Efficient Parameters Estimation of Target for Autonomous Vehicles Application

HUSNAIN SHAHID[1*], ABDUL REHMAN[2], ALI HASSAN SHAH[3]
[1]Electronics and Communication Engineering, Shanghai Jiao Tong University, CHINA
[2]Institute of Sesning and Navigation,Shanghai Jiao Tong University, CHINA
[3]School of Information Science and Engineering, Fudan University, CHINA
Correspondence: husnainshahid370@sjtu.edu.cn

Abstract— Vehicle radar has significant importance in autonomous vehicles and modern intelligent transportation network applications. The range and velocity estimation with high precision are one of the challenging tasks in this modern era. This work proposes some valuable improvements in the context of radar signal processing, emphasizes the range and Doppler estimation of moving targets which help to estimate the surroundings efficiently. At first, orthogonal frequency division multiplexing (OFDM) waveform is used for data transmission and radar processing while target parameters are efficiently estimated. In the previous research, authors used the approximations for velocity estimation of moving targets while this paper suggests the improvement in Doppler measurement by analyzing the frequencies of all the subcarriers of received echo with extended FFT and the maximum likelihood (ML) estimation algorithm. Moreover, cramer-rao lower bound (CRLB) is utilized to analyze the performance of the estimator. For practical analysis, MR3003 automotive radar is used which follows the frequency division multiplexing (FMCW) signal to detect and analyze the targets. In another context i.e. For some scenarios, the radar sensor leads to the false detection while camera output could not work in harsh weather. To overcome this problem, the amalgamation of both the sensors are used to extract the precise information. In order to perform this task, a deep learning algorithm includes a convolutional neural network (CNN) is implemented for detection and identification of vehicles in an optical video which further accumulates with the MR3003 radar image to identify the moving targets in both scenarios. Furthermore, the performance of the radar algorithms is analyzed in MATLAB while CNN is implemented in python. Theoretical study and experimental results reveal that the derived methods can attain the velocity accuracy and achieve a high resolution-velocity estimation of moving targets.

Keywords— Range and Doppler estimations, Orthogonal frequency division multiplexing, maximum likelihood, data fusion, convolutional neural network, vehicle radar.

1. Introduction

Sensors are providing a vital role in driverless cars. The inbuilt sensors, being able to detect the vehicles behind, ahead or side provides the data for a central controller. Generally, cars are being mounted with cameras, radar, ultrasound or LiDAR to acquire the information of surrounding, roads and other vehicles [1]. The vehicle radars can detect the target parameters that include the range, velocity and angle. For the dark or unpleasant environment, it's not feasible to utilize the camera and LiDAR. Consequently, radar has significant importance for mapping the target parameters in dark surroundings [2].

The automotive radar utilizes the carrier waveforms to sense the target. The basic approach of radar is that it sends the signals continuously, having properties of pulse repetition interval (PRI) and pulse width, while after the interaction from noisy surroundings, the transmitted waveform gets back to receiver with the range, Doppler, position information of targets which can be further estimated by the post-processing algorithms [3]. Although, radar technology is contributing a lot in detaining the social and environmental issues but there are some parameters that should be considered to achieve the accurate information. The most challenging task is to estimate the target parameters precisely while the type of transmitted waveform also participates in getting the precise results, it should be able to provide the considerable information while after interaction through target [4].

In the 21st century, the signal design is shifted to multicarrier waveforms that contain the promising ability to provide the efficient radar sensing theoretically as well as practically. To achieve a higher resolution, there is certainly a need of a higher bandwidth system. Moreover, radar sensing system should be capable enough to utilize the spectrum efficiently and perform the radar sensing with arbitrary transmitted data [5]. The second most challenging task in radar application is the design of post processing algorithms which are mainly contribute for processing the received information.

After the introduction of digital signal processing, the one of the most famous classical methods, discrete Fourier transform (DFT) is used to visualize the range and frequency information of the moving target [6] which is basically a correlation between the received waveform with discrete exponential signal where each sample of the received signal correlate with the sinusoid discrete signal samples and lead to estimation of the frequency content present in the signal while on the other hand, inverse discrete Fourier transform (IDFT) is unitized to analyze the time-delayed information of the received echo which describes the range information of moving target consequently [6,7]. Although it contributes to parameter estimation but in the given reference [6], the author used the approximation of subcarriers which is the solvable problem to extract the Doppler information more accurately.

The paper comprises of five sections. Section I provides the introduction and background. In Section II, we design the transmitted OFDM waveform and received echo, along with Doppler and range processing schemes i.e. extended FFT and maximum likelihood (ML) estimation algorithm. The parameter constraints or limitations are described in Section II. Section III illustrates the association of radar measurements and video tracking methodology. In Section IV, the simulation of the extended FFT, maximum likelihood estimation algorithm and deep learning is illustrated. Section V discusses the conclusion.

2. OFDM Signal Model

To achieve the high resolution target parameters, a platform is designed with a multicarrier waveform that contains a low bit error rate with negligible interference. Orthogonal frequency division multiplexing (OFDM) is widely used as a spread spectrum waveform for sensing in radar system. The major precedence to consider the multicarrier waveform is its ability to provide the wider bandwidth for radar sensing and improves the resistance to multipath fading.

The OFDM signal can be considered as several number of parallel subcarriers having the property of orthogonality i.e. all the subcarriers are orthogonal to each other and each subcarrier is modulated with digital data. Analytically, the baseband data is generated and taking symbols into spectral space with a digital modulation scheme (M-PSK, QAM etc.), then convert the spectra into the time domain for transmission by taking IDFT (Inverse Discrete Fourier Transform). Since IFFT (Inverse Fast Fourier Transform) is more cost-effective and beneficial to implement, it is mainly considered to make every carrier orthogonal [8]. The one precedence of using the OFDM signal is, it helps to avoid the (inter symbol interference) ISI during symbol transmission. Although, longer period of symbols could participate in the reduction of probability of ISI but not able to duly eliminate it. In order to properly eliminate the ISI, a cyclic prefix i.e. guard interval is added to each symbol period. An exact 25% copy of the cycle, taken from the end, added at the front. It helps the demodulator to perform efficient, even in case of uncertainty, up to the length of cyclic extension and still able to acquire the information for the entire symbol period which is useful for communication as well. The higher order of PSK concluded in larger symbol size, hence less no. of symbols require to be transmitted and higher data rate is achieved [9,10]. After converting the data into time domain, in order to occupy the available frequency bandwidth, all the carriers transmit in series. The transmitted signal is modelled as,

$$s(t) = \sum_{\mu=0}^{M-1}\sum_{n=0}^{N-1} a(\mu N + n)\exp(j2\pi f_n t) \qquad (1)$$

where n is the individual number of subcarriers and N represents the total number of subcarriers while μ donating the individual OFDM symbols from a total number of M symbols belongs to OFDM symbol duration. $\{a(n)\}$ representing the complex modulating symbol i.e. the baseband digital data modulated with quadrature amplitude modulation (QAM) or discrete phase modulation scheme (M-PSK).

The received signal in the presence of a moving target with velocity v at particular range R is reflected back. The received echo will have some fluctuation in frequency component f_d, which would be positive or negative, dependent on either target is moving towards the radar system or away from the system. After applying the FFT on every subcarrier, the signal is demodulated to provide the information of target with range, velocity and position parameters. The received signal is designed as,

$$x(t) = \sum_{\mu=0}^{M-1}\sum_{n=0}^{N-1} a_r(\mu N + n)\exp(j2\pi f_n t) \qquad (2)$$

where

$$a_r(\mu N + n) = \{a(\mu, n)\exp(j2\pi n f_d)t \qquad (3)$$

$$.\exp(-j2\pi n\Delta f\frac{2R}{c}).\exp(-j2\pi n f_d\frac{2R}{c})\} + z(t)$$

$z(t)$ is the additive white Gaussian noise (AWGN) with mean and variance. After demodulation and taking the FFT of the signal, it reveals that the signal is no more dependent on the payload data.

To make the processing elementary, the channel transfer function can be used for further processing in the frequency domain. Thus, comparing the received signal in equation (2) with the transmitted signal in equation (1) yields the transfer function for range processing along with velocity estimation [6].

$$I_{trans} = \frac{a_r(\mu, n)}{a(\mu, n)} \qquad (4)$$

The block diagram of the received signal is shown as,

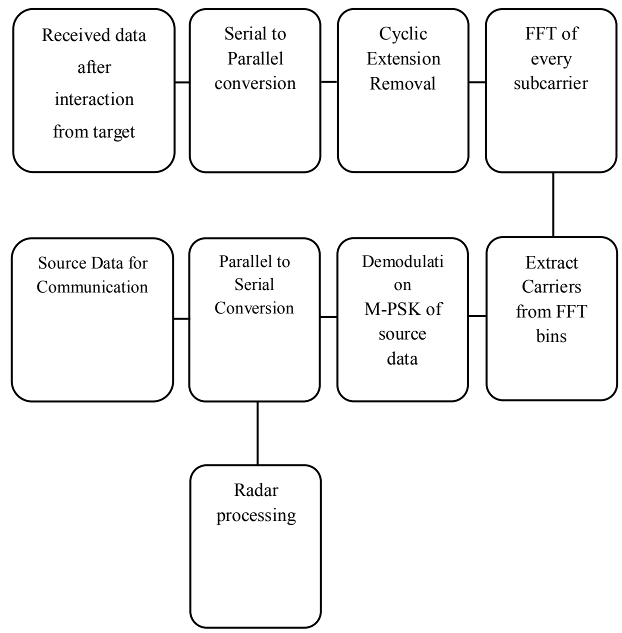

Figure 1. The block diagram of received OFDM signal

By taking the Fourier transform of exponential function containing Doppler frequency in equation (4) as well as the Inverse Fourier Transform of time delay exponential in equation (4), the 2D Range-Doppler graph of target can be acquired. The resultant 2D range Doppler graph will have imprecisions regarding the velocity of the moving target which will be addressed in later sections.

There are few limitations or constraints exist in the case of OFDM signal for automotive application. The most salient one is the subcarrier spacing. The subcarrier spacing is limited by Doppler frequency which has the capability to shift the arrangement of the subcarriers and hence deteriorate the orthogonality of the signal. The signal parameters are specified towards the automotive application since one of the intended areas for such a system is an intelligent transport system. The OFDM signal design parameters are as follows in Table 1.

Symbol	Parameters	Value
f_c	Carrier Frequency	$24GHz$
N	Number of Subcarriers	128
Δf	Subcarrier Spacing	$90.909kHz$
T_{sym}	Symbol Duration	$12.375\mu s$
$r_{\max}$	Maximum Unambiguous Range	$1650m$
B	Signal Bandwidth	$11.6MHz$

Table 1. The OFDM signal design parameters

2.1 Doppler Estimation by Extended FFT

After interaction through the moving target, the received echo is modeled as in equation (3). The received echo is firstly sampled which lead to be $N \times M$ matrix. By making the comparison of the received signal described in equation (3) with the transmitted signal in equation (1) yields the transfer function for range processing along with velocity estimation as in equation (4).

By the taking the FFT of the impulse response in equation (4) containing the Doppler information lead to the velocity parameter estimation.

$$Y(q) = FFT(I_{chan}(\mu))\,,\ q = 0, \ldots\ldots N_{fft} - 1 \tag{5}$$

where $Nfft$ is the length of the signal we have to calculate the Fourier Transform which is typically 2^M . The single sideband spectrum is shown as

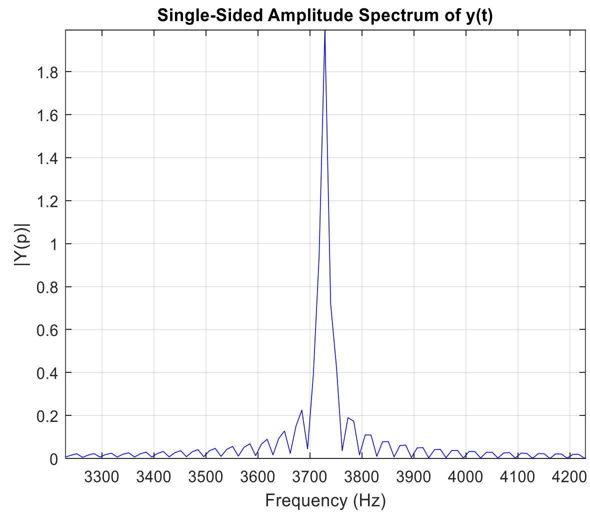

Figure 2. The single sideband spectrum

Then, convert the output samples into frequency domain by multiplying the samples with frequency resolution.

$$f = \frac{1}{\frac{t_s}{2}} \frac{1}{\frac{N_{fft}}{2} + 1} \tag{6}$$

After performing the FFT of the Doppler information channel response, extract the amplitude of maxima as well as the index.

$$[a,b] = \max\left|Y(p)\right|,\quad p = 1, \ldots\ldots\ldots \frac{N_{fft}}{2} + 1 \tag{7}$$

where a belong the amplitude of the maximum value while b reveals the information of position or index of the maxima in FFT output. The velocity component is extracted by utilizing all the subcarrier frequencies. By using equation (5) and equation (6) the velocity component can be estimated as

$$v(n) = \frac{f(\{\max(Y(p))\} + 1)c}{2(f_c + n\Delta f)} \tag{8}$$

where f belongs to the frequency resolution demonstrated in equation (6) and $\max(Y(p)) + 1$ in equation (7) can be written as equivalent to $b + 1$ calculated in equation (8).It can be seen that the velocity component is extracted from every subcarrier frequency instead of considering the approximation of the multicarrier waveform.

2.2 Symbol Contraints

For the extended version of FFT, there are few symbol constraints or limitations that need to be considered to achieve the improvement in Doppler estimation. According to velocity resolution equation.

$$\Delta v = \frac{\lambda}{2MT_{sym}} \tag{9}$$

Putting $\lambda = \frac{c}{f_c}$ in above equation, we will get

$$\Delta v = \frac{c}{2f_c}.\frac{1}{t_s} \tag{10}$$

From equation (6), the above equation can be written as:

$$\Delta v = \frac{c}{2f_c}.\frac{F_s}{2}\frac{1}{\frac{N_{fft}}{2}+1} \tag{11}$$

As the signal is bandlimited then F_s can be equivalent to $N\Delta f$ while N_{fft} would be considered to the equivalent of number of symbols M .The equation (11) can be written as:

$$\Delta v = \frac{c}{2f_c}.\frac{N\Delta f}{2}\frac{1}{M+1} \tag{12}$$

Hence the number of symbols should fulfill the bound to predict the performance of the extended method. If the symbol constraints unable to fulfill the designed bound, the result will be accurate for few velocities and contain the ambiguity for other few velocities. We consider this assumption.

$$\frac{c}{2}.\frac{1}{M+2} \le \frac{v}{10} \tag{13}$$

2.3 Doppler Estimation by Maximum Likelihood Estimation

In this section, the implementation of maximum likelihood (ML) estimation is illustrated for Doppler estimation of the target. The received echo after reflecting from the target at distance R comprises of time delay information which leads to calculate the range of the target i.e. double time is taken to reach at the distance R .If we consider the Gaussian distribution and after sampling the signal model in equation (3). The probability density function can be expressed as [11].

$$p(x;A,f_d) = \frac{1}{(2\pi\sigma^2)^{\frac{M}{2}}}\exp\left[\frac{1}{2\sigma^2}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(x(n,m)-A\exp(j2\pi nf_d m))\right]^2 \tag{14}$$

where A denotes the amplitude, $x(n,m)$ represents the $N\times M$ matrix and σ^2 is the variance. For getting the maximum likelihood, we need to minimize the following problem.

$$\min_{f_d \varepsilon f}(\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(x(n,m)-A\exp(j2\pi nf_d m)))^2 \tag{15}$$

For the estimation purpose, it could be assumed that

$$F(A,f_d,\phi) = (\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}(x(n,m)-C_1\sin(2\pi f_d(i)[M-1]) -C_2\cos(2\pi f_d(i)[M-1])))^2 \tag{16}$$

where C_1 and C_2 reveals about the angle information. Based on the real experiments, the data only contains the real part so we can let the definition [12].

$$\text{q}(i) = \left[1,\cos(2\pi f_d(i)[1],.......,\cos(2\pi f_d)(i)[M-1]\right]^T$$

where

$$i = 0,1........,N-1 \tag{17}$$

"T" represents the transpose.

$$y(i) = \left[0,\sin(2\pi f_d(i)[1],.........,\sin(2\pi f_d(i)[M-1]\right]^T$$

where

$$i = 0,1........,N-1 \tag{18}$$

Putting C_1, C_2 , $q(i)$ and $y(i)$ in equation (3-24) Then we have

$$F(C_1,C_2,f_d) = (x-G\alpha)^T(x-G\alpha) \tag{19}$$

where $G=[y,q]$ and $\alpha=[C_1,C_2]^T$

We could estimate $\hat{\alpha}$ by minimizing the equation (19)

$$\hat{\alpha}=[\hat{C}_1,\hat{C}_2]^T=(G^TG)^{-1}G^Tx \quad (20)$$

So plugging equation (20) into equation (19)

$$F(A,f_d)=(x-G(G^TG)^{-1}G^Tx)^T(x-G(G^TG)^{-1}G^Tx)$$

$$=x^T(I-G(G^TG)^{-1}G^{-1})x \quad (21)$$

where I represents the identity matrix and $I-G(G^TG)^{-1}G^T$ is an idempotent matrix. To find $\hat{f}_d$ we need to minimize the following derived equation [12]

$$\hat{f}_d=\min(x^T(I-G(G^TG)^{-1}G^T)x) \quad (22)$$

For the case of Doppler frequency estimation, the derived model is no more dependent on phase information, we can equally maximize the equation (21).

$$\hat{f}_d=\max_{f_d\varepsilon f}(x^T(G(G^TG)^{-1}G^T)x) \quad (23)$$

D. Performance Analysis with CRLB

As the name suggests, Cramer-Row lower bound (CRLB) is used to obtain the lowest possible variance of unbiased estimator. It is generally assumed that PDF given in (14) must satisfy the "regularity condition".

$$\mathrm{var}(\hat{f}_d)\geq\frac{12\sigma^2}{2\pi^2A^2M(M^2-1)} \quad (24)$$

where the expectation $E[.]$ is taken with respect to $p(x;A,f_d)$.The CRLB can be estimated by taking the inverse of fishing matrix. The fisher matrix is defined as [11]

$$E\left[\frac{\partial^2\ln p(x;A,f_d)}{\partial f^2{}_d}\right] \quad (25)$$

The CRLB bound is obtained by inverse of the fisher matrix. [11]

$$\mathrm{var}(\hat{f}_d)\geq-\frac{1}{E\left[\frac{\partial^2\ln p(x;A,f_d)}{\partial f^2{}_d}\right]} \quad (26)$$

$$=\frac{12\sigma^2}{2\pi^2A^2M(M^2-1)} \quad (27)$$

$$\mathrm{var}(A)\geq-\frac{1}{E\left[\frac{\partial^2\ln p(x;A,f_d)}{\partial A^2}\right]} \quad (28)$$

$$=\frac{2\sigma^2}{M} \quad (29)$$

CRLB gives us instinctive insights of unknown parameters while the variance of any received echo depends on the SNR and sampling numbers as in (27). By increasing the SNR and sampling number, the estimator becomes more efficient. Further simulations are illustrated in section IV.

3. Association of Radar Measurements and Video Tracking

After the deep analysis of estimation problem, it could be observed that the single sensor has drawbacks in some cases such as radar leads to false detections and the output results are not visual clearly for humans. On the other hand, built-in camera helps to capture the real-time videos to reveal the information of targets but video could not work in particular conditions especially in bad or harsh weather and the measurement accuracy becomes low eventually. Therefore, the information acquires by combining both sensors can lead to the solution and could give more accurate information.

The online available data set is explored. It composes of images taken from the GTI vehicle image data base [13], the KITTI vision benchmark suite [14]. The cars are labeled as 1.0 while non cars is considered as 0.0.

The total of 17760 samples are extracted from the above mentioned image data set. The split training set contains the ratio of 90% or 15984 samples while the testing set which comprises of 10% or 1776 samples of the entire data set. The data set distribution is shown as in Figure 3.

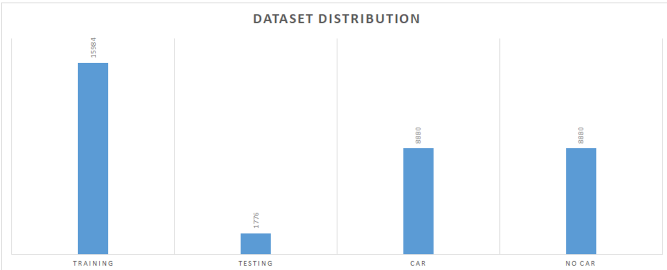

Figure 3. The distribution of training and testing data

It can be observed that the data set is fairly balanced. If the data set is not well balanced, the neural network could be considered as biased to either of the classes.

3.1 Convolutional Neural Network

As we know that, it is essentially a binary classification problem i.e. the neural network has to make decision about image either it contain the vehicle or not. The network parameters are given below in Table 2.

Layer (Type)	Output Shape	No. of Parameters
lambda_1 (Lambda)	(None,64,64,3)	0
conv1 (Conv2D)	(None,64,64,128)	3458
dropout_1 (Dropout)	(None,64,64,128)	0
conv2 (Conv2D)	(None,64,64,128)	147584
dropout_2 (Dropout)	(None,64,64,128)	0
conv3 (Conv2D)	(None,64,64,128)	147584
max_pooling2d_1	(None,8,8,128)	0
dropout_3 (Dropout)	(None,8,8,128)	0
dense1 (Conv2D)	(None,1,1,128)	1048704
dropout_4 (Dropout)	(None,1,1,128)	0
dense2 (Conv2D)	(None,1,1,1)	129

Table 2. The parameters of Neural Network

Total Parameters : $1,347,585$

Trainable Parameters : $1,347,585$

Non-trainable parameters : 0

Every frame from the input video fed into Neural Network, which has been used to detect vehicles everywhere in the frame. This network scales up to be compatible with whatever the input size is, as there is no fully-connected layer at the end, but just a convolution layer with max-pooling and dropout.

Once the vehicle is detected using the above trained neural network, the video is read using the Scikit video package and all video frames with vehicles being detected and bounding boxes drawn around with the help of the Cascade Classifier. Subsequently, the video frames were iterated over one by one and their coordinates or absolute pixel values of the positions of the detected vehicles were obtained, using the histogram of oriented gradients (HOG) classifier to track the region of interest (ROI) of the vehicles present in every frame.

Once the regions of interest of all the vehicles in the frames are obtained, the midpoints of the bounding boxes surrounding the vehicles are extracted, which is held as the" position" of the vehicle, which will be key for future frames. This process was repeated for all vehicles to create a list of midpoint values that are updated in every frame. The following model preferred to extract the information is due to the accuracy of the model after the literature of various other methods. In the case of accuracy, the current method achieves the 99% accuracy after 20 epochs of training. The detected results are shown as,

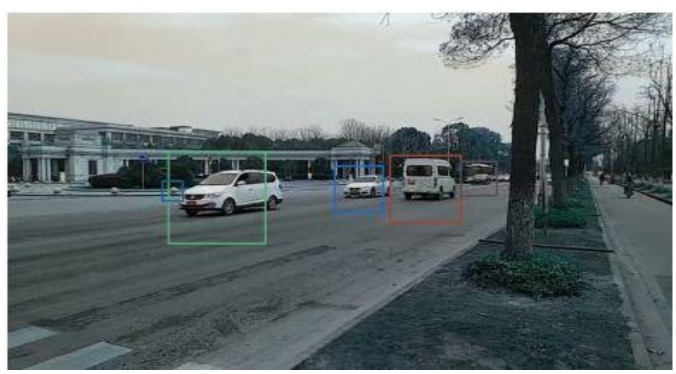

Figure 4. The detected results of neural network

3.2 Amalgamation of Radar Measurements and Optical Output

After the detection of vehicles in the optical video. The next task is to recognize or identify the vehicles in optical video corresponding to the radar video. The optical and radar data is collected at the same time and place. To estimate the velocity of the moving objects, the basic terms need to estimates are distance and time.

The distance, a particular vehicle traveled in the image plane is considered as the relative difference in pixels at different positions in succeeding frames. The time can be calculated by considering the rate at which the frames are being processed. In this case, it is assumed that 25 frames are succeeding in one second. In response to the above discussion, the distance in pixels is calculated by using this formula:

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{30}$$

where x and y parameters belong to the position of vehicle in successive frames. In order to calculate the speed, the other considerable parameter is time. The assumption regarding frame is 25 frames per second, the time between two consecutive frames will be equal to the time difference of two successive frames i.e.2* 0.04s. The height of the object is approximated in object plane is 4m which is obviously not the case for all the cars. If the difference is less than 10 pixels than the vehicle is considered as static. The flow chart of algorithm is shown as,

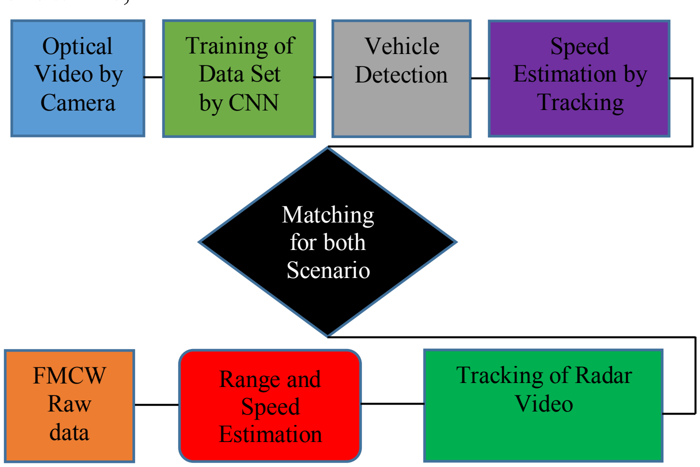

Figure 5. The block diagram of data association

4. Simulation and Results

In this section, the simulation of our proposed method on MATLAB and compare the results with the conventional approximated method is illustrated. The maximum likelihood (ML) estimation is performed on the real data acquired by some experiments and realized the CRLB by Monto Carlo simulations with 100 trials of repetition and $SNR = 20dB$ for estimation accuracy. The design of OFDM signal presented in Section II is implemented in MATLAB with the chosen values of sub-carrier frequency $\Delta f = 90.909kHz$, number of carriers $N = 128$ .The Bandwidth is chosen as $B = N\Delta f$ .The parameter M is selected by satisfying the designed bound .While $ts = \frac{1}{2B}$ represents the sampling rate. The symbol duration along with cyclic extension used for conventional model i.e. $T_{sym} = T + T_{cp} = 12.375\mu s$ where $T_{cp} = 1.375\mu s$ .For efficient communication and sensing at one platform the carrier frequency $f_c = 24GHz$ ISM band is chosen.

The additive white Gaussian noise (AWGN) with the same length as transmitted signal is added manually with zero mean and some variance The received echo is modeled as,

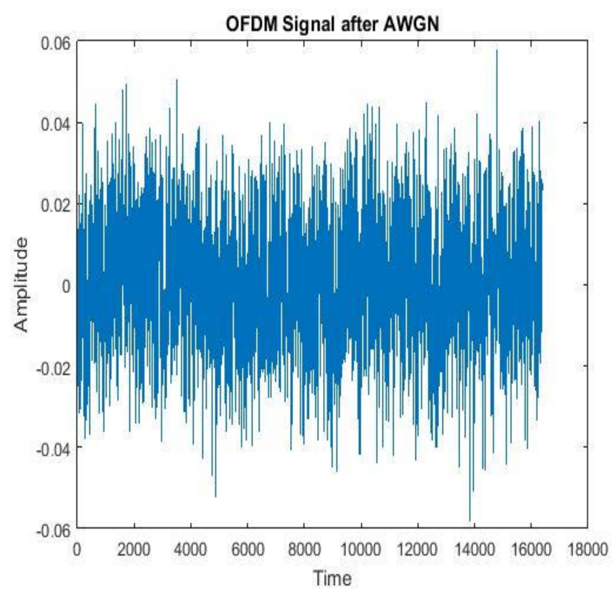

Figure 6. The received signal after AWGN

The conventional results contain the range and velocity information of moving target at $R = 20m$, $v = 23.29m/s$. The 2D Range-Doppler plot is shown as,

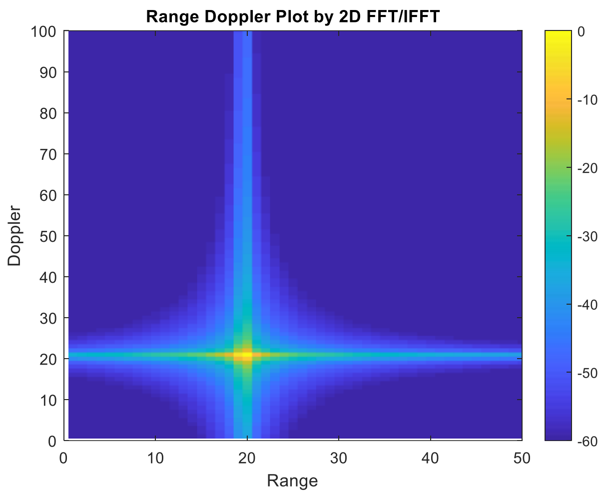

Figure 7. The 2D range Doppler plot of moving target by approximation method

4.1 Doppler Estimation by Extended FFT

The comparison between conventional method and extended method is elaborated in the following diagram. The velocity is set to be at $v = 23.29m/s$.

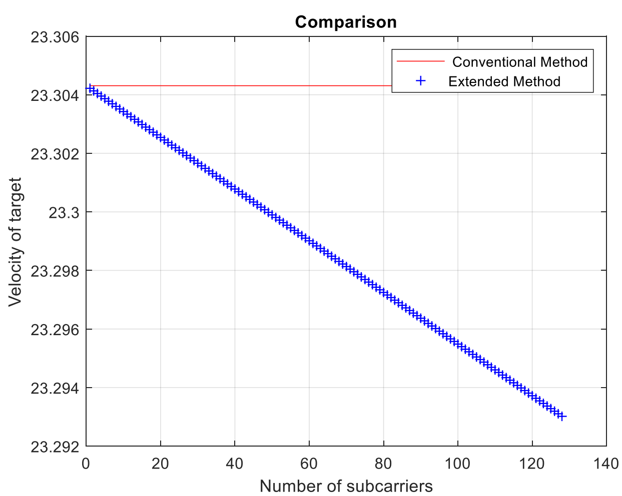

Figure 8. The Comparison results of both methods

The simulation results are achieved by analyzing every carrier phase shift individually and the results are improved by considering the average of the subcarrier output which is much closer to the real velocity. Blue symbol shows the velocity content on every subcarrier individually. It can be realized that the extended method could differentiate two moving targets with a velocity difference in fraction. The visualization is shown as,

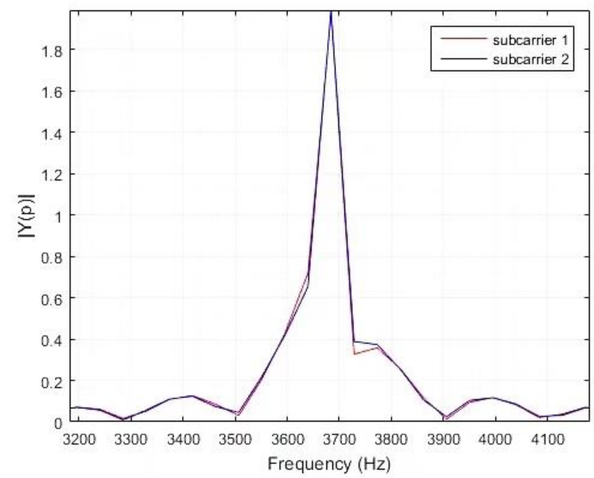

Figure 9. The frequency difference between two subcarriers

It can be seen that every subcarrier responds to different phase shift which demonstrates the effectiveness of proposed method.

4.2 The real Data Experimentations with MR3003 radar

The real data experimentation is performed with MR3003 radar in SJTU on campus. The FMCW signal is generated by radar during tracking of the moving object and the frequency analysis algorithms and estimation techniques are used to extract the information of the target. The radar data contains the random real values that make no sense of the signal. The signal parameters are extracted first with reference to the radar data sheet provided with MR30003RD [15]. The radar facilitates with the vector that contains the real values for different parameters. The useful signal parameters are aligned by discarding the raw information.

After referencing to the data sheet, the radar parameters including the mode either FMCW or CW corresponds to the 20th index of data, Range and Doppler configuration belongs to 21st index frequency index while detection parameters revealed on 25th and 26th index respectively. Like other parameters carrier frequency, receiver gain, and parameters for static objects, collision time, clutter band factor and number of frames are located on a particular index of raw data given by radar concerning the radar data sheet [15]. After that, the experiment is performed by taking an E-bike as a moving target. For this scenario, after applying the Hamming window to remove the 41 discontinuities in the received echo and 2D-FFT is applied. The ADC signal correspond to the real data is shown as,

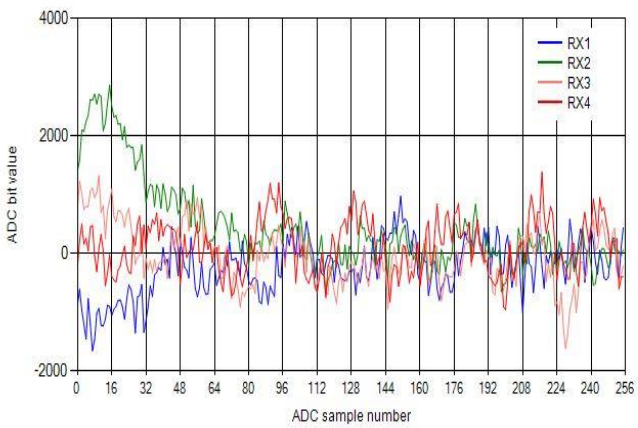

Figure 10. The ADC signal corresponds to each receiver

The velocity is set to be $v = 6km/h$ and data is recoded through radar which is eventually appeared as video data .One frame of the video data is extracted. The amplitude of the information matrix is then converted into dB and computed the lower bound and upper bound for the threshold in dB. The undesired index regions are computed and set them to –infinity. The 2D Range and Doppler of the moving target is shown below,

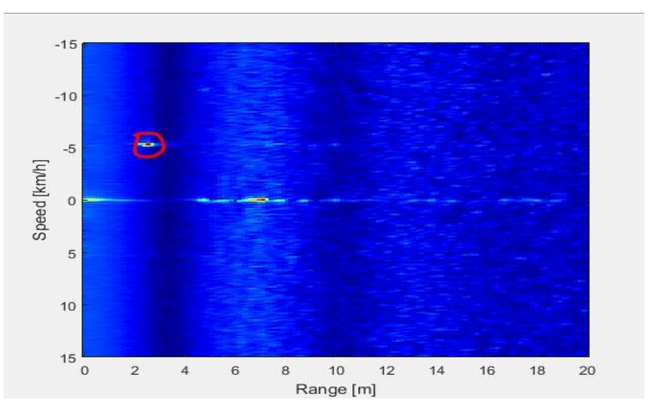

Figure 11. The Range and Doppler Estimation of one frame from real data experiment

4.3 Doppler Estimation by Maximum Likelihood Estimation

The method is implemented on MR3003 radar raw data. The output is showing the index along with frequency magnitude for every frame of the video. The frequency content is further converted into real velocity).The red circle represents the bike as a target with velocity $v = 6km/h$ and the method is simulated in MATLAB with same parameters used as above in FFT.In comparison with FFT, it can be seen through statistical analysis, ML estimation provides the high accuracy as compared FFT on experimental data

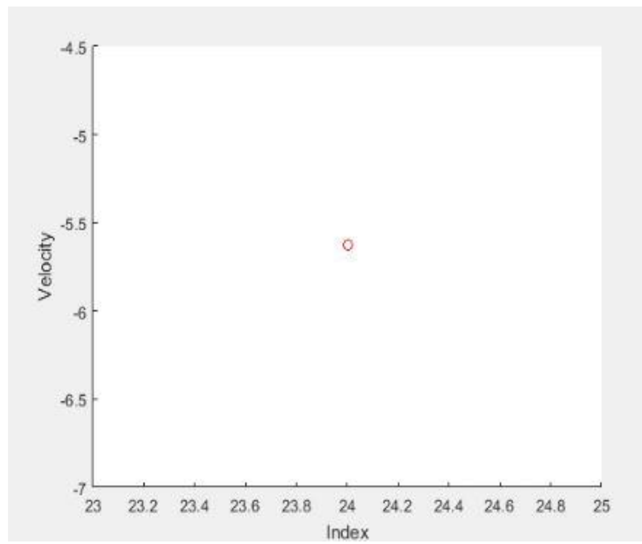

Figure 12. The Doppler Estimation of one frame from real data experiment by MLE

The MR3003_RD is a reference design based on NXP's MR3003 chipset. This design can build a high-end two dimension (2D) radar transceiver with three transmitters along with 4 receiving channels and a low phase noise. The radar chipset is shown as,

Figure 13. The MR3003-RD radar based on NXP chipset

Furthermore, to analyze the performance of ML estimation, The Monto-Carlo simulation results with 100 trials of repetition and SNR dB = 20 are shown in Table 3,

Estimation Parameters	$\hat{f}_d (kHz)$	$\hat{A}$
Actual Parameters	0.8	1
$SNR = 20dB$		
Mean	1.002	0.889
Variance	5.673×10^{-4}	3.565×10^{-4}
CLRB	7.875×10^{-5}	1.452×10^{-4}

Table 3. The Cramer Rao Lower Bound Parameter Estimation

4.4 Data Association of Radar and Optical Measurements

The given table elaborates the parameters estimation related to velocity of detected vehicles. The velocity measured by radar is $v_1 = 41km/h$ and $v_1 = 23km/h$ .For the optical case, the position of the vehicles are calculated by finding the x-y coordinates in both successive frames. After that the distance traveled by both vehicles in the image plane is calculated in terms of pixels. Later, the distance in pixel value is converted into the distance in meter by multiplying the distance in pixels*calibration factor. The calibration factor is calculated by approximating the ratio of the length of the vehicle in meter and the pixels occupied by the vehicle in an image. The table is shown as,

Speed from Radar Data (km/h)	X_1 (pixels)	X_2 (pixels)	$\Delta x = X_1 - X_2$ (pixels)	Δx (m)	Speed from optical Video (km/h)
41.00	(264,560)	(274,552)	12.8062	0.8723	39.2536
23.00	(242,691)	(246,696)	7.8102	0.4697	21.1386

Table 4. The Associated data measurements

After detection and estimating the velocity of both scenarios i.e. MR3003 radar data results by implementing the estimation algorithm (FFT) and optical image containing multiple targets by implementation of above described algorithm, the association with each other is shown as,

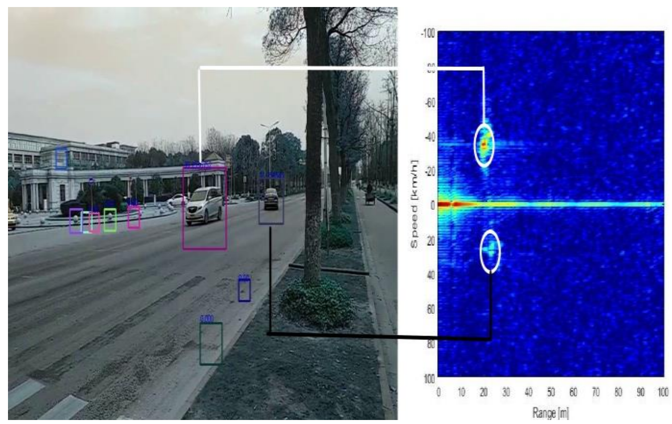

Figure 14. The visualization of two combined sensors

The parameters estimated in Table 4 and the identification is acquired by the fusion of both sensors which leads to the ease of getting and understanding the precise information regarding vehicles.

The detection of objects other than vehicle in Figure 14 is due to the approximation of multiple parameters, classifier used in neural network and the angle of optical video. Typically for surveillances purpose, it can give the accurate results but in case of automotive vehicles, the radar has to cover the surroundings from every angle, there is need of some approximated parameters which is solvable problem in future research.

5. Conclusion

This paper investigates the considerable problems in autonomous vehicle technology which is being used in intelligent transport system. The previous method gives the approximation of target parameters including range and velocity of the moving targets.

In this research work, the OFDM waveform is used for radar application along with a method is proposed that can improve the Doppler resolution of moving target. Although, the work is based on

OFDM radar which will be available in future. Most recent radar being used is based on FMCW. Furthermore, the real radar FMCW raw data is implemented with maximum likelihood (ML) estimation method and cramer rao lower bound (CRLB) analysis is performed to ensure the accuracy of the estimator. Eventually, the results acquired from both the methods are compared.

In the further part, the recognition problem of vehicles in radar measurements and optical measurements is analyzed. The optical video and MR3003 radar data is recorded at the same place and time i.e. in front of Shanghai Jiao Tong University. The deep learning based convolutional neural network (CNN) is trained to detect the vehicles first in a video after that the tracking and speed estimation is performed by analyzing the movement of vehicle's pixels in every frame. Eventually, both the data measurements are matched to recognize the particular vehicle.

References

[1] Hasch, J., Driving towards 2020: "Automotive radar technology trends", IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM). 2015.

[2] Juergen Dickmann, J.K., Markus Hahn,Nils Appenrodt,HansLudwig,Bloecher,Klaudius,"At-omotive radar the key technology for autonomous driving: From detection and ranging to environmental understanding", IEEE Radar Conference (RadarConf) 2016.

[3] Stefan Trummer, G.F.H., Richard Koerber,Uwe Siart,Thomas F. Eibert, "Performance analysis of 79 GHz polarimetrie radar sensors for autonomous driving",European Radar Conference (EURAD). 2017, IEEE Nuremberg, Germany.

[4] Yuanzhang Fan , Z.Y., Xiangyuan Bu, Jianping,"Radar waveform design and multi-target detection in vehicular applications", International Conference on Estimation, Detection and Information Fusion (ICEDIF). 2015, IEEE: Harbin, China.

[5] Christian Sturm, S.M.I., and Werner Wiesbeck, Fellow IEEE, "Waveform Design and Signal Processing Aspects for Fusion of Wireless Communications and Radar Sensing". Proceedings of the IEEE, 2011. **99**(7).

[6] Yoke Leen Sit, C.S., Lars Reichardt, Thomas Zwick, Werner Wiesbec , "The OFDM Joint Radar-Communication System: An Overview", The Third International Conference on Advances in Satellite and Space Communications. 2011, IEEE.

[7] Zhu, X.X.Z.C.Q.W.X., "Moving target detection of OFDM-MIMO radar based on ST-DFT", Electronics Letters 2016. **52**(2).

[8] Christian Sturm, M.B., Thomas Zwick, Werner Wiesbeck, "Multiple Target Doppler Estimation Algorithm for OFDM based Intelligent Radar Systems", P.o.t.t.E.R. Conferenc, Editor.

[9] Öztürk, A.E.r.H.K.E., "Design of OFDM on Digital Signal Processors",23rd Signal Processing and Communications Applications Conference (SIU). 2015, IEEE: Malatya, Turkey.

[10] Wu, J.-F.G.J.M.K., "Delay and Doppler shift estimation for OFDM-based radar-radio (RadCom) system", in IEEE International Wireless Symposium (IWS 2015). 2015, IEEE: Shenzhen, China.

[11] M.Kay, S., Fundamentals of Statistical Signal Processing: Estimation Theory. 1993.

[12] Natee Thong-un, W.W.W.T., "Doppler Frequency Estimation Using Maximum Likelihood Function For Low Ulltrasonic Velocity Profile", Acoust. Sci. & Tech., 2017.

[13] J. Arrspide, L.S., M. Nieto, "Video analysis based vehicle detection and tracking using an MCMC sampling framework", URASIP Journal on Advances in Signal Processing, 2012.

[14] Google, Tensorflow pre-trained Object Detection Models.https://github.com/tensorflow/models/tree/master/research/slim, 2017.

[15] Gallen, C.-S., www.rfbeam.ch, in Schuppisstrasse R.M. GmbH,Editor,datasheet.