INTERNATIONAL JOURNAL OF PRECISION ENGINEERING AND MANUFACTURING Vol. 18, No. 1, pp. 31-38 JANUARY 2017 / 31
DOI: 10.1007/s12541-017-0004-9 ISSN 2234-7593 (Print) / ISSN 2005-4602 (Online)

Identification of Unknown Parameter Value for Precise Flow Control of Coupled Tank using Robust Unscented Kalman Filter

Ji-Hoon Seung[1], Amir F. Atiya[2], Alexander G. Parlos[3], and Kil-To Chong[1,#]

1 Division of Electronic Engineering, Chonbuk National University, 567, Baekje-daero, Deokjin-gu, Jeonju-si, Jeollabuk-do, 54896 South Korea
2 Department of Computer Engineering, Cairo University, Cairo University Rd, Oula, Giza, Egypt
3 Department of Mechanical Engineering, Texas A&M University, College station, TX, 77843, USA
Corresponding Author / E-mail: kitchong@jbnu.ac.kr, TEL: +82-63-270-2478, FAX: +82-63-270-2394

KEYWORDS: Unknown parameter estimation, Mechanical system, Robust unscented kalman filter, Nonlinear filter

In this paper, we consider the problems of state estimation and parameter estimation. The goal is to consider Robust Unscented Kalman filter, and demonstrate their successful application on a Coupled Tank system. Traditional unscented kalman filter have a limitation to estimate the state and parameter of time-varying parameter system due to making use of fixed measurement covariance without updating measurement error between measured data and estimated data. Proposed method is Robust Unscented Kalman filter to perform the estimation of the changing parameter value. A structure of the Coupled Tank System consists of connected two tank with basin. The other goal is to make use of the considered filtering method to compare between the other methods. Extensive experiments by numerical simulations and experimentation using real hardware are performed. The study of the experimental results shows a proposed method concern various aspects, such as estimation accuracy, convergence speed, and the accuracy of estimating fixed parameter values. Overall, the proposed Unscented Kalman filter turned out the best of the other considered methods.

Manuscript received: February 6, 2016 / Revised: July 18, 2016 / Accepted: September 5, 2016

NOMENCLATURE

A_1 = cross-sectional areas of tank 1 (cm^2)
A_2 = cross-sectional areas of tank 2 (cm^2)
c_1 = orifice coefficient of tank 1
c_2 = orifice coefficient of tank 2
q_i = pumping rate (Volts)
k_{flow} = flow constant ((cm^2/sec)/volt)
ε_k = Innovation matrix
R_k = updated measurement covariance

1. Introduction

At the present time, there are many problems in science, here is a need to surmise the values of certain state variables from some noisy measurements. This is a universal problem of state estimation or filtering, in the field of engineering, medical or economic applications. For example, in a mechanical structure, we may need to estimate the motion variables for its constituent parts from external position and/or velocity measurements. Additionally, for an electric motor we can estimate internal magnetic field components from measurements of the current and the voltage, for the purpose of monitoring its condition.[1] In some applications the state is completely inaccessible, while in others costly sensors are needed. Therefore, an efficient state estimation algorithm could provide significant cost savings.

Typically, the system is described by a state equation that describes its evolution with time, and whose form is known. A number of outputs or measurements are observed, and from these we need to estimate the states. The pioneering work of Kalman is to obtain a full analytical solution for linear systems, recognizing that the majority of systems encountered in practice is nonlinear. There are several approaches have been developed for such systems. The Extended Kalman filter (EKF) is based on using the nonlinear equations for some aspects of the calculations and on using linearization for the other aspects. In that respect, it is not entirely optimal because of the partial linearization, even though it has a significant improvement over the basic Kalman filter, when dealing with nonlinear systems. The Unscented Kalman filter (UKF) attempts to tackle some of the limitations of EKF, especially the fact that the covariance matrix is propagated through a linearization of the system. The UKF is based on considering a number of sample points around the value of the state estimate. These points are then propagated through the non-linear functions, and the mean, also the covariance matrix of the estimate is then estimated. An entirely different approach based on Monte Carlo sampling, is a so-called Particle filter approach (PF). It is based on a probabilistic formulation of the states and the measurements. From these probability densities a number of sample points or particles are generated and propagated according the state equations, in order to model these densities. State estimates are then obtained based on these particle values, which express the posterior density of the states.

Another important problem encountered in many applications involving state equations is a so-called parameter estimation problem. Even though the form of the state equation is assumed to be known in the filtering problem, however, some of their fixed parameters could be unknown. For example, many of the mechanical and electrical systems used in the current industry are represented by second-order dynamics models comprised of mass, damper, spring, inductances, resistors, and capacitors. These possess values are generally constant, but could be unknown because, it is a possibility that, there values according to the data sheets are missing or inaccurate. In addition to estimating the states (such as velocity, angular velocity, acceleration, branch currents, etc.), one also needs to be estimated, the fixed parameters. Even if the parameter values are known beforehand, their values could drift slowly with time. The motivation to estimate the value often stems from the need to monitor the condition of the equipment. As it turns out the parameter estimation problem is frequently the harder of the two problems. This has because of the parameter values have an effect on all states and measurements of all times combined.

In this paper, we are going to consider on two problems, state estimation and parameter estimation. The goal of this study is as following;

A. Apply the state and parameter estimation methods on real mechanical system, with the aim of testing an ability to produce accurate estimates for the structures.
B. Utilize the proposed structures as a vehicle for comparing between the nonlinear state and parameter estimation methods, that are EKF, UKF, PF and proposed filter.
C. Apply the algorithms for a model using real hardware. This is for the purposed method can be improvement in estimating state and parameter of system better than the other considered method.

The proposed method is Robust Unscented Kalman filter (RUKF) with updating the measurement covariance in this paper. RUKF can be adaptively adjusted on various environment or external noise due to its updating characteristics related with priori measurement and real measurement. We consider that the mechanical system is a coupled tank system. The coupled tank system is widely used in a diversity of industrial field such as steel, nuclear, chemistry among others. Therefore, the state and parameter estimation of coupled tank system is exceedingly meaningful. In the proposed comparison, we consider several aspects of performance, such as steady state estimation accuracy, parameter estimation accuracy, transient behavior, and convergence speed. On most counts, the RUKF is the best as of the other considered algorithms, followed by PF, UKF then EKF. The details of the findings are given in the next sections.

The paper is organized as follows. We begin in Section II with a literature review, followed in Section III with a description of Robust Unscented Kalman filter. Section IV describes the coupled tank, which is the non-linear systems handled in this paper. Also in Section V, the state equations are derived and the state equation is modified to the state space matrix for the simulation. The computer simulation, experiments, and results are outlined in Section V. Finally, in Section VI provides a discussion and gives a conclusion for this work.

2. Literature Review

Filtering, or state estimation has been applied to numerous applications, in domains that include aerospace, electrical engineering, economics, and biological systems. The area concerned in this work is, state estimation for mechanical structures, such as a pendulum-based and coupled water tanks, has also seen some application in the literature. For example, Lichter and Dubowsky[2] applied a Kalman filter for the estimation of motions, positions, and deformations of large interacting mechanical structures. This could be a useful application for space missions, where robots are expected to inspect and maintain large space structures in orbit. Roffel and Narasimhan[3] apply the extended Kalman filter for the estimation of parameters and states of structures called Pendulum tuned mass dampers (PTMDs). These are employed in several applications for the purpose of attenuating excessive structural motions, which are mostly due to wind. Xie and Fang[4] apply the unscented Kalman filter, and its modification, called iterated unscented Kalman filter, to the problem of estimation of a nonlinear structural system. Matta et al.[5] apply the UKF to the problem of identification of a new prototype of rolling-pendulum tuned vibration absorber. They show that the proposed UKF is effective in identifying the structural parameters of the new device. Alkay[6] compared the EKF with UKF for the problem of state estimation for an inverted pendulum. Some novel techniques such as neural networks have also been applied to mechanical structures and pendulum-type systems. For example, Mori, Nishihara, and Furuta[7] consider a problem of the pendulum-cart system, and developed the methods for state estimation and control. Orlowska-Kowalska and Szabat[8] consider the use of neural networks for the state estimation of a two-mass drive system with elastic joints. Other applications to mechanical structures include the work of Parlos, Menon, and Atiya,[1,9] An, Atkeson, and Hollerbach,[10] Swevers et al.,[11] Oh et al.[12] Aksoy, Muhurcu, and Kizmaz,[13] and Zheng, Ikeda, Shimomura.[14]

Concerning coupled water tanks, Geetha, Jerome, and Devatha[15] applied EKF to the state estimation of a structure consisting of two interacting tanks. They have used the state estimation technique to develop a model predictive control scheme. Villez et al.[16] has proposed the use of both, the Kalman filter and the extended Kalman filter for the problem of state estimation of a nonlinear buffer tank system. They have shown the superiority of EKF. Moreover, they have used their estimator for actuator and sensor fault detection and identification. Bharath Kumar, Muthumari, and Jayalalitha[17] have applied the EKF for the estimation of a four tank system. It is a nonlinear system that follows the law of mass balance and energy equations. Following the state estimation, they applied model predictive control technique.

Several studies set out to compare between different filtering methods. For example, Kim et al.[18] compared the performance of the extended Kalman filter, the unscented Kalman filter, and the PF. In addition, a hybrid Rao-Blackwellized PF approach by combining the EKF with the PF is also considered. They have applied the comparison to the problem of estimating the state for some ballistic missile problem. St Pierre and Gingras[19] compared the performance of the EKF and the UKF in the context of position estimation for a navigation system. Daum[20] has presented an analysis and comparison between the EKF, the UKF and the PF. In particular, they have discussed the effect of the curse of dimensionality, and suggest ways to improve the PF by using quasi-Monte Carlo approaches. Chatzi and Smyth[21] also compared between the UKF and the PF for the problem of identification of non-collocated measurements, which is a three degree of freedom system, involving a hysteretic component.

3. Robust Algorithm based on UKF

The traditional UKF is developed to overcome some of the drawbacks of the EKF, especially the fact that in some aspects linearization was performed rather than taking into account the true nonlinear relation.[10] Specifically, the covariance matrix is propagated through a linearized version of the nonlinear model, and this can lead to an error. The UKF uses the unscented transform (UT), which is based on propagating a number of selected points through the nonlinear model, based on the spread of the points after the transformation, one can estimate the covariance matrix.

$$x_{k+1} = f(x_x, u_k) + w_k \tag{1}$$

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

where, $x_k \in \Re^n$ is the $n \times 1$ state vector, $z_k \in \Re^n$ is the $m \times 1$ observation vector, the process noise and measurement noise are denoted by $w_k \sim N(0, Q_k)$ and $v_k \sim N(0, R_k)$ respectively. The functions f, h represents the non-linear state update function and the measurement equation, respectively.

Unscented transform (UT) consisting of Two steps, is described as follows:

Step 1. Calculation of sigma points:

$$\chi^0_{k|k} = \hat{x}_{k|k} \tag{3}$$

$$\chi^i_{k|k} = \hat{x}_{k|k} + (\sqrt{(n+\lambda)P_{k|k}})_i \tag{4}$$

$$\chi^{i+n}_{k|k} = \hat{x}_{k|k} - (\sqrt{(n+\lambda)P_{k|k}})_{i+n} \tag{5}$$

χ_k is the sigma points of $\hat{x}_{k|k}$. $P_{k|k}$ is the state error covariance. $(\sqrt{(n+\lambda)P_{k|k}})_i$ is the i-th row of the matrix square root.

Step 2. Calculation of weighting coefficients:

$$w^{(m)}_0 = \lambda/(n+\lambda) \tag{6}$$

$$w^{(c)}_0 = \lambda/(n+\lambda) + (1-\alpha^2+\beta) \tag{7}$$

$$w^{(m)(c)}_i = 1/\{2(n+l)\} \tag{8}$$

$\lambda = \alpha^2(n+\kappa) - n$ is a scaling parameter, α determines the spread of the sigma points around x and is usually set to a small positive value (e.g., $1 \le \alpha \le 10^{-4}$). κ is a secondary scaling parameter that is usually set to 0, and β is used to incorporate prior knowledge of the distribution of x (for Gaussian distributions, $\beta = 2$ is the optimal choice). $w^{(m)}_i$ and $w^{(c)}_i$ denote the i-th weights of mean and covariance, respectively.

Initialize with:

$$\hat{x}_0 = E[x_0] \tag{9}$$

$$P_0 = E[(x_0-\hat{x}_0)(x_0-\hat{x}_0)^T] \quad k \in \{1, \ldots, \infty\} \tag{10}$$

Calculate sigma points using Eqs. (3)-(8):

$$\chi^i_{k-1} = [\hat{x}_{k-1}, \hat{x}_{k-1} + \sqrt{(n+\lambda)P_{k-1}}, \hat{x}_{k-1} - \sqrt{(n+\lambda)P_{k-1}}] \tag{11}$$

State Propagation:

$$\chi^i_{k|k-1} = f(\chi^i_{k-1}) \tag{12}$$

$$\hat{x}_{k|k-1} = \sum_{i=0}^{2n} w^{(m)}_i \chi^i_{k|k-1} \tag{13}$$

$$P_{k|k-1} = \sum_{i=0}^{2n} w^{(c)}_i [\chi^i_{k|k-1} - \hat{x}_{k|k-1}][\chi^i_{k|k-1} - \hat{x}_{k|k-1}]^T + Q_k \tag{14}$$

Each sigma point Z_i is obtained by non-linearity transformation $Z_i = f(\chi_i)$.

Observation Propagation:

$$Z^i_{k|k-1} = h(\chi^i_{k|k-1}) \tag{15}$$

$$\hat{z}_{k|k-1} = \sum_{i=0}^{2n} w^{(m)}_i Z^i_{k|k-1} \tag{16}$$

$$P^{zz}_{k|k-1} = \sum_{i=0}^{2n} w^{(c)}_i [Z^i_{k|k-1} - \hat{z}_{k|k-1}] \times [Z^i_{k|k-1} - \hat{z}_{k|k-1}]^T + R_k \tag{17}$$

$$P^{xz}_{k|k-1} = \sum_{i=0}^{2n} w^{(c)}_i [\chi^i_{k|k-1} - \hat{x}_{k|k-1}] \times [Z^i_{k|k-1} - \hat{z}_{k|k-1}]^T \tag{18}$$

The mean $\hat{z}_k$ and covariance P^z_k are determined by the new sigma points Z_k.

Update:

$$K = P^{xz}_{k|k-1}(P^{zz}_{k|k-1})^{-1} \tag{19}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K(z_k - \hat{z}_{k|k-1}) \tag{20}$$

$$P_{k|k} = P_{k|k-1} - K(P^{zz}_{k|k-1})K^T \tag{21}$$

where P_k is state error covariance, P^{xz}_k is correlation error covariance, $w^{(m)}_i$, $w^{(c)}_i$ are the weights calculated by Eqs. (6)-(8).

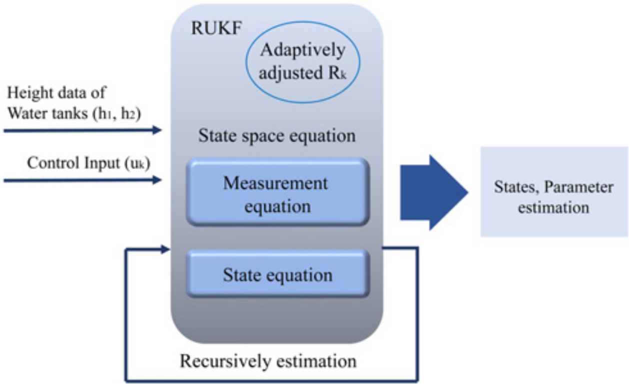

Fig. 1 Schematic diagram of proposed algorithm

Robust Rule:

$$\varepsilon_k = z_k - h(\hat{x}_k, u_k) \tag{22}$$

$$c_k = \frac{\sum_{i=k-L+1}^{k} \varepsilon_i \varepsilon_i^T}{L} \tag{23}$$

$$R_k = c_k + \sum_{i=0}^{2n+1} w_c^{(i)} [Z_{k|k-1}^i - z_k + c_k] \times [Z_{k|k-1}^i - z_k + c_k]^T \tag{24}$$

As it is mentioned, the RUKF is the estimation method that recursively calculates the state of the system based on UT and real-time update of measurement covariance by innovation matrix ε. It has similarities with the conventional Unscented Kalman filter. However, RUKF can apply to time-varying system although obtaining high noised measurement data. This means that RUKF has an advantage of applying to the nonlinear system.

Fig. 1 is structure of the RUKF algorithm. In chapter 5, we consider the estimation methods of EKF, UKF and PF to compare the results of parameter estimation.

4. Coupled Tank System

The dynamic system is utilized, described and derived in this section to estimate the state and parameter which is then realized in order to obtain the measurement data from the dynamic system. The derived equation is transformed into the form of a state space equation. The system is a coupled tank system. The coupled tank system is relatively simple with a second-order ODE but its orifice coefficient is important for the stability and control of the system.

4.1 System

The coupled tank system consists of two tanks, a pump and a water basin. The two tanks are mounted in such a way so that water from the first tank flows into the second while the outflow from the second tank goes into the water basin. Rubber tubing with appropriate couplings is used to pump in water into any one of the tanks. The output rate of the pump controls the output flow ratio of the two tanks. The performance of the control system is a function of the orifice coefficient of the two tanks and the output rate of the pump. A 3D modelling with block diagram of the system utilized are shown in Fig. 2.

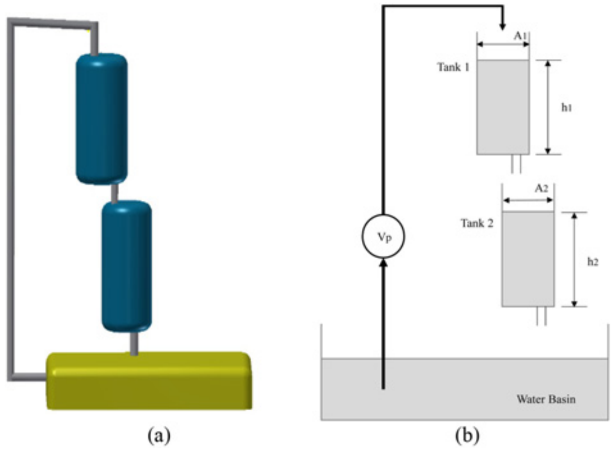

Fig. 2 (a) 3D modelling (b) block diagram of coupled tank system

4.2 Modelling

The mathematical model of the coupled tank can be written as:

$$\frac{dh_1}{dt} = f(h_1, q_{i1}) \tag{25}$$

$$\frac{dh_2}{dt} = f(h_2, q_{i2}) \tag{26}$$

where, h_1, and h_2 are the water level heights of tank 1 and tank 2 respectively, and q_{i1}, q_{i2} are the water flow rates into tanks 1 and 2.

The tank heights can be obtained by calculating the difference between inflow and outflow. Each outflow rate of the tanks is given by:

$$c_1\sqrt{h_1}\,,\ \ c_2\sqrt{h_2} \tag{27}$$

where, c_1 and c_2 are the orifice coefficients.

Since the inflow rate of tank 2 is the same as the outflow rate of tank 1, the total rate of change including the input from the pump can be derived as follows:

$$\begin{aligned} &q_{i1} - c_1\sqrt{h_1} - A_1\frac{dh_1}{dt} = 0 \\ &c_1\sqrt{h_1} - c_2\sqrt{h_2} - A_2\frac{dh_2}{dt} = 0 \\ &q_i = k_{flow} v_i \end{aligned} \tag{28}$$

where, k_{flow} is a constant in (cm^2/sec)/volt, v_i is the pump input, also A_1 and A_2 denote the inside areas of the tanks.

4.3 System transformation

$A_1\frac{dh_1}{dt} = A_1 h_1$ and $A_2\frac{dh_2}{dt} = A_2 h_2$ is defined in order to transform the equation into a form that can be applicable for filters. Eqs. (26) and (27) are then rearranged following Eq. (29) into:

$$\begin{aligned} A_1\dot{h}_1 &= k_{flow} v_i - c_1\sqrt{h_1} \\ A_2\dot{h}_2 &= c_1\sqrt{h_1} - c_2\sqrt{h_2} \end{aligned} \tag{29}$$

The following state space form is obtained:

Table 1 Setup of data acquisition system

Name	Specifications
Hewlett Packard 6253A	Regulation: 0.01% Ripple: 200 μV
BNC-2120 Connector Block	Analog I/O Digital I/O
NI PXI 8145-RT	Real-time Embedded Controller. Processor: 266 MHz low-power Intel Pentium MMX Interface: Serial, CAN, MXI-3 chassis expansion
NI PCI 6064E DAQ Board	Resolution: 12, 16 bit 1 Channel: 500 ks/s Multichannel: 250 ks/s
NI PXI 1031-Chassis	Accuracy: ±25 ppm Maximum Clock: 250 ps

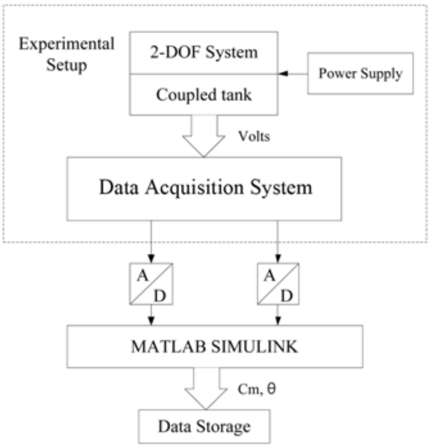

Fig. 3 Diagram of data acquisition system

$$\begin{bmatrix} \dot{h}_1 \\ \dot{h}_2 \end{bmatrix} = \begin{bmatrix} \dfrac{k_{flow}v_i - c_1\sqrt{h_1}}{A_1} \\ \dfrac{c_1\sqrt{h_1} - c_2\sqrt{h_2}}{A_2} \end{bmatrix} \tag{30}$$

Finally, we get the state space equation including unknown parameter is as follows:

$$\begin{bmatrix} \dot{h}_1 \\ \dot{h}_2 \\ \dot{c}_1 \\ \dot{c}_2 \end{bmatrix} = \begin{bmatrix} \dfrac{k_{flow}v_i - c_1\sqrt{h_1}}{A_1} \\ \dfrac{c_1\sqrt{h_1} - c_2\sqrt{h_2}}{A_2} \\ 0 \\ 0 \end{bmatrix} \tag{31}$$

4.4 Data acquisition system

The equipment description and specification for the experiments is given in Table 1. The following conditions are set for the coupled tank system: (i) the pump supplies a fixed amount of water into tank 1, (ii) the amount of water in tank 2 depends on the outflow from it. This is a continuing process until tank 1 is full. The measured variables are the height of the tanks while the sampling rate for measuring the data of voltage level is set at 100 Hz. The heights of the tanks are measured by a DAQ Board that is transmitted to MATLAB Simulink. The measuring equipment is calibrated based on the initial values of the system before running them. Fig. 3 gives the block diagram for the data acquisition process.

Table 2 Parameter specifications of coupled tank system

Description	Val.	Unit
Cross-sectional areas of tank 1	15.5179	cm^2
Cross-sectional areas of tank 2	15.5179	cm^2
Pumping rate	5	volt
Flow constant	6	(cm^2/sec)/volt
Orifice coefficient of tank 1	5	
Orifice coefficient of tank 2	5	

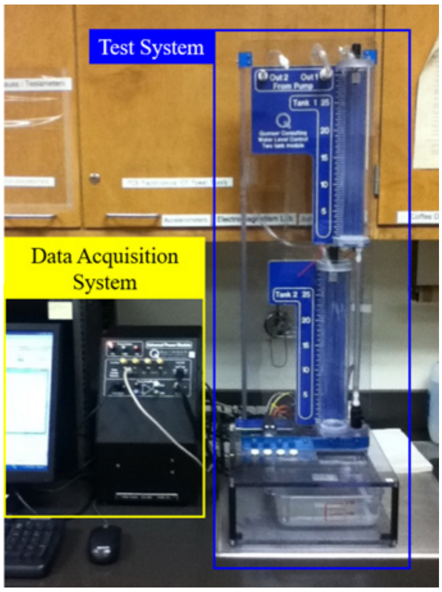

Fig. 4 Experimental system

5. Identification of Unknown Parameter

Before implementation, initial values of coupled system are define following its data sheets. The parameter description of the dynamic system is given in Table 2. The real-world experiments to compare the performances of EKF, UKF, PF and RUKF on coupled-tank system are presented in this section. To handle with estimating the state and parameter of system, we make a test system as Fig. 4. Parameter estimation is considered in addition to state estimation. The orifice coefficients of the tanks are unknown parameters that need to be estimated for precise control of a coupled tank system.

The different filtering algorithms are tested in this section using actual hardware setups in a physical setting of a coupled tank. The initial value for the test system is $x_0 = [0 \quad 0]$ and the system is continues to operate until the tank 1 is full. A fixed amount of water flows into tank 1 via a pump and the outflow from tank 1 goes into tank 2 by gravity. A critical element has to be estimated is the covariance matrix of the noise using a priori measurement and measurement obtained by test system. The initial filter settings for estimating the state and the parameters in

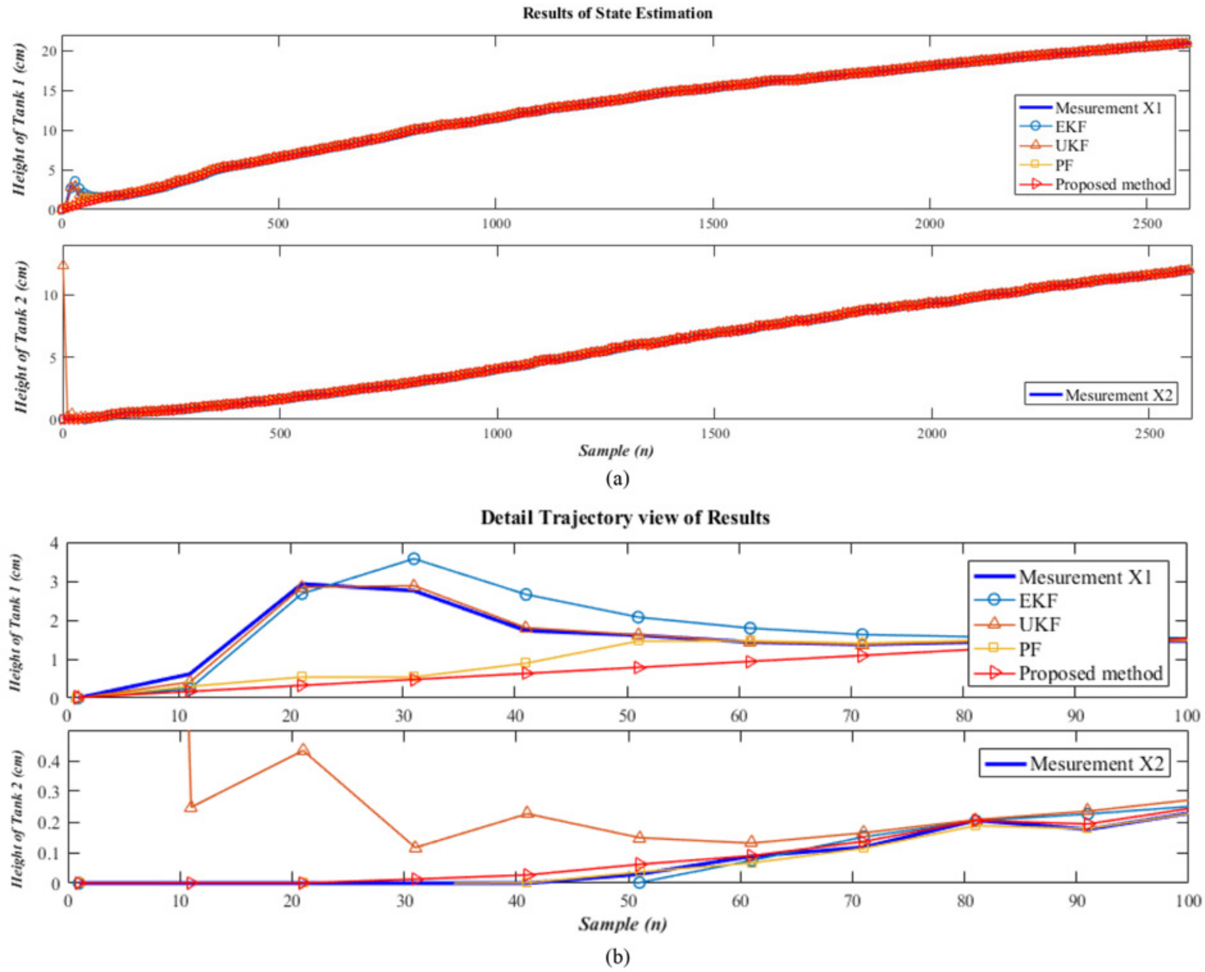

Fig. 5 (a) Result of state estimation (b) detail view of estimation results of sample 0 to 100

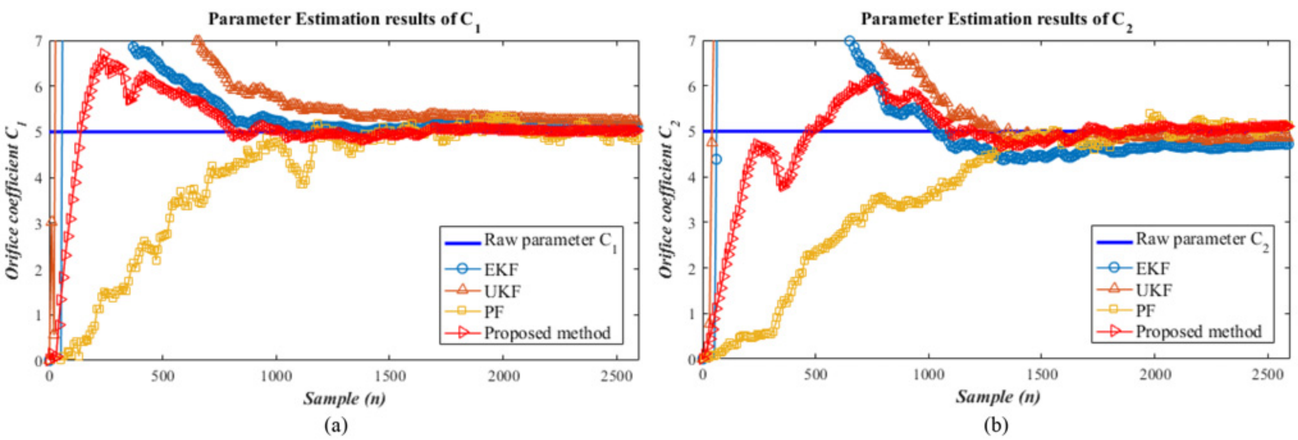

Fig. 6 (a) Trajectory of parameter estimation for orifice coefficient C_1, (b) Trajectory of parameter estimation for orifice coefficient C_2

experimental are assumed to be the same environments.

5.1 State estimation

The initial value and covariance of filters for system is defined as:

$$x_0 = 0_{1\times 4}, \quad P_0 = I_{4\times 4} \tag{32}$$

The RUKF and UKF algorithm's parameters are set as follows: $\alpha = 10$ and $\beta = 2$, while the number of particles for the PF is selected as 1000.

Fig. 5 shows the state estimation result using the different algorithms of EKF, UKF, PF and RUKF. In Fig. 5(b), we observe in the first part of the states' trajectory a bump in the height due to an initial rush of

Table 3 Performance of Parameter Estimation for Test System

Estimation methods (after converged from sample 1200~)	Unknown Parameter			
	c_1 (=5.00)		c_2 (=5.00)	
	Value	Error	Value	Error
Extended Kalman filter	5.1211	0.1211	4.6091	0.3909
Unscented Kalman filter	5.3062	0.3062	4.8883	0.1117
Particle filter	4.9876	0.0124	4.9493	0.0507
Proposed method (RUKF)	5.0084	0.0084	4.9842	0.0158

Table 4 Analysis of Estimating Time (offline test)

Algorithm	EKF	UKF	PF	RUKF
Estimating Time$_{(sec)}$	0.602	2.249	980.145	2.529

water from the pump until approximately sample 10 to 60. This bump is magnified in order to closely check the tracking behavior of such state trajectory. It can be observed that the proposed algorithms converge very well without that bump, but the three algorithms except proposed algorithm, however fails to catch the initial bump while EKF is a bit off.

5.1.2 Parameter estimation

The state and parameter estimation of test system are performed simultaneously to estimate the orifice coefficients of Tanks 1, 2, respectively. The trajectories of the parameter estimation of the different algorithms with time are shown in Fig. 6 while the steady state RMS errors are given in Table 3. Figs. 6(a) and (b) show that the proposed method converges fairly and quickly to the raw parameter values. One reason for the fast convergence is the efficient and speedy update of the error covariance P with robust rule (22-24). The convergence time to the true reference has been slow in the case of PF and the estimate fluctuates somewhat more and compared with that of other algorithms. It also can be observed that proposed estimation algorithm converges close to the true value quite well and faster than three algorithms. The EKF and UKF have the drawback of producing a large and problematic overshoot. There is no clear superior method in terms of the steady state error due to the mixed results. Overall, proposed algorithm RUKF seems to be generally the better of the algorithms from the point of view of convergence characteristics and tracking errors.

5.1.3 Comments of the results

By observing the results from the experiments, one can conclude that RUKF has high performance to estimate the state and parameter of Coupled Tank system. It generally produces a better state estimation, and better parameter estimation in both respects, the convergence speed and steady state error. One could see, for example, how successful it was in tracking the bump in the test system experiment. The performance of proposed method, is the experiment, where the steady state parameter estimation was better than UKF, EKF and PF. The EKF was generally in the middle of the pack, and should therefore be skipped in favor of RUKF. The PF algorithm could often obtain good or best steady state parameter estimates, but its parameter tracking speed is generally slower than the other competing methods in Table 4. Table 4 is performed in offline. This is due to the fact that RUKF is deterministic in nature, and therefore takes a direct approach towards obtaining the estimates. On the other hand, PF is a Monte Carlo type method, and therefore takes its time for estimates to emerge out of the data statistics.

6. Conclusion

In this paper, we proposed a robust estimation method based on unscented kalman filter by updating measurement covariance. And we considered the state and parameter estimation problems and a comparison has presented between the EKF, the UKF, the PF and the RUKF. The RUKF-proposed estimation algorithm-overcomes the limitation of traditional unscented kalman filter making use of updating measurement error between measured data and estimated data is derived in Section 3. We also considered the real mechanical system as the test bed for the comparison, namely coupled tank system. We have applied set of experiment: the water flow environments from tank 1 to tank 2 based on their equations and experiments were performed for consequently estimating the true states and parameters that are observed in the experiment. The comparison of estimation results shows that RUKF has more accuracy estimation performance than other methods. Both experiments confirm that RUKF is the best of the four methods. RUKF should therefore be the preferred model for state and parameter estimation for similar mechanical systems.

ACKNOWLEDGEMENT

The research is supported by BK21 PLUS, Research Base Construction Fund Support Program funded by Chonbuk National University in 2015, the Ministry of Trade, Industry and Energy (MOTIE) and Korea Institute for Advancement of Technology (KIAT) through the International Cooperative R&D Program (N046200012) and Business for Cooperative R&D between Industry, Academy, and Research Institute funded Korea Small and Medium Business Administration in 2016 (Grants No.1601001522).

REFERENCES

1. Parlos, A. G., Menon, S. K., and Atiya, A., “An Algorithmic Approach to Adaptive State Filtering using Recurrent Neural Networks,” IEEE Transactions on Neural Networks, Vol. 12, No. 6, pp. 1411-1432, 2001.

2. Lichter, M. D. and Dubowsky, S., “Shape, Motion, and Parameter Estimation of Large Flexible Space Structures using Range Images,” Proc. of the 2005 IEEE International Conference on Robotics and Automation, pp. 4476-4481, 2005.

3. Roffel, A. J. and Narasimhan, S., “Extended Kalman Filter for Modal Identification of Structures Equipped with a Pendulum Tuned Mass Damper,” Journal of Sound and Vibration, Vol. 333, No. 23, pp. 6038-6056, 2014.

4. Xie, Z. and Feng, J., “Real-Time Nonlinear Structural System Identification via Iterated Unscented Kalman Filter,” Mechanical Systems and Signal Processing, Vol. 28, pp. 309-322, 2012.

5. Matta, E., Ceravolo, R., De Stefano, A., Quattrone, A., and Zanotti Fragonara, L., “Unscented Kalman Filter for Non-Linear Identification of a New Prototype of Bidirectional Tuned Vibration Absorber: A

Numerical Investigation," Key Engineering Materials, Vols. 569-570, pp. 948-955, 2013.

6. Alkaya, A., "Unscented Kalman Filter Performance for Closed-Loop Nonlinear State Estimation: A Simulation Case Study," Electrical Engineering, Vol. 96, No. 4, pp. 299-308, 2014.

7. Mori, S., Nishihara, H., and Furuta, K., "Control of Unstable Mechanical System Control of Pendulum," International Journal of Control, Vol. 23, No. 5, pp. 673-692, 1976.

8. Orlowska-Kowalska, T. and Szabat, K., "Neural-Network Application for Mechanical Variables Estimation of a Two-Mass Drive System," IEEE Transactions on Industrial Electronics, Vol. 54, No. 3, pp. 1352-1364, 2007.

9. Parlos, A. G., Menon, S. K., and Atiya, A. F., "An Adaptive State Filtering Algorithm for Systems with Partially Known Dynamics," Journal of Dynamic Systems, Measurement, and Control, Vol. 124, No. 3, pp. 364-374, 2002.

10. An, C. H., Atkeson, C. G., and Hollerbach, J. M., "Estimation of Inertial Parameters of Rigid Body Links of Manipulators," Proc. of 24th IEEE Conference on Decision and Control, pp. 990-995, 1985.

11. Swevers, J., Ganseman, C., Tukel, D. B., De Schutter, J., and Van Brussel, H., "Optimal Robot Excitation and Identification," IEEE Transactions on Robotics and Automation, Vol. 13, No. 5, pp. 730-740, 1997.

12. Oh, S.-K., Pedrycz, W., Rho, S.-B., and Ahn, T.-C., "Parameter Estimation of Fuzzy Controller and Its Application to Inverted Pendulum," Engineering Applications of Artificial Intelligence, Vol. 17, No. 1, pp. 37-60, 2004.

13. Aksoy, S., Mühürcü, A., and Kizmaz, H., "State and Parameter Estimation in Induction Motor using the Extended Kalman Filtering Algorithm," Proc. of International Symposium Modern Electric Power Systems (MEPS), pp. 1-5, 2010.

14. Zheng, M., Ikeda, K., and Shimomura, T., "Estimation of Rotary Inverted Pendulum by using the Unscented Kalman Filter-Estimation of the Initial State," Proc. of SICE Annual Conference, pp. 1670-1673, 2007.

15. Geetha, M., Jerome, J., and Devatha, V., "Design of State Estimation based Model Predictive Controller for a Two Tank Interacting System," Procedia Engineering, Vol. 64, pp. 244-253, 2013.

16. Villez, K., Srinivasan, B., Rengaswamy, R., Narasimhan, S., and Venkatasubramanian, V., "Kalman-based Strategies for Fault Detection and Identification (FDI): Extensions and Critical Evaluation for a Buffer Tank System," Computers & Chemical Engineering, Vol. 35, No. 5, pp. 806-816, 2011.

17. Bharath Kumar, C., Muthumari, S., and Jayalaitha, S., "An Investigation of Extended Kalman Filter and Design of a Model Predictive Controller for Quadruple Tank System," International Journal of Applied Engineering Research, Vol. 9, No. 18, pp. 4255-4261, 2014.

18. Kim, J., Vaddi, S. S., Menon, P. K., and Ohlmeyer, E. J., "Comparison between Nonlinear Filtering Techniques for Spiraling Ballistic Missile State Estimation," IEEE Transactions on Aerospace and Electronic Systems, Vol. 48, No. 1, pp. 313-328, 2012.

19. St-Pierre, M. and Gingras, D., "Comparison between the Unscented Kalman Filter and the Extended Kalman Filter for the Position Estimation Module of an Integrated Navigation Information System," Proc. of Intelligent Vehicles Symposium, pp. 831-835, 2004.

20. Daum, F., "Nonlinear Filters: Beyond the Kalman Filter," IEEE Aerospace and Electronic Systems Magazine, Vol. 20, No. 8, pp. 57-69, 2005.

21. Chatzi, E. N. and Smyth, A. W., "The Unscented Kalman Filter and Particle Filter Methods for Nonlinear Structural System Identification with Non-Collocated Heterogeneous Sensing," Structural Control and Health Monitoring, Vol. 16, No. 1, pp. 99-123, 2009.