ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AN EFFICIENT RADAR SIGNAL DENOISING FOR TARGET DETECTION USING EXTENDED KALMAN FILTER

[1]JAMI VENKATA SUMAN, [2]JOSEPH BEATRICE SEVENTLINE

[1]Assistant Professor, Department of ECE, GMR Institute of Technology, Rajam, India.
[2]Professor, Department of ECE, GITAM Institute of Technology, Visakhapatnam, India.
Email: [1]jami.venkatasuman@gmail.com, [2]samsandra2003@yahoo.com

ABSTRACT

Nowadays target detection and tracking play a vital role in the field of aeronautical, spacecraft, wild area, Marine Corps, underwater scenario and so on. In the target detection, Radio Detection and Ranging (RADAR) signal is transmitted and the reflected signal has status of target information. In this paper the performance of radar signal generation and radar target detection (RTD) models simulated using MATLAB Simulink is discussed. The implementation of Extended Kalman Filter (EKF) using Register Transfer Level (RTL) Verilog- Hardware Description Language (HDL) and their analysis using for the Field Programmable Gate Array (FPGA) implementation in Xilinx tool and the Applications Specific Integrated Circuit (ASIC) implementation in cadence encounter tool with 180nm and 45nm library technologies are also presented in this paper. The Root Mean Square Error (RMSE) and Signal-to-Noise Ratio (SNR) values are evaluated by using MATLAB Simulink. On FPGA analysis, LUT, slices, flip flops, frequency and ASIC implementation area, power, delay, Area Power Product (APP), Area Delay Product (ADP) is improved in proposed EKF-RTD method than conventional methods.

Keywords: *RADAR, MATLAB Simulink, Extended Kalman Filter, Radar Target Detection, RTL, HDL, Xilinx, FPGA, Cadence, ASIC.*

1. INTRODUCTION

In today's technology, RADAR is playing a major role in the object detection in space. Radar is an object-detection system, which utilizes the radio waves to measure the velocity, range, and angle of the objects. It has received wide importance in the detection of objects such as spacecraft, aircraft, motor vehicles, ships, guided missiles, weather formations, and terrain. In [1] Tugac et.al has discussed about applications of Hidden Markov models (HMM) for radar target detection. This model can detect targets even when that object is present in the noisy environment. Kalman filter is an optimal state estimation method for stochastic signals that estimates the state of a discrete time controlled process by using a feedback control. The Kalman filter is applicable to linear Gaussian models but not applicable to the nonlinear models. In estimation theory, the extended Kalman filter is the nonlinear version of the Kalman filter which linearizes about an estimate of the current mean and covariance. A multisensory distributed extended Kalman filtering algorithm has been introduced for a nonlinear system [2]. In this paper the dynamic equations of the system and sensor measurement equations were linearized in the global estimates and global predictions are discussed.

The de-noising of the radar signal is the key task in the target detection as well as in target tracking system. In [3] Lagha et.al has discussed about de-noising of the weather radar signal by using multi thresholding method and wavelet method. It has been observed that this multi thresholding method has lost the information. In [4] Yuan Niu et.al has introduced the extended Kalman filter for moving object tracking system. In this work, the extended Kalman filter technique is applied for nonlinear motion model of the tracked moving object. The optimal estimated trajectory was achieved by integrating the equations of object tracking problem into EKF forms but in this paper the complicated object motion detection model is not discussed.

In [5] Wei Mei et.al has discussed about the application of extended Kalman filter for very long range radar tracking using pseudo measurement noise compensation (PMNCEKF). In this work the range filtering performance and filtering consistency has improved. In [6] Chan Zeng et.al has discussed about the application of extended Kalman filter for high dynamic tracking of GPS signal and this method is compared with the traditional tracking loop with

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

third order phase locked loop (PLL). It has been observed that this method is suitable for less complex environments only but it has to be improved by implementing in a more complex environment like weak and high dynamic signal. In [7] Kramer et.al has introduced tracking of multiple targets with several manoeuvre characteristics using single neural EKF. In this work neural EKF has the feature of adaptability. With this it can adapt and gives good tracking performance for several targets. In [8] Pichlík et.al has discussed about the applications of EKF for estimating the train velocity. Some of the train control systems have to know the train longitudinal velocity that is close to the train velocity. The train velocity can be determined from the wheel set velocity; this wheel set velocity is different from train velocity due to slipping velocity. These two velocities were nonlinear in nature; to overcome this extended Kalman filter has been used. The extended Kalman filter enables to solve the issues of a nonlinear dependence between wheel set velocity and the train velocity.

Underwater target detection is very much important in the seas and rivers, to detect the objects in the underwater. In [9] Liang et.al has discussed about an efficient 3D nested array system using maximum likelihood (ML) estimation algorithm for target size detection. In [10] Shubin et.al has discussed about the LASER based underwater object detection using Gabor transform. It has been observed that Gabor transform has processed the LASER signal in under water target detection and it also eliminates the random interference with low SNR and complexity. In [11] Pitchaiah et.al has discussed about high-speed implementation of Distributed Arithmetic (DA) based architecture for adaptive Least Mean Square filter. In this paper FPGA and ASIC implementations of LMS filters are discussed. It has also been proved that it requires more area, delay and power. In [12] Ahmad Abdul et.al has discussed about embedded hardware architecture for moving object tracking using Kalman filter. But this method is only applicable for linear systems and is not suitable for non-linear systems. In [13] Subrahmanyam et.al has discussed about delayed μ-law proportionate based adaptive LMS filters for Sparse system identification by using 3rd level HAAR type of wavelet transform. In this paper ASIC implementation of delayed LMS filters using 180nm CMOS technology is discussed. It has been observed that this filter implementation requires more area complexity and power.

In [14] Jing Cun et.al has introduced the new technique for underwater target detection and tracking using the combination of a particle filter (PF) and track-before detect (TBD) method. The simulated results concluded that the PF-TBD algorithm is better compared to the conventional MFP at low SNR values, and it's as good as the MFP at high SNRs. But robustness and efficiency are less and it has to be improved. In [15] M. Labbarian et.al has discussed the target tracking in pulse Doppler MIMO radar. The obtained results conclude that the target tracking by MIMO radar using target velocity is more accurate compared to the MIMO radar without using velocity vector. By using velocity vector as well as target location, radar can track the target very precisely.

In [16] Mohammad Shaifur Rahman et.al has discussed about the applications of EKF for Doppler radar cardiopulmonary monitoring system. It is observed that the EKF finds better or more robust solutions in the noisy environment for target detection. It has also been proved that the SNR is increased and target detection capability of radar in noisy environment has been increased. Principal component analysis algorithm has been used to extract the features. In [17] Ribeiro has illustrated the KF and EKF technique properties. The KF technique was based on linear functions, which is not fixed value on moving object. The EKF function based on non-linearity function that can be applied fixed value on moving objects. Furthermore, this work only discussed about properties and derivation of the KF and EKF techniques. But, this work was not discussed about VLSI implementation of KF and EKF has not been done. In [18] Belaabed et.al has discussed about FPGA implementation of tracking algorithms. In this paper FPGA implementation of KF filter was discussed. It has also been proved that it requires more area and power. So in this paper, the development of Extended Kalman filter for radar signal de-noising using MATLAB-Simulink to obtain better results is presented. The VLSI implementation of the developed extended Kalman filter to obtain less area, power and delay has also been discussed.

2. EKF - RTD METHODOLOGY

In this EKF–RTD method, we have implemented an efficient de-noising algorithm to increase the accuracy of the target detection in the free space environment. For de-noising, an algorithm is applied to the received signal so that it can remove the color noise, which is affected during the propagation of the signal in the free space. Using EKF technique can easily achieve signal de-noising with less complexity in terms of hardware as well as computational time.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The efficiency of target detection is directly proportional to the efficiency of the de-noising algorithm. In this paper, Simulink is used to model the RADAR transmitter and receiver. Commonly used Simulink blocks are used to model free space environment. De-noising algorithm used for the EKF is implemented by using Verilog-HDL and it is synthesized by using Xilinx FPGA. In this paper, signal generation, target modeling, and receiver are implemented by using MATLAB Simulink. For ASIC implementation, we used cadence encounter was used with 180nm and 45nm library.

Detection and tracking of moving targets are very challenging nowadays. Some of the techniques used are based on linear models. These linear models are not fit for moving object detection. The moving objects may be linear or nonlinear; the EKF has been used to detect the moving targets in the noisy environment.

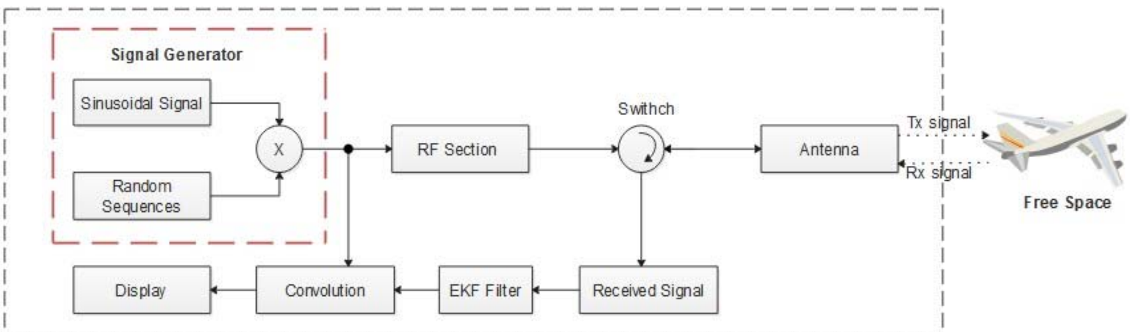


Figure 1: Block diagram of the proposed EKF-RTD methodology

The Figure 1 shows the block diagram of the proposed EKF-RTD methodology, it has a signal generator system includes sinusoidal signal and Barker code. Barker Code has various lengths such as 2, 3, 4, 5, 7, 11 and 13. To increase the efficiency of operation, 7-bit barker code is used to modulate the sine wave. The Radio Frequency (RF) section, switch, antenna, received signal, EKF filter, convolution, and display are included in the block diagram of EKF method. In this method, the modulator can send the sinusoidal signal through the RF section after this RF signal over the antenna. The transmitter can send the Radio signal through antenna as shows in the figure 1. It is passed through the space to detect objects, which are in space. The radar pulse with high velocity has to hit the target and it is reflected back. Depending on the reflected signal velocity, object velocity and its position from the base station are detected. The obtained signal is suppressed due to environmental disturbances and this can be eliminated by using a special kind of filter called EKF. After filtering the detected object parameters are processed, analyzed of the target and its position will be determined.

2.1 Kalman Filtering (KF)

In this section, formulates the general filtering issues and discuss the filtering conditions, which is the common filtering simplifies to a Kalman filter (KF). The filtering issue used for a non-linear system dynamic.

$$x_{k+1} = A_k x_k + B_k u_k + G_{wk} \qquad k \geq 0 \quad (1)$$

$$y_k = C_k x_k + B_k u_k + v_k \quad (2)$$

where

$x(k) \in R^n, x(k) \in R^m, w(k) \in R^n, v(k) \in R^r, y(k) \in R^r, \{w_k\}$ and $\{v_k\}$ are order of white Gaussian noise, zero mean, Gaussian noise with zero mean and joint covariance

$$E[w_k] = E[v_k] = 0, \quad (3)$$

Joint covariance matrix

$$E\left[\begin{pmatrix} w_k \\ v_k \end{pmatrix} (w_k^T v_k^T)\right] = \begin{bmatrix} Q_k & 0 \\ 0 & R_k \end{bmatrix} \quad (4)$$

The initial state x_0, is a Gaussian random vector with mean

$$E[x_0] = \bar{x}, \quad (5)$$

and covariance matrix

$$E[(x_0 - \overline{x_0})(x_0 - \overline{x_0})^T] = \Sigma_0 \quad (6)$$

The sequence $\{u_k\}$ is deterministic.

In this section, the issue of the state estimation can be formulated, which is determined as the estimation of a random parameter vector, and therefore the system (1), (2) The Kalman filter is the filter that obtains the minimum mean-square state error

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

estimate. In fact, when $x(0)$ is a Gaussian vector, the state and observations noise $w(k)$ and $v(k)$ are white Gaussian and the state and observation dynamics are linear,

- The conditional probability density functions $p(x_k) \mid y_k^1, u_0^{k-1}$ are Gaussian for any k,
- The mean, the mode, and the median of this conditional coincide,
- The Kalman filter, i.e., the filter that propagates the conditional $p(x_k) \mid y_k^1, u_0^{k-1}$ and obtains the state estimate by optimizing a given criteria, is the best filter among all the possible filter types and it optimizes any criteria that might be considered.

Let

$$p(x_k) \mid y_k^1, u_0^{k-1} \sim N(\hat{x}(k \mid k), P(k \mid k)) \qquad (7)$$

Represent the conditional as a Gaussian. The state estimate $(\hat{x}(k \mid k)$ is the conditional mean and the covariance matrix $P(k \mid k)$ quantifies the uncertainty of the estimate,

$$\hat{x}(k \mid k) = p(x_k) \mid y_k^1, u_0^{k-1}$$

$$P(k \mid k) = E[(x(k) - \hat{x}(k \mid k)) - \hat{x}(k \mid k))^T [\mid y_k^1, u_0^{k-1} \mid]].$$

From the equation (1) derives the filter dynamics in terms of the mean and covariance matrix of the conditional, i.e., it shows how the filter propagates the mean and the covariance matrix. This dynamics is recursive in the sense that to evaluate $\hat{x}(k+1 \mid k+1)$, the Kalman filter only requires the previous estimate, $\hat{x}(k \mid k)$, and the new observation, $y(k+1)$.

2.2 EKF Method

The EKF has been introduced for nonlinear models and it can be utilized for radar target detection. At each time step, the Jacobian [17] is evaluated with current predicted states. These matrices can be used in the filter equations. This process essentially linearizes the non-linear function around the current estimate.

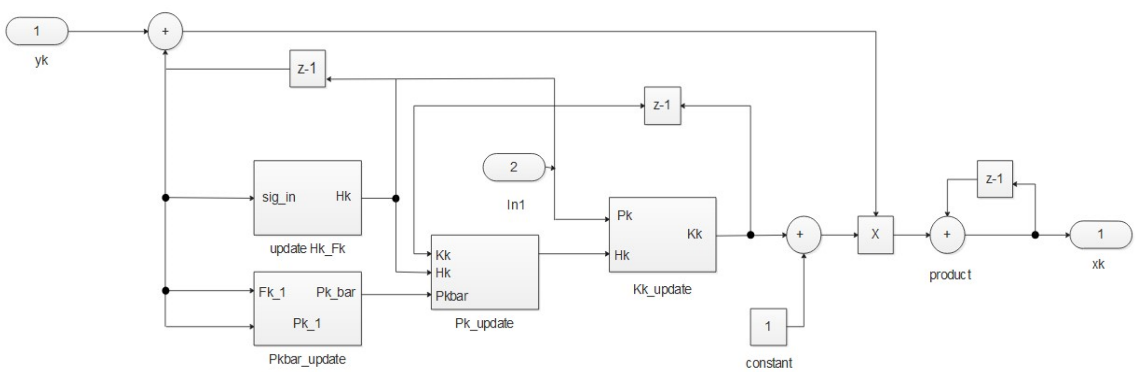


Figure 2: Block diagram of the EKF

In this section, the filtering problem is suitable if the system dynamics are nonlinear. With no loss of generality consider the system has no external inputs. Consider the nonlinear dynamic,

$$x_{k+1} = f_k(x_k, u_k) + w_k \qquad (8)$$

Equation (8) gives the difference between the real measurements obtained at the instant k+1 and measurement prediction obtained from the predicted value of the EKF state.

$$y_k = h_k(x_k) + v_k \qquad (9)$$

where,

$$x_k \in R^n, f_k(x_k) : R^n, \to R^n \qquad (10)$$

$$v_k \in R^r,$$

$$w_k \in R^n,$$

where $\{v_k\}$, $\{w_k\}$, is white Gaussian, independent random processes with zero mean, R_k, Q_k are covariance matrixes, f and h are non – linearity functions and u_k is control vector.

Journal of Theoretical and Applied Information Technology
15th December 2017. Vol.95. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

$$E[v_k u_k^T] = R_k,\ E[w_k e_k^T] = Q_k \tag{11}$$

$$x_0 \sim N\left(\bar{x}_0, \sum\nolimits_0\right).$$

Where x_0 is represents the system initial condition measured as a Gaussian random vector, $Y_1^k = \{y_1, y_2, ... y_k\}$ is represents a set of system measurements. The EKF's main aim is to obtain an estimation of the system states based on these measurements. The estimator is used to reduce the mean square error. In this method, the conditional PDF transitions $p(x_k \mid Y_1^k)$, $p(x_{k+1} \mid Y_1^k)$ and $p(x_{k+1} \mid Y_1^{k+1})$ are Gaussian.

The EKF produces calculation of the optimal estimate. The Non-linearity of the system's dynamics is approached by a linearizes type of the non-linear system around the final state estimate. For this estimation to be correct, this linearization could be better estimation of the non-linear system model in all unreliability domain connected with the state estimation.

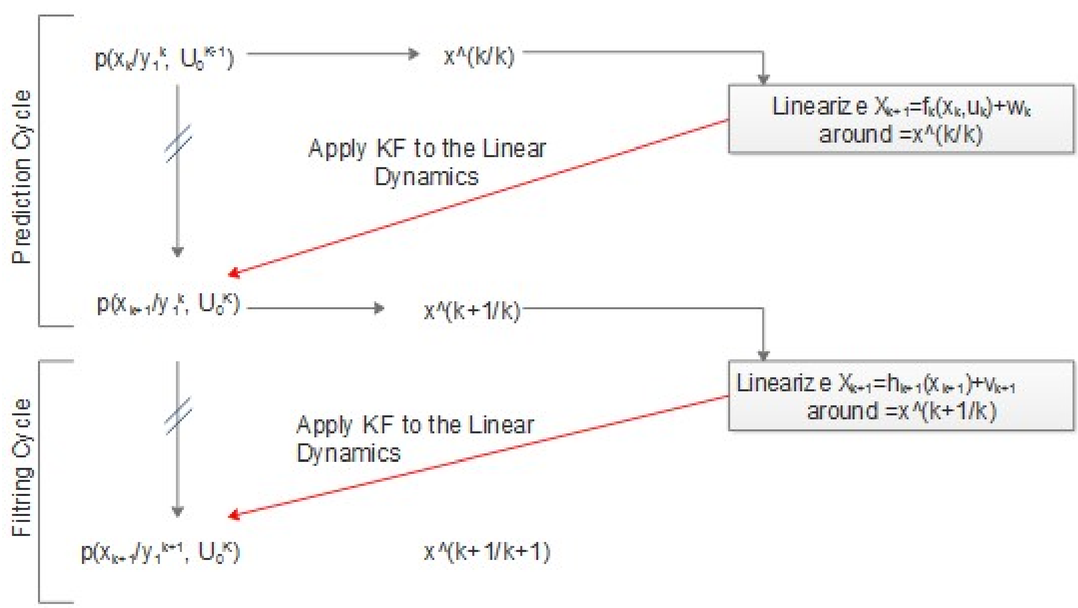


Figure 3: Dynamic concept of EKF

The figure 3 shows the one iteration of the successive prediction and filtering updates within the successive PDF transitions are shown below

$$p(x_k \mid Y_1^k, U_0^{K-1}) \rightarrow p(x_{k+1} \mid Y_1^k, U_0^1) \rightarrow p(x_{k+1} \mid Y_1^{k+1}, U_0^{\ k})$$

One orientation of the EKF is composed of the following successive steps,

- Consider final filter state estimation $\hat{x}((k \mid k))$
- Linearizes the system dynamic, $x_{k+1} = f_k(x_k) + w_{k\,around} \quad \hat{x}((k \mid k))$
- Apply the prediction step of the Kalman filter to the linearizes system dynamics just obtained,

  $\hat{x}\ (K+1 \mid k)\, and\ p(k+1 \mid k)$
- Linearizes the observation dynamics,

  $y_k = h_k(x_k) + v_{k\,around}\ \bar{x}(k+1 \mid k)$
- Apply the prediction step of the Kalman filter to the linearizes system dynamics just obtained,
- $\bar{x}(k+1 \mid k)\, and\ p(k+1 \mid k)$

Let $F(k)$ and $H(k)$ be the Jacobian matrices of the $f(.)$ and $h(.)$ represented by

$$F(k) = \nabla f_k \left| \bar{x}(k \mid k) \right|$$

$$H(k+1) = \nabla h \left| \bar{x}(k+1 \mid k) \right|$$

2.2.1 Predict cycle

Prediction Cycle Plug-in is a simple and free plug-in used for barker code, which separates the underlying cycle component from the rate and helps

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

to understand the current cycle. This gives a better perspective about the cycles happening in the larger time-frames and thereby better decision making. Equation (12) gives the taken predicted state estimate and also associated co-variance obtained by using the EKF algorithm,

$$\bar{x}(k+1|k) = f_k(\bar{x}(k|k))$$

$$P(k+1|k) = F(k)P(k|k)F^T(k) + Q(k) \quad (12)$$

2.2.2 Filtered cycle

$$\bar{x}(k+1|k+1) = \bar{x}(k+1|k) + K(k+1)[y_{k=1} - h_{k+1}(\bar{x}(k+1|k))]$$

$$k(k+1) = p(k+1|k)H^T(k+1)[H(k+1) P(k+1|k)H^T(k+1) + R(k+1)]^{-1}$$

$$P(k+1|k+1) = [I - K(k+1)H(k+1)] P(k+1|k)$$

It this important to state that the EKF is not an optimal filter, but rather it is implemented based on a set of approximations. Thus, the matrices $P(k|k)$ and $P(k+1|k)$ do not represent the true covariance of the state estimates.

Moreover, as the matrices F(k) and H(k) depend on previous state estimates and therefore on measurements, the filter gain $K(k)$ and the matrix $P(k|k)$ and $P(k+1|1)$ cannot be computed off-line as occurs in the Kalman filter. Contrary to the Kalman filter, the EKF may diverge, if the consecutive linearization is not a good approximation of the linear model in the entire associated uncertainty domain [17].

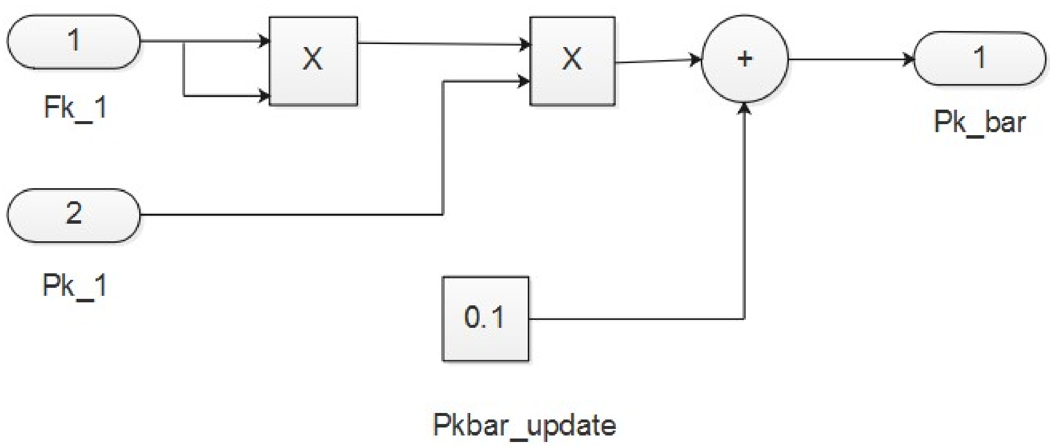


Figure 4: Block diagram of the Pkbar_update

Journal of Theoretical and Applied Information Technology
15th December 2017. Vol.95. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

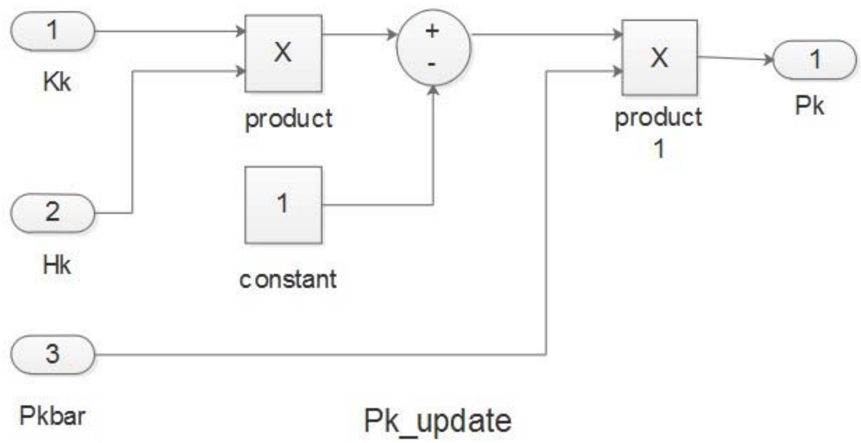


Figure 5: Block diagram of the Pk_update

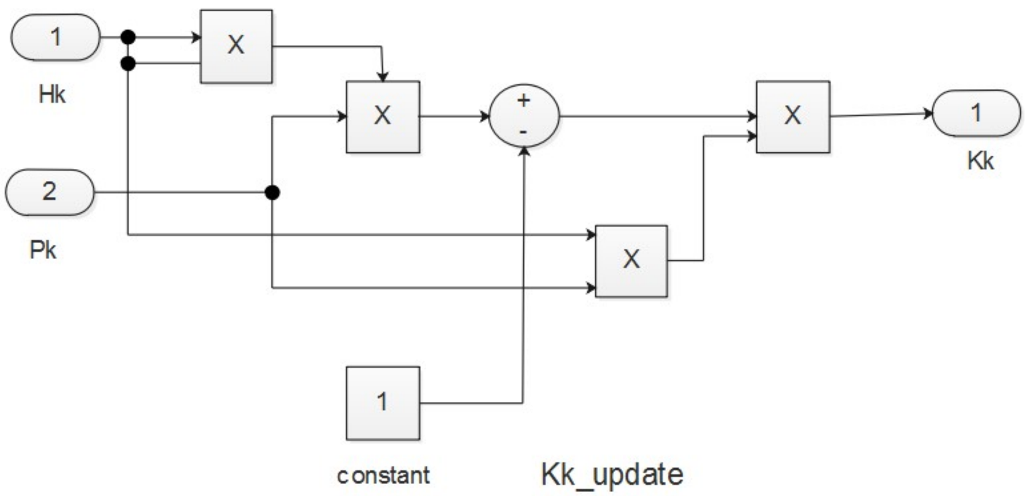


Figure 6: Block diagram of the Kk_update

Figure 4 Pkbar_update, figure 5 Pk_update and figure 6 Kk_update block diagrams are sub modules of figure 2, which are used for improving the EKF performance in terms of accuracy.

3. IMPLEMENTATION OF EKF METHOD

The EKF method was implemented in MATLAB version R2017a to obtain the noise free signal by using EKF. Xilinx ISE tool is used to find the number of Flip-flops, slices and LUTs. For the area, power and delay analyses cadence encounter tool with 180nm and 45nm library technologies are used and for RTL schematic generation Simplify pro software is used. The complete work was done by using the I_7 system with 8 GB RAM. A number of iterations were performed to de-noise radar signal and to obtain the minimized values of RMSE and better values of SNR.

4. RESULTS AND DISCUSSION

The Table 1 is the performance comparison of the parameters such as number of slice, LUTs and flip flops for different algorithms such as FIR, LMS, KF, and EKF. From this result table, we can easily understand that the number of slice, LUTs, flip flop has been reduced using proposed EKF method. Due to the reduction of those parameters, the area can be optimized in EKF filter. The EKF performance is shown in figure 7, which is obtained from Xilinx ISE software.

Journal of Theoretical and Applied Information Technology
15th December 2017. Vol.95. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

The Figure 7 shows the hardware performance of difference algorithm such as LMS, FIR, KF and EKF. This figure described the total number of used LUTs, slice and flip flop values of the LMS, FIR, KF and EKF method. Furthermore, the proposed EKF method reduces number of LUTs, slice and flip flop as compared with LMS, FIR and KF algorithms.

Table 1: The performance of a number of slices, LUTs, flips flops for different algorithms

Filter order	Algorithm	No. of slices	No. of LUTs	No. of flip flop
16 tap	[11] a	732/28800	2714/28800	449/2997
16 tap	[11] b	888/28800	1376/28800	681/1583
16 tap	[12]	855/207360	746/207360	475/1126
---	[18]	4924/5120	6296/10240	1898/10240
16 tap	FIR	225/5,472	230/10,944	204/10,944
8 tap	LMS	208/5,472	272/10,944	288/10,944
8 tap	KF	152/5,472	195/10,944	135/10,944
8 tap	EKF	95/5, 472	153/10,944	59/10,944

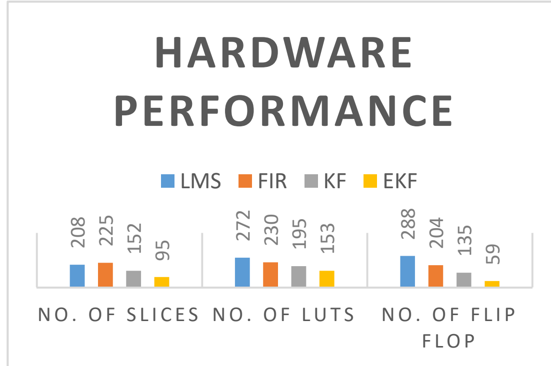


Figure 7: Performance of slices, LUTs and flip flop for different algorithms

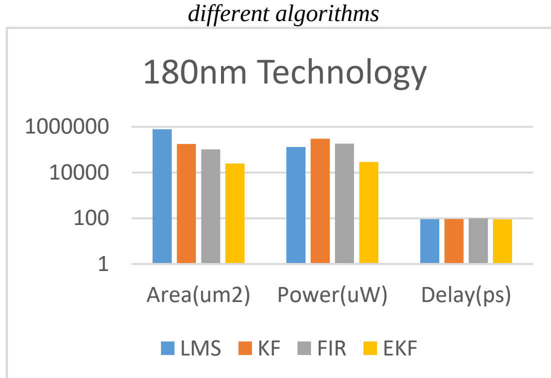


Figure 8: Area, power and delay performance of different algorithms using 180nm technology

The Table.2 Shows the proposed EKF algorithm by considering the parameters such as area, power, delay, APP and ADP for the ASIC implementation using cadence encounter tool with 180nm and 45nm technology. From this result table, we can clearly observe that all the parameter values are minimized in the proposed EKF algorithm as compared with LMS, FIR and KF algorithms.

Table 2: The performance of area, power and delay for different algorithms by using ASIC - cadence encounter tool with 180nm and 45nm technology

Technology	Filter Order	Algorithm	Area (µm2)	Power (µW)	Delay (ps)	Area and Power Product (APP)	Area and Delay Product (ADP)
180nm	16 - tap	[13]	863061	58310	---	50325086910	---
	32 - tap	[13]	1722799	115165.6	---	198407180514.4	---
45nm	16 - tap	[11].a	5924	107076.059	6077	634318573.516	650701210.54
		[11].b	5515	85092.633	3593	469285870.995	305737830.36
	32 - tap	[11].a	38949	532424.22	8624	20737390944.78	4591626473.2
		[11].b	10526	160081.16	4096	1685014290.16	655692431.36
180nm	8 - tap	LMS	777578	130095.822	91.6	1011595403737.116	71226144.8
	8 - tap	KF	177507	303096.005	92.7	53801662559.535	16454898.9
	16 - tap	FIR	103075	183794.540	100	18944622210.5	10707500

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

	8 - tap	Proposed EKF	24959	28709.638	90.5	716563854.842	2258789.5
45nm	8 - tap	LMS	81913.03	104463.764	256.6	8556943457.380	21018883.498
	8 - tap	KF	17804.77	26723.439	270.8	475804696.221	4821531.716
	16 - tap	FIR	9899.88	19614.238	100	194178602.491	989988
	8 - tap	Proposed EKF	2336.64	3217.718	270.8	7518649.311	632762.112

The Figure 8 and Figure 9 are shows the area, power and delay performance bar-graph comparison between FIR, LMS, KF and EKF algorithms for both 180nm and 45nm technology.

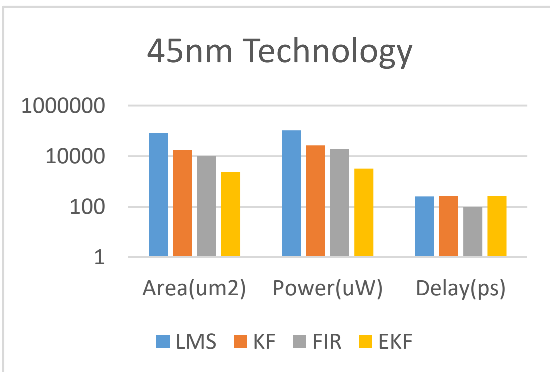


Figure 9: Area, Power and delay performance of different algorithms using 45nm technology

The Table.3 shows the RMSE values can be reduced and SNR value is increased for the EKF compared with LMS, FIR and KF algorithms. As discussed earlier, the entire system is modeled and simulated by using MATLAB Simulink environment. Similarly, for ASIC implementation cadence encounter with 180 and 45nm libraries are used. The Simulink provides customizable block libraries, a graphical editor, and solvers for simulating and modeling dynamic systems. It is integrated with MATLAB, enabling to incorporate MATLAB algorithms into models then export simulation results to MATLAB for more analysis. The EKF algorithm target detection tracking model consists of radar transmitter (sine wave, repeating square star, rate transition 1 and 2, and product) selector, switch, target, receiver part (buffer, mean, product1, and EKF filter). In this paper, the modulator will send the signal through the selector after this radar signal over the target as shown in the Figure 10.

Table 3: SNR and RMSE performance of different algorithms

Algorithm	RMSE	SNR
EKF	0.70539792703	36.874321695761
KF	0.705659980538	29.0945684649902
LMS	0.705932617187	27.756614670204
FIR	0.705519652201	32.352605854000

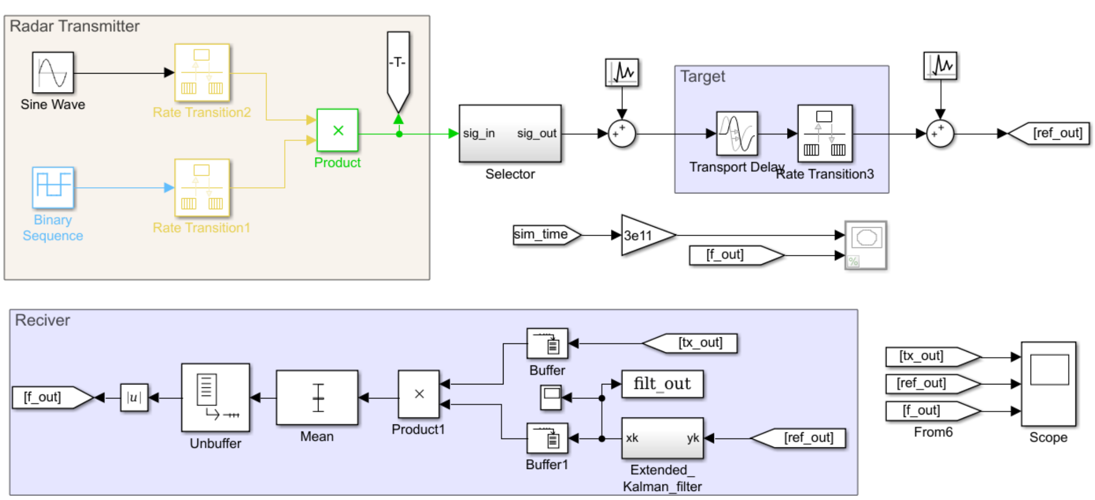
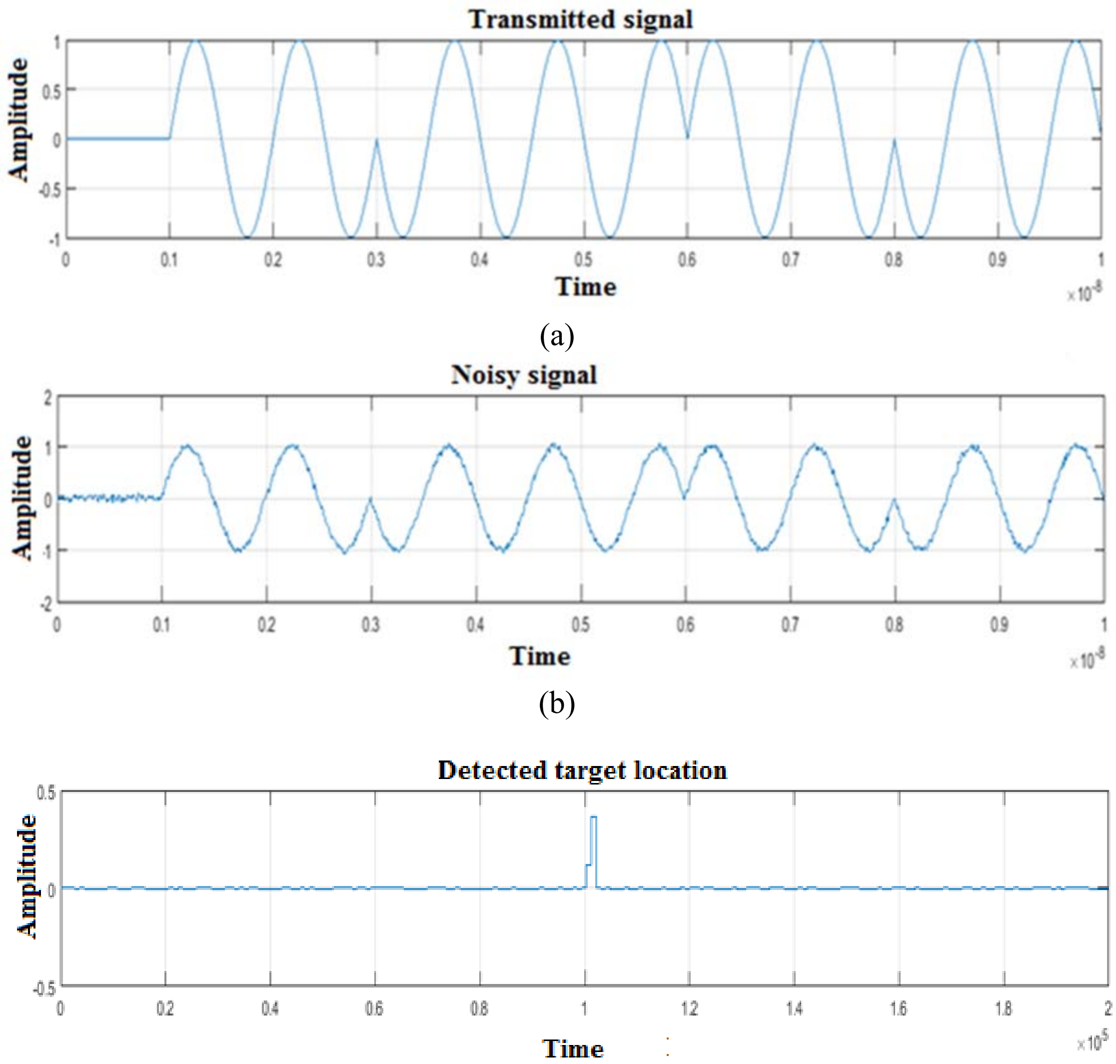


Figure 10: Proposed target detection tracking model using MATLAB Simulink

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

It is transmitted towards the target to detect objects which are in space. The radar pulse with high velocity has hit to target and it is reflected back. Depending on the reflected or received signals velocity, target velocity from the base station can be measured. Noise can be suppressed by using a special kind of filter called Extended Kalman Filter. Finally, the detected object parameters are processed analyzed of the target and motion will be determined.



(c)

Figure 11: (a) Transmit signal (b) Reflected signal (c) Detected target location

Journal of Theoretical and Applied Information Technology
15th December 2017. Vol.95. No 23

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

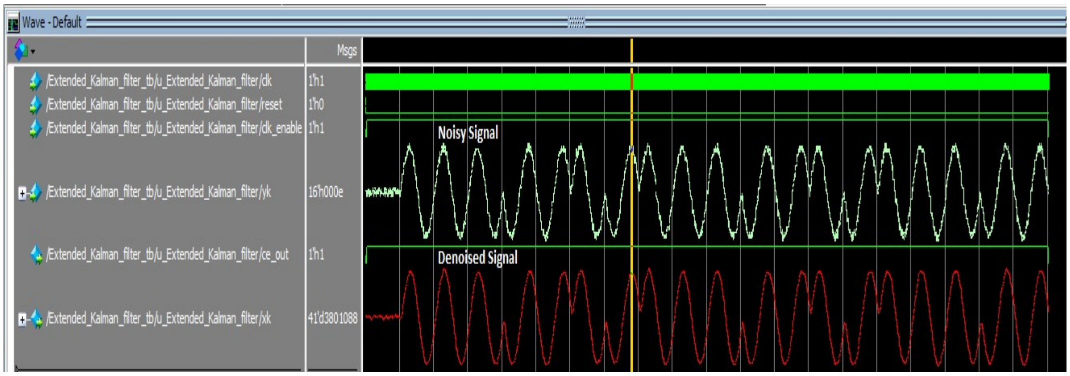


Figure 12: Proposed EKF method simulation result using Modelsim

The Figure 11.a show the modulated sine wave sequence which is used to transmit towards the target with respect to time. Figure.11b shows the noisy signal which is affected by additive white Gaussian noise. Figure 11.c shows the detected target location in terms of distance from transmitter. Figure. 12 shows the simulation output waveform which is obtained after simulation of proposed EKF Verilog code in Modelsim tool. In figure 12, the first sinusoidal signal is the noisy signal and the second signal is de-noised signal. The RTL schematic of EKF filter is shown in Figure 13. This schematic obtained from Simplify pro by using Verilog HDL code which is written for EKF. We have developed a separate module for each block such as update Fk_Hk, Pkbar_update, Pk_update and Kk_update.

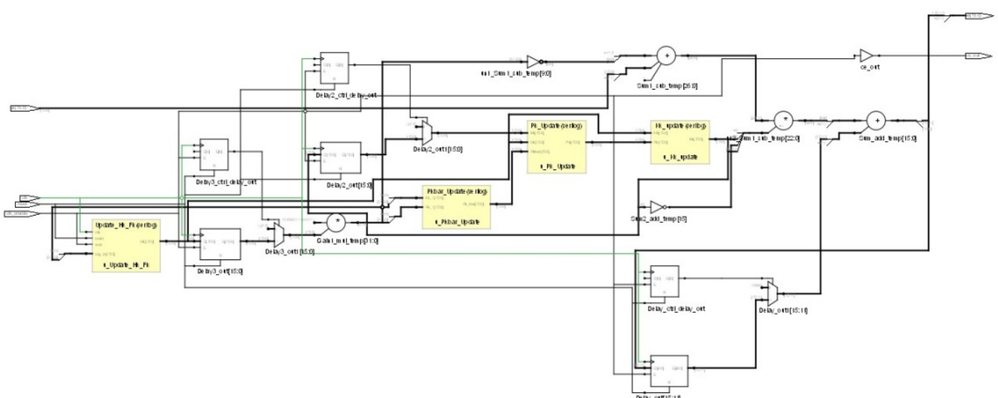


Figure 13: RTL schematic of EKF

5. CONCLUSION

In this paper a new efficient radar target detection using radar signal de-noising with an EKF to suppress the white Gaussian noise which is added in free space is presented. In order to validate and compare the performance of the proposed EKF-RTD design with existing designs, RMSE and SNR values are evaluated by using MATLAB Simulink, number of slices, LUTs and flip-flops are evaluated using Xilinx ISE FPGA tool and area, power, delay and other parameters are evaluated using Cadence ASIC with 180nm and 45nm library technology. From the simulation results, it is concluded that the proposed model yielded better results in terms of SNR, RMSE, less hardware and computational complexity as compared to existing models. This work will be extended by using optimization techniques, which is used to further improving the performances of SNR, area, power, delay and minimize RMSE value.

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