NOISE REDUCTION IN MULTIPLE RFID SENSOR SYSTEMS USED IN AEROSPACE ENGINEERING

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DOI: 10.19062/2247-3173.2017.19.1.12

Abstract: *In the recent years, Radio Frequency Identification (RFID) has included smart tags which can monitor the various surroundings of an area. To create such a tag one must have an accurate measurement system. Sometimes, noisy signals are generated because of the surrounding changes. In the following paper we will propose an improved Kalman filter to obtain a better noise reduction and a more precise data acknowledgement. The Kalman filter performance stand in their noise covariance's which are called R and Q variables. These variables are found in the Kalman filter algorithm. Still, to obtain the best results we must choose the correct R and Q variables. More specifically, the main purpose of the paper is to propose an improved Kalman filter to locate an aircraft. The covariance is used only for a simple architecture and could be adjusted using neural networks. Using this method, we can obtain a more detailed database from the RFID tags. In a simulation, the proposed improved Kalman filter will show a more précised location of an aircraft compared to the old gain amplifier, due to the multitude of sensors which are being used. The performance of the Kalman filter will be demonstrated in a simulation program.*

1. INTRODUCTION

In the technology field of Radio Frequency Identification (RFID), an enormous variety of RFID sensors have emerged. RFID Sensor Labels are also known as RFID intelligent tags, which measure and calculate data. Intelligent RFID tags functions can be combined to form a single small-size device. These functions are: detection, computing and communication. The need for solutions regarding detection and localization is highlighted in legislative and regulatory demands. Here we have requirements for certain industries such as: dangerous goods transport, pharmaceuticals, explosives, etc. Low temperatures is a key requirement for pharmaceutical products and perishable items. [1]

Modern RFID systems become incredibly complex, thus intelligent system demands keep rising, as well as one-sensor RFID tag monitoring systems. Often they are unable to meet the new needs of society. Intelligent RFID tags combined with multiple sensors and container with various products can provide integrated services and information to managers and customers. This can be achieved by combining different sensor data from its detection materials.

For example, the information provided by temperature, humidity and oxygen sensors from an RFID tag attached can provide conditions for an item/product and protect customers. So far, an intelligent single sensor RFID tag provides the information using multiple labels. Finally, by integrating multiple sensors into an RFID tag, we can imply a low-cost, high-power RFID system with an adequate radius [2].

Multiple sensors can be combined to form a smart RFID tag. These sensors: resistive, capacitive or inductive can extract important data which represents various states, such as: freshness or vitality. In a multi-sensor environment, RFID tags obtain data using one or more ports.

The Kalman filter has been widely applied to solve the problem of measuring system noise. The Kalman filter optimally estimates model states with known parameters. However, variations of measurement noise should be evaluated from empirical noise data, as it is difficult to obtain data in most cases. If the measurement noise statistics are unknown, the Kalman filter can not guarantee optimal resolution of the problem [3]. To solve this problem, we propose an adaptive filtering method based on the Kalman filter using neural networks.

2. SENSITIVE ENVIRONMENT

When system designers organize multi-sensor system, it is not sure that each sensor will work properly due to factors that disrupt their activity. These factors: noise and interference are caused by the measurement system in a multi-sensor environment. The RFID Multi-Sensor System is composed of a multi-electron system and a sensor board combined with sensors, as shown in Figure 1. The multi-electronics system is a RFID detection platform and is connected to a PC via a USB port to measure and compile data.

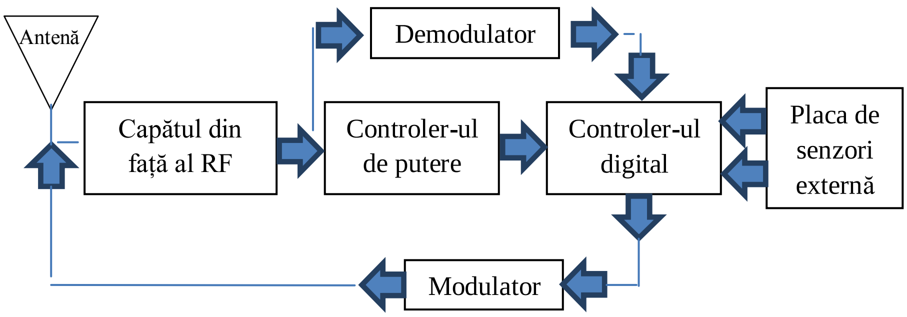

FIG. 1. Block diagram of the measurement system configuration

3. IMPROVEMENTS FOR KALMAN FILTERS

The Kalman filter requires accurate knowledge of all dynamic processes and noise, even when the noise processes are zero, meaning there is white noise. If the theoretical and the actual behavior do not match, there will be a divergence problem. When the error covariance is calculated using data from the current measurement error, we will obtain satisfactory results, without divergence. Kalman filter noise acts as a bandwidth controller and modulates Kalman gain.

The abnormal choice of noise covariance is one of the most important factors that make the difference between Kalman filters. The objective of this method is to estimate the noise covariance. Thus, by using neural networks we will try to prevent Kalman filter divergence.

The variables w_k and v_k represent, respectively, the process and the noise measurement. They are supposed to be independent of each other, and with normal probability distributions [4,5]:

$$x_{k+1} = Ax_k + Bu_k + w_k$$
(1)

$$z_k = Hx_k + v_k$$
(2)

Matrix A in an differential equation (1) relates the state to the previous *k-1* state with the state at the current *k* stage.Matrix B makes reference to the optional control input, while matrix H correlates the state with the z_k in the measurement equation (2):

$$P(w) \sim N(0, Q)$$
(3)

$$P(v) \sim N(0, R)$$
(4)

Q represents the process noise covariance and R is the covariance of the measurement noise. Derivating the Kalman filtering formula, we start with an equation that calculates a state estimate of previous results. Simultaneously we calculate a linear combination of an a priori estimate and a weighted difference between a real and a prediction measurement [4,6] .

Time equations are responsible for moving the current state and error covariance estimates. This will be done so that we can obtain a priori estimates for the next step. Measurement update equations are responsible for the feedback, and they also incorporate a new measurement in a priori estimation so that we can obtain an improved posterior development:

$$\hat{x}_{k/k} = \hat{x}_{k/k-1} + K_k\{z_k - H\hat{x}_{k/k-1}\}$$
(5)

$\hat{x}_{k/k-1}$ is an a priori estimation of k, and x_k, and $\hat{x}_{k/k}$ to be our posterior state estimate for the measured k-stage. z_k is the noisy observation vector. $H\hat{x}_{k/k-1}$ is a presumption for the pre-measurement value. $\hat{x}_{k/k}$ can be presented (6):

$$\hat{x}_{k/k-1} = A\hat{x}_{k-1/k-1} + Bu_k$$
(6)

The Kalman gain K_k minimizez a posterior state estimate by incorporating measurements. Here $E\{e_{k/k}e_{k/k}{}^T\}$ is the Kalman filter equation. The purpose of this equation is to find a Kalman gain K_k. Equation (7) expresses the posteriori estimative errors:

$$e_{k/k} = x_k - \hat{x}_{k-k}$$
(7)

The derivation of the covariance equation is shown by equation (8):

$$E\{e_{k/k}e_{k/k}{}^{T}\} = P_{k/k-1} + K_{k}HP_{k/k-1}H^{T}K_{k}{}^{T} + K_{k}RK_{k}{}^{T} - P_{k/k-1}H^{T}K_{k}{}^{T} - K_{k}HP_{k/k-1}$$
(8)

The value above is equivalent to minimizing traces of the a posteriori estimative covariance matrix. The trace is minimized when the matrix derivative is zero, as in equation (9). Solving equation (9) for K_k leads to Kalman's gain, which is the optimal gain (10):

$$\frac{\partial E\{e_{k/k}e_{k/k}e_{k/k}{}^{T}\}}{\partial K_{k}} = 2HP_{k/k-1}H^{T}K_{k}{}^{T} + 2RK_{k}{}^{T} - HP_{\frac{k}{k}-1} - \left\{P_{\frac{k}{k}-1}H^{T}\right\}^{T} = 0$$
(9)

$$K_{k} = P_{k/k-1}H^{T}\{HP_{k/k-1}H^{T} + R\}^{-1}$$
(10)

Kalman filters estimate a process by using a form of feedback control. In other words the filter evaluates the state of the process, while at the same time obtains a feedback. In common parts, we can devide the Kalman filter equations into two groups: time update equations and measurement update equations. Time updating equations can also be considered as predictive equations, while equations for measuring updates can be considered as correcting equations [7]. Still, in the final estimation algorithm we can resembles the correct predictors or algorithms for solving numerical problems.

3.1. Kalman Filter Improvements

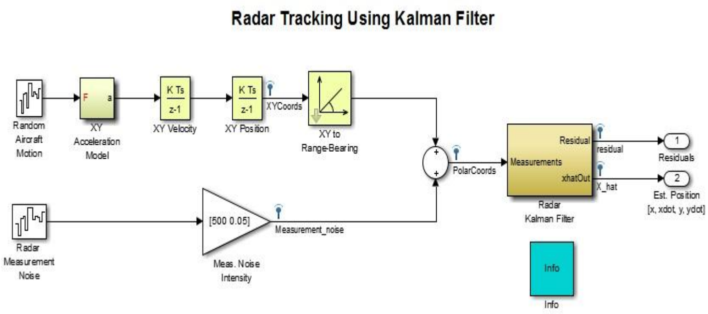

FIG. 2. Using a Kalman filter to improve radar data

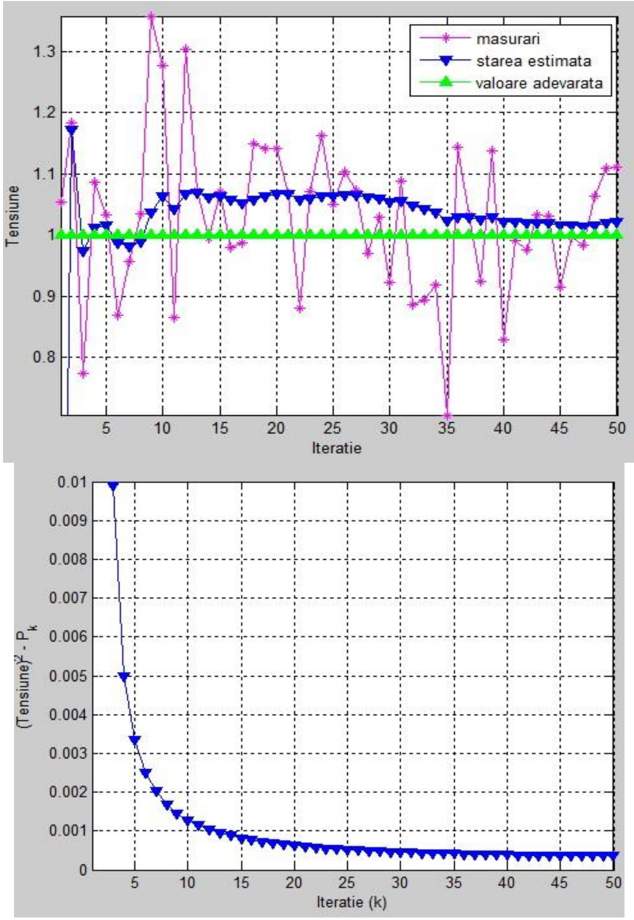

FIG.3. The results of the Kalman filter for radars

Comparing the results of the Kalman Joint Method and the Kalman Enhanced Filter, we examined the simulations with an assumed measured covariance. The Kalman filter can offer optimal solutions, if the system model is correctly defined and if the measurement and system noise statistics are fully acknowledge [8]. Figure 3 presents the simulation results with the assumed measured tension of the Kalman filter. This is done so we can evaluate the performance of the Kalman joint filter.

4. CONCLUSSIONS

These results show that the Kalman filtering method is good for reducing measurement noise. The previous method for determining the measurement noise covariance (R) for the Kalman filter depends on the analysis of the empirical data of each sensor and its modification. Because there are no perfect sensors, their performance are reduced with time. This determines the uncertainty in the previous Kalman filter method, which has a considerable impact on the performance of the Kalman filter [10].

The Kalman filter R value affects the weight on which the filter applies between existing process information and the most recent measurements. Failure in any of them may result in the filter being suboptimal or even cause divergences.

5. ACKNOWLEDGEMENTS

The authors wish to thank the "*Transilvania*" University of Braşov and "*Henri Coandă*" Air Force Academy of Braşov for supporting the research necessary for writing this article.

REFERENCES

[1] Pesonen, N.; Jaakkola, K.; Lamy, J.; Nummila, K.; Marjonen, J. Smart RFID Tags. In *Development and Implementation of RFID Technology*; Turcu, C., Ed.; InTech: Rijeka, Croatia,2009; pp. 159-178;

[2] Ho, L.; Moh, M.; Walker, Z.; Hamada, T.; Su, C. A Prototype on RFID and Sensor Networks for Elder Healthcare: Progress Report. In *Proceedings of ACM SIGCOMM Workshop on Experimental Approaches to Wireless Network Design and Analysis*, Philadelphia, PA, USA, 22 August 2005; pp. 70-75;

[3] Gibson, J.D.; Koo, B.; Gray, S.D. Filtering of Colored Noise for Speech Enhancement and Coding. *IEEE Trans. Sign. Process.* 1991, *39*, 1732-1742;

[4] Hagan, M.; Demuth, H.; Beale, M. *Neural Network Design*; PWS Publishing: Boston, MA, USA,1996;

[5] Yu, D.L.; Chang, T.K.; Yu, D.W. Adaptive Neural Model-Based Fault Tolerant Control for Multi-Variable Processes. *Eng. Appl. Artif. Intell.* 2005, *18*, 393-411.*Sensors* 2011, *11*10282;

[6] Wang, J.; Ding, W.; Wang, J. Improving Adaptive Kalman Filter in GPS/SDINS Integration with Neural Network. In *Proceedings of ION GNSS 2007*, Fort Worth, TX, USA, 25–28 September 2007;

[7] Haykin, S. *Neural Networks (A Comprehensive Foundation)*; Prentice-Hall International: UpperSaddle River, NJ, USA, 1999;

[8] Kalman, R.E. A New Approach to Linear Filtering and Prediction Problems. *Trans. ASME J.Basic Eng.* **1960**, *82*, 35-45.