Forward Collision Vehicular Radar with IEEE 802.11: Feasibility Demonstration through Measurements

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Abstract

Increasing safety and automation in transportation systems has led to the proliferation of radar and IEEE 802.11 dedicated short range communication (DSRC) in vehicles. Current implementations of vehicular radar devices, however, are expensive, use a substantial amount of bandwidth, and are susceptible to multiple security risks. Consider the feasibility of using an IEEE 802.11 orthogonal frequency division multiplexing (OFDM) communications waveform to perform radar functions. In this paper, we present an approach that determines the mean-normalized channel energy from frequency domain channel estimates and models it as a direct sinusoidal function of target range, enabling closest-target range estimation. In addition, we propose an alternative to vehicular forward collision detection by extending IEEE 802.11 dedicated short-range communications (DSRC) and WiFi technology to radar, providing a foundation for joint communications and radar framework. Furthermore, we perform an experimental demonstration using existing IEEE 802.11 devices with minimal modification through algorithm processing on frequency-domain channel estimates. The results of this paper show that our solution delivers similar accuracy and reliability to mmWave radar devices with as little as 20 MHz of spectrum (doubling DSRC’s 10 MHz allocation), indicating significant potential for industrial devices with joint vehicular communications and radar capabilities.

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I. INTRODUCTION

Radar is a key technology for frontal collision avoidance. Vehicular radars have several advantages over competing sensor technologies. For example, light detection and ranging (LIDAR) sensors are expensive and are sensitive to low-visibility conditions \cite{1}, \cite{2}, ultrasonic sensors have limited range and suffer from degraded performance in several common environments \cite{3}, and dedicated short range communication (DSRC) networks (which can be used to exchange GPS-based location and velocity information) only work when the colliding vehicle has a radio \cite{4}.

Despite their importance in vehicle safety, existing forward vehicular radar products have several limitations. First, current vehicular radars are implemented at high carrier frequencies and require large bandwidth allocations (i.e., hundreds of MHz), forcing them to exploit the millimeter wave (mmWave) spectrum. mmWave radars feature complex antenna array structures and high power analog hardware, leading to increased cost relative to IEEE 802.11 transceivers \cite{5}. This affects the original equipment manufacturers (OEMs) of economy vehicles that deploy vehicular radars as well as consumers needing to replace damaged parts, since radars are mounted on the front bumper of vehicles and are susceptible to collision damage. Second, mmWave radar antennas cannot be decoupled from the analog and RF circuits due to cable losses at mmWave frequencies \cite{6}. Consequently, all of the circuitry of mmWave radars is contained within a single package, leading to devices that are obtrusive, either degrading aerodynamics and visual appeal or requiring extra effort to conceal when placed on vehicles \cite{7}. Third, existing vehicular radars are known to be susceptible to certain security risks \cite{5}, \cite{8}, \cite{9}. Traditional vehicular mmWave radars leverage a specific signal structure with strong autocorrelation properties but exhibits no inherent authentication \cite{10}. Without additional authentication from a supplemental state-of-the-art communication network, these radars remain vulnerable to spoofing attacks. Fourth, because there is no uniformly-adopted standard for vehicular radar waveforms, electromagnetic interference may eventually limit the scale of deployment \cite{11}.

The proliferation of dual radio devices, however, supports the use of IEEE 802.11 communication networks for vehicular safety. In addition, the Federal Communications Commissions (FCC) has allocated spectrum at the 5.9 GHz band specifically for DSRC as part of IEEE 802.11p. Vehicles equipped with DSRC for active safety applications have already been deployed in Japan and are ready for deployment in the United States \cite{12}, \cite{13}. 
Successful integration of ranging capabilities into existing IEEE 802.11 wireless communication devices provides substantial opportunities for automotive OEMs and its customers. Attaching sufficient ranging capabilities to such devices, however, is challenging due to bandwidth limitations. Current frequency-modulation continuous wave (FMCW) vehicular radars with digital receiver processing require 150 MHz of bandwidth for 1 m range resolution [14]. In contrast, IEEE 802.11p waveforms only operate on 10 MHz spectrum allocations and IEEE 802.11a/g/n waveforms often only occupy 20 MHz or 40 MHz spectrum allocations (IEEE 802.11ac has optional 80 MHz and 160 MHz modes [15]).

There has been considerable research on passive bistatic and multistatic radar with IEEE 802.11 packets demonstrating refined single and multiple-target localization in indoor and outdoor environments [16]–[21]. Passive radar, though, is not suitable for automotive safety applications since it requires a high density of infrastructure. Active high-resolution radar has recently been demonstrated for through-the-wall human detection (through measurements) and vehicular radar (through simulation) using IEEE 802.11 OFDM waveforms [22], [23]. Both of these methods rely on a complete redesign of the digital baseband receiver [23]. Unfortunately, this will delay product deployment and partially erode the cost benefit afforded to IEEE 802.11 based radars, making widescale deployment of active high-resolution radars impractical.

Current monostatic radar approaches that leverage OFDM signal structure in IEEE 802.11 packets fail to achieve sufficient accuracy for vehicular applications [24]–[26]. Other OFDM radar approaches require large amounts of bandwidth unavailable to DSRC [27]–[31]. While [32] claims to have achieved accuracy of less than 2m for IEEE 802.11p OFDM vehicular radar using traditional radar techniques, they require an additional 60 MHz spectrum from an adjacent ISM band, which may not be available for use in the deployment stage. CohdaWireless claims that they have achieved 360-degree vehicular radar using frequency-domain channel estimates from DSRC devices using a correlator approach [33]. Unfortunately, no details of their demonstration are available [34]. As a result, we believe that our paper provides the first technical description and feasibility study of this technology.

In this paper, we design a simple algorithm for computing high-resolution ranging and target detection metrics from frequency domain channel estimates obtained from an IEEE 802.11 OFDM receiver without modification to the digital baseband receiver. We assume that the return channel can be well-modeled by the two-path model, that is, the receive signal consists of a direct path and a single reflected path. Under this assumption, the mean-normalized channel
energy computed from the frequency domain channel estimates can be well-approximated by a direct sinusoidal function of target range. This enables us to directly estimate target range through parameter optimization of sinusoidal functions. We apply a three-dimensional brute-force optimization algorithm to estimate the time delay associated with the reflected path, which directly corresponds to the range of the closest target.

In simulation, we show that meter-level accuracy can be achieved using IEEE 802.11 packets with a 20 MHz channel bandwidth. We validate our simulation results through measurements using a prototype IEEE 802.11a/g over-the-air campaign with vehicle targets. This prototype was implemented with an off-the-shelf software radio transceiver and two directional antennas. Using standard IEEE 802.11a transmission, our prototype achieves meter-level accuracy with meter-level resolution for a single vehicle target up to 50m away.

The immediate consequences of our study are threefold. First, since IEEE 802.11 networks are already being transferred into automotive environments for dedicated short-range communications (DSRC) through IEEE 802.11p [35], we have essentially enabled immediate market access to dual purpose radar and communication (RadCom) devices [36]. This benefit is strengthened by the observation that mmWave communication systems, the previous communications standard candidate proposed for RadCom [37], are only starting to penetrate the marketplace [6]. Second, our study proves that cost-effective vehicular radar solutions in a convenient form factor are possible. Finally, our results show that a new sophisticated radar waveform and medium access control (MAC) layer standard is not required to provide existing vehicular radar networks with coexistence, security, and power management features [35].

The remainder of this paper is organized as follows. Section II describes the system model for the IEEE 802.11 channel and summarizes key assumptions. Section III discusses the algorithmic approach used to determine range estimation based on receive channel energy. Section IV presents simulation results and discusses the impact of these results on the overall study. Section V describes the measurement platform of the study. Section VI discusses the measurement method and environment and presents the results of the study. Section VII discusses the implications of the results, concludes the paper, and provides suggestions for future work.

**Notation:** The real coordinate space with \( N \) dimensions is denoted by \( \mathbb{R}^N \). The natural coordinate space is denoted by \( \mathbb{N} \).
In this study of IEEE 802.11-based vehicular ranging feasibility, we assume that a vehicle is equipped with an IEEE 802.11 transceiver. The transmit and receive antennas exhibit sufficient separation such that a direct signal path from transmit to receive antenna exists. Further, we assume that the receive RF chain is able to operate simultaneously with the transmit chain. This configuration can be found in commercial IEEE 802.11 devices, for example, to enable channel reciprocity through calibration. As such, our algorithm will operate under the assumption of a pseudo-monostatic active radar configuration. In addition, we assume that signals can be transmitted at a rate adequate for performing range detection in a constantly fluctuating vehicular environment.

Consider the continuous-time complex-baseband link model with time index $t$, transmitted signal $x(t)$, received signal $y(t)$, wireless channel impulse response $h(t)$ with $\tau$ excess delay, and additive noise signal $v(t)$ such that $y(t) = h(t) \star x(t) + v(t)$ where $\star$ is the convolution operator. For IEEE 802.11, it is generally assumed that the channel impulse response will remain fixed over the duration of a single packet, but may change between packets due to mobility.

Now, we simplify our general link model to a two-path channel model to address the vehicular ranging application: forward collision detection with a primary target (the vehicle directly ahead). Two-path channel models are commonly used in single-target bistatic radar applications [16], [18]. To incorporate certain advantages from bistatic radar processing, we adopt this model under the assumption that we are able to effectively create a direct path between transmit and receive antennas for monostatic radar. This special case is illustrated in Figure 1.

Consider the pseudo-complex baseband channel equivalent [6]

$$h_p(t) = \alpha \delta(t) + \beta e^{-j(2\pi f_c \tau - \phi_0)} \delta(t - \tau).$$  

(1)
where $\delta(\cdot)$ is the Dirac delta function, $f_c$ is the carrier frequency, $\phi_0$ is the constant phase shift of the reflected signal with respect to the direct signal, $\tau$ becomes the time delay associated with target reflection, $\alpha$ is the path loss associated with the direct path (Path 1), and $\beta$ is the path loss associated with the reflected target (Path 2). Note that since we use the relative phase shift between the direct and reflected path $\phi_0$, the phase shift of the reflected direct path is omitted. The direct path behaves as a reference point for the target reflection path, enabling accurate estimation of the delay between the direct path arrival and the target reflection arrival. The path loss of the direct path, $\alpha$, is a function of the transmit power ($P$), the path loss coefficient of the direct path between the transmit and receive antenna ($L_1$), the signal power feed-through coefficient between the transmit and receive paths in the analog/RF circuit ($F$), and the gain based on radiation pattern in the unintended direction of the transmit and receive antennas ($G_{1}^{(TX)}$ and $G_{1}^{(RX)}$, respectively) such that

$$\alpha = \sqrt{PF} + \sqrt{PG_{1}^{(TX)}G_{1}^{(RX)}}L_1. \quad (2)$$

Note that IEEE 802.11 transceivers generally experience signal power feed-through within the analog/RF circuit. Our model assumes that the direct path is a combination of the effects from internal feed-through and external line-of-sight propagation.

Similarly, the path loss of the reflected path, $\beta$, is a function of the transmit power ($P$), the single-direction path loss coefficient between the transmit antenna and the reflecting object ($L_{2,1}$), the single-direction path loss coefficient between the reflecting object and the receive antenna ($L_{2,2}$), the reflection power loss coefficient ($R$), and the gain based on the radiation pattern of the transmit and receive antennas ($G_{2}^{(TX)}$ and $G_{2}^{(RX)}$, respectively) such that

$$\beta = \sqrt{PG_{2}^{(TX)}G_{2}^{(RX)}}L_{2,1}L_{2,2}R. \quad (3)$$

The Friis transmission equation determines the path loss coefficients $L_1$, $L_{2,1}$, and $L_{2,2}$. The radar cross section (RCS) equation determines the reflection power loss coefficient $R$ as a function of wavelength ($\lambda$) and a RCS parameter ($\sigma$):

$$R = \frac{4\pi\sigma}{\lambda^2}. \quad (4)$$
For bandwidth $B$, the continuous-time channel impulse response can then be represented as

$$h(t) = \alpha B \text{sinc}(Bt) + \beta e^{-j2\pi f_c \tau} B \text{sinc}(B(t - \tau))$$

(5)

where $\text{sinc}(x) = \sin(\pi x)/\pi x$. Assume that the receive signal is perfectly bandlimited. For symbol period $T = 1/B$, the discrete-time channel impulse response is

$$h[n] = Th(nT)$$

(6)

$$= \alpha \text{sinc}(Btn) + \beta e^{-j2\pi f_c \tau - \phi_0} \text{sinc}(BTn - B\tau)$$

(7)

$$= \alpha \delta[n] + \beta e^{-j2\pi f_c \tau - \phi_0} \text{sinc}(n - B\tau).$$

(8)

For frequency $f$, the discrete-time Fourier transform (DTFT) of (8) is

$$H(e^{j2\pi f}) = \alpha + \beta e^{-j(2\pi f_c \tau - \phi_0)} e^{-j(2\pi f \tau - \phi_1)}$$

(9)

where $\phi_1$ is the frequency varying phase shift of the reflected signal with respect to the direct signal and $f \in [-\frac{1}{2}, \frac{1}{2}]$.

Current IEEE 802.11 standards use OFDM; thus, frequency domain channel estimates enabled by the discrete Fourier transform (DFT) are typically provided by OFDM transceivers. Assuming perfect synchronization, perfectly band-limited signals, and perfect estimation algorithms, if $\tau$ is smaller than the duration of the OFDM cyclic prefix, for subcarrier bandwidth $\Delta$ and $N$ nonzero subcarriers $m \in \{-N/2, -N/2 + 1, \ldots, N/2\}$, $m \neq 0$, the baseband OFDM frequency domain channel estimate of the two-path channel, obtained by sampling the DTFT at each subcarrier, is

$$\hat{H}[m] = \alpha + \beta e^{-j(2\pi m \Delta \tau - \theta)}.$$  

(10)

where $\theta = \phi_0 + \phi_1$ is the overall phase shift of the reflected signal with respect to the direct signal. For the sake of notation, we will omit the carrier frequency term. Note that practical channel estimates will include noise and various filter contributions.

To determine the mean-normalized channel energy, we define the magnitude of the channel coefficients, which we call the energy of the channel estimates, as

$$E_{\hat{H}}[m] = |\hat{H}(m\Delta)|^2$$

(11)

$$= \alpha^2 + \beta^2 + 2\alpha\beta \cos(2\pi m \Delta \tau - \theta).$$

(12)
Finally, we define the empirical mean over all subcarriers as

\[ \tilde{E}_{\hat{H}} = \frac{1}{N} \sum_{n} E_{\hat{H}}[n] \]  
(13)

and compute the mean-normalized channel energy

\[ \overline{E}_{\hat{H}}[m] = \frac{E_{\hat{H}}[m]}{\tilde{E}_{\hat{H}}} \]  
(14)

For the two path channel,

\[ \overline{E}_{\hat{H}}[m] - 1 = \frac{\alpha^2 + \beta^2 + 2\alpha\beta \cos(2\pi m \Delta \tau - \theta)}{\frac{1}{N} \sum_{n} \alpha^2 + \beta^2 + 2\alpha\beta \cos(2\pi n \Delta \tau - \theta)} - 1 \]  
(15)

\[ \approx \frac{2\beta}{\alpha} \cos(2\pi m \Delta \tau - \theta) \]  
(16)

where (a) follows from \( \alpha \gg 2\alpha\beta \gg \beta \). This enables us to directly estimate target range by determining the delay \( \tau \) from the adjusted channel estimate energy.

Recall that we have omitted the phase shift of the direct path in our channel model. For phase shifts \( \theta_d \) and \( \theta_r \) of the direct and reflected paths respectively, consider briefly redefining the channel frequency response as

\[ \tilde{H}[m] = \alpha e^{j\theta_d} + \beta e^{-j(2\pi m \Delta \tau - \theta_r)} \]  
(17)

\[ = e^{j\theta_d}(\alpha + \beta e^{-j(2\pi m \Delta \tau - \theta)}) \]  
(18)

where the relative phase shift of the reflected path has the relation \( \theta = \theta_r - \theta_d \). Now the mean-normalized channel energy would be

\[ E_{\tilde{H}}[m] = |\tilde{H}(m\Delta)|^2 \]  
(19)

\[ = |e^{j\theta_d}|^2(\alpha^2 + \beta^2 + 2\alpha\beta \cos(2\pi m \Delta \tau - \theta)) \]  
(20)

\[ = \alpha^2 + \beta^2 + 2\alpha\beta \cos(2\pi m \Delta \tau - \theta) \]  
(21)

which is the same as before. Thus, to simplify notation, we have omitted the phase shift of the direct path.

Mobile OFDM systems exhibit Doppler effects, which generates inter-carrier interference between OFDM subcarriers and degrades performance [39]. Estimates of the Doppler spread can be used to mitigate the negative effects of a highly mobile wireless channel [40]. In addition,
Doppler is a critical parameter for estimating target velocity in radar [41]. Standard radar methods for Doppler frequency estimation require long transmissions since waveforms are coherently processed for many consecutive milliseconds (ms) [14]. IEEE 802.11 packets, however, are rarely more than 1 ms in duration, making it difficult to directly estimate Doppler from a single packet. Nevertheless, target velocity can be estimated between packets through differential computations on ranging estimates from packets. Doppler frequency is not expected to significantly distort channel estimates since the duration the long training field of IEEE 802.11p waveform is 3.2 microseconds (µs) and the Doppler frequency in vehicular environments, assuming a maximum differential velocity of 160 km/h, does not exceed 875 Hz [42]. Hence, channel estimation is based on training sequences whose worst-case Doppler is less than 3 degrees per OFDM symbol per target. For the scope of this feasibility study, we do not explicitly consider Doppler effects in our model and reserve the topic of velocity detection for future work.

III. ALGORITHM FOR RANGING AND DETECTION

In this section, we describe an algorithm for range estimation that applies a brute-force minimization of the least-squared error between sinusoidal functions, which is a parametric estimation. In various radar implementations, spectrum estimation is used to determine ranging based on a channel impulse response [43], [44]. This strategy is effective in many existing antenna system applications, including MIMO radar systems [45], [46]. We chose brute-force optimization over alternative procedures for two primary reasons: (1) We are interested in testing the feasibility of vehicular ranging with our proposed approach. A parameterized brute-force approach is a good baseline for system performance and ensures that any performance limitations discovered are not due to the optimization algorithm. (2) Vehicular radar estimates are performed over durations large enough such that algorithm complexity is not likely to be a limiting factor (e.g., 50 ms update interval on Delphi Electronic Scanning radars [47]). Future work should examine the effect of alternative optimization procedures such as spectrum estimation to reduce algorithm complexity.

A. Model Error Minimization

Based on (16) in Section II, we propose a brute-force optimization algorithm that matches a sinusoid to the received mean-normalized channel energy. Consider mean offset \( A \in \mathbb{R} \),
cosine magnitude candidate \((B \in \mathbb{R})\), initial phase candidate \((C \in [0, 2\pi])\), and phase increment \((D \in \mathbb{R})\). Using (16), we can model the estimated mean-normalized channel energy \(\hat{x}\) as

\[
\hat{x} = A + B \cos(C + Dm).
\]  

(22)

Given received mean-normalized channel energy \(x\), the error function

\[
\epsilon(x, \hat{x}) = |\hat{x} - x|^2 
\]

(23)

\[
= \left| \hat{x} - \frac{2\beta}{\alpha} \cos(2\pi m \Delta \tau - \theta) \right|^2
\]

(24)

is minimized when the parameters of \(\hat{x}\) correspond to those of \(x\), i.e., \(A = 2\beta/\alpha, C = -\theta\), and

\[
D = \frac{4\pi f_s \rho}{cN} = 2\pi \Delta \tau
\]

(25)

assuming the received mean-normalized channel energy has a specific time delay and given PHY sample rate \(f_s\), \(\rho\) is the target range candidate, \(\tau\) is the time delay associated with the target reflection, and \(c\) is the speed of light. This algorithm performs minimization over three parameters: (1) the ratio of the path loss of the reflected path to the path loss of the direct path jointly represented by \(A\) and \(B\), (2) the phase offset \(C\), and (3) the time delay associated with the target reflection \(\tau\), which we will model as a function of target range candidate \(\rho \in [0, \infty)\).

Brute-force three-dimensional minimization is implemented over a specified set of \(A, C, \) and \(\rho\). Cosine magnitude candidate \(B\) is empirically determined from sample of the received mean-normalized channel energy. For each time delay \(\rho\) in the set, the algorithm finds the path loss ratio \(A\) and phase offset \(C\) that returns the minimum least-squared error between the estimated mean-normalized channel energy \(\hat{x}\) and the received mean-normalized channel energy \(x\), solving the minimization problem \(\min_{\hat{x}} |\hat{x} - x|^2\). Once all phase increments \(D\) corresponding to a set of ranges \(\rho\) have been tested, the algorithm chooses the phase increment with the least residual error and returns the corresponding range \(\rho\) as the range estimate.

The steps taken in this paper for range parameter determination from a single frequency domain channel estimate listed in order, are as follows.

1) Define variables \(A \in \mathbb{R}, B \in \mathbb{R}, C \in [0, 2\pi), D \in \mathbb{R}, \rho \in [0, \infty), x \in \mathbb{R}^N, \) and \(\hat{x} \in \mathbb{R}^N\) for iteration \(k \in \mathbb{N}\) as specified above. In addition, define the minimum residual error \(\epsilon_{\text{min}} \in \mathbb{R},\) and the target range candidate corresponding to minimum error \(\rho_{\text{min}} \in [0, \infty)\).

2) Define the predefined working set for \(A, C, \) and \(\rho\) as \(\mathcal{S}_A, \mathcal{S}_C,\) and \(\mathcal{S}_\rho = \{\rho_0, \rho_1, \ldots, \rho_M\}\),
respectively, such that \( A \in S_A, \ C \in S_C, \) and \( \rho \in S_\rho. \) Let \( 0 \leq k < M \) where \( M \) is the number of elements in \( S_\rho. \) Define the residual error threshold constant \( \epsilon_t \) such that if \( |\hat{x} - x|^2 > \epsilon_t \) for all \( \hat{x}, \) then no target is present within the channel.

3) Set the received mean-normalized channel energy \( x = \overline{E_H} - 1 \) and initialize \( k = 0 \) and \( \epsilon_{\text{min}} = \epsilon_t. \)

4) Use \( x \) to empirically determine \( B. \) Ideally, \( B \) would be set to the maximum magnitude of the mean-normalized channel energy in \( x \) to minimize error between \( x \) and \( \hat{x}. \) In practice, due to noise and model imperfections, our algorithm estimates the cosine magnitude by taking an order statistic of the magnitudes of the mean-normalized channel energy.

5) Select \( \rho_k \) in \( S_\rho \) and define the corresponding phase increment, \( D = 4\pi f_s \rho_k/(cN). \)

6) Iterate through every combination of \( A \in S_A \) and \( C \in S_C. \) Use \( A, \ B, \ C, \) and \( D \) to define the metric value estimate \( \hat{x} = A + B \cos(C + Dm). \)

7) For each \( \hat{x}, \) if \( |\hat{x} - x|^2 < \epsilon_{\text{min}} \) then redefine \( \epsilon_{\text{min}} = |\hat{x} - x|^2 \) and \( \rho_{\text{min}} = \rho_k. \)

8) Increment \( k = k + 1 \) and repeat steps 5-8 until all elements in \( S_\rho \) are exhausted.

9) If \( \epsilon_{\text{min}} < \epsilon_t, \) a target has been determined to be present with target range of \( \rho_{\text{min}}. \)

B. Verification

To verify the estimation between (15) and (16), we quantify the error as a function of range. The mean-normalized channel energy as defined in (16) was simulated for a channel with a single target at ranges between 0.5 and 50m at 0.5m increments. Assuming that all parameters except the delay \( \tau \) are known, we determined the optimal delay \( \hat{\tau} \) that minimizes the least-squares error between (15) and the simulated mean-normalized channel energies. We determined the optimal delay using the Nelder-Mead simplex method [48] with the actual delay as an initial guess and found the optimal range for each simulated mean-normalized channel energy using (25).

The plots for RMS range error between the actual range and optimal range found when simulating the mean-normalized channel energy using a 10 MHz over 1000 Monte Carlo simulations are shown in Fig. 2. For a 10 MHz channel, the error introduced by the estimation between (15) and (16) does not exceed 3m when the range of the target is larger than 10m. In addition, as actual target range increases, the estimation generally becomes more accurate. This implies that our model is more effective for long-range radar applications, which have a minimum detection distance of 10m [5]. Our estimation, however, fails to achieve the meter-level accuracy
Fig. 2. RMS range error between actual range of single target in a 10 MHz channel and optimal range based on the simulated mean-normalized channel energy defined in (16). At 10 MHz, the estimation error does not exceed 3m when the target range is larger than 10m.

required for vehicular radar when using a 10 MHz bandwidth. As a result, we assess estimation performance using a 20 MHz bandwidth.

For a 20 MHz channel, the estimation error does not exceed 1m when the range of the target is larger than 5m. Estimation accuracy improves as actual target range increases, similar to the 10 MHz case. The majority of the error in our range estimation algorithm described in Section III-A should be from this estimation, indicating that we should be able to get very close to meter-level accuracy at single-target ranges greater than 5m using a 20 MHz channel. Since this is a feasibility study, we will primarily use a 20 MHz bandwidth to demonstrate IEEE 802.11 vehicular ranging. Using an optimal algorithm, we claim that vehicular ranging is still feasible with the 10 MHz provided by DSRC and will reserve this discussion for future work.

C. Discussion

Ideally, the brute force optimization does not need the offset parameters (A and C). Empirical results, however, have shown that a mean offset often occurs in practice. For example, when $\tau f_s < 1$, a full cosine cycle is not represented in the metric value. Consequently, $\text{mean}(E_H)$ does not accurately estimate $\alpha^2$ and the simplification in (16) breaks down and yields an additive constant. Signal processing in other parts of the transceiver, including band-limiting filters, signal conversion, analog circuits, etc. have non-ideal impulse responses. Subsequently, phase offsets are present.
Fig. 3. RMS range error between actual range of single target in a 20 MHz channel and optimal range based on the simulated mean-normalized channel energy defined in (16). At 20 MHz, the estimation error does not exceed 1m when the target range is larger than 5m.

It should also be noted that as $\alpha$ and $\beta$ approach each other in value, simplifying assumptions of the mean-normalized channel energy in (16) also break down, leading to distortions of the sinusoidal form. Hence, $\alpha$ and $\beta$ should be significantly different, as assumed by the current system model.

Unfortunately, we still need to ensure that the power differential between $\alpha$ and $\beta$ does not exceed the maximum resolvable signal to noise ratio (SNR) of the receiver. To address this, we assume the OFDM transceiver used in our system is capable of leveraging analog self-interference cancellation techniques, as described in [49]. Active monostatic radar is a key component of our proposed system, and, as previously mentioned, all circuitry for vehicular radar is contained within a single package. Thus, it is reasonable to assume that our system has the necessary hardware capabilities to perform analog cancellation techniques designed to improve the performance of full-duplex OFDM. Resolving targets at long ranges may require an adjustable level of analog cancellation of the direct path. This cancellation should be achievable since empirical results show that a difference of $30 - 40$ dB should be acceptable for small targets at large distances (full duplex transceivers, for example, require much more stringent direct path isolation [50]).

Consider Fig. 4 which shows the mean residual error for an IEEE 802.11 target detection at 5.89 GHz with a single target with RCS $\sigma = 1$ m as a function of the actual target range and
Fig. 4. Residual error in cosine model from (16) as a function of actual target range and the range parameter ($\rho$) used during the minimization procedure in Section III-A when a single target is present with RCS $\sigma = 1.0$ m. No second target is present, which is addressed by setting the RCS of the second target to 0.0 m.

the range parameter used for brute-force minimization. A 1m RCS represents the reflectivity of an average human, and is used as a benchmark for simulation representing the smallest-sized target the radar is responsible for detecting. The minimization residual error is very small when the actual target range matches the range parameter since the model used by the minimization algorithm is true. This verifies that the error function in (23) is minimized when the range parameter corresponds the actual target range, enabling single-target range estimation through brute-force optimization.

Our proposed algorithm also extends to multiple target environments, under the constraint that one target (our desired target) is stronger than the other targets. Next, consider Fig. 5 which shows the mean residual error of the optimization with two targets present. This plot shows us that when the first target has a range substantially larger than 25 m, the fixed location of the second target, the minimization algorithm has a low residual error for target ranges at 25 m. The effect is that the proposed ranging algorithm will always focus on the stronger target. When the two target reflections are of similar strength (around 25 m), the target range estimate is distorted and detection is somewhat compromised.

### IV. Simulation Results

This section quantifies the performance of IEEE 802.11 ranging through simulation of the 2-path link model with the proposed minimization procedure in Section III-A. To validate
Fig. 5. Residual error in cosine model from (16) as a function of first target range and the range parameter ($\rho$) used during the minimization procedure in Section III-A when two targets are present, both with RCS $\sigma = 1.0$. The second target is fixed at a range of 25 m.

In our algorithm, we simulated an IEEE 802.11p OFDM communication model. The summary of parameters of the simulations in this section are listed in Table I.

In our simulation, we used the IEEE 802.11p long training field (LTF) to determine receive channel estimates for each target range $r$ defined in Table I. The sample rate of the PHY and the channel model are, while both oversampled, at different rates due to variable fidelity requirements. $4 \times$ oversampling in the PHY is required to both faithfully represent the spectral mask and allow for low-complexity OFDM transceiver processing with 256-point (I)FFTs. $100 \times$ oversampling in the channel model is required to represent the reflections with high fidelity. 25 : 1 interpolation and 1 : 25 decimation filters are used after the transmitter and before the receiver, respectively, to interface the channel model with the PHY.

Using the receive channel estimates determined from each target range $r$, we implemented the minimization algorithm described in Section III-A using $S_A, S_C, S_\rho$ as specified in Table I. For each $r$, we found the corresponding range estimate $\rho_{\text{min}}$ returned by the minimization algorithm and determined its root mean square (RMS) error relative to the actual target range $r$. Fig. 6 shows the RMS error of the range estimate (compared to the larger energy target) with IEEE 802.11p and 10 MHz spectral bandwidth using the procedure in Section III-A as a function of target range, for various target RCS values. In the first three plot lines on this figure, only one RCS value is included (2nd target $\sigma = 0$). The last plot line reflects two targets with RCS $\sigma = 1.0 \text{ m}^2$: the first with variable range and the second target with fixed range at 25 m.
| Simulation Parameter       | Value(s)                     |
|---------------------------|------------------------------|
| Physical layer            | IEEE 802.11a/g/p             |
| Center frequency          | 5.89 GHz                     |
| Spectrum bandwidth (BW)   | {10, 20} MHz                |
| PHY sample rate ($f_s$)   | $4 \times$ BW               |
| Channel sample rate ($f_s$)| $100 \times$ BW             |
| Spectral mask             | IEEE 802.11p                 |
| Target 1 range ($r$)      | {5, 10, ..., 50} m           |
| Target 2 range ($r$)      | 25 m                        |
| $S_A$                     | {−1, −0.5, 0, 0.5, 1}        |
| $S_C$                     | {0, π/16, ..., 15π/16}       |
| $S_\rho$                  | {5, 6, ..., 50} m            |
| Channel model             | Radar range equation        |
| RCS ($\sigma$)            | {0.01, 0.1, 1.00} m²        |
| Noise figure              | 5 dB                        |
| $\epsilon_t$             | 25                           |
| Path phase                | ~ Uniform                   |
| Thermal noise             | ~ Complex Gaussian           |
| Monte Carlo iterations    | 5000                        |
| Transmit power            | 20 dBm                      |
| Direct path range         | 0.1 m                       |
| $G_{1\text{TX}}, G_{1\text{RX}}$ | 0 dBi                  |
| $G_{2\text{TX}}, G_{2\text{RX}}$ | 15 dBi                  |
| $F$                       | −70 dB                      |
| Channel estimation        | Least squares on LTF        |

25 m. This figure shows that strong targets ($\sigma = 1.0 \text{ m}^2$), in the absence of other targets, can be accurately estimated at distances greater than 15 m. Below 15 m, the cosine term in (16) does not complete one full cycle. Consequently, mean offsets are magnified, resulting in occasionally poor estimates. For weaker targets ($\sigma \leq 0.1 \text{ m}^2$), range estimates cannot occur accurately at 50 m, and are unreliable outside different range boundaries (45 m for $\sigma = 0.1$ and 35 m for $\sigma = 0.01 \text{ m}^2$). Fortunately most vehicular targets are significantly greater than $\sigma = 1.0 \text{ m}^2$. With two targets, performance is slightly degraded, especially when the two targets have similar, but unequal strength (first target range near 25 m). Note that the jaggedness of the RMS range error across different range targets is mostly due to artifacts of the brute-force algorithm as seen from Fig. 2 and 3 and may be improved with more complex algorithms.
Fig. 6. RMS range error when minimization procedure in Section III-A is used on IEEE 802.11 packets in a 10 MHz channel with two targets and variable RCS values. The first target has variable range (5 – 50 m) and the second target is fixed (25 m).

Fig. 7. Probability of false alarm (a) and probability of detection (b) when minimization procedure in Section III-A is used on IEEE 802.11 packets in a 10 MHz channel with two targets and variable RCS values. The first target has variable range (5 – 50 m) and the second target is fixed (25 m).

Fig. 6 does not consider detection probability, $p_d$, the probability of false alarm, $p_{fa}$, or the residual error threshold, $\epsilon_t$ (target detection when residual error exceeds $\epsilon_t$). To determine the best $\epsilon_t$, we must consider the probability of false alarm, or the probability of detection. If we assume that ranging estimates will be provided every 50 ms and require that the expected number of false alarm detections $< 1$/hour, this implies $p_{fa}$ is at worst $1 \times 10^{-5}$. Extrapolating from Fig. 7a, we say that achieving an expected number of false alarm detections $< 1$/hour requires residual error threshold $\epsilon_t \leq 25$. In practice, false alarm detection is not confined to the radar
sensor. Other sensors on vehicles, for example vision systems, can be used to determine if a target is valid and improve false alarm rates. We also plot $p_d$ in Fig. 7b with $\epsilon_t = 25$. We note that, as the target range increases and the target RCS decreases, $p_d$ does as well. Note that there is a region where $p_d$ is reliable, but the range estimate is not. This suggests that a more conservative $\epsilon_t$ might be desirable to prevent target detection when range estimates are inaccurate. In the presence of two targets, detection probability is consistent, despite the loss in range precision. This further motivates a more conservative value for $\epsilon_t$.

Traditional radar signal processing operates under the assumption that range resolution is limited by half the time duration between received digital samples. While the accuracy of ranging with 10 MHz IEEE 802.11p packets is much better than suggested from traditional radar signal processing, which suggests no better than 15 m precision, the performance shown in Fig. 6 is not meter-level accurate. As mentioned above, for ranges less than 15 m, the cosine term in (16) does not complete one full cycle within the mean-normalized channel energy, degrading the performance for the optimization algorithm. In this case, alternative approaches to range estimation are necessary for accurate detection at close ranges. These concepts, however, introduce substantial complexity to the system and fall outside the scope of this initial study.

To mitigate the effect of algorithm performance degradation at close ranges, we increase the bandwidth of our channel to 20 MHz (IEEE 802.11a/g). Although we can no longer interface directly with the IEEE 802.11p standard, we are confident that the results demonstrated in IEEE 802.11a/g channels with 20 MHz bandwidth can be extended to 10 MHz through algorithm refinement and finer processing. Additionally, the majority of OFDM transceivers have IEEE 802.11a/g capabilities. By using a 20 MHz bandwidth, we retain all of the concepts previously developed for a 10 MHz channel while significantly improving algorithm performance. Note that at ranges less than 5 m, a 20 MHz channel suffers from performance degradation, i.e., the cosine term in (16) does not complete one full cycle within the mean-normalized channel energy. We omit ranges less than 5 m from our detection environment because this performance is acceptable for various applications of vehicular radar, such as mid and long-range radar. As mentioned before, other range estimation techniques may be employed to improve performance at short ranges, which we reserve for future work.

We simulated the target scenarios from Fig. 6 with 20 MHz IEEE 802.11a/g channels in Fig. 8. Note that probability of detection and false alarm did not change significantly, and have not been plotted to save space. Fig. 8 clearly shows that, in the simulated environment of this paper, our
proposed ranging methodology provides sufficient accuracy for vehicular environments. In single-target environments, meter-level accuracy is achieved at 20 MHz when the RCS is sufficiently large. At a RCS $\sigma = 0.01 m$, we see that detection breaks down at 25m. For much larger vehicular targets, it is possible to achieve meter-level accuracy up to a maximum range of 240 m with 10 MHz of bandwidth based on cyclic prefix duration of the IEEE 802.11p LTF (120 m with 20 MHz of bandwidth). Although multi-target effects still noticeably impact system accuracy, the effects are lower than with a 10 MHz channel. Based on these results, we motivate the use of a 20 MHz channel for our system implementation.

V. RadCom Measurement Platform

This section describes the hardware and software platform used to develop our RadCom prototype. We implemented our algorithm on a host desktop machine and connected it to a software radio transceiver. By attaching two powerful directional antennas to the transceiver, we were able to extract IEEE 802.11 OFDM channel estimates, which were processed locally through the host machine. Antennas with high gain and directionality enabled us to reduce the effect of non-target multipath components within the vehicular environment. The host machine reported ranging estimates to the user, which were used to demonstrate the performance of the RadCom prototype.

To complete over-the-air validation of ranging performance through IEEE 802.11 channel estimates, we leveraged a powerful and configurable IEEE 802.11a/g MAC+PHY LabVIEW
FPGA 2014 implementation on the National Instruments (NI) Universal Software Radio Peripheral (USRP) Reconfigurable I/O (RIO), provided through the NI lead user program. This implementation allows a host processing device, i.e., PC computer with LabVIEW host software, to extract channel estimates through a direct memory access (DMA) first-in, first-out (FIFO) buffer on the USRP RIO physically connected to the host through a PCIe interface. Channel estimates are associated with individual packets which are received correctly (cyclic redundancy check (CRC) passes).

Because the channel estimates were already available in the reference lead user design, we did not need to modify any of the LabVIEW FPGA source or recompile the FPGA design. Instead, we implemented the algorithm from Section III on the host machine in LabVIEW by creating a new virtual instrument. This algorithm determined the mean-normalized channel energy from a single received IEEE 802.11 channel estimate. Using three loops to iterate over the target range candidate, mean offset, and phase offset through a predefined set of parameters, the closest-target range estimate was determined through brute-force minimization. We defined our working set of parameters to be the same as the ones used in our simulations, that is, $S_A = \{-1, -0.5, 0, 0.5, 1\}$, $S_C = \{0, \pi/16, \ldots, 15\pi/16\}$, and $S_\rho = \{5, 6, \ldots, 50\}$m.

With this implementation, demonstrated in Figure 9, we were able to compute ranging estimates on intervals of 150 msec. With a FPGA implementation of the algorithm in Section III, we could have pushed this update interval much lower, but this was not necessary for feasibility testing.
In standard IEEE 802.11 communication links, the transmitter and receiver do not operate simultaneously. This is also the case our design. Consider Fig. 10 which shows how different pieces of the 802.11 implementation are allocated on different platform resources. The key observation from this figure is that a FIFO of configurable size is placed between the analog to digital converter (ADC) and the receiver PHY. If the FIFO size is large enough, a sufficient delay is created between the transmit and receive paths of the same device. In this case the IEEE 802.11a/g implementation can send and receive its own packet. This step is critical for radar processing.
Fig. 11. Block diagram of I/O relationship of measurement platform. Antennas are attached to the NI USRP RIO, which communicates with LabVIEW on the host desktop via DMA FIFO links.

Fig. 12. Block diagram description of RF components in the measurements campaign. The reflected path (from the antennas) uses 0.5 m of SMA cable, but the direct path (from coupled port to combiner port) only uses 0.25 m of SMA cable, which artificially adds 0.125 m to the target range (results have been adjusted accordingly).

The NI USRP-2953R has a tunable center frequency from 1.2 GHz to 6 GHz with a 40 MHz per channel real-time bandwidth and supports an 800 MB/s connection to the host. The bandwidth and data rate provided by the USRP RIO are more than sufficient for the purposes of this study. Figure 11 illustrates the I/O relationship between the NI USRP RIO and software.

We chose a lower center frequency of 4.89 GHz for our study instead of 5.9 GHz due to the limited power output of the transceiver hardware. All of the RF components in our measurement setup are compatible with this frequency. Focusing on targets and isolating non-target multipath components requires high directionality and gain from antennas. For this purpose, we attached L-COM 23 dBi HG4958-23P Broadband Patch Antennas to the transmitter and receiver SMA ports on the USRP RIO through a microwave component network. To optimize the performance of our implementation, we chose patch antennas with especially high gain. This ensured that low energy signals and maximum detectable range would primarily be due to our system model and algorithm and not due to hardware limitations. In practice, smaller antennas with lower gain
| **Hardware**              | **Specifications**                        | **Value(s)**                      |
|--------------------------|-----------------------------------------|-----------------------------------|
| NI USRP-2953R            | Frequency                               | 1.2 – 6.0 GHz                     |
|                          | Frequency Step                          | < 1 kHz                           |
|                          | Maximum Output Power                    | 17 dBm to 20 dBm @ 1.2 – 3.5 GHz, |
|                          |                                         | 7 dBm to 15 dBm @ 3.5 – 6 GHz     |
|                          | Frequency Accuracy                      | 25 ppb (unlocked)                 |
|                          | Maximum Instantaneous Real-Time Bandwidth| 40 MHz per Channel                |
|                          | Digital-to-Analog Converter             | Sample Rate 400 MS/s,             |
|                          |                                         | Resolution 16 bit, Spurious-free  |
|                          |                                         | Dynamic Range 80 dB               |
| L-COM 23 dBi             | Frequency Range                         | 4750 – 5850 MHz                   |
| Broadband Patch          | L-COM Item #                            | HG4958-23P                        |
| Antennas                 | Dimensions                              | 315 x 315 x 25 mm                 |
|                         | Gain                                    | 20 dBi @ 4.9 GHz/23 dBi @ 5.8 GHz |
|                         | Polarization                            | Vertical or Horizontal             |
|                         | Horizontal Beam Width                   | 11°                               |
|                         | Vertical Beam Width                     | 11°                               |
| Dell Desktop Precision   | Processor                               | Intel® Xeon® CPU, X5650 @ 2.67 –  |
| T5500                    |                                         | GHz, 2.66 GHz (2 processors)      |
|                          | System Type                             | 64-bit Operating System           |

should be used to reduce cost while maintaining high performance. Future work should study the effect of lower gain antennas on the RadCom platform.

The RF component configuration attached to the NI USRP RIO device is depicted in Fig. **12**. The transmitter SMA port output feeds into the input port (coupler port 1) of a 3-port Narda 4053-30 directional coupler through a variable-resistance RF attenuator at the output port (coupler port 3) followed by a 0.25 m SMA cable and an input port (combiner port 3) of a 3-port RF combiner. The directional coupler was chosen over an RF splitter/combiner to isolate the direct path from the signals captured on the transmit antenna. Note that we use the RF attenuator value to scale the direct path appropriately in relation to the reflected path of our two-path model. The strength of the reflected path varies as target distance varies, so different
| Parameter          | Value(s)                                      |
|--------------------|----------------------------------------------|
| Center Frequency   | 4.89 GHz                                     |
| TX Power           | 10 dBm                                       |
| Operation Mode     | RF, with delay                               |
| Modulation Scheme  | QPSK, rate 3/4                               |
| Transmission Mode  | 20 MHz (IEEE 802.11a/g)                      |

Attenuator values were used during the experiment. The coupled port (coupler port 3) serves as the direct path source and the output port (coupler port 2) serves as the antenna source. The output port of the directional coupler (coupler port 2) feeds into the transmit antenna through another 0.25 m SMA cable. The receive antenna feeds into the remaining combiner input port (combiner port 2) through a 0.25 m SMA cable, and the combiner output port (combiner port 1) feeds directly into the receiver SMA port. The approximate scattering matrix of the Narda directional coupler and the RF combiner are

\[
\begin{bmatrix}
-20 & 0 & -50 \\
0 & -20 & -50 \\
-30 & -50 & -20
\end{bmatrix}
\quad
\begin{bmatrix}
-20 & -6 & -6 \\
-6 & -20 & -6 \\
-6 & -6 & -20
\end{bmatrix}
\]

where the values in the scattering matrix are defined in decibels.

A 1000 W DC-to-AC converter was attached to the battery of a mid-sized vehicle to support the power requirements of the NI USRP RIO platform and the Dell Desktop Precision T5500 host PC. The antennas were attached to the USRP and placed roughly one-third of a meter off the ground as illustrated in Fig. [13]. During measurements the outside edges of the antennas were separated by a minimum of 0.5 m, which is larger than depicted in this figure. During preliminary studies, we observed an irregular effect in the channel impulse response when the antennas were located too close to the ground. We determined that the antennas should be located sufficiently above the ground on the vehicle in implementation. Based on existing vehicular design, the ideal locations for the antennas would be in close proximity to the vehicle headlights.
VI. Measurement Results

The measurements reported in this paper were conducted in a vacant parking lot of Austin Community College in North-Central Austin. This site was chosen to isolate a vehicle target in a forward collision scenario (using the vehicle rear end as the radar cross section). The measurement location is visualized in Fig. 14.

Both the transmit and receive antenna are pointed towards the target, the rear surface of a 2002 Toyota Camry. The RadCom platform from Fig. 13 was initially positioned at a distance of 30 m from the target. To collect measurements, we transmitted IEEE 802.11 beacon messages with the configuration in Table III every 250 milliseconds. After a sufficient number of channel estimates were obtained at 30 m from the target, the RadCom platform moved 5 m in a straight line toward the target. After a sufficient number of channel estimates were obtained at 25 m distance from the target, the RadCom platform moved another 5 m towards the target. This process continued until measurements were obtained at all 5 m target distance increments.
To ensure that the energy of the direct path did not overwhelm the reflected path, the RF attenuation in the direct path was adjusted between $0 - 30$ dB, depending on the distance. These values of attenuation were empirically determined and allow the target reflection path energy to remain comparable to the direct path’s energy, which ensured that the target reflection path component was accurately resolved in the channel estimate. The direct path also experienced $30$ dB attenuation due to the coupling effect and $6$ dB attenuation in the combiner for a total of $6 - 66$ dB attenuation in the direct path. The RCS equation predicts $\approx 39 - 70$ dB attenuation for the target reflection path when 23 dBi antennas are used with a $1 \text{ m}^2$ RCS target. Hence, the empirical observation seems reasonable from simple link budget analysis.

During data capture we periodically measured the frequency domain channel response of the direct path by terminating the antenna path. While the energy of the channel impulse response of the direct path was linear, there was often a gradual linear slope. This slope resulted in a fluctuation of a few dB from the left edge subcarrier to right edge subcarrier. Essentially, the direct path could not accurately be modeled by a single tap, but instead required two taps separated by a very small delay (less than the sample period). The non-ideal direct path is likely due to internal feedthrough or internal reflections in microwave components. A product-ready solution would not have these effects. When the antenna path was activated for data capture, the presence of this second tap in the direct path (and third tap overall) degraded the performance of the ranging algorithm. Fortunately, a simple procedure was discovered to calibrate the data and remove the impairment caused by the non-ideal direct path. For example, consider that a
three tap channel can be modeled in the frequency domain channel response with

\[ H[m] = \alpha + \beta e^{-j(2\pi m \Delta \tau + \theta)} + \gamma e^{-j(2\pi m \Delta \tau_D + \phi)} \]  

where the last additive term is due to the addition of a second tap in the direct path \( \tau_D \) seconds after the first tap represented by \( \alpha \). Next, consider the energy of the frequency domain channel response with this model as follows.

\[ E_H[m] = C + \alpha \beta \cos (2\pi m \Delta \tau + \theta) + \alpha \gamma \cos (2\pi \Delta \tau_D m + \phi) \]
\[ + \beta \gamma \cos (2\pi m (\tau - \tau_D) + \theta - \phi) \]
\[ \approx C + \alpha \beta \cos (2\pi m \Delta \tau + \theta) \]
\[ + \alpha \gamma \cos (2\pi \Delta \tau_D m + \phi) \]

given \( C \triangleq \alpha^2 + \beta^2 + \gamma^2 \). The approximation follows from the assumption that \( \beta, \gamma \ll \alpha \). Hence, the channel energy with the non-ideal term simply includes an additional cosine term. Empirically we observed that \( \tau_D \) is small compared to the sample time and that the 50% coherence bandwidth is larger than the channel bandwidth [51]. A linear function approximation was sufficient to estimate the slope that resulted from the contribution from the second tap in the direct path. Therefore, we manually removed any slope in the frequency domain channel impulse response before algorithm processing. This slope was easily discovered since we were able to analyze its effect over many continuous channel estimates.

The statistics of the range estimates extracted from measurements are presented in Table IV. The root mean square (RMS) error of the range estimate is plotted in Fig. 15. The results of this

| Distance | Data Points | Estimate Mean | Estimate STD |
|----------|-------------|---------------|--------------|
| 5 m      | 100         | 6.00 m        | 0.00 m       |
| 10 m     | 100         | 9.96 m        | 0.67 m       |
| 15 m     | 100         | 14.03 m       | 0.30 m       |
| 20 m     | 87          | 19.48 m       | 0.50 m       |
| 25 m     | 100         | 25.96 m       | 0.24 m       |
| 30 m     | 100         | 29.12 m       | 0.33 m       |
study have demonstrated feasibility for IEEE 802.11 radar in a vehicular environment. Based on our setup from Section V, our system can be implemented on currently existing IEEE 802.11 devices with minimal modification to the physical layer, supporting a secure and extremely cost-effective design. We suggest that with slight modifications, the results from this study can be extended to a DSRC-based platform with a 10 MHz bandwidth. Future work will address ways to mitigate the effect of bandwidth reduction in IEEE 802.11 radar.

VII. CONCLUSIONS

We propose a collision avoidance system design incorporating IEEE 802.11 radar. As stated previously, IEEE 802.11 radar uses frequencies in a 2–6 GHz range, which significantly reduces cost compared to industrial vehicular mmWave radars. In addition, IEEE 802.11p based radar can be directly integrated with DSRC. This enables off-the-shelf marketing of collision avoidance systems to DSRC-capable vehicles, substantially reducing the cost and improving the efficiency of installing collision avoidance systems or replacing damaged parts. Furthermore, IEEE 802.11 radar is supplemented by a state-of-the-art communication network, which provides additional signal authentication and eliminates the risk of a spoofing attack.

Although the proposed system addresses the disadvantages and security vulnerabilities of existing mmWave systems, more work is needed to improve performance in practical vehicular radar environments. Currently, the proposed system has been designed to be suitable for long-range radar solutions, exhibiting a spatial resolution of 1 m. For various applications such as

Fig. 15. RMS range error when minimization procedure in Section III is used on IEEE 802.11 packets in a 20 MHz channel with one target as in scenario from Section V. The target has variable range from 5 to 30 m. Post-calibration estimates are presented.
short-range radar, however, resolution and accuracy up to 10 cm is required \[52\]. Future work needs to focus on improving accuracy for close-target detection as well as overall resolution and accuracy through algorithm optimization. With these improvements, IEEE 802.11 radar has the potential to compete with existing industrial vehicular radar as a more cost-effective, secure, and accessible solution to collision detection and avoidance.

In this paper, we designed a simple algorithm to provide high-resolution ranging and detection through IEEE 802.11 packets for vehicular radar applications. We demonstrated meter-level accuracy through both simulations and measurements with minimal modification to current IEEE 802.11 devices. In a controlled vehicular environment, our implementation achieves meter-level precision with only 20 MHz of bandwidth in contrast to requirements for current vehicular radars, which suggests a minimum of 150 MHz. Our results have significant consequences for cost-reduction and proliferation in intelligent transportation, especially in the area of supporting and/or replacing expensive mmWave radar designed for frontal automatic collision detection and avoidance.

This paper enables several directions for future work. This paper only considers a single vehicle. Roadways, however, feature a multitude of targets with variable RCS values. Future work is needed to design multi-target algorithms for IEEE 802.11 radar and evaluate the degree to which ranging performance suffers. Future work will also need to determine how well IEEE 802.11 radars can address dynamic range requirements in multi-vehicle environments. Previous work at mmWave frequencies has shown that the RCS of different vehicles can vary from 16 dBsm for large trucks to 14 dBsm for small vehicles to −1 dBsm for motorcycles \[53\]. A significant challenge will be the adaptive configuration of the IEEE 802.11 RadCom link such that small targets are not overshadowed by large targets. This configuration will require adaptive antenna processing and dynamically-configured direct-path attenuation. Adaptive configuration is especially critical given the constraint that important vehicle targets may reach ranges up to 200m \[14\].

The IEEE 802.11 medium access control (MAC) efficiently accesses the spectrum such that each IEEE 802.11 packet does not consume a large duration. This limits the estimation of target Doppler (velocity) from a single packet. For example, coherent processing in vehicular radars may consume multiple milliseconds to enable accurate target Doppler estimate \[14\], whereas IEEE 802.11 packets are typically much shorter. Consequently, IEEE 802.11 radar will be forced to use differential range computation for velocity estimates. This also creates target ambiguities at
a fixed radius, increasing the importance of multiple antenna processing. Fortunately, multiple antenna processing is already a requirement for vehicular radars in providing target azimuth angle information. Future work will need to prescribe the multiple antenna processing necessary for IEEE 802.11 RadCom links in the context of the existing multiple antenna processing supported by the IEEE 802.11n and IEEE 802.11ac standards.

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