UACEE International Journal of Advances in Computer Networks and its Security – IJCNS
Volume 3 : Issue 2 [ISSN 2250 – 3757]
Publication Date : 05 June 2013

Vehicle Kinematic Parameters Estimation Using Modified Linear Kalman Filter

Dnyaneshwar V. Avatirak, Dr. S.L. Nalbalwar, Prof . N.S.Jadhav

Abstract— **This paper proposes a system that can estimate kinematic parameters of the target vehicle like location, velocity, and acceleration to avoid possible vehicle collision. Kinematic parameters are extracted from radar signal with appropriate waveform modulation. Hybrid linear frequency modulation (LFM) and frequency- shift keying (FSK) is used in radar so that more than one target is detected with high range resolution and high time update. Extracted kinematic parameters are than process using Modified Linear Kalman Filter (MLKF) along with trilateration process. Extended Kalman Filter (EKF) is also use to compare response of the two systems. Sensor network is useful for 360 degree protection of individual car. Sensors used in sensor network are 77GHz wide range radar and 24GHz ultra-wide band (UWB) short range radar (SRR).**

Keywords— Automotive Safety, Collision Avoidance (CA), kalman filter, Radar.

I. Introduction

A study shows that 60% of rear-end collisions can prevented if driver get 0.5s of early warning [1]. In car accidents million people die and more than 30 million are injured every year in the world [2]. In many of the cases, the driver did not hit the brake before an accident, because they either not aware of the danger or had less time to react. Radar based an autonomous cruise-control (ACC) scheme can be help in avoiding rear-end collisions, and a lane-departure warning, and that will significantly reduce the number of car accidents.

For total 360 degree protection it is needed to use sensor network because single radar sensor has some range and azimuthal angle limitation. Today in the market different type of radars are available such as 77GHz wide range radar with maximum range of 200m and it has azimuthal range of $\pm 10°$ and 24GHz ultra-wide band short range radar with maximum range of 30m and it has azimuthal range of $\pm 70°$[8]-[9].

The important requirement for collision avoidance system is the simultaneous target vehicle kinematic parameter measurement with high resolution. For this purpose there is need to use appropriate waveform modulation technique to get accuracy even in multi-target situations. Hybrid linear frequency modulation (LFM) and frequency- shift keying (FSK) is used in radar so that more than one target is detected with high range resolution and high time update [3].

For proper working of Collision avoidance system the signal receives from radar network must be noiseless but due to noisy environment there is no guaranty of getting noiseless signal. To remove noise, receive signal must process using filter. MLKF is used along with trilateration process to estimate kinematic parameter of target vehicle. Initially MLKF takes some time to converse to its true value.

In this paper, propose system contain MLKF which improve accuracy of estimated kinematic parameters. The propose approach explain in section III A. EKF is explained in section III B. The two filters are compared under different scenarios in section IV.

II. Radar in collision avoidance system

In collision avoidance system many type of sensor are used like radar, lidars and image sensor [5]. Propose system uses radar sensor because it has advantages. These are:

- A relative distance and velocities can be measure with good accuracy.
- Multiple targets can be detected.
- Measurements time is very short.
- Robots against changing light conditions.

Different types of Radars are available in a market. For 360 degree protection of individual vehicle, multiple numbers of radars are useful. 24GHz radar is useful for Collision warning, Collision mitigation, Blind spot monitoring, parking aid (forward and reverse),Lane change assistant, Rear crash collision warning. It has detection range of 0.2 to 30 m, a range resolution of 15 cm, a range accuracy of 7.5 cm and opening angle of $\pm 70°$. During overtaking there is need of long range object detection, for this purpose 77GHz radar can be useful. It has range from less than 1m to up to 200 m, up to ±14° opening angle in long range and a relative velocity range of up to ±260 km/h [8].

Dnyaneshwar V. Avatirak
Dr. Babasaheb Ambedkar Technological University, Lonere
India
dvavatirak@dbatu.ac.in

Dr. S.L. Nalbalwar
Dr. Babasaheb Ambedkar Technological University, Lonere
India
nalbalwar_sanjayan@yahoo.com

Prof . N.S.Jadhav
Dr. Babasaheb Ambedkar Technological University, Lonere
India
nsjadhav@dbatu.ac.in

For proper protection of vehicle like car, 10 radars of short range and 2 radars of long range can be used. Figure 1 shows placement of radar on car. These Radars are grouped into four different subsystems like front subsystem, right subsystem, left subsystem, rear subsystem. Front subsystem consists of two 24GHz radars and two 77GHz radar. These radars are useful for collision warning, Precrash and stop and Go. Right and left subsystem consist of three radars each of 24GHz type. These are useful for Blind Spot Detection and Cut-in collision warning. Rear subsystem consists of two 24GHz radars for Parking Aid and Rear-end collision warning. Figure 1 show that Maximum area around vehicle is covered by two or more radars for trilateration process.

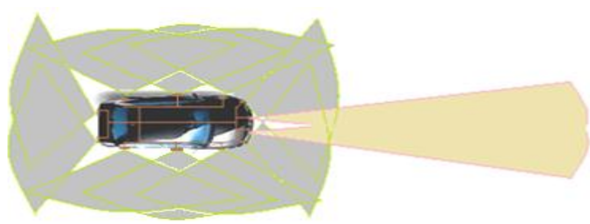

Figure 1. Sensors network on vehicle and their covered area

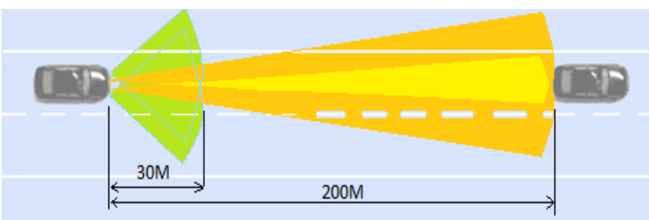

Figure 2. use and range of 24GHz radar and 77GHz radar

III. Filters

A. i] Modified Linear Kalman Filter

Equation of Kalman filter in [4] and modified equations are given as

$\hat{x}[n+1|n]=F[n+1|n].\ \hat{x}[n|n]$ (1)

$K[n+1|n]= F[n+1|n].K[n|n].F^T[n+1|n]+Q_1$ (2)

$R[n]=c[n].\ K[n|n-1].C^T[n]+ Q_2$ (3)

$G[n]= K[n|n-1].C^T[n]/ R[n]$ (4)

$\hat{x}[n|n]= \hat{x}[n|n-1]+G[n].\alpha[n]$ (5)

$\alpha[n]=y[n]-C[n].\ \hat{x}[n|n-1]$ (6)

$K[n|n]=K[n|n-1]-G[n].C[n].\ K[n|n-1]-D[K[n|n-1]]$ (7)

Where

$\alpha[n]$= Innovation vector at time n.

$y[n]$= Observation at time n.

$\hat{x}[n|n]$= filtered estimate of the state vector at time n.

$\hat{x}[n+1|n]$= Predicted estimate of the state vector at time n.

$G[n]$= Kalman gain at time n.

$K[n|n]$= Correlation matrix of error in $\hat{x}[n|n]$

$K[n+1|n]$= Correlation matrix of error in $\hat{x}[n+1|n]$

$C[n]$= Measurement matrix at time n.

Q_1= Correlation matrix of process noise.

Q_2= Correlation matrix of measurement noise.

$D[K[n|n-1]]$=Modification function of $K[n|n-1]$

$$D[K[n|n-1]] = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & e^{K_{mxm}[n|n-1]} \end{bmatrix}$$

The measurement vector and dynamic state vector for *i*th sensor is define as

$$y_i[n]=\begin{bmatrix} r_{i[n]} \\ v_{i[n]} \\ a_{i[n]} \end{bmatrix} \qquad \hat{x}_i[n]=\begin{bmatrix} \hat{r}_{i[n]} \\ \hat{v}_{i[n]} \\ \hat{a}_{i[n]} \end{bmatrix}$$

For j=2. The state transition matrix can be derived as

$$F[n+1|n]=\begin{bmatrix} 1 & T & T^2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix}$$

where T is the time interval for state update.

Initial condition for matrices is as follow.

$$Q_2 = \begin{bmatrix} \sigma_r^2 & 0 & 0 \\ 0 & \sigma_v^2 & 0 \\ 0 & 0 & \sigma_a^2 \end{bmatrix} \qquad Q_1 = 0 \qquad C[n]=I_{3x3}$$

$K[1|0]=I_{3x3}$

$$D[K[n|n-1]] = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & e^{K(3,3)} \end{bmatrix}$$

Where $e^{K(3,3)}$ means last element of 3x3, $K[n|n-1]$ matrix varies exponential.

ii] Trilateration

Now let's consider two sensors are located at(x_1,0) and (x_2,0) location on vehicle. These sensor tracking the target located at ($\hat{X}, \hat{Y}$), moving at velocity ($\hat{v}_x$, $\hat{v}_y$), acceleration ($\hat{a}_x$, $\hat{a}_y$). Estimated parameter from sensors given to MLKF for filtering process and then filtered signal is used in trilateration process to calculate target relative distance, velocity and acceleration in x-y direction [6].

The range from two sensors can express as

$$\widehat{r_1^2}=(\hat{X}- x_1)^2+\hat{Y}^2 \qquad \widehat{r_2^2}=(\hat{X}- x_2)^2+\hat{Y}^2 \tag{8}$$

After eliminating $\hat{y}$, we get

$$\hat{X}=\frac{x_1^2-x_2^2-\hat{r}_1^2+\hat{r}_2^2}{2(x_1-x_2)} \tag{9}$$

Then, $\hat{y}$ can be determined as

$$\hat{Y}=\sqrt{\frac{\hat{r}_2^2+\hat{r}_1^2-(\hat{X}-x_1)^2-(\hat{X}-x_2)^2}{2}} \tag{10}$$

Target velocity and acceleration can be derived as

$$\begin{bmatrix} \hat{v}_x \\ \hat{v}_y \end{bmatrix}=\begin{bmatrix} \frac{\hat{X}-x_1}{\hat{r}_1} & \frac{\hat{Y}}{\hat{r}_1} \\ \frac{\hat{X}-x_2}{\hat{r}_2} & \frac{\hat{Y}}{\hat{r}_2} \end{bmatrix}^{-1} . \begin{bmatrix} \hat{v}_1 \\ \hat{v}_2 \end{bmatrix} \tag{11}$$

$$\begin{bmatrix} \hat{a}_x \\ \hat{a}_y \end{bmatrix}=\begin{bmatrix} \frac{\hat{X}-x_1}{\hat{r}_1} & \frac{\hat{Y}}{\hat{r}_1} \\ \frac{\hat{X}-x_2}{\hat{r}_2} & \frac{\hat{Y}}{\hat{r}_2} \end{bmatrix}^{-1} . \begin{bmatrix} \hat{a}_1 \\ \hat{a}_2 \end{bmatrix} \tag{12}$$

B. *Extended Kalman Filter*

Extended Kalman Filter is nonlinear filter so Taylor approximation is applied to linearize the transition matric [7]. After approximation Equation become

$\hat{x}$[n+1|n]=F[n+1|n]. $\hat{x}$[n|n] (13)

K[n+1|n]= F[n+1|n].K[n|n].F^T[n+1|n]+Q_1 (14)

R[n]=c[n]. K[n|n-1].C^T[n]+ Q_2 (15)

G[n]= K[n|n-1].C^T[n]/ R[n] (16)

$\hat{x}$[n|n]= $\hat{x}$[n|n-1]+G[n].α[n] (17)

α[n]=y[n]-C[n, $\hat{x}$[n|n-1]] (18)

K[n|n]=K[n|n-1]-G[n].C[n]. K[n|n-1] (19)

Where

y[n]= Observation at time n.

C[n,x[n]]= nonlinear Measurement matrix at time n.

Q_1= Correlation matrix of process noise.

Q_2= Correlation matrix of measurement noise.

The measurement vector and dynamic state vector for system containing two sensors at(x_1,0) and (x_2,0) location on vehicle is define as

$$Y[n]=\begin{bmatrix}\hat{r}_1[n]\\ \hat{r}_2[n]\end{bmatrix}$$

$$\hat{x}[n]=\begin{bmatrix}\hat{X}[n] & \hat{v}_x[n] & \hat{a}_x[n] & \hat{Y}[n] & \hat{v}_y[n] & \hat{a}_y[n]\end{bmatrix}^T$$

The state transition matrix can be derived as

$$F[n+1|n]=\begin{bmatrix}1 & T & T^2/2 & 0 & 0 & 0\\ 0 & 1 & T & 0 & 0 & 0\\ 0 & 0 & 1 & 0 & 0 & 0\\ 0 & 0 & 0 & 1 & T & T^2/2\\ 0 & 0 & 0 & 0 & 1 & T\\ 0 & 0 & 0 & 0 & 0 & 1\end{bmatrix}$$

Linear Measurement matrix can derive as

$$C[n]=\begin{bmatrix}\frac{\hat{X}[n]-x_1}{\hat{r}_1[n]} & 0 & 0 & \frac{\hat{Y}[n]}{\hat{r}_1[n]} & 0 & 0\\ \frac{\hat{X}[n]-x_1}{\hat{r}_2[n]} & 0 & 0 & \frac{\hat{Y}[n]}{\hat{r}_2[n]} & 0 & 0\end{bmatrix}$$

Initial condition for matrices is as follow.

$$Q_2=\begin{bmatrix}\sigma_r^2 & 0 & 0\\ 0 & \sigma_v^2 & T\\ 0 & 0 & \sigma_a^2\end{bmatrix} \qquad Q_1=0 \qquad K[1|0]=I_{3x3}$$

Take T=200μs, σ_r=0.05m, σ_v=0.02m/s, σ_a=1m/s^2[6]- [7]

IV. Comparison of filters

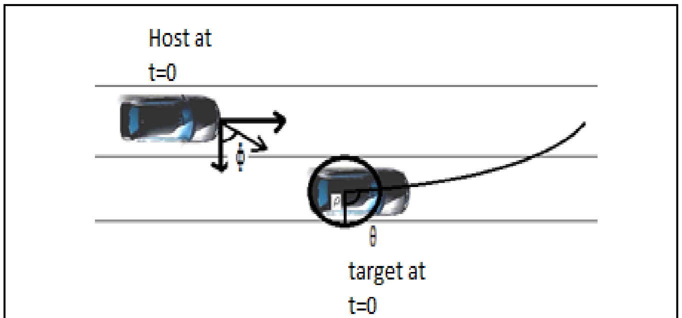

Figure 3.Target vehicle makes a left turn in front of the host vehicle

For different scenarios both modified linear kalman filter and extended kalman filter are compared in this paper. Let consider two vehicles are moving on XY- plane. Host vehicle is moving with constant velocity in Y-direction and target vehicle tries to take left turn in front of host vehicle with different speed and acceleration.

The center of mass of target vehicle is at ($x_{tc}(t), y_{tc}(t)$) and center of front bumper of host vehicle is origin of reference coordinate. ρ is the radius from center of mass of target vehicle to its longest edge. θ is the polar angle of vehicle motion. ϕ is the initial azimuthal angle of the polar coordinate with respect to reference coordinate. Trajectory of target vehicle can be given by following equation.

$x_t(t)$=$x_{tc}(t)$+ ρ cos θ (t) (20)

$y_t(t)$=$y_{tc}(t)$+ ρ sin θ (t) (21)

θ (t)= $tan^{-1}[\frac{v_{ty}(t)}{v_{tx}(t)}]$+ ϕ- 90^0 (22)

Where $v_{tx}(t) and\, v_{ty}(t)$ are target vehicle velocity in x and y direction respectively.

The radial parameter between given target point and ith sensor thus be express as [6]

r_1^2 (t)=$(X'(t)-\ x_1)^2+(Y'(t)-\ y_1)^2$ (23)

r_2^2(t)=$(X'(t)-\ x_2)^2+(Y'(t)-\ y_2)^2$ (24)

$$\begin{bmatrix}v_1(t)\\ v_2(t)\end{bmatrix}=\begin{bmatrix}\frac{X'(t)-x_1}{r_1} & \frac{Y'(t)-y_1}{r_1}\\ \frac{X'(t)-x_2}{r_2} & \frac{\hat{Y}'(t)-y_2}{r_2}\end{bmatrix}.\begin{bmatrix}v'_x(t)\\ v'_y(t)\end{bmatrix} \quad (25)$$

$$\begin{bmatrix}a_1(t)\\ a_2(t)\end{bmatrix}=\begin{bmatrix}\frac{X'(t)-x_1}{r_1} & \frac{Y'(t)-y_1}{r_1}\\ \frac{X'(t)-x_2}{r_2} & \frac{Y'(t)-y_2}{r_2}\end{bmatrix}.\begin{bmatrix}a'_x(t)\\ a'_y(t)\end{bmatrix} \quad (26)$$

$X'(t)$= $x_t(t)$-$x_h(t)$ $Y'(t)$= $y_t(t)$-$y_h(t)$ (27)

$v'_x(t)$= $v'_{tx}(t)$- $v'_{hx}(t)$ $v'_y(t)$= $v'_{ty}(t)$- $v'_{hy}(t)$ (28)

$a'_x(t)$= $a'_{tx}(t)$- $a'_{hx}(t)$ $a'_y(t)$= $a'_{ty}(t)$- $a'_{hy}(t)$ (29)

Where $x_t(t)$, $y_t(t)$, $v'_{tx}(t)$, $v'_{ty}(t)$, $a'_{tx}(t)$, $a'_{ty}(t)$ are position, velocity, and acceleration of closest point of target vehicle from host vehicle.

Similarly $x_h(t)$, $y_h(t)$, $v_{hx}(t)$, $v_{hy}(t)$, $a'_{hx}(t)$, $a'_{hy}(t)$ are position, velocity, and acceleration of reference point on host vehicle.

For demonstration point of view, let's consider length and width of both vehicles are 4m and 1.8m respectively. The center of front bumper of host vehicle is chosen as origin of reference coordinate. The two sensors are placed at 0.8m (i.e. (0.8,0) and (-0.8,0))away from center of front bumper towards right and left side.

Scenario 1: Initial Kinematic parameters for both vehicles are chosen as follow.

$x_t(t)=5m$, $y_t(t)$ = 10m , $v'_{tx}(t)$ = 0m/s, $v'_{ty}(t)$ =11m/s, $x_h(t)=0m$, $y_h(t)$ = 0m, $v'_{hx}(t)$ = 0m/s, $v'_{hy}(t)$= 21m/s, $a'_{hx}(t)$= 0 m/s^2, $a'_{hy}(t)$= 0 m/s^2. Suffix h stand for host vehicle and t stand for target vehicle. At t=0 target vehicle begins to take a left turn with a velocity $v'_{ty}(t)=11m/s$ and turn radius R=15m. Due to circular motion, acceleration of magnitude $a'_{tx}(t)$ =-8. 06 m/s^2 (a=v^2/R) will act on vehicle. The RMS errors of estimated

UACEE International Journal of Advances in Computer Networks and its Security – IJCNS
Volume 3 : Issue 2 [ISSN 2250 – 3757]
Publication Date : 05 June 2013

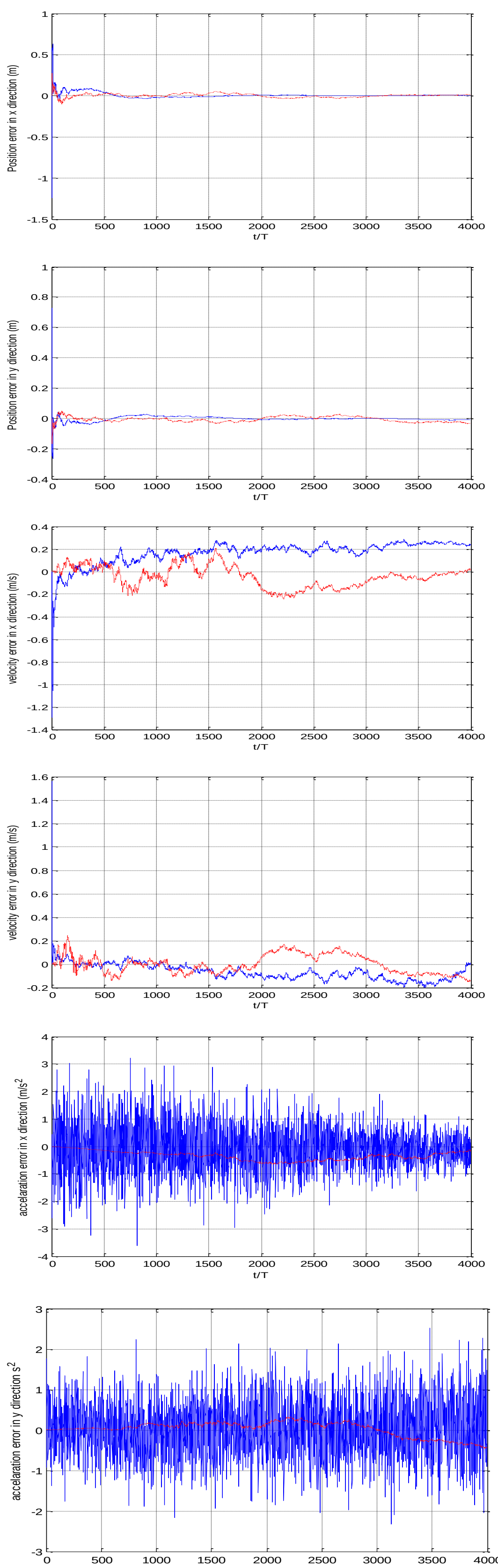

Figure 4. Estimation errors. (Solid line) MLKF and (dash-dot line) EKT

kinematic parameters for system containing MLKF and EKF at *t* = 0.8 s are listed in the column s1 in Table I.

Figure 4 shows evolution of kinematic parameter for scenarios '1' using both filter approaches. The RMS error for estimated kinematic parameter are given by

$$\varepsilon_\gamma = \sqrt{\frac{1}{M}\sum_{n=1}^{M}[\hat{\gamma}(n) - \gamma]^2} \quad (30)$$

Here $\gamma = x, y, v_x, v_y, a_x, a_y$ and superscript (n) denote nth trial of Monte Carlo simulation with M=100.

Scenario 2: Initial Kinematic parameter for target vehicle is chosen as, $v'_{ty}(t)$ =30m/s. At t=0 target vehicle begins to take a left turn with a velocity $v'_{ty}(t) = 30m/s$ and turn of radius R=10m, $a'_{tx}(t)$ = -90 m/s^2 . The RMS errors of estimated kinematic parameters for system containing MLKF and EKF at *t* = 0.4 s are listed in the column s2 in Table I.

Scenario 3: Initial Kinematic parameter for target vehicle is chosen as, $v'_{ty}(t)$ =20m/s. At t=0 target vehicle begins to take a left turn with a velocity $v'_{ty}(t) = 20m/s$ and turn of radius R=15m, $a'_{tx}(t) = -8.06 m/s^2$. The RMS errors of estimated kinematic parameters for system containing MLKF and EKF at *t* = 0.6 s are listed in the column s3 in Table I.

TABLE I. RMS ERROR OF ESTIMATED KINEMATIC PARAMETERS

	MLKF (s1)	EKF (s1)	MLKF (s2)	EKF (s2)	MLKF (s3)	EKF (s3)
ε_x	0.0057	0.0124	0.0179	0.6232	0.0202	0.6194
ε_y	0.0119	0.0244	0.0115	0.0813	0.0113	0.0809
ε_{vx}	0.2760	0.0760	0.4801	4.8145	0.4879	4.7501
ε_{vy}	0.0751	0.1220	1.6222	0.2584	1.6149	0.2642
ε_{ax}	0.3702	0.3164	1.3555	13.762	1.1348	13.689
ε_{ay}	0.5013	0.3738	0.9077	8.6387	0.9540	8.5746

s1: Scenario 1
s2: Scenario 2
s3: Scenario 3

From table I.it is clear that EKF fails to track the target due to its nonlinear transformation from the radial kinematic parameters to those in the Cartesian coordinates without trilateration. Estimated kinematic parameters error varies with different scenarios.

V. Conclusion

Proposed system contains MLKF to estimate kinematic parameters of target vehicle. MLKF has high accuracy than EKF. In different scenarios estimate parameter variation in EKF is more than MLKF. The overall performance of MLKF is better than EKF. Three scenarios are used to demonstrate the effectiveness of proposed system.

References

[1] Motor Vehicle Accidents--Number and Deaths. [Online]. Available: http://www.census.gov/compendia/statab/cats/transportation/motor_vehicle_accidents_and_fatalities.html

[2] The Commissions Intelligent Car Flagship Under the i2010 Initiative,

Brussels, Feb. 21, 2006. [Online]. Available: http://europa.eu/rapid/pressReleasesAction.do?reference=MEMO/06/86.

[3] H. Rohling and M. M. Meinecke, “Waveform design principles for automotive radar systems,” in Proc. IEEE Radar, Oct. 2001, pp. 1–4.

[4] S. Haykin, Adaptive Filter Theory., 4th ed. Englewood Cliffs, NJ: Prentice-Hall, 2002.

[5] S. G. Wu, S. Decker, P. Chang, T. Camus, and J. Eledath, “Collision sensing by stereo vision and radar sensor fusion,” IEEE Trans. Intell. Transp. Syst., vol. 10, no. 4, pp. 606–614, Dec. 2009.

[6] J. V. Kleff, J. Bergmans, and L. Kester, Multiple-hypothesis trilateration and tracking with distributed radars. [Online]. Available: http://staff.science.uva.nl/~jvanklee/Publications/data/174.pdf .

[7] Y. N. Chung, D. L. Gustafson, and E. Emer, “Extended solution to multiple maneuvering target tracking,” IEEE Trans. Aerosp. Electron. Syst., vol. 26, no. 5, pp. 876–887, Sep. 1990.

[8] J. Wenger, “Automotive radar—Status and perspectives,” in Proc. IEEE Compound Semicond. Integr. Circuit Symp., Oct. 2005, pp. 21–24.

[9] M. Klotz, “An automotive short range high resolution pulse radar network,” Ph.D. dissertation, Technische Univ. Hamburg-Harburg, Hamburg, Germany, 2002.

Dnyaneshwar V. Avatirak was born in Maharashtra, India, on October 09, 1987. He received the B.E degree in Electronics and telecommunications engineering from SRTM University, Maharashtra, India, in 2010 and pursuing the M.Tech degree in Electronics and telecommunications engineering from Dr. Babasaheb Ambedkar Technological University, Lonere, Maharashtra, India.

Sanjay Nalbalwar has received B.E. (CSE) in 1990 and M.E. (Electronics) in 1995 from SGGS College of Engineering and Technology, Nanded, MS. He has completed Ph.D. from IIT Delhi in the year 2008. He has around 22 years of teaching experience and is working as a Professor & Head of Electronics and Telecommunication Engineering Department at Dr. Babasaheb Ambedkar Technological University, Lonere,Raigad, Maharashtra State(India). His area of interest includes Multirate Signal Processing and Wavelet, Stochastic Process Modeling. He has to his credit around 150 papers in national and international conferences and 50 papers in the international journals. He is member of professional bodies like ISTE, IETE, IEEE, CSI,IE. He is also working on various research projects in the area of biomedical signal processing, signal representation, signal matched wavelets, smart grid. Guided about 50 M.Tech projects and about 200 B.Tech. projects. Also presently guiding 6 Ph.D students..

Prof. Narendra Jadhav received the B.Tech. and M.Tech degree from the Dr. BATU Lonere, Raigad Maharashtra, INDIA, in 2004, in Electronics and Telecommunication engineering.. His research interests include gesture recognition, artificial intelligence, and FPGA System in Signal Processing.