PERFORMANCE ANALYSIS OF WIENER AND KALMAN FILTER FOR MULTI- SENSOR DATA FUSION

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ABSTRACT

Sensor fusion is a method of integrating signals from multiple sources. It allows extracting information from several different sources to integrate them into single signal or information. In many cases sources of information are sensors or other devices that allow for perception or measurement of changing environment. Information received from multiple-sensors is processed using "sensor fusion" or "data fusion" algorithms.

The purpose of this paper is to provide a practical introduction to the discrete filters. This introduction includes a description and some discussion of the basic wiener filter and Kalman filter, and a relatively simple example with simulation results using MATLAB & its simulation results.

***Key Words*: Sensor Fusion, Kalman Filter, MATLAB, Weiner Filter**

1. INTRODUCTION

The problem with industrial automation is the fault monitoring system which has always been an area of much importance for the research departments in the industries. And this importance becomes more prioritized when we are dealing with the non-linear systems. Monitoring of uncommon behavior of the system and detecting the unprecedented changes in system are the essential steps to maintain the health of the system, followed by covering the removal of faulty components, replacement with the better ones, restructuring system architecture, and thus improving the overall system reliability. However, with the increasing complexity of the modern nonlinear systems process have made engineers to face tough challenges to understand and trouble-shoot possible system problems.

Many researchers have been working on the implementation and to improve performance of the use of various filters like wiener and kalman filter. For example areas like choosing kalman filter over wiener filter which is best suited for liner systems and also to increase performance in areas like numerical stability improvement, the computation time reduction or the study of effective implementations. The main objective of this paper is to provide an introductory approach on clearing theidea of using linear and non-linear type filtering systems on transactions on the industrial applications and implementation of the Kalman filter is to highlight the latest theoretical and experimental advances and to emphasize practical implementation. This performance analysis is done in order to use the more efficient filter for the work to be carried out on the topic "Implementation of Fuzzy logic controller with Kalman filter for multi-sensor data fusion".

Next chapter deals with mainly with the background survey of wiener filter and kalman filter.

II DATA FUSION

A process dealing with the association, correlation, and combination of data and information from single and multiple sources to achieve refined position and identity estimates, and complete and timely assessments of situations and threats, and their significance. The process is characterized by continuous refinements of estimates, assessments and the evaluation for the need of additional sources, or modification of the process itself, to achieve improved results [1].

The concept of multisensor data fusion is hardly new. As humans and animals evolved, they developed the ability to use multiple senses to help them survive. For example, assessing the quality of an edible substance may not be possible using only with the sense of vision; the combination of sight, touch, smell, and taste is far more effective. Similarly, when vision is limited by structures and vegetation, the sense of hearing can provide advanced warning of impending dangers. Thus, multisensory data fusion is naturally performed by animals and humans to assess more accurately the surrounding environment and to identify threats,thereby improving their chances of survival. Interestingly, recent applications of data fusion have combined data from an artificial nose and an artificial tongue using neural networks and fuzzy logic.

The technology of multisensor data fusion is rapidly evolving. There is much concurrent research ongoing to develop new algorithms, to improve existing algorithms, and to assemble these techniques into an overall architecture capable of addressing diverse data fusion applications.

The most mature area of data fusion process is level 1 processing using multisensor data to determine the position, velocity, attributes, and identity of individual objects or entities. Determining the position and velocity of an object on the basis of multiple sensor observations is a relatively old problem. Gauss and Legendre developed the method of least squares for determining the orbits of asteroids. Numerous mathematical techniques exist for performing coordinate transformations, associating observations to observations or to tracks, and estimating the position and velocity of a target. Multisensor target tracking is dominated by sequential estimation techniques such as the Kalman filter. Challenges in this area involve circumstances in which there is a dense target environment, rapidly maneuvering targets, or complex signal propagation environments (e.g., involving multipath propagation, co channel interference, or clutter). However, single-target tracking in excellent signal-to-noise environments for dynamically well-behaved (i.e., dynamicallypredictable) targets is a straightforward, easily resolved problem.

The reasons to use multisensor data fusion:

1. There is no substitute for a good sensor.
2. Downstream processing cannot absolve the sins of upstream processing.
3. The fused answer may be worse than the best sensor.
4. There are no magic algorithms.
5. There will never be enough training data.
6. It is difficult to quantify the value of data fusion.
7. Fusion is not a static process.

The original issues identified (viz., that fusion is not a static process, and that the benefits of fusion processing are difficult to quantify) still hold true.

Overall, this is an exciting time for the field of data fusion. The rapid advances and proliferation of sensors, the global spread of wireless communications, and the rapid improvements in computer processing and data storage enable new applications and methods to be developed.

Data fusion has suffered from a lack of rigor with regard to the test and evaluation of algorithms and the means of transitioning research findings from theory to application. The data fusion community must insist on high standards for algorithm development, test, and evaluation; creation of standard test cases; and systematic evolution of the technology to meet realistic applications.

Taking this advantage we have planned to implement a industrial application using themultisensor data fusion. The next chapters deal with choosing of appropriate filter for our application which produces accurate and more error free results.

III THE WIENER FILTER

The Wiener filter is used in image processing to remove noise from a picture; it is commonly used to de-noise audio signals, especially speech, as a preprocessor before speech recognition.

The goal of the Wiener filter is to filter out noise that has corrupted a signal. It is based on a statistical approach, and a more statistical account of the theory is given in the MMSE estimator article.

Typical filters are designed for a desired frequency response. However, the design of the Wiener filter takes a different approach. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the linear time-invariant filter whose output would come as close to the original signal as possible. Wiener filters are characterized by the following:

1. Assumption: signal and (additive) noise are stationary linear stochastic processes with known spectral characteristics or known autocorrelation and cross-correlation
2. Requirement: the filter must be physically realizable/causal (this requirement can be dropped, resulting in a non-causal solution)
3. Performance criterion: minimum mean-square error (MMSE). This filter is frequently used in the process of deconvolution; for this application, see Wiener deconvolution.

IV THE KALMAN FILTER

The Kalman filter, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone. More formally, the Kalman filter operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state.

Experimental measurements are never perfect,[3] even with sophisticated modern instruments. The problem of estimating the state of a stochastic dynamical system from noisy observations taken on the state is of central importance in engineering. Noise filtering is an important part of processing a real signal sequence. There are many kinds of filters could be used for estimation purpose, such as mean filter, median filter, Gaussian filter, and so on. In this article, we discuss the performances of Kalman filter and fuzzy Kalman filter. There are two basic processes that are modeled by the Kalman filter. The first process is a model describing how the error state vector changes in time. This model is the system dynamics model. The second model defines the relationship between the error state vector and any measurements processed by the filter, and it is the measurement model. Intuitively, the Kalman filter sorts out information and weights the relative contributions of the measurements and of the dynamic behavior of the state vector. The measurements and state vector are weighted by theirrespective covariance matrices. The Kalman filter estimates a process by using a form of feedback control: the filter estimates the process state at some time and then obtains feedback in the form of (noisy) measurements. As such, the equations for the Kalman filter fall into two groups: time update equations and measurement update equations. The time update equations are responsible for projecting forward (in time) the current state and error covariance estimates to obtain the a priori estimates for the next time step. The measurement update equations are responsible for the feedback i.e. for incorporating a new measurement into the a priori estimate to obtain an improved a posteriori estimate.

The Kalman filter is an optimal recursive data processing algorithm[2] that provides a linear, unbiased, and minimum error variance estimate of the unknown state vector **X,** E *31"* at each instant ***k*** = 1.2, ..., (indexed by the subscripts) of a discrete-time controlled process described by the linear stochastic difference equations:

$$\mathbf{x_{k+1} = A_k x_K + B_K u_K + w_k \ldots. \ (1)}$$

$$\mathbf{z_k = H_k x_k + v_k \ldots\ldots \ (2)}$$

where ***Xk***is an ***n*** **x** 1 system state vector, ***Ak***is an ***n*** **x** ***n*** transition matrix, ***Uk***is an ***1*** **x** **1** vector of the input forcing function, ***Bk***is an ***n*** **x** ***1*** matrix, ***wk***is an ***n*** **x** 1 process noise vector, ***zk***is a ***m*** **x** 1 measurement vector, ***Hk***is a ***m*** **x** ***n*** measurement matrix, and ***vk***is a ***m*** **x** 1 measurement noise vector. Both ***w.4*** and ***vk***are assumed to be uncorrelated zero-mean Gaussian white noise sequences with covariance.

$$E\{w_k w_i^T\} = \begin{cases} Q_k, & i = k \\ 0 & i \neq k \end{cases} \qquad (3)$$

$$E\{v_k v_i^T\} = \begin{cases} R_k, & i = k \\ 0 & i \neq k \end{cases} \qquad (4)$$

$$E\{w_k v_i^T\} = 0 \qquad \text{for all } k \text{ and } i \qquad (5)$$

Where **E { . }** is the statistical expectation, superscript **T** denotes transpose, **Qk**is the process noise covariance matrix, and **Rk**is the measurement noise covariance matrix. The Kalman filter algorithm can be organized in two groups of equations,

1) Time update (or prediction) equations

$$\hat{x}_{k+1}^- = A_k \hat{x}_k + B_k u_k \qquad (6)$$

$$P_{k+1}^- = A_k P_k A_k^T + Q_k \qquad (7).$$

These equations project, from time step ***k*** to step ***k+l,*** the current state and error covariance estimates to obtain the ***a priori*** (indicated by the super minus) estimates for the next time step.

2) Measurement update (or correction) equations:

$$K_k = P_k^- H_k^T [H_k P_k^- H_k^T + R_k]^{-1} \quad (8)$$
$$\hat{x}_k = \hat{x}_k^- + K_k [z_k - H_k \hat{x}_k^-] \quad (9)$$
$$P_k = [I - K_k H_k] P_k^- \quad (10).$$

These equations incorporate a new measurement into the ***a priori*** estimate to obtain an improved ***a posteriori*** estimate. In the above equations, ***ik***is an estimate of the system state vector ***Xk,*** and ***Pk***is the covariance matrix corresponding to the state estimation error defined by,

$$P_k = E\left\{(x_k - \hat{x}_k)(x_k - \hat{x}_k)^T\right\} \quad (11)$$

the term ***H*** is the one-stage predicted output referred to as the innovation sequence or residual, generally denoted as rand defined as

$$r_k = (z_k - H_k \hat{x}_k^-) \quad (12).$$

V IMPLEMENTATION

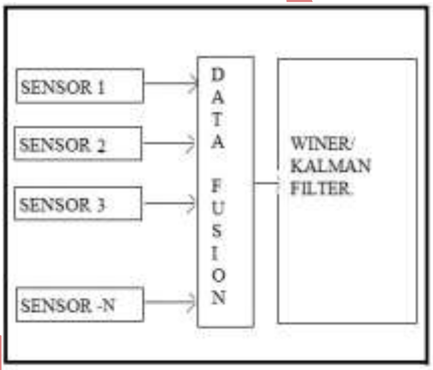

Fig.1: Proposed Architecture

If the multisensor data are commensurate (i.e., if the sensors are measuring the same physical phenomena such as two visual image sensors or two acoustic sensors) then the raw sensor data can be directly combined. Techniques for raw data fusion typically involve classic estimation methods such as Kalman filtering. Conversely, if the sensor data are non-commensurate then the data must be fused at the feature/state vector level or decision level.

The paper describes implementation and test results of the two filters using MATLAB, the figure shows a basic proposed diagram of the system under implementation,

Here we have planned to use three different heat sensors which are of nonlinear type and thus will result in errors while data fusion hence in order to rectify these errors the MATLAB implementation iscarried out to choose between kalman and wiener filters.

The working environment in the MATLAB an powerful tool for mathematical processing of the data provides suitable tools to implement the project. As a first step the comparative implementation and test results have been shown. A constant sine wave signal source is been fed as input which can be taken as the data from the sensor, along with it a noise source is been added to provide test environment of the multisensor data fusion.

The figure 2 shows an implemented result of wiener filter which provides not much smoothening of signal.

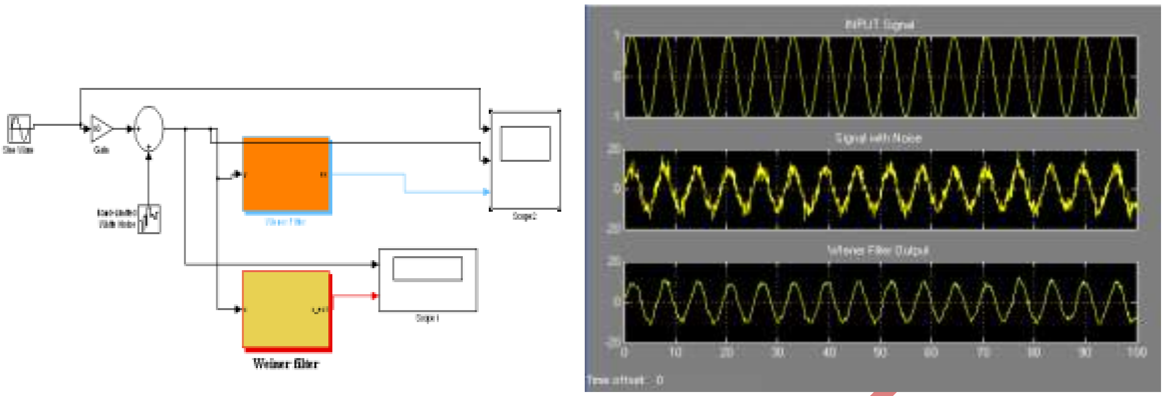

Fig.2: Weiner Filter Implementation With Simulation

which is not suitable for the range of sesor data we have planned to fuse so the kalaman filter implementation was tested which shown moreprecise filtering and unchanged input actual data, figure 3 shows implmenation and its test results in MATLAB environment. The kalman filter due to its feedback and predict and correct type of approch provieds grater stablity and sensitivity towards the input and output singnals.

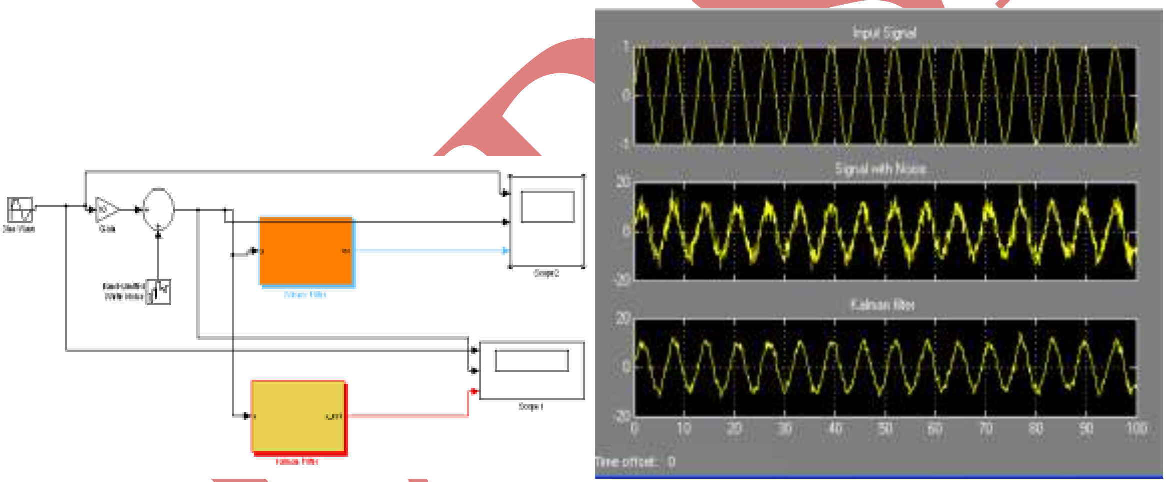

Fig.3: Kalman Filter Implementation With Simulation

Since 3 sensors are been planned to use, the Adaptive kalman filtering and fuzzy logic estimator has been planned which is under progress.

VI CONCLUSION

By observing the comparison of the simulation it is observed that the wiener filter will respond in linear increment of noise in the given limits. If noise signaladded in the input no linearly the output of the filter was not as per the equation. Whereas same situation comes for the simulation using kalman filter the output is as per the equation. It will be concluded that if nonlinear situation occurs then Kalman filter will be better.

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