Kalman filtering to real-time trace water level measurements using ultrasonic sensor

B H Iswanto*, I F Parmono and M Delina
Department of Physics, Universitas Negeri Jakarta, Jl. Rawamangun Muka, Jakarta 13220, Indonesia

*bhi@unj.ac.id

Abstract. Water level monitoring systems are needed in various related fields. However, to accurately determine water levels typically difficult due to the effect like sloshing in dynamic environments. In this paper, we proposed Kalman filter based approach to reduce uncertainty in the water level measurements. Experiments have been performed by filling the tank with water and installing an ultrasonic sensor module at the top center of the tank. The water tank is vibrated with an artificial vibrator, then measuring the water level is done by the ultrasonic sensor. To reduce measurement errors we introduced the Kalman filtering. This technique is developed for improving the precision of water level measurements in the presence of various noise sources. The Kalman filter performance is demonstrated to be adaptive to real-time noise. Experiment results indicate reducing the errors of measurement significantly up to about 60% for a dynamic water condition by adjusting appropriately the Kalman filter tuning parameters.

1. Introduction
Real-time water level monitoring is needed in various related fields, such as water supply systems, hydroelectric power plants, and pre-floods warning systems. Indeed, in these fields, the measurement accuracy may not be very important, but in certain fields, it is very important, such as monitoring of water in a tank. Meanwhile, a dynamic environment is often difficult to control so that causing variations in measurement.

Many studies have been carried out to measure water levels using various techniques. Among others was carried out by developing a water level measurement system using ultrasonic sensors [1]. The system was not equipped with filtering so it was vulnerable to dynamic environmental conditions. Terzic et al. studied fluid level measurement in a dynamic environment using ultrasonic sensor and support vector machine (SVM) [2]. They reported that the v-SVM model using the RBF kernel function and the moving median filter has produced the most accurate outcome compared with the other signal filtration methods in terms of fluid level measurement. The other system was developed by Wallebäck by employing Kalman filter [3], an adaptive filtering technique, to tunable fuel level estimation for heavy vehicles [4]. The author reported that the level measurement results in a good performance and more steady and not that easily affected by fuel movements. But, the system needs a longer time to find the true estimate if the fuel level sensor gives false values during start up. The other author applied Kalman filtering to tunable liquid level estimation in dynamic condition [5,9]. They reported the effectiveness of Kalman filter applied on a prototype model using the ultrasonic sensor but did not explain the level
of disturbance on the object under study. In this paper, we focus on an adaptive filtering technique, known as Kalman filtering, implemented to the real-time water level measurement built using the ultrasonic sensor. Our study also considered the performance of the system for different levels of disturbance.

2. Method
The method of this research with Kalman filtering algorithm was first developed by Kalman and published in 1960 on his famous paper describing a recursive solution to the discrete data linear filtering problem [6]. In this section, we describe the application of Kalman filtering to address the problem of determining an optimal estimate of water level by adapting the formulation of Kalman filtering developed by Leleux et al. [7]. For this problem, the Kalman filter estimates the water level by using a form of feedback control. The filter estimates the water level at some given time and then obtains feedback in the form of measurements possessing a noise component. Intrinsically, the Kalman filter cycle consists of two parts: (i) measurement update; and (ii) time update equations. The first step in the sequence is started by selecting initial values for the water level estimate $x_{k-1}$ and the variance of the error $P_{k-1}$. The next step involves taking a measurement update from the sensor by first computing the Kalman gain $K_k$. Subsequently, the sensor performs a water level measurement to obtain $z_k$ and followed by calculating a water level estimate $\hat{x}_k$ and an error variance estimate $P_k$. After the posterior estimate of water level and variance is obtained, a time update is processed. This step projects the water level and variance estimates from time step $k$ to step $k+1$. Complete Kalman filter cycle can be seen in Figure 1.

![Kalman filter cycle](source:[7])

Here, $Q = \sigma_w^2$ and $R = \sigma_v^2$ represent the true water level variability and the measurement noise variance introduced by the sensor respectively. Once the measurement system has reached equilibrium, then $\lim_{\tau \to \infty} Q = w$, where $t$ is the time the system has been operating and $w$ is a constant. Therefore, the changing of parameters $w$ is one of the central features in tuning the Kalman filter to provide the optimal sensor performance.
3. Results and discussion
Experiments were proposed to study the Kalman filtering to real-time trace water level measurements using the ultrasonic sensor. For this purpose, an ultrasonic sensor module was placed at high $h$, near the top center of the water tank. The distance the module to the water surface is actually calculated as $(x + dx)$, where $dx$ is the position uncertainty. By utilizing the propagation time of ultrasonic wave, the distance can be calculated easily through the equation $(x + dx) = c(t_1 + t_2)$, where $c$ is the velocity of ultrasonic waves in air and $t$ is the propagation time. The high water level can be calculated through the equation $L_x = h - (x + dx)$. Figure 2 shows an overview of the experimental setup. For the experiment, a cylindrical shape tank was used and filled water about 70% of total volume. For the sloshing effect, vibrations are artificially generated using a vibrator motor of 730 rpm.

Figure 2. Sensor module placement on the water tank.

The experiments involved performing several data collection runs for different values of tuning parameter $w$, the ratio of $Q$ and $R$, in order to ascertain the effects of varying the Kalman filter tuning parameters. The value of tuning parameter $w$, ratio of $Q$ and $R$, were varied from 0.01, 0.10, 1.00 and 10.00. For each parameter value, water level measurements were conducted for about 15 second and 150 measurement of water level were collected. By adjusting the parameters, the optimal parameter estimate of the measurement will be obtained [8], so that the measurements can be made as accurately as possible. Experimental results and output of the Kalman filters for two different values of the tuning parameters are shown in Figure 2. The thin lines show the measurement data without Kalman filtering (raw data), while the Kalman filter calculation data are shown by thick lines. As shown in the graph, the measurement data without using the Kalman filter fluctuates significantly compared to filtered data.

Our experimental result using Kalman filtering show that the optimal value obtained in the tuning parameter $w = 0.001$ with a measurement variance reduction reaches 59.78% (Figure 3a). While a poor result was achieved by tuning parameter values of $w = 10.00$ with a reduction of measurement variance of 4.14 %, almost no filtering on the measurement data (Figure 3b). From the observations, the filtering results show that for small adjustment parameters, Kalman's filtering value will be slower to respond to measurements, thereby reducing the estimation of variance. While the filter responds to measurements quickly, increasing the estimated variance, for large tuning parameters. These results are in accordance with simulation using Kalman filtering for different value of tuning parameters as reported [6, 10, 11].
Figure 3. The output of Kalman filter for different tuning parameters: (a) $w = 0.001$, resulting in reduced estimate variance, and (b) $w = 10.00$, resulting in increasing the estimate variance of the water level measurement.

4. Conclusion
Kalman filters can be used significantly to reduce the measurement errors of water level using ultrasonic sensor by tuning a constant $w$, ratio of the true water level variability $Q$ and the measurement noise variance $R$, appropriately according to sloshing level of the water environment. Experimental result show that the greater the parameter value of $w$, the system will be more responsive to the results of actual measurements, and vice versa.

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