

# MEASURING RADAR STATISTICS BY USING KALMAN FILTER

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## ABSTRACT

A simple approach for interrogating the residual sequence of Kalman filter is presented in this article. It has been found that the variance parameter of an input noise of radar can be successfully estimated by using a recursive formula. After employing some simulation examples, the suggested formula shows acceptable results and thus can be practically adopted to produce the required statistics.

## 1 INTRODUCTION

Target trackers, whether they are passive or active, are examples of electronic instrumentation setups that are usually impaired by some sort of noise. The noise is expected in times when the tracker is practically operated. Generally, the most common type of this noise is the White Gaussian that has different means and variances,  $N(\eta, \sigma)$ . The style of this process depends on the target behavior and the surrounding environment. The target dynamic behavior can be estimated for each track whereas no perfect knowledge is a priori assumed. While, on the other hand, the radar observation errors should be calibrated and tolerated to the minimum acceptable ranges. To calculate the observation statistics for each new radar setup, some kind of assessment policy should be examined and approved in advance. Then, accurate values for these attributes can be referenced in the manual of that radar. In some other circumstances, charts might be useful to describe these inclinations under different environmental conditions, such as foggy, raining, or dusty flying scenarios.

## 2 PROBLEM ANALYSIS

Suppose that we have a scalar measurement system (for range channel for instance) defined by the following stochastic model:

$$y(k) = x(k) + n(k)$$

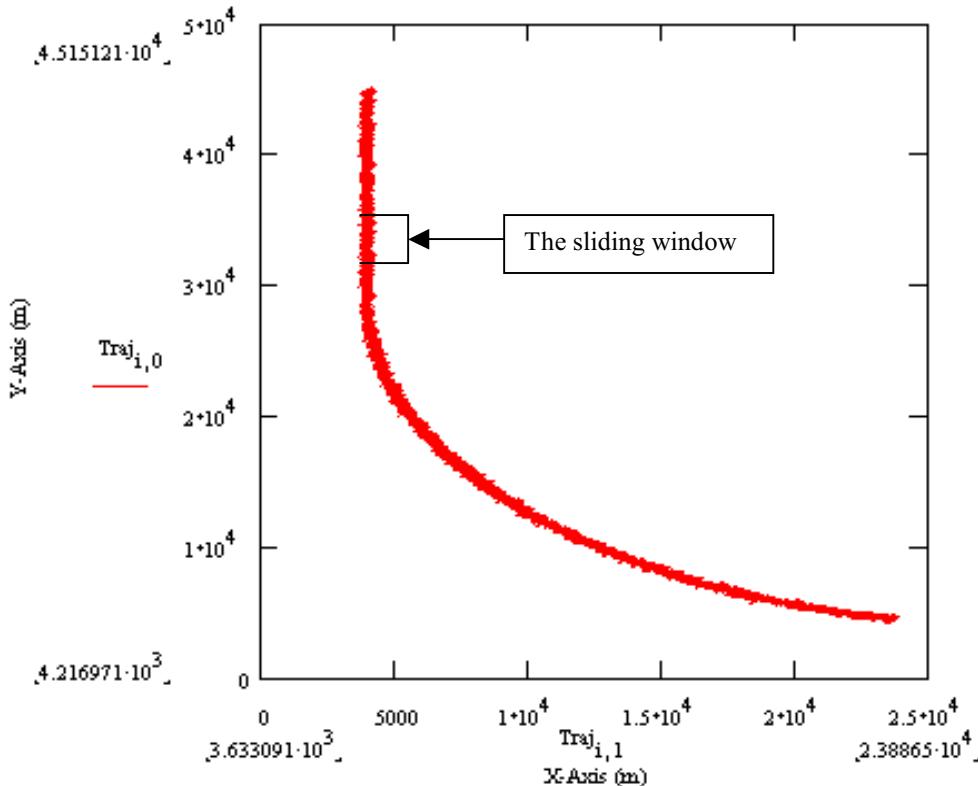
for which the following residual sequence formula can be derived [1-4]:

$$\gamma(k+1) = y(k) - \hat{x}(k+1/k)$$

It might be convincing to assume  $x$  as a deterministic constant value added to the input noise profile, which is acquired at time slots much more smaller than the time periods over which the target aims to change its attitude. Thus,  $x$  could be replaced by the state estimate  $\hat{x}$  that is carried out by the tracking processor. Accordingly, the input is justified to approximate same statistical characteristics of the residual sequence. Sequential covariance and mean estimators have been suggested in the literature [2, and 3]. Using moving windows over the state and measurement error sequences of Kalman filter propagation formulas basically approaches the proposed algorithms. However, those methods yield complications and they are computationally demanding. On-line feedback correction terms are always required by their recurrence formulas. Conceptually, when the target behaves smoothly, reliable assessments of the systems' errors should be worked out to retain the filter performance acceptable.

### 3 SIMULATION RESULTS AND DISCUSSIONS

Using the computer, a simple deterministic trajectory of a 90°-curvature movement has been simulated. This trajectory assumes neither fluctuations nor sudden changes in the target-flying course and for the parameters as depicted in Fig.1. Letting the filter reaches its steady-state status should initialize the mean and variance sequential estimates of the innovation process. A sliding window of 100-samples length is implemented over the entire trajectory to



**Fig.1 A 90°-curvature simulated trajectory.**

While two scenarios with input noise variances and means as illustrated in Fig.2 and Fig.3, the anticipated results show a promising agreement to the real statistical values. On the other hand, inferior performance is gained when the actual means take on different values other than zero. Surprisingly, this confirms to the Kalman filtering interpretation for which two White Gaussian processes of zero mean are entailed to conceive the performance optimality. The estimated values are evidently believed stationary along the period of maintaining the measurement experiment since the same device is employed and external disturbances are not

accomplish the statistical estimates according to the following recursive algorithms:

$$m_\gamma(j) = m_\gamma(j-1) + \frac{1}{j} \gamma(j)$$

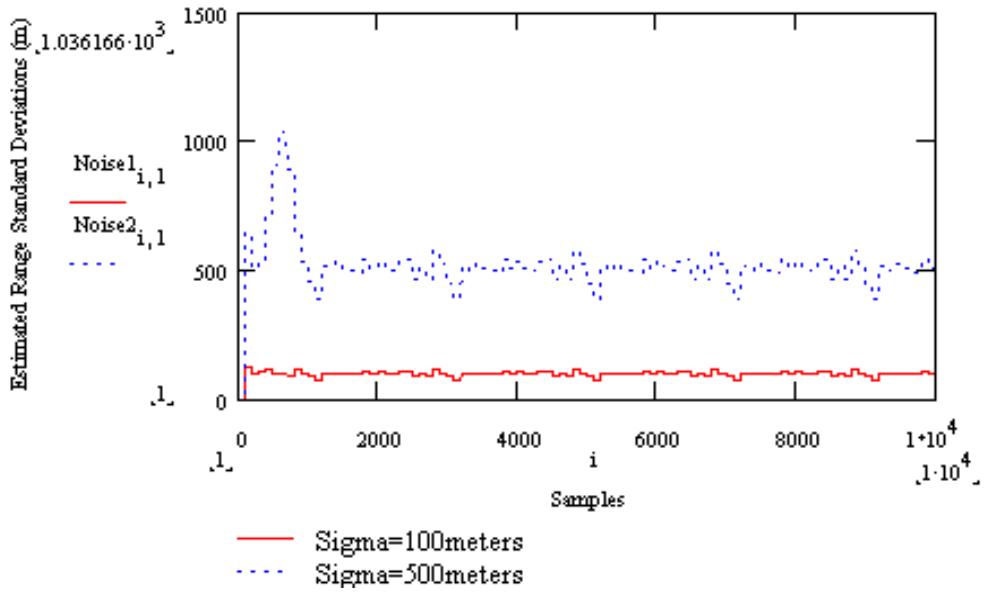
$$\sigma_\gamma^2(j) = \sigma_\gamma^2(j-1) + \frac{1}{j} (\gamma(j) - m_\gamma(j))^2$$

where  $m(\cdot)$ ,  $\sigma(\cdot)$ , and  $\gamma(\cdot)$  are the mean, standard deviation, and residual sequence, respectively.

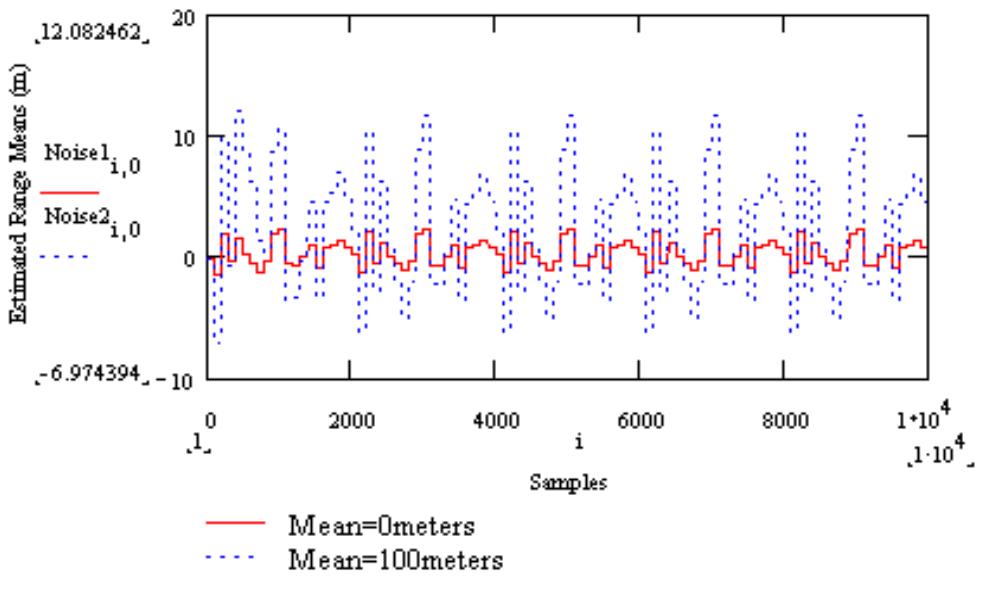
imposed. Thus, variances are ensured to experience some certain values; however, for different weather conditions the experiment should be tolerated. These figures should be documented and hence handed to the customer by the operational data sheets of the purchased equipment. Clear statements of the weather conditions should also be indicated. Thus, for civilian applications as a special case, winter characteristics of the tracking systems are highly different than those for summer season. While for a system under harsh maneuvers, the tracker should be supplied with the proper adaptation processor to circumvent the probability of loosing the

target trace. Achieving more evaluation on the statistical target maneuver intensity can significantly enhance the tracker performance against inconveniences of modeling errors and approximations resulted as elusive changes occurred in the target attitude. In such hindrances, the residual posses non-zero valued means and consequently a bias removal technique

might be investigated as proposed in the literature [4]. As for comparison with other methods, the main advantage of this method lies in its simplicity and modest computation. Other methods are well pretty computational demanding and usually their algorithms take longer times as for convergence.



**Fig.2 Estimated input-noise deviations for target attributes: Velocity=100m/s, Acceleration=1m/s<sup>2</sup>, Acquisition time=10ms, Range error=1m, Maneuver error=1m/s<sup>2</sup>.**  
**— Actual range error deviation= 100m.**  
**- - - - Actual range error deviation= 500m.**



**Fig.3 Estimated input-noise averages for the same target attributes.**  
**— Actual range error mean= 0m.**  
**- - - - Actual range error mean= 100m.**

## References

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