Online De-Noising of Radar Data using Multi Resolution Analysis

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Abstract: Target Tracking is an active research area, which encompasses various applications in Defence as well as Commercial applications. For estimating state vectors of tracked objects, Kalman filtering techniques are widely used, and the performance of Kalman filter depends on priory assumptions like state transition models and measurement uncertainties. In practical real time applications, all these priory assumptions are not available always and existing models are not suitable for target dynamics, which have an impact on the tracking quality, and some times filter, may diverge also. Recently Wavelet based multi resolution analysis has become a powerful tool, for image compression and de-noising applications and does not require explicit priory knowledge like Kalman filter for noise suppression. However, It is found that during real time de-noising, wavelet analysis exhibits poor performance due to certain artifacts. In order to improve the performance, a method is proposed and implemented that utilizes variable moving window and symmetric extension techniques.

Keywords:- *De-noising , Multi resolution Analysis, Wavelets, Real-time de-noising*

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I. INTRODUCTION

The aim of target tracking is to estimate the state of a moving target based on the measurement data. Estimation of accurate state vectors under noisy environment is an essential requirement for Target tracking applications. Separation of random gaussian noise from the corrupted signals is a classical problem. Various techniques were developed to enhance the robustness and accuracy of the solution. Among the all, Kalman filter is a method gained more importance in target tracking applications. Kalman filter propagates the error covariance matrix recursively to estimate the state vectors for a linear dynamic system [1]. However, Kalman filtering technique assumed priory knowledge about system dynamic models, process noise variances and measurement noise variances. The performance of a Kalman filter is optimal, if all these values are appropriate and assumed dynamic models meeting the target dynamics. In practical real time applications, lack of these priory assumptions lead to degrade the tracking quality.

Recently wavelet based multi resolution analysis has become a powerful tool, for many applications. Performing data processing using a combination of different levels of data granularity is called multiple resolution filtering [7]. These techniques are successfully applied in image compression and image processing applications. As multi resolution techniques do not require any explicit models and noise characteristics of the sensors, to remove the random noise from the noisy plot data received from the Radar. It was found that during offline denoising, wavelet based multi resolution analysis exhibits optimal performance. However it's performance is degraded in real time. It is well known that certain artifacts like border distortion and Gib's phenomena cause erroneous denoising. However to over come the problems to track the target in real time, a method consists variable window with symmetric extension using Translation Invariant denoising technique is proposed and experimented to control border distortion and Gib's phenomena artifacts. In this study, symlet8 is used as a bases function to denoise the random disturbances in the observed Radar plot data. The remainder of the paper is arranged as follows. In Section 2 a brief introduction of Kalman filter is given. In section 3, Wavelets and multi resolution analysis is introduced. In Section 4, a method based on variable moving window denoising is proposed. Section 5 discusses simulation results, In Section 6. Future work is proposed and section 7 draws conclusions.

II. KALMAN FILTER

Kalman filter is an optimal recursive data processing algorithm and it is used for filtering random noise. The following diagram (Fig 1) represents a typical Kalman filter application [2].

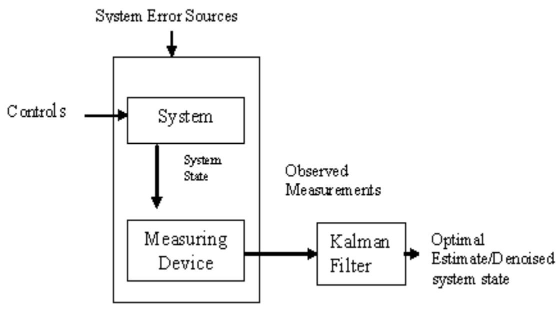

Fig 1 Kalman filter Block Diagram

Filter Dynamics and measurement models are considered as

$x_{k+1} = Ax_k + u_k$ and $z_k = Hx_k + v_k$ (1)

Where x_k and x_{k+1} are state vectors at time k and k+1 respectively. A is system dynamics matrix. u_k is system noise and v_k is zero mean gaussian white noise matrix. H is measurement matrix.

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120 - 123

Kalman filter needs system models shown in (1) and system and measurement uncertainties (Q and R matrix) which are variances of u_k and v_k . Using equations connected to time update and measurement update, Kalman filter estimates the optimal state vectors recursively. In order to de-noise the measurements Kalman filter utilizes Q, R and A matrix. Kalman filter provides good results , if Q, R and A values are known in advance. Some real time applications, all these priory assumptions are not available always, which have an impact on the tracking quality.

III. WAVELET BASED MULTI RESOLUTION

A wavelet is a wave-like oscillation with an amplitude that starts out at zero, increases, and then decreases back to zero. Wavelets can be combined, using a "shift, multiply and sum" technique called convolution, with portions of an unknown signal to extract information from the unknown signal. Wavelet transforms are classified into continuous wavelet tranforms and descrete wavelet transforms. The following diagram (Fig 2) describes a mother wavelet (symmlet 8) .

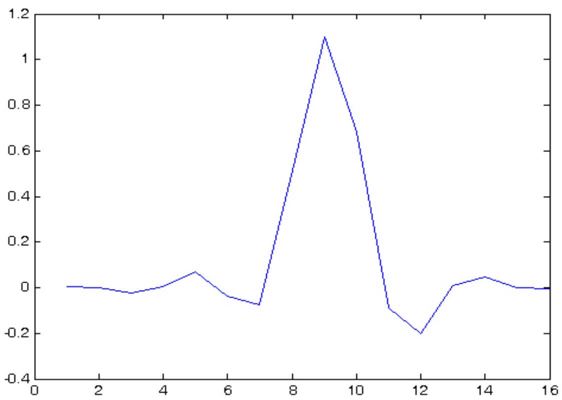

Fig 2: - Mother wavelet function plot of Symmlet 8

Wavelet based multi resolution analysis is an extension of Fourier analysis, the classical technique, that decomposes a signal into it's frequency components. However, Fourier analysis can't determine the exact time at which a particular frequency occurred in the signal. On the other hand wavelet analysis allows frequency structure of time-varying signals [5]. Wavelet analysis consists of decomposing a signal or an image into hierarchical set of approximations and details. The levels of decomposition are based on dyadic scale. From the signal analysis point of view, wavelet analysis is a decomposition of the signal by using orthogonal functions.

The main key advantage of wavelet transform is that signal energy is transformed into relatively small number of large coefficients [3]. Based on this concept Mallat developed a method called wavelet shrinkage to use the thresholding in wavelet domain. It was found that the wavelet shrinkage used for denosing the signals corrupted with additive Gaussian noise is near optimal.

3.1 Discrete wavelet Transform (DWT)

A discrete wavelet transform (DWT) is a wavelet tranform in which wavelets discretely sampled. A discrete dyadic signal can be represented at multiple resolutions by decomposing it on a family of wavelet functions [4]. Filtering the original signal using a high pass filter of length r, g = [g_1 g_2 .. g_r] , derived from the wavelet basis functions. The decomposition process is described schematically in Fig 3. The original signal is sum of all detail signals.

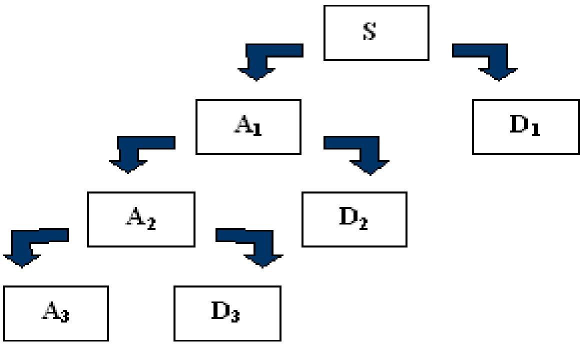

Fig 3: - Wavelet Decomposition

The wavelet packet method is a generalization of wavelet decomposition that offers range of possibilities for signal analysis. In wavelet analysis, a signal (S) is splitted into an approximation (A_1) and a detail (D_1) [5] . The approximation is then itself split into a second-level approximation (A_2) and detail (D_2), and the process is repeated. For an n-level decomposition, there are n+1 possible ways to decompose. The following equations represent the decomposition process.

$$\begin{aligned} S &= A_1 + D_1 \\ &= A_2 + D_2 + D_1 \\ &= A_3 + D_3 + D_2 + D_1 \end{aligned} \qquad (2)$$

For this experimental study, Symlets are considered as a base wavelet. The main steps for wavelet based denoising are decomposition of the signal, thresholding elimination of small coefficients and reconstruction of the signal. Donoho [6] proposed a simple thresholding rules which sets all the coefficients smaller than the universal threshold ($\sigma\sqrt{2\log n}$) to zero, (where σ is standard deviation of input and n is the input length) and shrinks the rest of the coefficients by the threshold (soft-thresholding or leave them without chance (hard-thresholding). The following equations 3, 4 represent soft and hard-thresholding.

$$y = \begin{cases} \text{sgn}(x) \ \text{for} \ f(|x| - \sigma) & \text{for} \ |x| \geq \sigma \\ 0 & \text{for} \ |x| < \sigma \end{cases} \qquad (3)$$

$$y = \begin{cases} x \ \text{for} \ |x| \geq \sigma \\ 0 \ \text{for} \ |x| < \sigma \end{cases} \qquad (4)$$

IV. VARIABLE MOVING WINDOW BASED REAL TIME DENOISING

Wavelet based de-noising techniques have shown it's strength in off-line processing. But in Target tracking applications, state vectors have to be estimated in real time. So that off line processing does not meet the requirement. As existing wavelet denoising technique suffer with artifacts and directly not suitable for real time denoising applications. However, using TI (Translation Invariant) denoising methods, effect of artifacts is reduced certain extent for online applications. In order to control the problems like Pseudo-Gibs phenomena and border distortion, new type of wavelet processing, comprising variable moving window and symmetric extension technique are considered to remove random disturbances from observed plot data.

Consider estimating an unknown discrete –time signal x[n] where $n \in [0, N-1]$ from a noise – corrupted signal.

y[n]= x[n] + d[n], where d[n] is additive noise.

Let X[n] = W(x[n]) denote the discrete wavelet transform of x[n] .

By applying the wavelet transform of the noisy signal y[n] and inverse wavelet transformation to the thresholded signal, the denoised estimate $\hat{x}$ [n] is computed. The following equation (5) represents, computation of denoised estimate

$$\hat{x}[n] = D(y[n]) = W^{-1}(\wedge t(W(y(n)))) \qquad (5)$$

Where ^t is the thresholding operator that removes the wavelet coefficients less than the threshold t.

Although Wavelet shrinkage plays critical role in denoising, it can hardly satisfy the real time requirement. In order solve the problem, a dynamic moving window with variable length is considered. Based on the signal length, it considers window size with optimal dyadic length. This concept enables to filter the noise from the beginning samples rather than waiting for a required window size (ex 128 samples). As normal wavelet processing suffers from border distortion, a novel symmetric extension of a dynamic window is implemented in the present algorithm. The following equation (6) describes symmetric extension.

$$W_i = \begin{cases} \text{None} & \text{if } i < 4 \\ x(i-3), \ldots x(i)\ \underbrace{,x(i), \ldots x(i-3)}_{\text{Symmetric Extension}} & \text{if } i = 4 \\ x(i-8), \ldots x(i),\ \underbrace{x(i), \ldots x(i-8))}_{\text{Symmetric Extension}} & \text{if } i = 8 \end{cases} \qquad (6)$$

V. SIMULATION AND RESULTS

In order to evaluate the performance of the proposed method, software is developed using Matlab and TI based wavelet transformations (wavelab) developed by Stanford University. By considering maneuvers, an aerodynamic target trajectory is created. The initial position of the target is given by [x(1),y(1),z(1)] = [1500.0 meters ,–1285 meters, 6000 meters] with an initial velocity $[v_x(1),v_y(1),v_z(1)]$ = [38m/sec ,-32m/sec, 1.0m/sec], Target moves with constant velocity up to 20 seconds with sampling rate of 100 ms. Then it starts to maneuver with the acceleration $[a_x(201),a_y(201),a_z(201)]$ = [-2 m/sec^2, -2m/sec^2, 0] and this acceleration continues until t = 30 seconds. At t = 30.1 sec target starts another maneuver with acceleration value $[a_x(301),a_y(301),a_z(301)]$ = [4 m/sec^2, 4 m/sec^2, 0] and this acceleration is continued till t = 40 sec . At t= 40.1 sec target starts another maneuver with acceleration value $[a_x(401),a_y(401),a_z(401)]$ = [-1 m/sec^2, -1 m/sec^2, 0]. Target moves with this acceleration up to end. All inputs, which are in ENV frame, are converted to spherical co-ordinates (Range, Elevation, Azimuth) and added random noise with the variances $[\sigma^2_r, \sigma^2_{el}, \sigma^2_{az}]$ = [10.0 meters, 0.003 radians, 0.003 radians] for creating a simulated plot data considered for the evaluation of the developed software. The following diagrams (Fig 4 – Fig 7) describes the comparison of noisy and denoised azimuth and elevation data before and after processing.

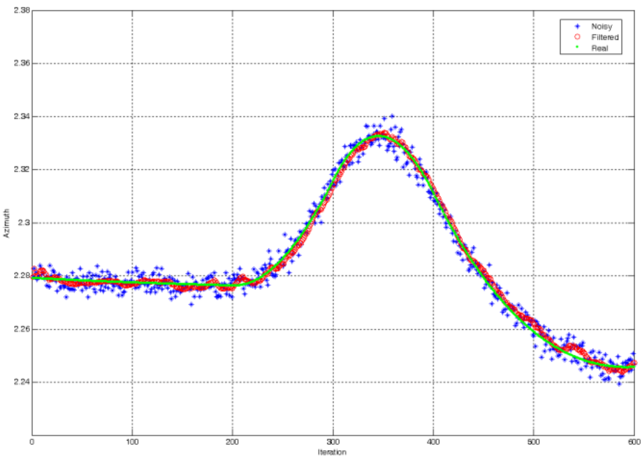

Fig 4: - Comparison of noisy and denoised azimuth data

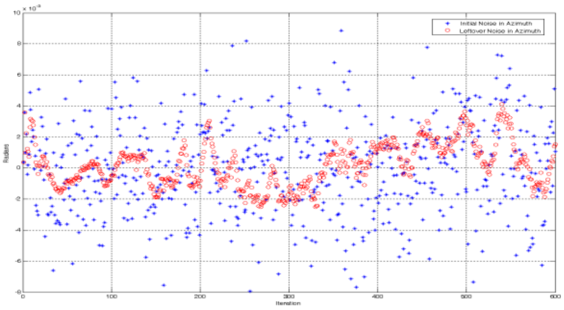

Fig 5:- Azimuth errors (Before and after denoising)

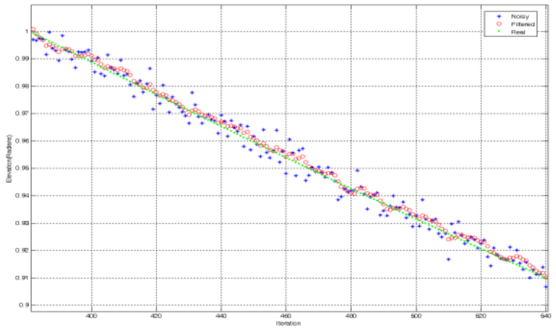

Fig 6:- Comparison of noisy and denoised elevation data

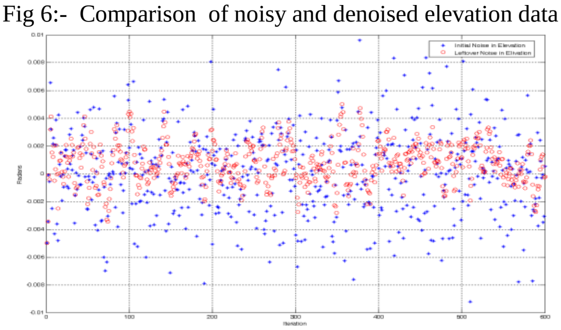

Fig 7:- :- Elevation errors (Before and after denoising)

In order to evaluate the performance of the method , Root Mean Square error (RMS) (Re) of the denoised data is computed using following equation (7)

$$R_e = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x(i)-\hat{x}(i))^2} \qquad \text{-------- (7)}$$

Where R_e indicates mean square error (RMS) and noisy signal is denoted by $x(i)$ and de-noised signal is indicated with $\hat{x}(i)$. indicates number of samples. The following table (Table 1) compares Root mean square (RMS) errors of azimuth and elevation of experimented trajectory, before and after the de-noising.

Initial RMSE of Azimuth Data	After Denoising RMSE of Azimuth Data	Initial RMSE of Elevation Data	After Denoising RMSE of elevation data
0.003 radians	**0.0014 radians**	**0.003 radians**	**0.0016 radians**

Table 1 :- RMS errors

VI. FUTURE WORK

In this experimental study, value of decomposition level for each dyadic length of the input is considered as constant. In order to get better results during maneuvering and non-maneuvering, decomposition level is changed accordingly by identifying the shift in the R_e value (7) of finite sliding window.

VII. CONCLUSIONS

In this paper a method is proposed and implemented for real time denoising using wavelet based multi resolution technique. To minimize the effect of artifacts occurring in real time processing, variable window based symmetric extension technique is experimented. Developed software is tested with 20 sets of simulated data by considering additive random noise. During the study, it was found that parameter decomposition depth plays critical role for effective denoising. As processing load, increases with the dyadic length of the input signal, the size of upper limit for variable window is restricted to 2^7. The experimented results indicated that proper tuning of decomposition depth gives effective online de-noising of radar signals in target tracking applications.

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