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Radar Image Enhancement Model Using Adaptive Kalman Filter

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Abstract- Echo and noise is one of the critical disturbances that alter the quality of radar images. To reduce the echo and noise in radar images we used adaptive Kalman filter. For radar image enhancement, denoising and echo cancellation are need of the system. In this paper an adaptive Kalman filter based model is proposed to reduce the echo and noise in radar images. The Kalman filter is compared with different parameters. Form experimental results the new proposed adaptive Kalman filter based model gives promising results for echo cancellation and denoising of radar images.

Keywords- Adaptive Kalman filter, echo cancellation, denoising, deblurring, radar images.

I. INTRODUCTION

RADAR stands for Radio Detection and Ranging System. It is basically an electromagnetic system used to detect the location and distance of an object from the point where the RADAR is placed. It works by radiating energy into space and monitoring the echo or reflected signal from the objects. It operates in the UHF and microwave range. Radar images are generally a map view of reflected particles for a specified area surrounding the radar. Depending on the intensity of the precipitation, different colours will appear on the map. Each colour on the radar display will correspond to a different level of energy pulse reflected from precipitation. The strength of the pulse returned to the radar depends on the size of the particles, how many particles there are, what state they are in and what shape they are. After making many assumptions about these factors and others, the approximate radar image can be estimated [6].

We have reviewed some papers of radar image processing and found many advantages and drawbacks in it. My purpose to present this paper on radar images is for noise and echo cancellation, so that it can be used in research areas and defense sector. For removing noise and echo of radar images, Adaptive Kalman filter is used. Many proposed adaptive filters [6], helps to remove noise from radar images. But the echo cancellation and denoising done from adaptive Kalman filter is excellent compared to other adaptive filters. The adaptive Kalman filter is an intelligent filter. 3 cases are assumed in this paper. 1st for blurred radar images, 2nd for Gaussian noise radar images and 3rd is radar images with Echo noise.

In this paper an adaptive Kalman filter is proposed for echo cancellation and denoising of radar images. The rest of the paper is organized as follows: In section II, theory of adaptive Kalman filter and some terms III, proposed algorithm is discussed. In section IV, the experimental results are discussed where the effectiveness of our Adaptive Kalman filter is checked and finally in section V, conclusion of the work is made.

II. THEORY

Adaptive Filter

Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing statistical noise and other inaccuracies, and produces estimates of unknown variables that tend to be more accurate than those based on a single measurement alone, by estimating a joint probability distribution over the variables for each timeframe [2],[3]. The Kalman filter keeps track of the estimated state of the system and the variance or uncertainty of the estimate. The estimate is updated using a state transition model.

The algorithm works in a two-step process. In the prediction step, the Kalman filter produces estimates of the current state variables, along with their uncertainties. Once the outcome of the next measurement (necessarily corrupted with some amount of error, including random noise) is observed, these estimates are updated using a weighted average, with more weight being given to estimates with higher certainty. The algorithm is recursive. It can run in real time, using only the present input measurements and the previously calculated state and its uncertainty matrix; no additional past information is required [4],[5].

Predict

Predicted (*apriori*) state estimate

$$\hat{\mathbf{x}}_{k|k-1} = \mathbf{F}_k \hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_k \mathbf{u}_k \quad \ldots\ldots(1)$$

$$\mathbf{P}_{k|k-1} = \mathbf{F}_k \mathbf{P}_{k-1|k-1} + \mathbf{Q}_k \quad \ldots\ldots(2)$$

Updated (*a posteriori*) state estimate

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \tilde{\mathbf{y}}_k \quad \ldots\ldots(3)$$

Updated (*a posteriori*) estimate covariance

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{Kk\ Hk})\, \mathbf{P}_{k|k-1} (\mathbf{I} - \mathbf{K}_k\, \mathbf{H}_k)\mathbf{T} + \mathbf{K}_k \mathbf{R}_k \mathbf{K}_K^T$$

Measurement post-fit residual

$$\tilde{\mathbf{Y}}_{k|k} = \mathbf{Z}_k - \mathbf{H}_k\, \hat{\mathbf{x}}_{k|k}$$

The formula for the updated (a posteriori) estimates covariance above is valid for any gain K_k and is sometimes called the Joseph form. For the optimal Kalman gain the formula further simplifies to

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k)\, \mathbf{P}_{k|k-1} \quad \ldots\ldots(4)$$ [4],[5]

Deblurring

Deblurring is the process of removing blurring artifacts from images, such as blur caused by defocus aberration or motion blur. The blur is typically modelled as the convolution of a (sometimes space- or time-varying) point spread function with a hypothetical sharp input image, where both the sharp input image (which is to be recovered) and the point spread function are unknown [7].

Denoising

Noise reduction is the process of removing noise from a signal. All signal processing devices, both analog and digital, have traits that make them susceptible to noise. Noise can be random or white noise with an even frequency distribution, or frequency dependent noise introduced by a device's mechanism or signal processing algorithms [8].

Echo cancellation

Echo is a reflection of sound or data that arrive at the user with delay. The delay is proportional to the distance of the reflecting surface from and user. Radar images with echo construct by arriving reflection of same images with delay. Echo cancellation is the process of cancelling echo noise. In reference paper for cancelling multipath interference delay and doppler are derived [1].

III. PROPOSED ADAPTIVE KALMAN BASED MODEL

The Kalman filter is a recursive estimator. This means that only the estimated state from the previous time step and the current measurement are needed to compute the estimate for the current state. In contrast to batch estimation techniques, no history of observations and/or estimates is required. These below models are based on Simon Haykin 4th edition book.

Noise Cancellation Model

In this noise cancellation model x(k) is input radar image value which is noisy radar image. d(k) is reference signal. For different values of x(k) and reference signal recursive Adaptive Kalman filter gives different estimated values. e(k) is the estimated value of radar image. y(k) is filtered output.

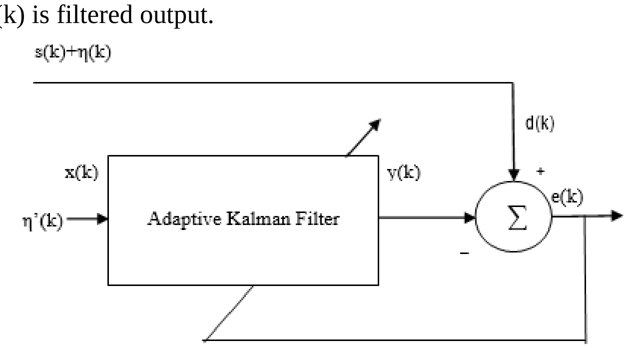

Figure 1. Adaptive Kalman Filter based noise cancellation model

Echo Cancellation Model

In this Echo cancellation model $x(K)$ is input radar image value which is noisy radar image. $d(k)$ is reference signal.

For different values of $x(k)$ and reference signal recursive Adaptive Kalman filter gives different estimated values. $E(k)$ is the estimated value of radar image. $y(k)$ is filtered output.

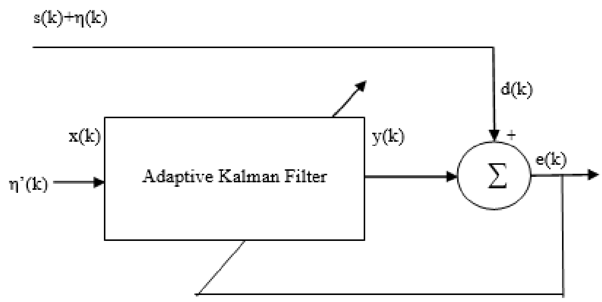

Figure 2. Adaptive Kalman Filter based Echo cancellation model

Adaptive Kalman filter is to cancel unknown Echo and noise contained in a primary signal, with the cancellation is optimized in some sense. The primary signal servers as the desired response for Adaptive Kalman filter. A reference signal is employed as the input to the Adaptive Kalman filter. The reference signal is derived from the sensor or set of sensors located in relation to the sensor supplying the primary signal in such a way that the information being signal component is weak or essentially undetectable. Figure 1. and Figure 2. shows diagram for noise and Echo cancellation by Adaptive Kalman filter.

MMSE (Minimum Mean Square Error)

Filters are designed to minimize the mean squared error between a desired image and the available noisy or distorted image. Suppose we are given a noisy or distorted image x and we want to estimate the image y by applying a linear filter to x.

The estimate ˆys at lattice location s can then be written as ˆys = zsθ where zs = [xs, xs+r1 , . . . , xs+rp−1] is a row vector of pixels from a window surrounding xs, and θ is a column vector of filter coefficients. In MMSE filtering, the goal is to find the vector θ that will minimize the expected mean square prediction error MSE = E[|ys − ˆys|2]

IV. EXPERIMENTAL RESULTS

In this section, the proposed algorithm is evaluated by couple of case studies. Three images are considered in case studies: each of size 504×632 of noise and echo radar image which is a real time image. The experiments are performed using MATLAB version R2016a.

Case Study 1

Input Radar image is blurred- In this case input radar image is blurred image. Figure 4(a). shows original radar image, Figure 4(b). shows artificially corrupted radar image which is input image. Figure 4(c). shows estimated output image. While varying no of iterations, different MMSE we get. The plot between no of iterations and MMSE shown in Figure 4(d). While varying Learning rate, different MMSE we get. The plot between Learning rate and MMSE shown in Figure 4(e).

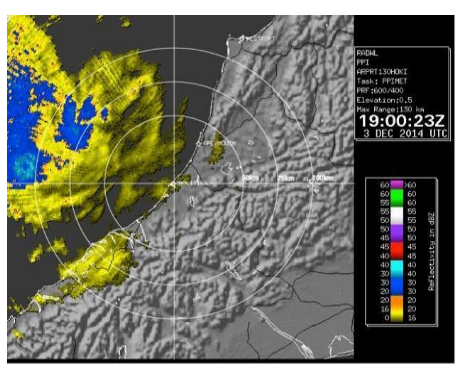

Figure 4(a). Original Radar image

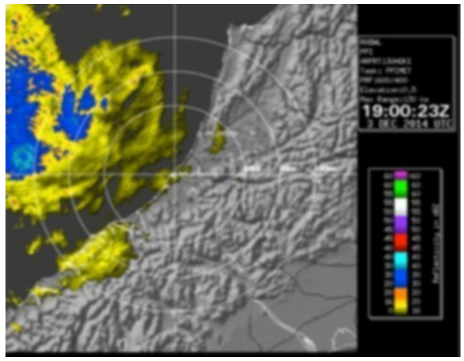

Figure 4(b). Input Noisy Radar Image

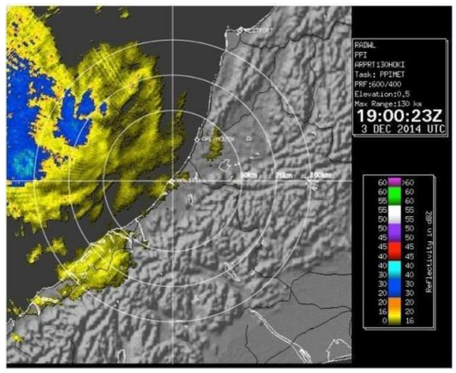

Figure 4(c). Denoised Image

Minimum MSE calculated=0.0001. Plot iteration Vs error.
In this plot 10 number of iterations have taken i.e. from 1 till 10. And we got different values of MSE which is 0.0009 to 0.0001 and the Minimum MSE we got is 0.0001.

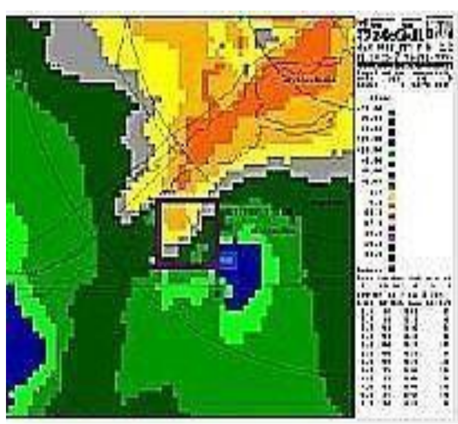

Figure 4(d). Iteration Vs MMSE

Plot Learning Rate Vs MMSE
Learning rate is very important parameter of Adaptive Kalman filter. While varying learning rate MMSE variates accordingly. When the learning rate is minimum, we get minimum Mean Square Error. The plot shown below.

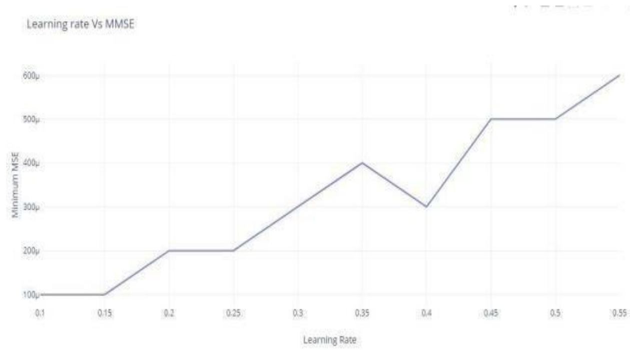

Figure 4(e). Learning rate Vs MMSE

Case Study 2

When Input is Echo radar image

In this case input radar image is image with Echo. Figure 5(a). shows original radar image, Figure 5(b). shows artificially corrupted radar image which is input image. Figure 5(c). shows estimated output image. While varying no of iterations, different MMSE we get. The plot between no of iterations and MMSE shown in Figure 5(d). While varying Learning rate, different MMSE we get. The plot between Learning rate and MMSE shown in Figure 5(e).

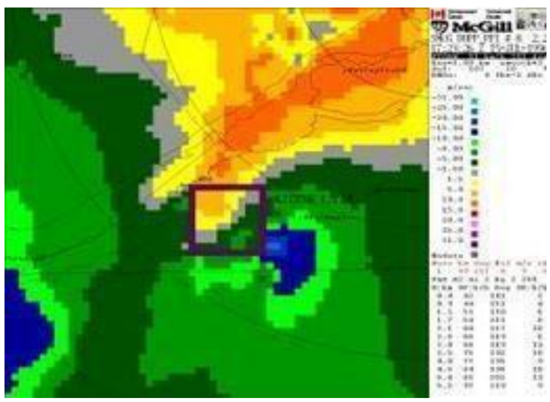

Figure 5(a). Original Image

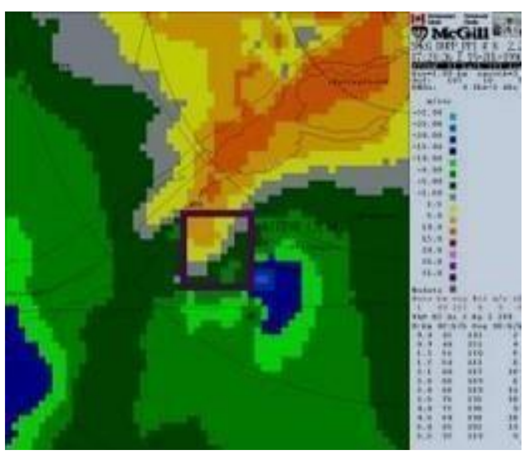

Figure 5(b). Input Noisy Image

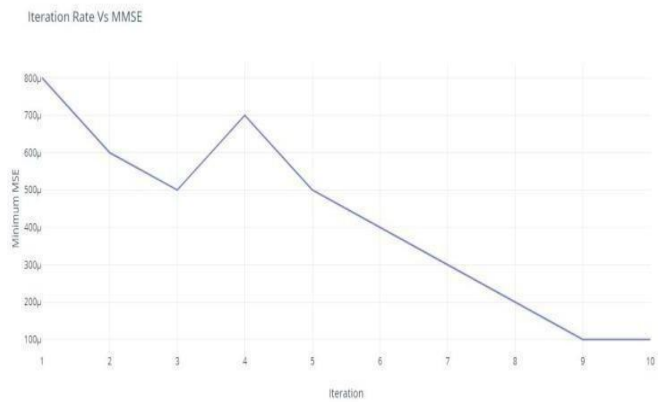

Figure 5(c). Denoised Image

Minimum MSE in this case is-0.0001.

Plot Iteration Vs MMSE.

In this plot 10 number of iterations has taken i.e. from 1 till 10. And we got different values of MSE which is 0.0009 to 0.0001 and the Minimum MSE we got is 0.0001.

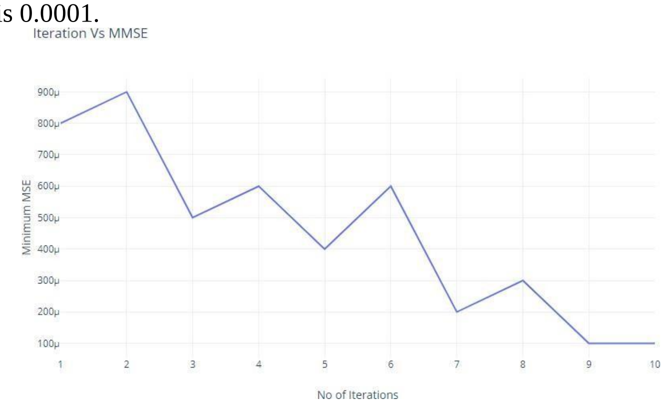

Figure 5(d). Iteration Vs MMSE

Plot Learning Rate Vs MMSE.

Learning rate is very important parameter of Adaptive Kalman filter. While varying learning rate MMSE variates accordingly. When the learning rate is minimum, we get minimum Mean Square Error. The plot shown below. no of iterations, different MMSE we get. The plot between no of iterations and MMSE shown in Figure 6(d). While varying Learning rate, different MMSE we get. The plot between Learning rate and MMSE shown in Figure 6(e).

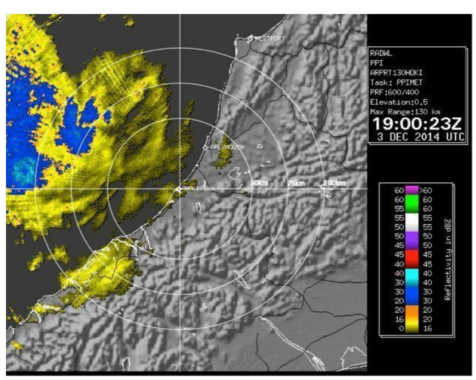

Figure 6(a). Original Image

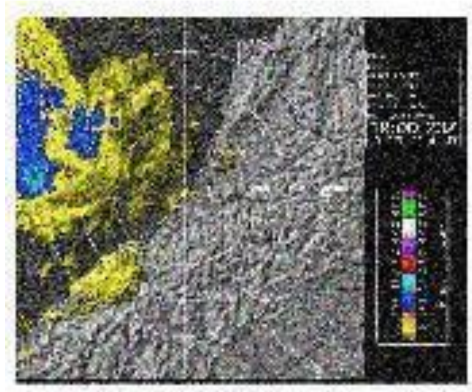

Figure 6(b). Input echo image

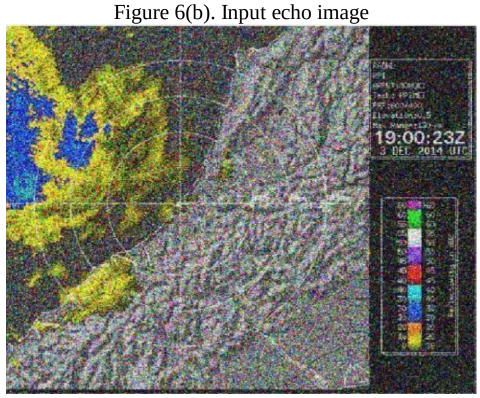

Figure 6(c). Input echo image

Case Study 3

Figure 5(e)

Minimum MSE calculated in this case is-0.0001. (5). Plot Iteration Vs MMSE in this plot 10 number of iterations has taken i.e. from 1 to 10. And got different values of MSE which is 0.0009 to 0.0001 and the Minimum MSE got is 0.0001.

When Input is Noisy Radar Image (Gaussian Noise)

In this case input radar image is Gaussian noisy image. Figure 6(a). shows original radar image, Figure 6(b). shows artificially corrupted radar image which is input image. Figure 6(c). shows estimated output image. While varying

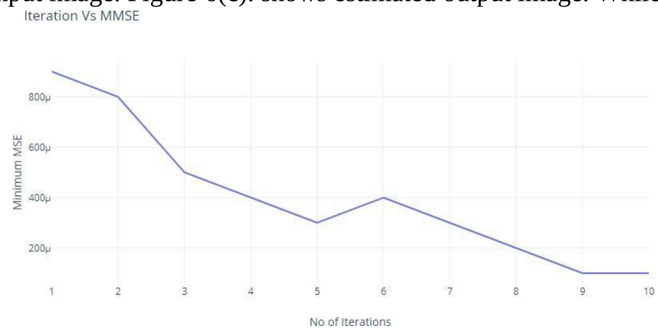

Figure 6(d). Iteration Vs MMSE

Plot Learning rate Vs Minimum MSE

Learning rate is very important parameter of Adaptive Kalman filter. While varying learning rate MMSE variates accordingly. When the learning rate is minimum, we get minimum Mean Square Error. The plot shown below.

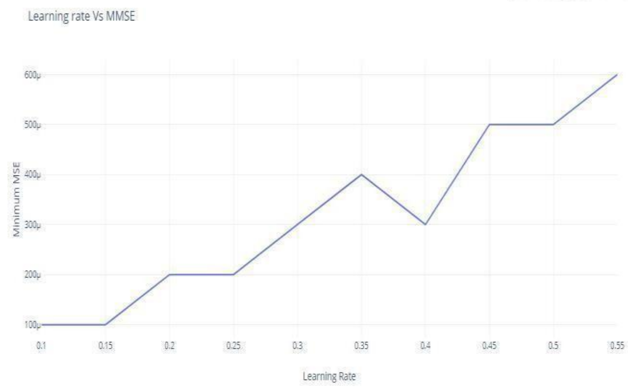

Figure 6(e). Learning rate Vs MMSE

4.4. Comparison of proposed algorithm with existing algorithm

In this section, the proposed Adaptive Kalman filter based Echo cancellation algorithm is compared with the existing RLS and NLMS algorithm [1]. Table 1 and Table 2 compares the Delay (sec) of both the cases. In Table 1 Comparison between RLS Algorithm [1] & proposed Echo cancellation model has done and in Table 2 Comparison between NLMS Algorithm [1] & proposed model has done.

Table.1 Delay (sec) of Adaptive Kalman Filter based Echo cancellation model comparison with RLS algorithm [1]

Algorithm	**Delay Time (Sec)**
RLS Algorithm [1]	6.5
ed model for Echo cancellation	1.943

Table.2 Delay of Adaptive Kalman filter based echo cancellation model comparison with NLMS algorithm [1]

Algorithm	**Delay Time (Sec)**
NLMS Algorithm [1]	3.5
Proposed model for Echo cancellation	1.941

Table 1 & Table 2 concludes that the result obtained from the proposed algorithm is better as compared to the existing algorithm.

V. CONCLUSIONS

The Proposed Adaptive Kalman filter based Echo and noise cancellation model has been successfully implemented. The presented work is found efficient in removing echo and noise of radar images. Experiments conducted for evaluating the performance of the proposed Adaptive filter shows that it is quite better than the existing Adaptive filter and is promising in removing echo and noise from a radar image. Thus, other Adaptive filters [1] are able to reduce echo and noise in radar image but in the proposed Adaptive Kalman filter is quite efficient Adaptive filter and can be used anywhere practically in for the echo cancellation and denoising of radar images.

REFERENCES

[1]. Mohamed Amine ATTALAH, Toufik LAROUSSI, Aladdine AOUANE, Ali MEHANAOUI"Adaptive Filters for Direct Path and Multipath Interference Cancellation: Application to FM- RTL-SDR Based Passive Bistatic Radar" 7th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (SETIT) 2016, pp 461- 465.

[2]. Paul Zarchan; Howard Musoff (2000). Fundamentals of Kalman Filtering: A Practical Approach. American Institute of Aeronautics and Astronautics, Incorporated. ISBN 978-1-56347- 455-2.

[3]. Kalman, R. E. (1960). "A New Approach to Linear Filtering and Prediction Problems". Journal of Basic Engineering. 82: 35. Doi:10.1115/1.3662552.

[4]. Kelly, Alonzo (1994). "A 3D state space formulation of a navigation Kalman filter for autonomous vehicles" (PDF). DTIC Document: 13. 2006 Corrected Version

[5]. Reid, Ian; Term, Hilary. "Estimation II" (PDF). www.robots.ox.ac.uk. Oxford University. Retrieved 6 August 2014.

[6]. Fakhrul Razi Ahmad, Zakuan; et al. (2018). "Performance Assessment of an Integrated Radar Architecture for Multi-Types Frontal Object Detection for Autonomous Vehicle". 2018 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS). Retrieved 9 January 2019.

[7]. Ahi, Kiarash (26 May 2016). "Modeling of terahertz images based on x-ray images: a novel approach for verification of terahertz images and identification of objects with fine details beyond terahertz resolution". Proc. SPIE 9856, Terahertz Physics, Devices, and Systems X: Advanced Applications in Industry and Defense, 985610. doi:10.1117/12.2228685. Retrieved 26 May2016.

[8]. Chen, Yangkang; Fomel sergey (November-December 2015). "Random noise attenuation using local signal-and-noise orthogonalization". Geophysics. 80 (6): WD1- WD9_doi:10.1190/GEO2014-0227.1.

[9]. Federico Garc´ıa-Rial, Luis Ubeda-Medina, Jesus´ Graja "Real- time GPU-based image processing for 3-D THz radar" DOI 10.1109/TPDS.2017.2687927, IEEE Transactions on Parallel and Distributed Systems 2017, vol. 28, issue 10, pp 1-13, oct 2017.

[10]. Xianru Liu and Zixing **"**Advanced Obstacles Detection andTracking by Fusing Millimeter Wave Radar and Image Sensor Data" International Conference on Control, Automation and Systems 2010 Oct. 27-30, 2010. [4] B. B. Mohapatra, Vishal Mahajan, Abid Hussain VALRDE, DRDO Bangalore, India, "Post Processing Techniques for Inverse. Synthetic Aperture Radar Imaging" IEEE 2016, Volume: 3. pp 1115-1120.

[11]. B.B Mohapatra, vishal Mahajan, Abid Hussain VA "Post Processing Techniques for Inverse Synthetic Aperture Radar Imaging" 2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC).

[12]. Qian Bao 1, Yun Lin 1, Wen Hong 1, Bingchen Zhang1 "Multi-circular synthetic aperture radar imaging processing procedure based on compressive sensing" 4th Int. Workshop on Compressed Sensing on Radar, Sonar, and Remote Sensing 2016, pp 47-50.

[13].Thomas Wagner "Radar Signal Processing for Jointly Estimating Tracks and Micro-Doppler Signatures" Graduate Student Member, IEEE, Reinhard Feger, Member, IEEE and Andreas Stelzer, Member, IEEE 2017, Volume: 5, pp-1220- 1238.

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