_b pT_p} + z[n] * (G_{p,512}[-n] + G_{p+1,512}[-n]),
\]

(10)

where the last approximation is due to the assumption that the Doppler shifts are nearly identical for the two Golay sequences \( G_{p,512} \) and \( G_{p+1,512} \) to utilize the zero side-lobe property of \( \chi_{DT} \). In order to locate the targets in the delay-Doppler plane, the range-time space is discretized into 512 bins of \( cT_c/2 \) resolution. We then create a delay-Doppler map by taking a 512-point Discrete Fourier Transform (DFT) of the radar channel estimates for each Doppler shift bin. Then, the delay and Doppler frequencies of the point scatterers on the target are given by the location of the \( B \) peaks on this 2D delay-Doppler map. For each \( m \)th CPI, the peaks along the Doppler axes for each range bin are coherently summed to obtain the time-varying high range resolution profile \( \chi_{DT}[m, r] \). Similarly, the peaks along the range axes for each Doppler bin are coherently summed to obtain the Doppler (or velocity) - time spectrogram \( \chi_{VT}[m, f_D] \).

B. Doppler-resilient 802.11ad

When a target is moving, the Doppler based phase shifts across the two waveforms may differ. For example, a point scatterer moving with a Doppler shift of \( f_{D_b} \) will give rise to a phase shift of \( \theta \approx 2\pi f_{D_b} T_p \) between \( h_{p} \) and \( h_{p+1} \). In this case, the perfect autocorrelation would no longer hold, i.e.,

\[
\langle G_{p,N}[n] * G_{p,N}[-n] \rangle + \langle G_{p+1,N}[n] * G_{p+1,N}[-n] \rangle e^{-j\theta} \neq 2N\delta[n],
\]

(11)

resulting in high side-lobes along the range. For example, consider a simple nonfluctuating point scatterer of unit reflectivity at \( (r_b = 20 \text{ m}, \nu_b = 10 \text{ m/s}) \) over 1 CPI of \( P = 2048 \) packets. For this set of waveform parameters, Fig. 4 plots the range-Doppler ambiguity function (AF) obtained by correlating the waveform with its Doppler-shifted and delayed replicas. The AF completely characterizes the radar’s ability to discriminate in both range and velocity of its transmit waveform. The complementary Golay AF shows a very high sidelobe level of \(-20 \text{ dB} \) at non-zero Doppler frequencies. This would result in high false alarms especially at low signal to noise ratios (SNR).
The limitation described above can be overcome by using Doppler-tolerant Golay sequences such as the one proposed in [27]. Without loss of generality, assume \( P \) be even and generate the Prouhet-Thue-Morse (PTM) sequence \([30], (q_P)^{(P-1)/2}\) which takes values in the set \( \{0,1\} \) by following Boolean recursion:

\[
q_p = \begin{cases} 
0, & \text{if } p = 0 \\
q_2^p, & \text{if } (p \text{ modulo } 2) = 0 \\
\overline{q_2^p}, & \text{if } (p \text{ modulo } 2) = 1,
\end{cases}
\]

(12)

where \( \overline{q_2} \) denotes the binary complement of \( q_2 \). As an example, when \( P = 16 \), the PTM sequence is \( q_0 = \{0,1,1,0,1,0,0,1\} \).

Based on the values of \( q_P \), we transmit the following Golay pairs:

\[
\sum_{p=0}^{P-1} e^{j\pi p} (G_{p,N}[n] * G_{p,N}[n]) \approx
0(G_{0,N}[n] * G_{0,N}[n]) + 1(G_{1,N}[n] * G_{1,N}[n]) + 2(G_{2,N}[n] * G_{2,N}[n]) + \cdots + (P-1)(G_{P-1,N}[n] * G_{P-1,N}[n]).
\]

(14)

Using PTM sequence, the above summation can be made to approach a delta function. The key is to transmit a Golay sequence that is also complementary with sequences in more than one packet. For instance, when \( P = 4 \), the PTM sequence dictates sending following signals in consecutive packets: \( G_{1,N}[n] \), \( G_{2,N}[n] \), \( -G_{2,N}[-n] \) and \( G_{1,N}[-n] \) for an arbitrary Golay pair \( \{G_{1,N}[n],G_{2,N}[n]\} \). In such a transmission, not only the first and last two sequences are Golay pairs but also the second and fourth signals. This implies

\[
\sum_{p=0}^{3} e^{j\pi p} (G_{p,N}[n] * G_{p,N}[n]) \approx 1(G_{1,N}[n] * G_{1,N}[n]) + 2(G_{2,N}[n] * G_{2,N}[n]) + 3(G_{3,N}[n] * G_{3,N}[n])
\]

\[
= 1((G_{1,N}[n] * G_{1,N}[n]) + (G_{3,N}[n] * G_{3,N}[n])) + 2((G_{2,N}[n] * G_{2,N}[n]) + (G_{3,N}[n] * G_{3,N}[n])) = (2N + 2(N))\delta[n] = 6N\delta[n].
\]

(15)

III. MEASUREMENT DATA COLLECTION

Unlike previous 802.11ad radar studies that assume only simple point targets at long ranges, real world automotive targets such as pedestrians, bicycles and cars appear as extended scatterers to the radar, more so at close ranges. We demonstrate this aspect with measured data in this section. We collected narrowband micro-Doppler data of a pedestrian, bicycle and a car using a monostatic radar consisting of a N9926A FieldFox vector network analyzer (VNA) and two horn antennas (HF907) (Fig. 3). The VNA was configured to carry out narrowband \( f_{21} \) parameter measurements at a carrier frequency of 7.5 GHz, with transmitted power set at 3 dBm and sampling frequency at 370 Hz (maximum frequency that can be obtained in the narrowband mode). The gain of both horn antennas is 10 dBi. The return echoes of targets were recorded separately.

The time-domain narrowband data, \( x_R[n] \), are processed using discrete-time short-time Fourier transform (STFT) to obtain the Doppler-time spectrum, \( \chi_{DT}[m,f_d] \):

\[
\chi_{DT}[m, f_d] = \sum_{n=-\infty}^{\infty} x_R[n] w[n-m] e^{-j2\pi f_d T_{\text{short}}},
\]

(16)

where \( w[n] = 0.54 - 0.48 \cos(2\pi n/N) \) is the Hamming window of duration \( T_{\text{short}} = 0.05 \) s \((N = 20)\).
The trajectories of the three targets are shown in Fig. 6. First, we consider a pedestrian of height 1.73 m. The subject walks towards the radar from a distance of 8 m (Fig. 6a) with an approximate speed of 1 m/s. The resulting micro-Doppler spectrogram (Fig. 6b) demonstrates that the pedestrian must be regarded as an extended target because micro-Doppler features from the torso, arms and legs are clearly visible on the radar. All the micro-Doplers are positive when the pedestrian is approaching the radar. The swinging motions of the legs give rise to the highest Dopplers, followed by the arms and the torso. Next, we consider a bicycle target of height 1.1 m, length 1.8 m and wheels of 0.45 m radius. The bicycle starts from a distance of 10 m and then turns left 2 m before the radar (Fig. 6c). The corresponding spectrogram (Fig. 6d) indicates that when the bicycle is moving straight towards the radar, only the micro-Dopplers from its frame are visible. However, when it executes a turn before the radar, multiple Doppler components arise from this single target. Besides the translational motion of the bicycle, the rotational motion of the two wheels turning at different velocities with respect to the radar; the motion of the pedals, and the small adjustments of the handle bars required for maintaining the balance of the bicycle also produce micro-Dopplers. These features are best observed during the compound body at the center of the axle connecting the two front wheels of the car. The root has six primary degrees of freedom (DOF) - translation along the three Cartesian axes and rotation around the same axes. A user drives the vehicle at the desired speed and along the desired trajectory by prescribing specific kinematic trajectories to the root. Secondary parts such as wheels are connected to the primary body through joints or hinges. The simulator then computes forces and torques that actuate the secondary DOFs of the joints to follow freely based on forward dynamics. The resulting motions of all the bodies comprising the vehicle are constrained by a control system in the software to realize realistic animation of the vehicle at a frame rate of 60 Hz. With the radar at the origin, we considered a trajectory of the car as shown in Fig. 6e. The car accelerates from start, moves along a straight line to the left of the radar and then performs a U turn and moves towards the radar on a path to its right and then decelerates to a halt. The car is always within the maximum unambiguous range of the radar.

In the case of the bicycle, we consider a bicycle frame with a cross bar frame and two wheels as shown in Fig. 6f. For the sake of simplicity, we do not model the human rider on the bicycle. Through the PyBullet software, we obtain a realistic animation model of the two wheels, the bicycle frame and the front handle bars along the trajectory shown in Fig. 6g. The bicycle accelerates from halt and

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### TABLE I

| Parameter                        | Proposed V2P Radar |
|----------------------------------|--------------------|
| Carrier frequency (GHz)          | 60                 |
| Bandwidth (GHz)                  | 1.76               |
| Range resolution (m)             | 0.085              |
| Maximum unambiguous range (m)    | 44                 |
| Pulse repetition interval (µs)   | 2                  |
| Velocity resolution (m/s)        | 0.3                |
| Maximum unambiguous velocity (m/s)| 625               |

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Fig. 5. Monostatic radar configuration using vector network analyzer in narrowband mode and two horn antennas.

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IV. TARGET MODELS

There are multiple methods for generating animation models of dynamic bodies [34]. In this work, we derive the animation data of pedestrians from motion capture technology and use a physics-based simulator to model the motion of a car and bicycle.

A. Animation model of car and bicycle

We employed pyBullet - a Python based open source software development kit (SDK) - for generating motion data of a car and bicycle [35]. PyBullet uses Bullet Physics, a physics-based animation package, for describing motions of dynamic bodies [36]. In this environment, each vehicle is designed as a collection of interconnected rigid bodies such that they do not undergo any type of physical deformation during motion. We modeled the car with a lateral wheel axle length of 2 m, front axle to rear axle length of 3.5 m and a wheel radius of 0.48 m as shown in Fig. 7. We simulated "front wheel driving" of the car by considering the root of the compound body at the center of the axle connecting the two front wheels of the car. The root has six primary degrees of freedom (DOF) - translation along the three Cartesian axes and rotation around the same axes. A user drives the vehicle at the desired speed and along the desired trajectory by prescribing specific kinematic trajectories to the root. Secondary parts such as wheels are connected to the primary body through joints or hinges. The simulator then computes forces and torques that actuate the secondary DOFs of the joints to follow freely based on forward dynamics. The resulting motions of all the bodies comprising the vehicle are constrained by a control system in the software to realize realistic animation of the vehicle at a frame rate of 60 Hz. With the radar at the origin, we considered a trajectory of the car as shown in Fig. 8. The car accelerates from start, moves along a straight line to the left of the radar and then performs a U turn and moves towards the radar on a path to its right and then decelerates to a halt. The car is always within the maximum unambiguous range of the radar.
Fig. 6. Trajectories followed by (a) pedestrian, (b) bicycle and (c) car during measurement data collection. Micro-Doppler spectrograms of (d) pedestrian, (e) bicycle and (f) car obtained by performing STFT on 7.5 GHz narrowband measurement data.

Fig. 7. Velocity of point scatterers distributed along a rotating wheel reaches a steady velocity and then performs two right turns before halting.

B. Animation model of pedestrians

The animation data of a walking human was obtained from motion capture technology at Sony Computer Entertainment America. The data describes the time-varying three-dimensional positions of a collection of markers distributed over the body of a live actor at a frame rate of 60 Hz over a duration of 5 s. There are 24 markers located at the head, torso (both front and back), upper arms, hands, knees and feet. We assume that these markers correspond to the point scatterers on the body of the pedestrian as shown in Fig. 8c. The trajectory followed by the subject is shown in Fig. 8f. Here the pedestrian approaches the radar and then turns around and walks away from the radar.

C. Electromagnetic model of extended targets

We integrate the animation data of the pedestrian, bicycle and car with electromagnetic models of radar scattering using the primitive modeling technique [34] which has been extensively employed for modeling radar returns from dynamic human motions [37]. We first interpolate the animation data from the video frame rate to the radar sampling rate. Then, each of the dynamic bodies is modelled as an extended target made of multiple primitives with point scatterers distributed along its body. The car is assumed to be composed of 56 triangular plates. The wheel-rims and car body have been modeled as metallic plates. The windows, front windscreen and rear windscreen screen are modelled as glass. The radar cross section of each $b^{th}$ plate at each $n^{th}$ discrete time instance is:

$$\sigma_b[n] = \frac{4\pi A_b^2 \cos^2 \theta_b[n]}{\lambda^2} \left( \frac{\sin \left( kd_b \sin \frac{\theta_b[n]}{2} \right)}{kd_b \sin \frac{\theta_b[n]}{2}} \right)^4,$$

(17)

where $A_b$ is the area of the triangle, $d_b$ is the dimension of the triangle along aspect angle and $k = \frac{2\pi}{\lambda}$ is the phase constant for $\lambda$ wavelength [38]. The aspect angle $\theta_b[n]$ is defined as the angle between the incident ray from the radar and the normal to the triangular plate.

In the case of the bicycle, we have modelled the Argon 18 Gallium bicycle. The bicycle frame consists of 9 metal cylinders of 6cm radius of differing lengths. The front wheel has 18 spokes and the rear wheel has 25 spokes, each of which are of 2mm radius and 34.5 cm length. The radar cross-section of a cylinder [38] of length $L_b$ and radius $a_b$ is:

$$\sigma_b[n] = \frac{2\pi a_b L_b^2}{\lambda} \cos^2 (\theta_b[n]) \left( \frac{\sin \left( kL_b \sin \theta_b[n] \right)}{kL_b \sin \theta_b[n]} \right)^2,$$

(18)

For the pedestrian, 21 different body parts - torso, arms and legs - are modelled as ellipsoids while the head is approximated as a sphere. The longest dimension of each ellipsoid spans the length of the bone in the skeleton structure of the motion capture data. The radar cross section of an ellipsoid [38] of length $H_b$ and radius $R_b$ is:

$$\sigma_b[n] = \frac{\frac{1}{4} R_b^4 H_b^2 \sin^2 \theta_b[n]}{R_b^2 \sin^2 \theta_b[n] + \frac{1}{4} H_b^2 \cos^2 \theta_b[n]},$$

(19)

The radar cross-section fluctuates with time due to the variation in angle $\theta_b[n]$ between incident wave and the major length axis of ellipsoid. We assume that the ellipsoids are made of single layer dielectric with a dielectric constant 80 and conductivity 2.

If we assume that the transmitted power and antenna processing gains of the transmitter and receiver antennas is unity, then the strength of the scattered signal from the $b^{th}$ part of the extended target depends on the material properties, aspect angle and the
position of the scattering center on the primitive with respect to
the radar. We incorporate the material properties of the target into
the RCS estimation through Fresnel reflection coefficient, $\Gamma$, for
planar interfaces at normal incidence. The attenuation of 60GHz
wave through the air medium is modeled through $\alpha$. Since all the
scattering centers may not be visible to the radar at each time
instant due to shadowing by other parts of the same target or other
channel conditions, we incorporate stochasticity in the scattering
center model by including a Bernoulli random variable of mean 0.5,
i.e. $\zeta_b[n] \sim \text{Bernoulli}(0.5)$, in the RCS. A point scatterer is seen
by the radar with a probability of 50% at every time instant. The
reflectivity of a primitive at any time sample is

$$a_b[n] = \zeta_b[n] \Gamma(\theta_b[n]) \sqrt{\sigma_{b}[n]} e^{-j\frac{2\pi}{\lambda} r_b[n] - 2\alpha r_b[n]} r_b^2[n]. \quad (20)$$

The received signal, $x[n]$, is obtained from the sum of the convolution of the scattered signal from each $b^{th}$ part and the transmitted signal as shown in (19). The noise is modeled as an additive zero-mean Gaussian noise with variance $N_p$. The primitive-based technique, presented here, is computationally efficient and relatively accurate in generating micro-Doppler signatures and high range resolution profiles. However the method does not capture the multipath effects.

V. EXPERIMENTS

We evaluated our proposed approach through numerical experiments for common automotive targets such as a car, bicycle and a pedestrian. We compared the results for both SG and MG waveforms. The noise variance in all experiments is $-100\text{ dbm}$.

A. Car

Figure 9a shows the ground truth of the range-time for different point scatterers situated on the moving car. The range increases as the car moves away from the radar and then make a U turn at $t = 8\text{ s}$ after which the range again begins to reduce. The range-time plots for SG and MG in Fig. 9b and c, show very good agreement with the ground truth range-time plot. In the inset, we observe the micro-range features that arise from the different point scatterers on the car. Due to the effect of shadowing, the range tracks show some discontinuities. The range resolution of the radar is sufficient at some time instances in resolving these micro-range tracks. The SG signature shows significant range sidelobes due to the motion of the car. These sidelobes are absent in the case of the MG signatures.

Figure 9d shows the ground truth of the velocity time behaviour of the point scatterers. The velocity-time results (Fig. 9e and f) show that there is considerable variation in the velocities of the different point scatterers on the body of the car and especially from the wheel. The velocities of different points on the chassis of the car also show variation depending on their proximity and aspect with respect to the radar. The velocity-time radar signatures for both standard and modified Golay agree with the ground truth velocity-time plots. The micro-Doppler tracks of the different point scatterers can be easily observed. Results for SG and MG are nearly identical. This is because the motion of the car only affects the range dimension and not the Doppler dimension.

B. Bicycle

The micro-range and micro-Doppler features from the motion of the bicycle are presented in Fig. 10. The ground truth range-time plots of the different point scatterers on the two wheels show a very narrow range spread except during the turns (at 1.5s and 7s) - especially in comparison to the car. The high range resolution profiles for SG and MG waveforms are very similar to the ground truth plots. However, the high range sidelobes are evident in the SG plots. The velocity-time plots show a significantly greater Doppler spread due to the rotating wheels. The spread is greatest during turns which is similar to the results from the experimental measurements. The results from SG and MG look nearly identical here and are very similar to the ground truth results.
Fig. 9. (a) Trajectory of a car before the radar (b) Range-time plot of point scatterers on the car. (c) Radial velocity versus time of point scatterers on the car. Radar signatures: (d) SG range-time (e) MG range-time (f) SG Doppler-time (g) MG Doppler-time

Fig. 10. (a) Range-time plot of the point scatterers on the bicycle. Radar Signatures: (b) SG range-time, (c) MG range-time (e) Doppler-time plot of the point scatterers on the bicycle. Radar Signatures: (f) SG Doppler-time (g) MG Doppler-time

Fig. 11. (a) Range-time plot of point scatterers on the pedestrian, (d) Radial velocity versus time of point scatterers on the pedestrian. Radar signatures: (b) SG range-time (c) MG range-time (e) SG Doppler-time (f) MG Doppler-time
\section*{C. Pedestrian}

Next, we study the radar signatures of the pedestrian in Fig. 11. We observe again that the range-time plots for SG (Fig. 11b) and MG (Fig. 11c) sequences are in agreement with the ground truth results (Fig. 11a). Due to the smaller spatial extent of the pedestrian across the range dimension, the micro-range tracks are difficult to observe except at some time instants. The inset shows the micro-range from the right and left legs and arms. The pedestrian is always within the maximum unambiguous range and the field of view of the radar. The radar cross-section of the pedestrian is typically lower than that of the car. However, since the pedestrian’s trajectory is within 2m to 8m while the car moved from 10m to 40m, the signal strengths from both the cases are comparable. Again, we observe that the range-time plots of the SG sequence have high sidelobes levels when compared to the peak signal strength. These sidelobes are suppressed with the MG sequence. The Doppler velocity-time spectrograms in Fig. 11d-f show excellent agreement with the ground truth results. We observe the micro-Dopplers from the feet, legs, arms and torso. The Dopplers are positive when the pedestrian approaches the radar and are negative when the pedestrian moves away from the radar. The strongest Dopplers arise from the torso. As observed before in the results with the car, the signatures from the standard and modified Golay are nearly identical in the Doppler domain.

\section*{D. Detection performance}

We now examine the impact of range sidelobes on the radar detection performance. From the minimum possible radar cross-section ($\sim 30$ dBsm) and the maximum range (43 m) of the radar, we estimate the minimum detectable signal of the radar to be $-100$ dBm from [5]. We define the minimum signal-to-noise-ratio (SNR) of the radar receiver to be the ratio between the minimum detectable signal of the radar and the average noise power ($N_o$). In our study we vary the SNR from $-30$ to $+5$ dB. We consider a scenario where both a car and a pedestrian move simultaneously before the radar following the trajectories shown in Fig. 10d and (f), respectively. The received radar signal is therefore the superposition of the scattered signals from the two targets along with noise. In order to study the detection performance of the radar, we consider the radar range-time results ($\chi_{RT}[m,r]$) where $m$ denotes the CPI and $r$ denotes the discrete range bin. We multiply the signal at every bin with the quadratic power of the corresponding range. This step is crucial while detecting multiple targets of differing cross-sections because it removes the dependency of signal strength on the distance of the target from the radar. The extended targets are spread across multiple range bins and the radar cross-section of a target (car or pedestrian) at each CPI is obtained by the coherent integration of the range compensated signal across multiple range bins determined by the ground truth range-time plots (the rest of the range bins have noise). For instance, the radar cross-section of the car $\sigma_{ca}$ at every $m^{th}$ CPI is obtained by

$$\sigma_{ca}(m) = \left| \sum_{b=1}^{B} \chi_{RT}[m,r_b]^2 e^{j2\pi\frac{m}{B}r_b} \right|^2$$

where $\{r_b\}_{b=1}^{B}$ denotes range bins determined from the ground truth car data for that CPI.

In Fig. 12 we plot the histogram distribution of the noise and target returns for both SG and MG sequences, from all the CPIs, under two different SNRs: $-20$ and $+5$ dB. The histograms of the car and pedestrian RCS do not show significant variation for SG and MG. Hence, we show a single distribution for each of these targets. It is evident that the RCS of the car fluctuates from $-10$ dBsm to $30$ dBsm with a mean of $10$ dBsm. In case of pedestrian, the RCS is in the range $-20$ to $+5$ dBsm. The variation in the RCS arises from the change in aspect angle with respect to the radar. The car thus has noticeably higher RCS than the pedestrian, as expected. The noise returns are higher under poor SNR conditions. From both histograms, it follows that the noise returns for SG are higher than those for MG because noise is added to high range sidelobes in case of SG.

The empirical probability of detection ($P_d$) of the radar is estimated from the area under the target histograms that falls above a RCS threshold, $\gamma$ (indicated by the dashed line in the Fig. 12). Similarly, the empirical probability of false alarms ($P_f$) is determined from the area under the noise histograms that falls above threshold. The $P_d$ for SG and MG are plotted as a function of $\gamma$ in Fig. 12. The $P_d$ for both targets expectedly decrease as we increase the threshold. The SG and MG waveforms show similar detection results because the modification in the Golay sequences affects only the range sidelobes, not the peak signal strength. At a threshold of $-15$ dBsm, the detection is close to 99% and for $-20$ dBsm, it is 100%.

Next, we examine the $P_d$ in Fig. 12 for three different thresholds. With the increase in threshold, $P_d$ decreases. We do not opt for thresholds above $-15$ dBsm because it leads to low $P_d$. When the threshold is $-15$ dBsm, SG exhibits higher $P_d$ than MG by approximately 2.5% for low SNRs ($-20$ to $0$ dB). This is even more pronounced for the $-20$ dBsm threshold curve because the high SG range sidelobes with additive noise show up as false alarms. When the noise is very high ($-30$ dB), the noise peaks are above the range sidelobe levels. Hence the $P_d$ of SG and MG become similar. For moderate-to-high SNR, i.e., $0$ to $+5$ dBsm, $P_d$ for SG is higher than MG for $-20$ dBsm threshold.

\section*{VI. Summary}

We presented a USRR which employs the 512-bit Golay codes in 802.11ad link for range estimation up to 40 m with a resolution of 0.085 m. The codes in consecutive packets form Golay complementary sequences based on the PTM sequence that results
in very low sidelobe levels for most automotive targets moving up to 144 km/hr. We demonstrated detection of high range resolution profiles and micro-Doppler spectrograms of common automotive targets - pedestrian, bicycle and car. Each of these targets were animated and modeled as extended targets with multiple scattering centers distributed along their body. The signatures from the targets show distinctive micro-motion features such as the rotation of the wheels and the swinging motions of the arms and legs. The detection performance of the radar shows a marked reduction in the $P_{fa}$ for the MG when compared to SG for low and moderate SNRs.

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