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Didactic Strategies For The Understanding Of The Kalman Filter In Industrial Instrumentation Systems

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Abstract

This paper presents an application of the Kalman filter in signal processing in instrumentation systems when the conditions of the environment generate a large amount of interference for the acquisition of signals from measurement systems. The unwanted interferences make important use of the instrumentation system resources and do not represent useful information under any aspect. A simulation is presented using the Matlab tool, which remarkably facilitates the information processing so that the corresponding actions are taken according to the information obtained, taking advantage of the current resources offered by the embedded systems and the required measurements are obtained with enough accuracy.

Keywords: Data acquisition; Kalman filter; instrumentation systems; Matlab; signal conditioning

1. Introduction

One of the essential needs of industrial processes is to monitor the variables involved in them in the best possible way to optimize the processes (Sharma, K. L. S., 2016).

Industrial instrumentation systems are a vital part of the process affected by the noise produced by external agents (power elements such as three-phase and single-phase motors, conductors, electronic equipment, etc.) and by the system's electronics (thermal noise, shot noise) (Pałczyńska, B., 2022). Noise affects the information and the operation of some devices, generally affecting the system operation (Himali, S., Arpan, C., Kumar, M., 2022).

To solve this problem, the Kalman filter ((used to identify the hidden (non-measurable)) is used due to its advantages, mainly because it allows estimating signals with statistical properties such as 1, among others, which can vary over time compared to other filters such as Wiener (Impraimakis, M., Smyth, A. W., 2022), (Areny, R. P., 2005), (Ollero, A., 1991), (Kullaa, J., 2003), (Angrisani, L., Baccigalupi, A., 2006).

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Taking advantage of the remarkable capacity of current embedded systems to incorporate algorithms that can replace some physical elements of signal conditioning, this new technology can be incorporated into measurement systems to simplify the hardware and reduce noise levels that occur in industrial environments (Saddik, A., et al., 2022).

The Kalman filter in its basic structure continues to be applied and variants such as the extended Kalman filter and new methodologies in artificial intelligence should be considered to achieve better results in the accuracy and precision of the instruments (Naoual, T. et al., 2022).

2. Structure

The general structure of an instrumentation system is shown in Figure 1 and consists of the following block diagram (Blake, A., 2002).

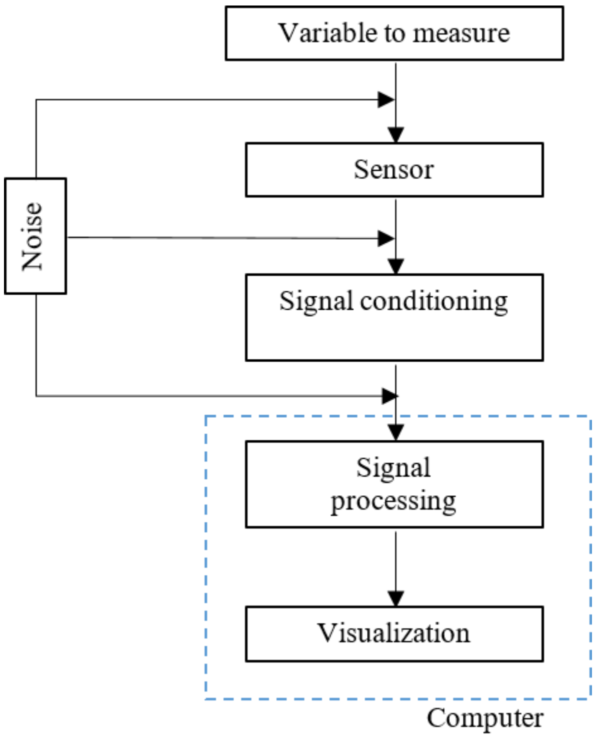

Figure 1. Diagram of an Instrumentation System

Initially the variable or phenomenon to be measured enters the sensor, to which is added the noise due to multiple sources present in the particular process (Bently, J. P., 2005). Due to the fact that the signal delivered by the sensor has non-optimal characteristics for it to be adequately processed by the next stage. The signal conditioning stages consist of:

- Linearization: it is necessary to linearize the signal delivered by the sensor when it is of non-linear type as it occurs in most cases in industrial systems in order to have a response according to the measured variable.
- Amplification: when the signal has a very low amplitude either in voltage, current or frequency.
- Filtering: if unwanted signals or interferences are present in the information obtained from the process.
- Analog to Digital Conversion (ADC) if the information will be processed by a digital system (microcontroller, microprocessor, PC, etc.).

In some cases, it is indispensable to apply all the above-mentioned stages or only some of them depending on the particular conditions of the industrial process. In the signal processing stage, the operations corresponding to mathematical calculations, information recording, etc. are performed. Finally, the information will be presented to the user to take the corresponding actions according to the information presented.

It is very important to emphasize that the quality of the information obtained depends on the capacity of the instrumentation system to reduce unimportant information or interference due to the medium, since it makes use of the medium's resources and it is essential to employ the necessary mechanisms to achieve this purpose.

3. Kalman Filter

The Kalman filter is due to the electrical engineer Rudolf Emil Kalman Ph.D. who was a recognized researcher in mathematics and its applications to engineering, highlighting the development of his filter around 1958.

The Kalman filter consists of a set of equations that compute an estimator of a system at time t based on the information available at t-1 and that also updates the information available at t. This filter assumes that the system is described by a linear stochastic model, where the error associated with both the system and the additional information that is incorporated has a normal distribution with zero mean and given variance (Charles, K., Guanrong, C., 2017).

The solution is optimal since the filter combines all the observed information and prior knowledge about the system behavior to produce an estimate of the state such that the error is statistically minimized. Each time there is a new observation the filter recalculates the solution (Kim, P., 2011).

Figure 2 shows the basic components of the Kalman Filter, which are the propagation cycle and an actualization cycle.

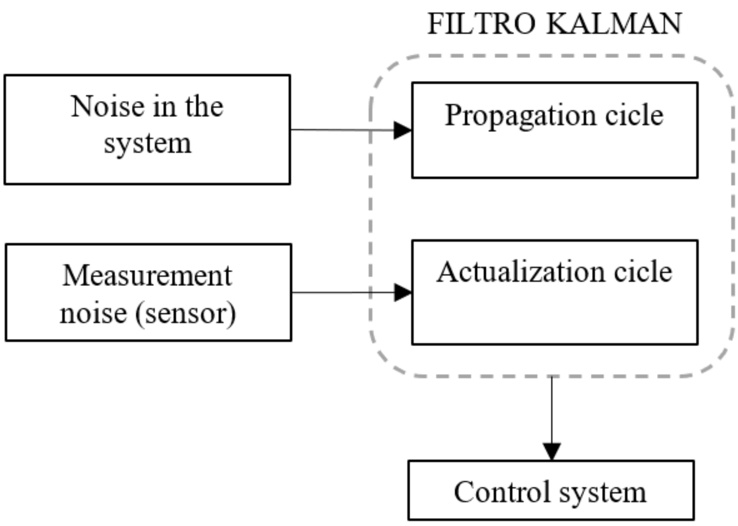

Figure 2. Kalman Filter Basic Components

In the propagation cycle, the state vector is estimated at instant t+1 knowing the measurements up to instant t and at the same time the covariance of the estimation error vector is calculated. It can be said that this cycle is "a priori".

In the update cycle, the estimate made in the propagation cycle is modified using the least squares method in order to minimize the error and reduce the noise present in the signal. This cycle is considered "posteriori".

The dynamic system to be treated must be represented by the state-space form described by the state variables, which are assumed to be undetermined and therefore stochastic processes introduce a degree of uncertainty to the system (Kovvali, N., Banavar, M., Spanias, A., 2022).

The Kalman equations for a discrete linear system are as follows:

$$Xt = AX_{t-1} \quad W_{t-1} \qquad (1)$$

$$Zt = HX_{t} \quad V_{t} \qquad (2)$$

Where Wt and Vt represent the noises in both the system and the measurements, they are assumed to be independent and to be white noise. The matrix A relates the state in the previous period t-1 to the state at time t. Matrix H relates the state to the measurement Zt. These matrices may change over time, but are generally assumed to be constant (Mohinder, S., Grewal, A., Andrews, P., 2008).

4. Simulation

The simulation was carried out with the help of Matlab software, in which the algorithm presented in Figure 3 was structured.

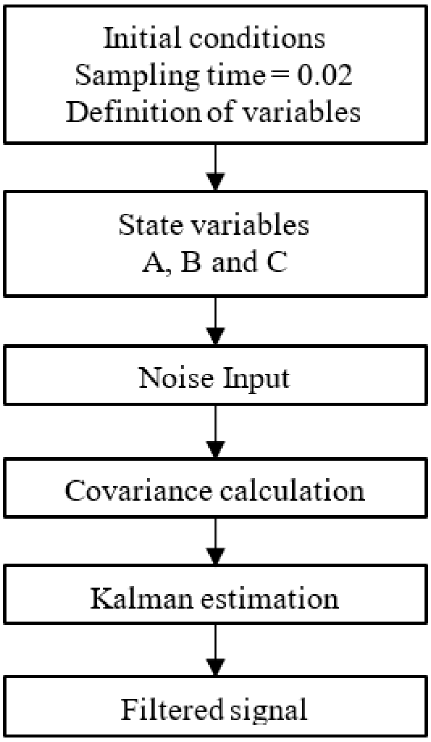

Figure 3. Simulated algorithm

Initially, the noise signals corresponding to the noise present in the environment (white Gaussian noise) or dynamic noise are obtained. In this case, this noise was obtained from a matrix of random numbers with normal distribution that replaces the dynamic noise mentioned above, see Figure 4.

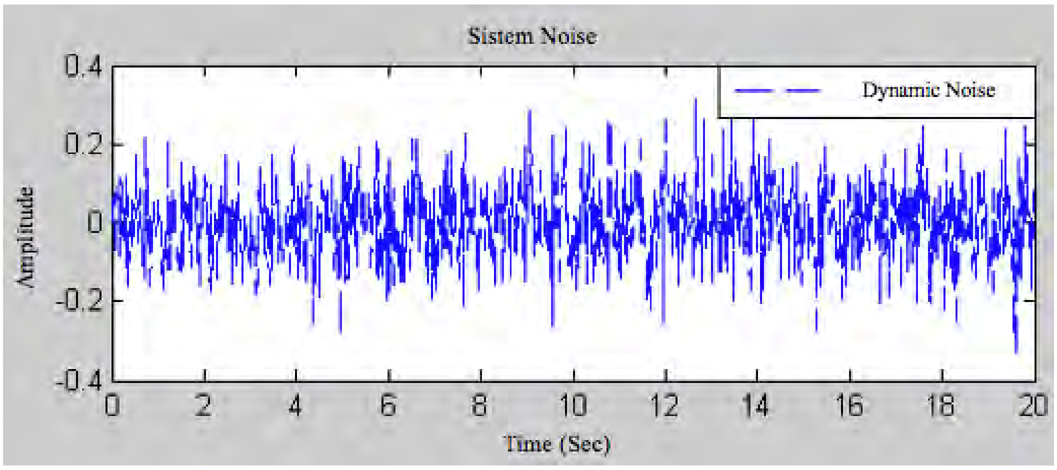

Figure 4. System dynamic noise

It is also presented the sensor's own noise that will affect the information obtained from the particular process or system noise, for this case this noise was obtained from a matrix of random numbers with normal distribution that replaces the system noise mentioned above. See Figure 5.

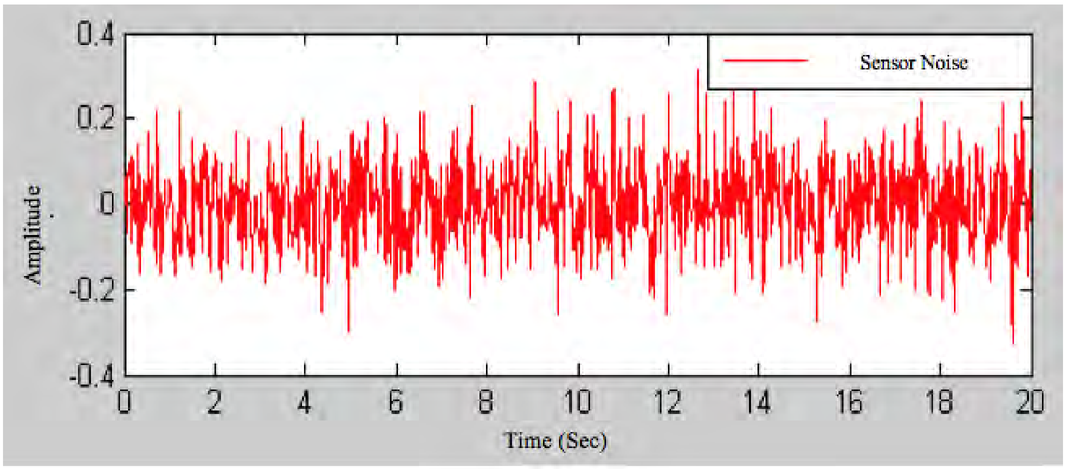

Figure 5. System noise

The system responses were obtained for multiple conditions which are signal with dynamic noise and system noise, signal with system noise and without dynamic noise and signal with dynamic noise and without system noise, which are presented in Figure 6.

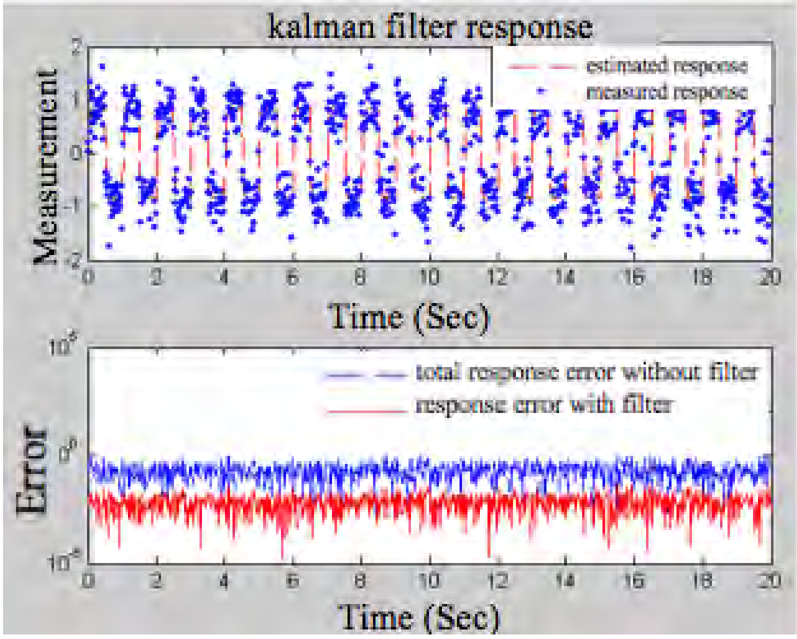

Figure 6. System response to multiple noise conditions

Figure 7 shows the signal with noise that will be introduced to the Kalman filter (measured response) to verify its performance and the estimated signal after applying the Kalman filter (estimated response).

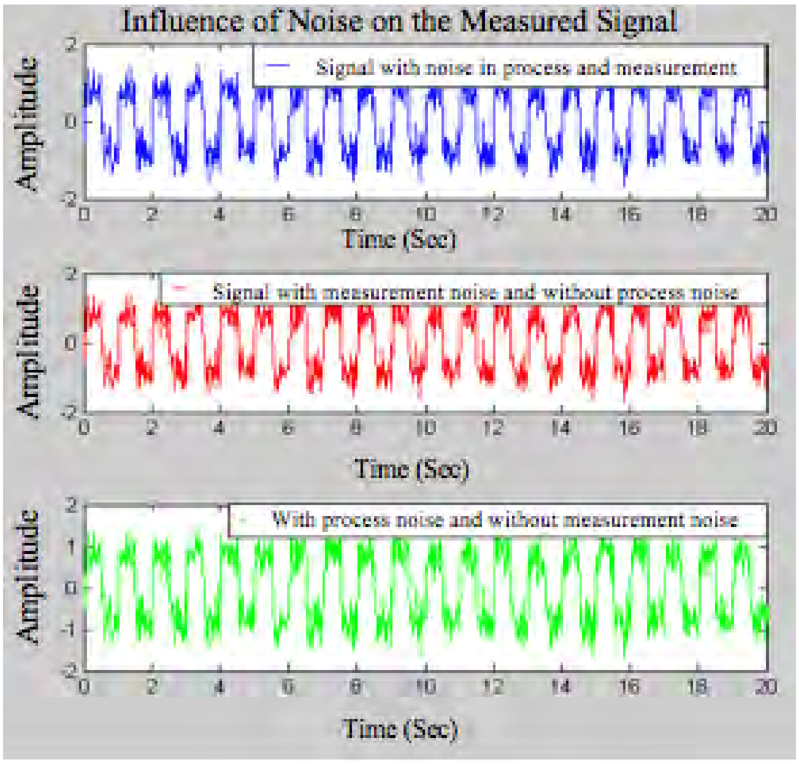

Figure 7. Kalman filter response

The estimation is performed several times until a constant value is found, which represents the minimum error that can be obtained.

5. Conclusions

It is observed that the Kalman filter is a recursive filter which allows to reduce noise components present in a system, through the approach of mathematical models that characterize it, which through the Kalman filter allow to make estimates of present values based on previous measurements or assumption of initial conditions, presenting an algorithm for its realization.

The Kalman filter differs from other filters because it allows estimating signals whose statistical properties vary with time. Another important feature is that the filter performs recurrent estimations, until it reaches a constant value, which indicates or shows a considerable noise decrease.

Thanks to the MATLAB Toolbox in which the Kalman filter is located, the mathematical calculations are greatly facilitated, such as the development of the least square's method, covariances and time reduction in its development make this a useful and practical tool in this topic.

This type of filter can avoid the implementation of hardware-based filters (Butterworth and Chebyshev) according to the interference signals, which saves design time and constituent elements.

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