Iranian Journal of Oil & Gas Science and Technology, Vol. 3 (2014), No. 3, pp. 62-74
http://ijogst.put.ac.ir

A New Method for Multisensor Data Fusion Based on Wavelet Transform in a Chemical Plant

Karim Salahshoor[1*], Mohammad Ghesmat[1], and Mohammad Reza Shishesaz[2]

[1] Department of Automation and Instrumentation, Petroleum University of Technology, Ahwaz, Iran
[2] Department of Technical Inspection Engineering, Petroleum University of Technology, Abadan, Iran

Received: January 11, 2013; *revised:* June 23, 2013; *accepted:* September 29, 2013

Abstract

This paper presents a new multi-sensor data fusion method based on the combination of wavelet transform (WT) and extended Kalman filter (EKF). Input data are first filtered by a wavelet transform via Daubechies wavelet "db4" functions and the filtered data are then fused based on variance weights in terms of minimum mean square error. The fused data are finally treated by extended Kalman filter for the final state estimation. The recent data are recursively utilized to apply wavelet transform and extract the variance of the updated data, which makes it suitable to be applied to both static and dynamic systems corrupted by noisy environments. The method has suitable performance in state estimation in comparison with the other alternative algorithms. A three-tank benchmark system has been adopted to comparatively demonstrate the performance merits of the method compared to a known algorithm in terms of efficiently satisfying signal-to-noise (SNR) and minimum square error (MSE) criteria.

Keywords: Multisensor, Data Fusion, Wavelet Transform, Extended Kalman Filter, Minimum Mean Square Error (MMSE)

1. Introduction

Obtaining valid and noiseless data poses a critical subject in all the sciences. Various methods have been introduced in the literature to cope with this challenging issue. Multi-sensor data fusion is an attractive method to tackle this problem in noisy environments. It is, in fact, the process of combing information from a number of different sources to provide a robust and complete description of an environment or process of interest. Data fusion has special significance in applications where a large amount of data must be combined, fused, and distilled to obtain appropriate information and integrity.

To implement data fusion in a multi-sensor system, the algorithm used plays a key role and, hence, its development has been a topical area of research in recent years (Xu et al., 2004). Multi-sensor data fusion (MSDF) is a technique that effectively fuses collected data from multiple sensors installed on a process to provide a more robust and accurate estimation of the measured state. Typical area applications include autopilot implementation (Wasif et al., 2012), image data fusion (Salman et al., 2012), the assessment of physical activity (Shaopeng et al., 2012), and fire detection (Wang et al., 2011).

* Corresponding Author:
Email: salahshoor@put.ac.ir

Multi sensor data fusion can be realized via various algorithms. Rao et al. (2000) proposed an interesting coherent estimator that fuses the least mean square (LMS) estimation and wavelet denoising. The multiple inputs are first averaged and the average is then denoised using a wavelet filter. However, as the method uses the arithmetic average for the LMS estimation, it is not optimum in terms of minimum mean square error. Xu et al. (2004) carried out a study on the optimum estimation of a time-varying parameter from multiple observation sequences derived from multiple sensors. In this method, the input data are first measured by several sensors and the results are then fused via importance weights, which can be obtained from data variance. Thus the variance of the fused signal would naturally be less than the minimum variance of the input signals. However, the fused signal will not be an appropriate estimation of the expected signal, if the noise of the input data is more than some limits. De Dona et al. (2009) and Sunet et al. (2004) presented another method based on Kalman filter, which utilized two layers. In the first layer, the system outputs are measured and then data are classified in several observable sets with respect to the state-space matrices. Then, Kalman filter is separately applied to the data sets, leading to several state variable sets. In the second layer, the extracted sets are then fused together proportional to variance matrix. High performance state estimation will be obtained only when Kalman filter is applied to all system states. Therefore, this method will not have suitable performance, because it is often applied only to a set of system states. Moreover, the method demands high computation time. It should be also noted that Kalman filter should be run for every system output set in each sample time. The fused estimates can ultimately be utilized by a time-consuming controlling algorithm to maintain the system performance. Therefore, a fusion algorithm with low computation effort is practically preferable to realize the fusion objective.

This paper presents a new method for data fusion based on the wavelet transform. A system with several outputs, each of which is measured by a multi-sensor, is considered. The sensor outputs are first filtered by wavelet transform and the data variances are then calculated accordingly. The outputs corresponding to every system state, being measured by several sensors, are considered as a separate set. Then, appropriate weights can be obtained via the equation mentioned in Xu's work (Xu et al., 2004). Set components are consequently fused by their corresponding weights, yielding one optimum. Because the resultant weights have optimum values, the LMS error drawback will be improved. At the next step, Kalman filter is applied to the complete state set. In this method, Kalman filter is fired just after data fusion procedure and it is consequently used only one time at each sample time. For this reason, the required computation time is less than the method proposed by De Dona et al. (2009). In addition, Kalman filter uses all the states, which results in a better state estimation.

This paper is organized in three further sections. In the next section, the proposed method is developed. For this purpose, an EKF-based filter is first exploited. Then, wavelet transform will be introduced. The proposed method is finally formulated using an EKF filter and wavelet transform. The performance of the developed method is evaluated in a simulation case study and the obtained results are investigated in section 3. Section 4 summarizes significant conclusions.

2. Development of the proposed method

2.1. Extended Kalman filter (EKF)

Kalman filter is a recursive method that tries to estimate the states $x \in R^n$ of a discrete-time process. The Kalman filter dynamics results from the consecutive cycles of prediction and filtering.

The dynamics of these cycles is derived and interpreted in the framework of Gaussian probability density functions. When either the system state dynamics or the observation dynamics is nonlinear, the conditional probability density functions that provide the minimum mean-square estimate are no longer Gaussian. The optimal non-linear filter propagates these non-Gaussian functions and evaluates their mean, which causes a high computational burden. A non-optimal approach to solve the problem, in the frame of linear filters, is the extended Kalman filter (EKF). The EKF implements a Kalman filter for a system dynamics that results from the linearization of the original non-linear filter dynamics around the previous state estimates.

Let us assume that the equations of the process dynamics and measurement are described by:

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \tag{1}$$

$$z_k = h(x_k, v_k) \tag{2}$$

where, $x \in R^n$ and $z \in R^m$ represent the state and measurement vector respectively. f and h are non-linear functions and random variables w and v denote process and measurement noise respectively. In practice, however, one does not know the individual values of the noises w and v at each time step. However, one can approximate the state and measurement vectors as read:

$$\tilde{x}_k = f(\hat{x}_{k-1}, u_{k-1}, 0) \tag{3}$$

$$\tilde{z}_k = h(x_k, 0) \tag{4}$$

$\tilde{x}_k$ is a posteriori estimate of the state.

To estimate a process with non-linear dynamics and measurement relationships, Equation 1 should be linearized as given below:

$$x_k = \tilde{x}_k + A(x_{k-1} - \hat{x}_{k-1}) + Ww_{k-1} \tag{5}$$

$$z_k = \tilde{z}_k + H(x_k - \tilde{x}_k) + Vv_k \tag{6}$$

where, A and W indicate Jacobian matrices, consisting partial derivatives of f with respect to x and w respectively. Similarly, H and V are Jacobian matrices, including partial derivatives of h with respect to x and w respectively. Then, the posteriori state can be estimated by:

$$\hat{x}_k = \tilde{x}_k + \hat{e}_k \tag{7}$$

$$\hat{x}_k = \tilde{x}_k + K_k(z_k - \tilde{z}_k) \tag{8}$$

$$\tilde{z}_k = h(\tilde{x}_k, 0) \tag{9}$$

$\hat{e}_k$ is the prediction error and K_k is Kalman filter gain, which can be obtained at each iteration via the following recursive equations:

$$\bar{P}_k = A_k P_{k-1} A_k^T + W_k Q W_k^T \tag{10}$$

$$K_k = \bar{P}_k H_k^T (H_k \bar{P}_k H_k^T + V_k R_k V_k^T)^{-1} \tag{11}$$

$$P_k = (I - K_k H_k)\bar{P}_k \tag{12}$$

where, Q and R represent process and measurement noise covariance matrices respectively (Welch et al., 2006).

2.2. Wavelet

A wavelet is a wave function with a compact support. It is called a wave due to its oscillatory nature, and the diminutive –let suffix is used because of the finite domain where it is different from zero (the compact support). The scaling and translation of the basic wavelet $\psi(x)$ (i.e., the "mother" wavelet) can be defined via the wavelet basis:

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi(\frac{x-b}{a}),\ a > 0 \tag{13}$$

By choosing appropriate values for the scaling parameter a and the translation parameter b, the small segments of a complicated form may be represented with a higher resolution (zooming on sharp, brief peaks), while the smooth sections can be represented with a lower resolution.

Wavelet transform is a tool whereby data, functions, or operators are being decomposed into various frequency components. Then, each component is analyzed at the resolution best fit for its scale. Wavelet transform provides an excellent time resolution of high-frequency components and a frequency (scale) resolution of low-frequency components.

In wavelet analysis, it is usually talked about approximations and details. Approximations indicate the low frequency components of a function on large scale represented by the first addend, while the details denote the high-frequency components of a function on smaller scales represented by the second addend in Equation 14. The wavelet transform of a function includes output scaling function coefficients $a_{j,k}$ (approximation) and wavelet coefficients $b_{j,k}$ (details).

$$f(x) = \sum_{k \in z} a_{J,k}\varphi_{J,k}(x) + \sum_{j=1}^{J}\sum_{k \in z} b_{j,k}\psi_{j,k}(x) \tag{14}$$

For determining the wavelet and scaling function coefficients, one step of the analysis consists of the separation of the approximation and details of the discrete signal, thereby yielding two signals as a result. The procedure described is the sub-band coding in signal processing and can be repeated for further decomposition. Figure 1 illustrates the decomposition for further levels.

The algorithm described, which represents the essence of the discrete wavelet transform, is used for the analysis, i.e. the decomposition of signals. Assembling the components in order to gain the initial signal with no loss of information is called reconstruction. The wavelet analysis includes filtering and compression, while the wavelet reconstruction process is composed of decompression and filtering (Radunovic, 2009).

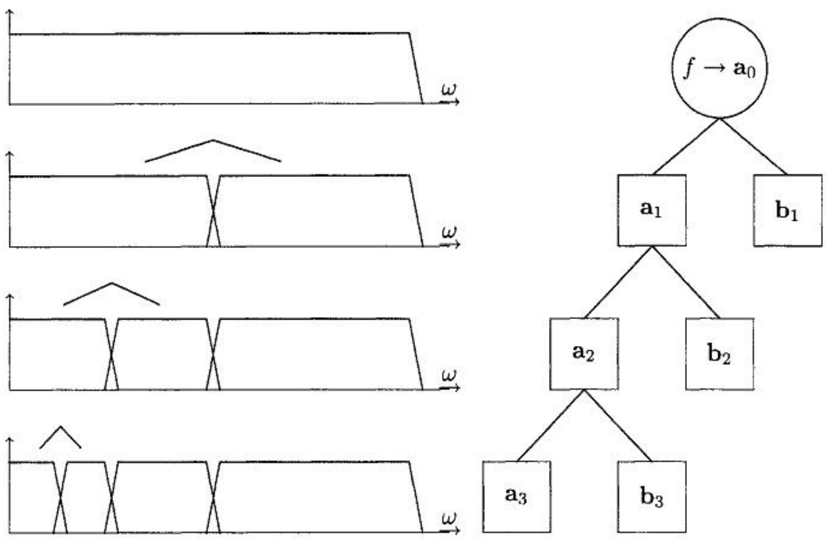

Figure 1
Discrete wavelet transform decomposition (Radunovic, 2009).

2.3. The proposed method

A new method is developed for multisensor data fusion based on wavelet transform and Kalman filter in a recursive manner. To explain how the method operates, a general system is considered with the following characterized state-space model equations:

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \tag{15}$$

$$z_k^i = h(x_k, v_k^i) \qquad i = 1, 2, \ldots, l \tag{16}$$

where, $x \in R^n$ and $z \in R^m$ represent the state and measurement vectors respectively; f and h are non-linear functions and random variables w and v denote process and measurement noises respectively. In Equation 16, i is sensor index. Each state of the system is measured by l sensors. Therefore, every state is measured several times and data fusion algorithm is implemented on these outputs. To perform the data fusion algorithm, wavelet transform (WT) is recursively applied to sensor data at each sample time. To apply WT, it is required to have a block or a horizon of data; thus a horizon is considered with a length of L sample time intervals. As the system is presumed to have n states and every state is measured with l sensors, the horizon encompasses $n \times l$ rows and each row is assigned to one sensor. This horizon is updated at each sample time. Upon entering each new data into the horizon, the oldest data are removed or, in other words, the horizon moves one step forward in the sample time direction. After updating the horizon, WT is applied to the result. WT can extract the approximations and details of the signal at different levels. The number of levels is chosen with respect to measurement noise; if output signal has high noise, a higher number of levels will then be allocated. For data filtering, the approximation signal in the last level is selected as the output. After applying WT to the horizon, a set of approximation signals is obtained for each sensor. It is supposed that data is in the form of a matrix which is represented by H, having $n \times l$ rows and L columns. This matrix is subsequently divided into n sub-matrices, represented by $h_i, \{i = 1,2, \ldots, n\}$, which individually have l rows and L columns. Each sub-matrix contains sensor outputs that belong to one state.

In the succeeding step, data fusion is separately performed on every h_i sub matrix. For this purpose, a parameter is needed in data fusion to indicate data reliability. Variance is employed as a useful measure for this fusion objective. For variance calculation corresponding to each sub matrix row, the mean value of each column is computed and each component difference from the calculated mean value is then squared. Therefore, the variance is determined by averaging all of these values in each row according to Figure 2. It should be noted that Figure 2 has been drawn only for state 1 for the sake of simplicity.

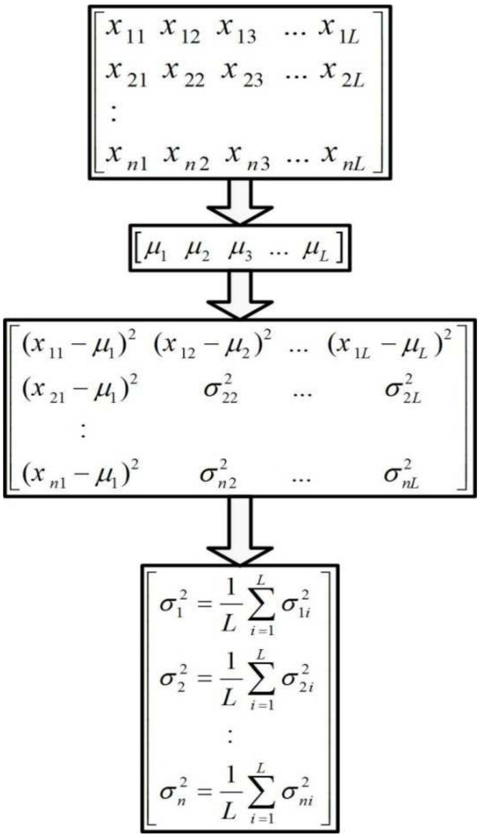

Figure 2
Variance calculation procedure.

After variance calculation, appropriate weights are needed to be determined for data fusion. Xu et al. (2004) presented an optimum weight scheme based on variance using the minimization of mean square error. Suppose there are l sensors in a multi-sensor system to measure each state variable. The observations are denoted by $\{x_{ij}\}(j = 1,2, \ldots, l, i = 1,2, \ldots, n)$. The outputs can then be described as follows:

$$x_{ij}(t)=x_i(t)+n_{ij}(t) \tag{17}$$

where, $n_{ij}(t)$ denotes the white noise added to the original signal $x_i(t)$ in the output $x_{ij}(t)$. The variance of $n_{ij}(t)$ is defined as $\sigma_{ij}^2(t) = E[n_{ij}^2]$, and $E[x]$ is the mathematical expectation of x.

If the observations are unbiased and independent from one another, the measured $x_i(t)$ can be estimated using the following LMS estimator:

$$\hat{x}_i = \sum_{j=1}^{l_i} w_{ij} x_{ij} \tag{18}$$

where, x_i shows ith state of the system; w_{ij} is the weight applied to x_{ij} and $\sum_{j=1}^{l} w_{ij} = 1$. The variance of x_i is given by:

$$\sigma_i^2 = \sum_{j=1}^{l_i} w_{ij}^2 \sigma_{ij}^2 \tag{19}$$

where, σ_{ij}^2 denotes the variance of jth sensor of ith state. If the weights are identical and be equal to $w_{ij} = \frac{1}{l_i}$ for all j's, x_i estimated from Equation 18 will naturally be the arithmetic average of the observation. The variance of this estimate is given by:

$$\sigma_{i_{avr}}^2 = \frac{1}{l_i} \sum_{j=1}^{l_i} \sigma_{ij}^2 \tag{20}$$

Although the arithmetic average has extensively been applied to estimate variables from multiple independent observations, the estimated result is not optimum in terms of MMSE.

Minimizing the polynomial of Equation 19 subject to $\sum_{j=1}^{l} w_{ij} = 1$ yields the following optimum weighs:

$$w_{ij} = \frac{1}{\sigma_{ij}^2 \sum_{j=1}^{L} \frac{1}{\sigma_{ij}^2}} \tag{21}$$

where, n and l are the number of states and sensors respectively, $i = 1,2,\dots,n$ and $j = 1,2,\dots,l$; the minimum variance of the estimation of x_i can be calculated by:

$$\sigma_{i_{\min}}^2 = \frac{1}{\sum_{j=1}^{l_i} \frac{1}{\sigma_{ij}^2}} \tag{22}$$

It can be proved that the result is not only smaller than the variance of any observation sequences but also smaller than the one determined by Equation 20. Furthermore, Equations 2 and 5 can be used to obtain the optimum estimation of the measurable parameters in terms of MMSE (Xu et al., 2004).

The method has some adjustable parameters for achieving the desired results:

- ✓ Length of horizon L: if it is aimed to put more strength on the past sample time effect on data fusion, a larger number should be selected for L.
- ✓ Number of sensors: it is obvious that for having more accurate data, more sensors are needed to be applied.
- ✓ Wavelet transforms level: if the sensor output has high noise, it should be better to select a greater WT level.

After data fusion, one set of values are obtained for all the states. Kalman filter is then applied to the obtained complete state set.

3. Results and discussion

According to Figure 3, to evaluate the performance of the proposed algorithm, a hydraulic system consisting of three identical cylindrical tanks with equal cross-sectional area *S* has been considered. These tanks are connected by two pipes with the same cross-sectional area, denoted by S_p, having the same outflow coefficients represented by μ_{13} and μ_{32}. The nominal outflow located at tank 2 has the same cross-sectional area as the coupling pipe between the tanks with a different outflow coefficient, denoted by μ_{20}.Two pumps are used in the first and second tanks to provide adequate flow rates shown by q_1 and q_2. The maximum flow rate drawn from pump i is denoted q_{imax}. The level in tank *i* and its maximum level in that tank are denoted by l_j and l_{jmax} respectively. The system dynamics can be derived using the following mass balance equations:

$$\begin{aligned} \frac{dl_1(t)}{dt} &= \frac{1}{S}\left(q_1(t) - q_{13}(t)\right) \\ \frac{dl_2(t)}{dt} &= \frac{1}{S}\left(q_2(t) + q_{32}(t) - q_{20}(t)\right) \\ \frac{dl_3(t)}{dt} &= \frac{1}{S}\left(q_{13}(t) - q_{32}(t)\right) \end{aligned} \tag{23}$$

where, q_{mn} represents the flow rate passing from tank *m* to tank *n* $(m, n = 1,2,3 \ \forall \ m \neq n)$ which, based on the Torricelli law, obeys the following relationship:

$$q_{mn}(t) = \mu_{mn} S_p \, sign\left(l_m(t) - l_n(t)\right) \times \sqrt{2g\left|l_m(t) - l_n(t)\right|} \tag{24}$$

q_{20} represents the flow rate which can be described as follows:

$$q_{20}(t) = \mu_{20} S_p \sqrt{2gl_2(t)} \tag{25}$$

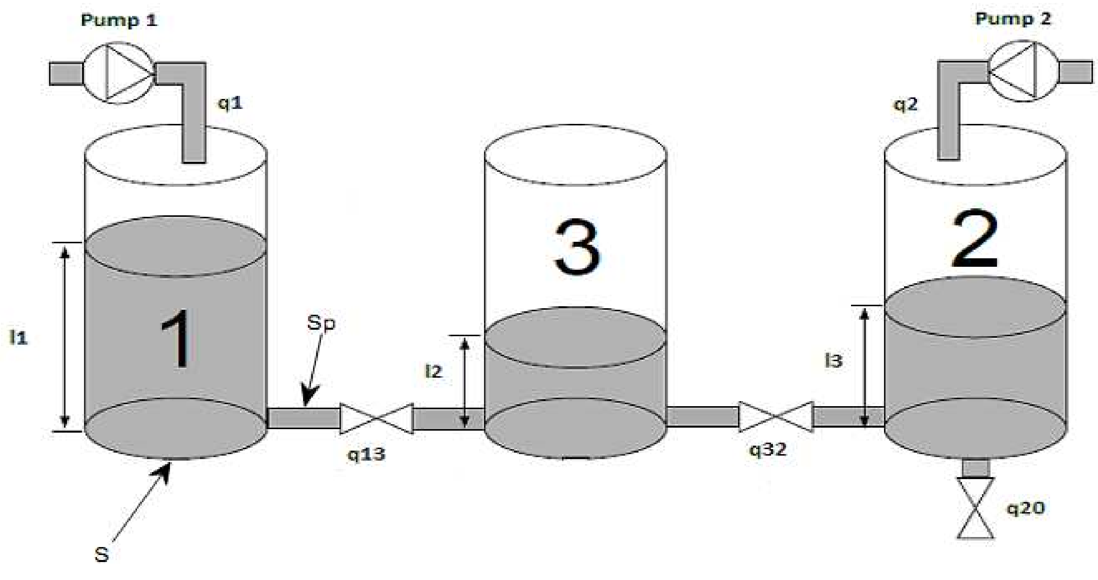

Figure 3
Three tank system descriptions.

Further details on this system are available elsewhere (Mendonca et al., 2008). The parameters of three tank system are given in Table 1.

Table 1
Three tank system parameters.

Variable	Notation	Parameter values
Tank cross sectional area	S	$0.0154\ m^2$
Inter tank cross sectional area	S_p	$5 \times 10^{-5}\ m^2$
Outflow coefficient	$\mu_{13} = \mu_{32}$	0.5
Outflow coefficient	μ_{20}	0.675
Maximum flow rate	$q_{imax}\ \ i \in [1,2]$	$1.2 \times 10^{-4} m^3/s$
Maximum level	$l_{imax}\ \ \ i \in [1,2,3]$	$0.62\ \ m$

To properly demonstrate the comparative capability of the proposed algorithm, the developed algorithm together with the alternative algorithm presented by Xu et al., (2004) is applied to the simulated system and their results are compared. It is supposed that each state is measured with three sensors in a multi-sensor system and the outputs of the sensors $y_i, \{i = 1,2\}$ are assumed to be under the influences of Gaussian white noise v with variances of 0.8, 0.7, and 0.6 having the mean value of zero. Meanwhile, it is supposed that an uncertainty noise w in the form of Gaussian white noise with a variance of 0.2 and a mean value of zero induces the states.

The simulation is conducted for 15 seconds and the length of horizon is selected equal to 10 sample times. This means that H matrix will contain 10 sample times and the algorithm is thus used for this number of data at each sample time. Daubechies wavelet "db4" is chosen as the wavelet function and the wavelet transform level is selected to be set at 2. A high level of wavelet transform can be chosen when the sensor noises are high. The outputs are shown in Figure 4.

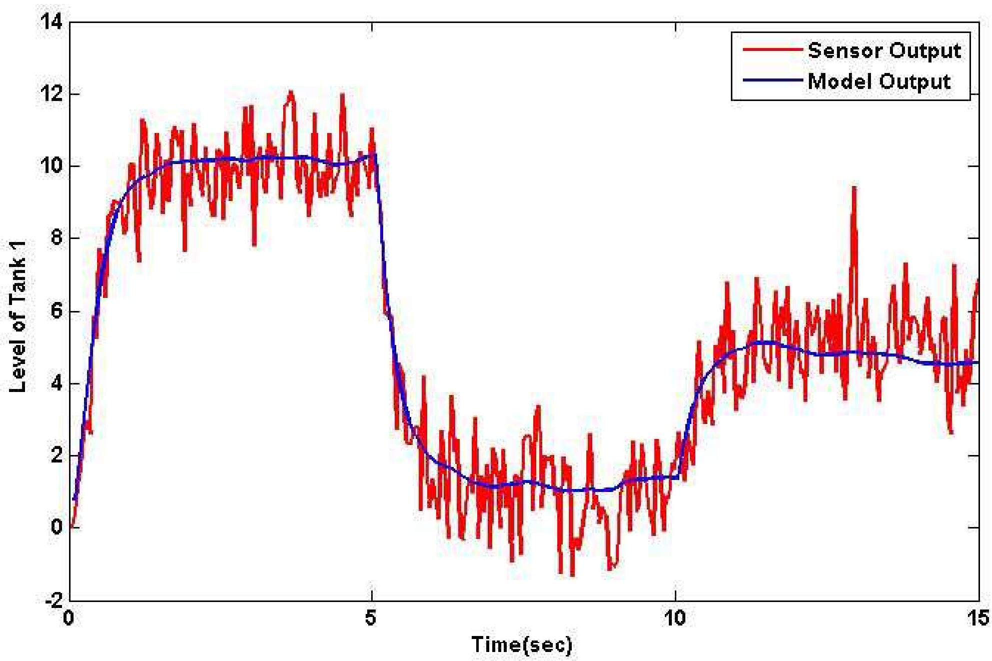

Figure 4
Sensor output of state 1.

The output of the first sensor corresponding to state 1 and the optimized outputs of state 1 estimated by the proposed algorithm are illustrated in Figure 5. It can be seen that the optimized output is close to the real signal. The effectiveness of the algorithm for state 2 is quite similar to state 1. Furthermore, the first manipulated variable of the system, q_1, is shown in Figure 6, which shows how it changes to follow the set point.

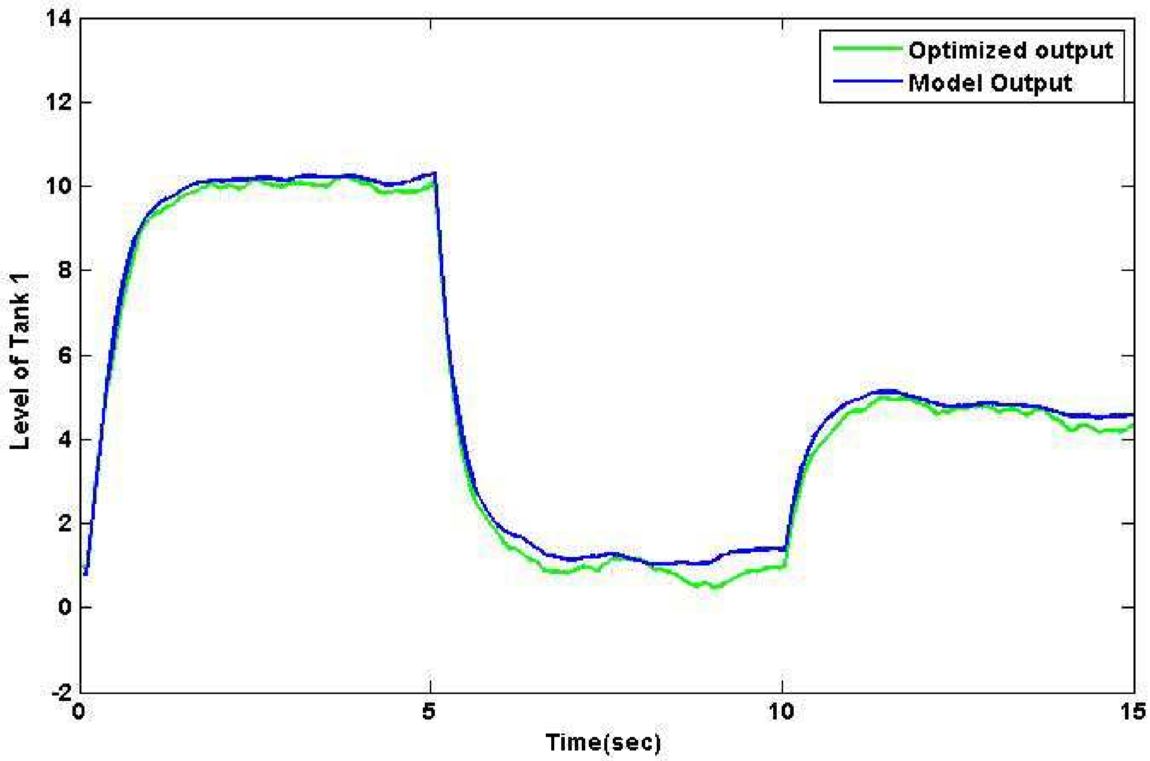

Figure 5
Optimized output of state 1.

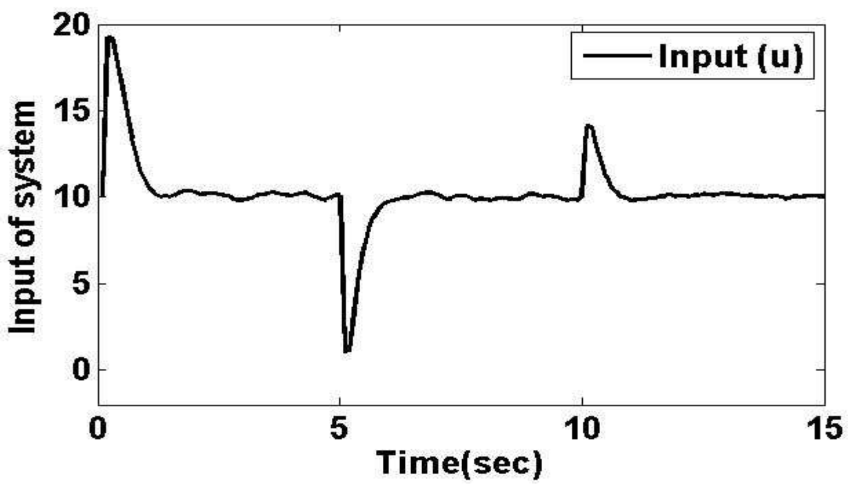

Figure 6
Manipulated variable (q_1)

To compare the results of the proposed algorithm with an alternative algorithm presented by Xu et al. (2004), the system has been undergone through the same test experiment using this algorithm and the result has been demonstrated in Figure 7 for state 1. The close observation of the obtained results clearly verifies that the proposed algorithm has better performance. To provide quantitative measures for a precise comparison, MSE and SNR values for each of the three results are calculated and listed in Table 2 for states 1 and 2. For the better calculations of the results, both algorithms are run for five consecutive times and the similar outputs are then averaged to produce more reliable outcomes. The calculated SNR and MSE values are listed in columns 2 and 3 of Table 2 respectively. The required computational times to carry out each candidate algorithm during each sample time are summarized in column 4 for comparison purposes. It can be observed that each sample time takes 0.1 second and the computational times corresponding to both tested algorithms are less than the sample time. Table 2 clearly states that the SNR of the proposed system is improved in comparison with the original system and the second algorithm. Moreover, the MSE value of the presented algorithm has been improved (decreased) compared to the second algorithm. According to the results obtained, it is clear that the proposed algorithm is able to perform better than the second algorithm presented by Xu et al. (2004).

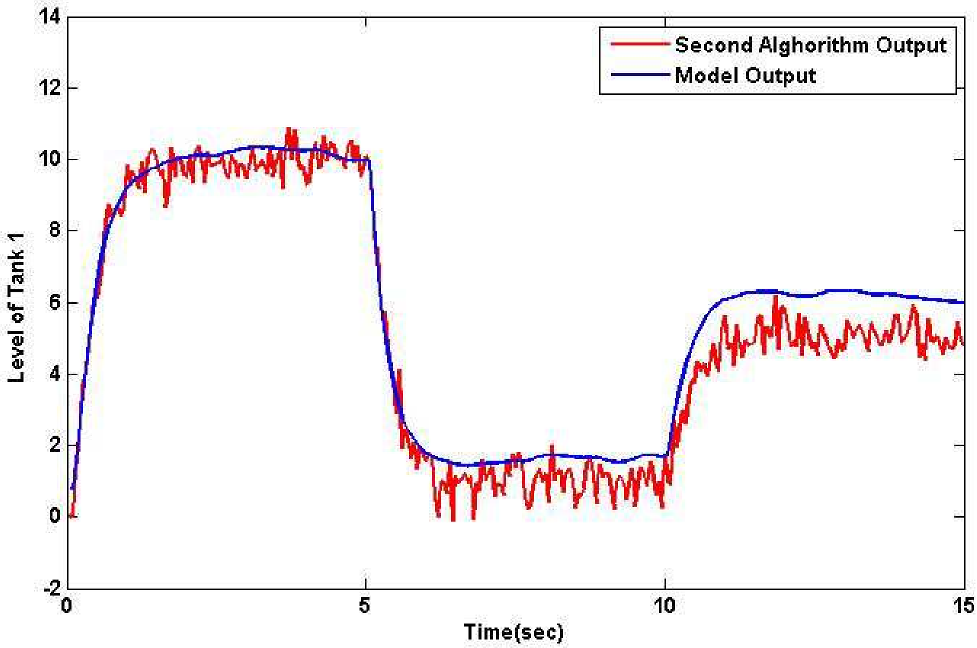

Figure 7
The second algorithm output of state 1.

Table 2
Comparison of the results of the presented and the second algorithm.

	SNR (db)		MSE		Computation time (second/sample time)
	State 1	State 2	State 1	State 2	
System	13.7	19.64	1.67	0.64	-
Presented algorithm	20.84	31.8	0.36	0.21	0.051
Second method	16.1	24.75	0.73	0.44	0.047
Wavelet part	15.3	22.23	0.53	0.49	0.021

As explained earlier, the developed algorithm is composed of two parts. In the first part, wavelet transform is applied and then the variance of the data is extracted to exercise the data fusion. Then, Kalman filter is used in the second part for the final state estimation. To clearly reveal the importance of applying each part, it is useful to show the output obtained by the first part in terms of state 1 in Figure 8. The corresponding SNR and MSE values are listed in the last row of Table 2.

Figure 8 demonstrates that the first part of the algorithm filters the input signal and fuses the data. It is naturally expected that the output of the first part is close to real data. Table 2 also confirms that the SNR corresponding to the first part output is increased, while its respective MSE is decreased in comparison to the system outputs. Thus, the obtained results clearly show the important role of the first part in the developed algorithm.

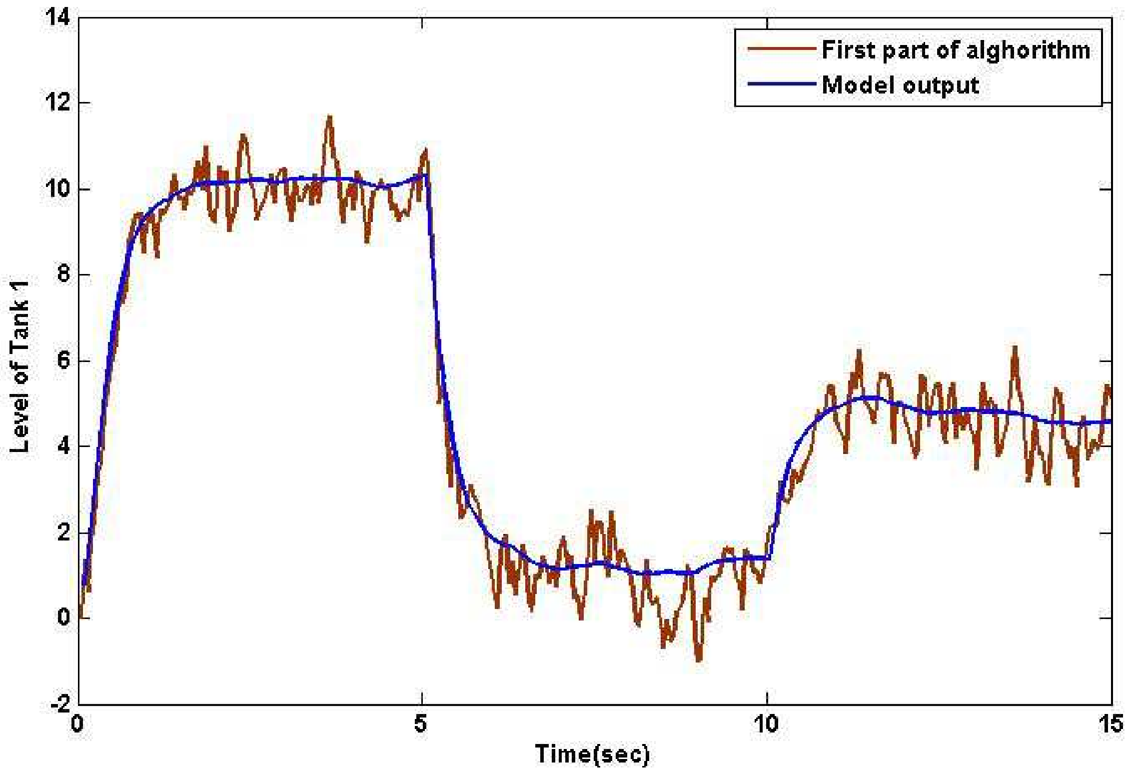

Figure 8
State 1 after applying wavelet and data fusion layer.

4. Conclusions

A multisensor data fusion algorithm was introduced for non-linear systems being faced with noisy environments. The proposed method was developed using the combined wavelet transform and the EKF filter in a recursive formulation. Several scenarios were conducted in a three-tank benchmark system under different noisy conditions to demonstrate the performance of the proposed algorithm in comparison with an alternative algorithm (Xu et al., 2004) in terms of SNR and MSE evaluating parameters.

Acknowledgements

Here, the author would like to thank Mr. Khadem Olama and Mr. Zare Reyisabadi for their help.

Nomenclature

EKF	: Extended Kalman filter
LMS	: Least mean square
MMSE	: Minimum mean square error
MSE	: Minimum square error
MSDF	: Multisensor data fusion
SNR	: Signal to noise ratio
WT	: Wavelet transform

References

De Dona Jose, A., Seron Maria, M., and Yetendje, A., Multisensor Fusion Fault-tolerant Control with Diagnosis via a Set Separation Principle, IEEE Conference on Decision and Control, p. 7825-7830, Shanghai, 15-18 December, 2009.

Mendonca, L. F., Sousa, J., and Costa, J. M. G., Fault Accommodation of an Experimental Three-tank System Using Fuzzy Predictive Control, IEEE International Conference on Fuzzy Systems, p. 1619-1625, Hong Kong, 1-6 June 2008.

Radunovic, D., Wavelet from Math to Practice, Academic Mind, Springer-Verlag, 2009

Rao Anil, M. and Jones Douglas, L., A Denoising Approach to Multisensor Signal Estimation, IEEE Trans on Signal Processing, Vol. 48, No. 5, p.1225-1234, May 2000.

Salman, A., Lars, B., and Brendan, H., Image Data Fusion for the Remote Sensing of Freshwater Environments, Applied Geography, Vol. 32, p. 619-628, 2012

Shaopeng, L., Multisensor Data Fusion for Physical Activity Assessment, IEEE Trans on Biomedical Engineering, Vol. 59, No. 3, p. 687 - 696, March 2012.

Wasif, N., Sutton, R., and Xu T., An integrated Multisensor Data Fusion Algorithm and Autopilot Implementation in an Uninhabited Surface Craft, Ocean Engineering, Vol. 39, No. 1 , p. 43-52, 2012.

Sun Shu, L. and Deng Zi, L., Multisensor Optimal Information Fusion Kalman Filter, Automatica, Vol. 40, No. 6, p. 1017-1023, 2004.

Wang, H., Yugui, Z., Ling, M., and Zhikun, Ch., The Research of Fire Detector Based on Information Fusion Technology, Conference on Electronic & Mechanical Engineering and Information Technology, Harbin, Heilongjiang, Vol. 9, p. 3678-3681, 2011.

Xu, L., Zhang, J. Q., and Yan, Y., A Wavelet-based Multisensor Data Fusion Algorithm, IEEE Trans. Instrum. Meas., Vol. 53, No. 6, p. 1539-1545, 2004.