International Journal of Innovative
Computing, Information and Control
Volume 8, Number 3(B), March 2012

ICIC International ©2012 ISSN 1349-4198
pp. 2173–2180

UNSCENTED KALMAN FILTERING FOR GREENHOUSE CLIMATE CONTROL SYSTEMS WITH MISSING MEASUREMENT

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Received February 2011; revised June 2011

Abstract. *A stochastic unscented Kalman filter is designed in an attempt to solve the state estimation problem of the greenhouse climate control systems with missing measurements. The missing measurements are described by a binary switching sequence satisfying a conditional probability distribution. In order to accommodate the effects of randomly varying arrival of measurement data, the stochastic unscented transformation coupled with certain parts of the classic Kalman filter is applied to estimate the greenhouse states and filter out the noises, where some or all measurements are lost in a random fashion. The simulation results demonstrate the performance degradation of state estimation caused by random measurement data loss.*

Keywords: Unscented Kalman filter, Greenhouse, Nonlinear systems, State estimation

1. **Introduction.** The greenhouse climate control system is a very complex dynamic system covered with thin and transparent materials. This system satisfies the conditions for plant growth, but creates difficulties in regulating the greenhouse environment because of highly coupled nonlinear dynamics and strong disturbances from the surroundings, such as global radiation, wind speed and direction, and external air temperature and humidity. In order to create a favorable environment to accelerate the crop development and to minimize the production costs in terms of raw materials and energy consumption, researchers have used a wide variety of control techniques in different fields, from the conventional or classic strategies (pole placement control and linear quadratic regulation [1,2]), intelligent control algorithms (fuzzy logic, neural networks, genetic algorithms [3-6]), advanced control techniques (predictive control, adaptive control [7,8]), to robust control strategies [9], no-linear and optimal control [10,11], and fault detection and isolation in greenhouse [12]. It is well known that, the most advanced control structures, ensuring very good performance of the system, are based on control structures with additional feedback from system state variables, such as temperature and humidity in greenhouse. Therefore, acceptable control of the greenhouse climate systems requires the accurate estimation of the states variables.

On the other hand, the efficiency of plant production in greenhouses relies on the measurements provided by several electronic sensors located inside and outside the greenhouse. Environmental conditions such as the direct exposure of sensors to sunlight and the deterioration of connections between sensors and the controllers could result in very noisy and incomplete measurements which may impair the greenhouse operation. It may also increase the number of false alarms received from fault detection and isolation systems.

To ensure the accurate state estimation, it is necessary to develop a suitable filtering technique to filter out the noises and estimate the states of greenhouses. However, to the best of our knowledge, the important state estimation problem for greenhouse climate control systems with noises has not been reported in the literature.

It is well known that the optimal filter for linear systems is the Kalman filter [13-19]. State estimation for nonlinear systems is a difficult problem, and the extended Kalman filter (EKF) can cope with some nonlinear systems by using linearization of the state equation around the predicted state. Although the EKF is a widely used filtering strategy, and has been used successfully in many applications [20-22], in practice, the derivation of the Jacobian matrices is nontrivial and often leads to significant implementation difficulties. What is more, linearization can produce highly unstable filters if the assumption of local linearity is violated.

A recent improvement to the EKF is the unscented Kalman filter (UKF). The UKF is a nonlinear filter, and was first proposed by Julier and Uhlmann [23]. This filter is more accurate than the EKF and easier to implement for nonlinear systems without the linearization steps required by the EKF. So the UKF has found a number of applications in high-order nonlinear complex systems, including navigation systems for high-speed road, public transformation systems, underwater vehicles, and target tracking, etc. [24-26].

The ability of the UKF to accurately estimate nonlinearities makes it attractive for implementation on greenhouse climate control systems. This paper represents the first attempt to apply the UKF to estimate the states and filter out the noises of greenhouse climate control systems with missing measurement, which are described by a binary switching sequence satisfying a conditional probability distribution. General simulation results are given and a brief comparison is made between state estimation performance of the UKF with and without measurement data loss.

In the next section, a more detailed description about the operation of the UKF is given. In Section 3, the model of greenhouse climate control system configured for UKF is presented and analyzed. Section 4 investigates the simulation results of the UKF and makes a comparison between the performance of the UKF with and without measurement data loss. Conclusions about the results are summarized in Section 5.

2. **Unscented Kalman Filter.**

The UKF was developed with the underlying assumption that approximating a Gaussian distribution is easier than approximating a nonlinear transformation [27]. The fundamental component of UKF is the unscented transformation, which uses a set of samples, or sigma points to capture the true mean and covariance of the state probability distribution. These sigma points undergo the nonlinear transformation. The posterior mean and covariance of the state are then calculated from the transformed sigma points. This approach gives the UKF better convergence characteristics and greater accuracy than the EKF for nonlinear systems.

Suppose the nonlinear system equations obey the following nonlinear relationships:

$$\begin{cases} x(k+1) = f(x(k), u(k), k) + w(k) \\ y(k) = h(x(k)) + v(k) \\ z(k) = \alpha(k) y(k) \end{cases} \tag{1}$$

where $x(k)$ is the state vector, $u(k)$ is the control input, $y(k)$ is the raw measurement vector, $z(k)$ is the received measurement vector, $w(k)$ is the process noise vector assumed to be additive, white, and Gaussian, with zero mean and covariance defined as Q, $v(k)$ is the measurement noise vector defined the same as $w(k)$ but with the different covariance

R, and $\alpha(k)$ is a Bernoulli distributed white sequence with

$$\begin{aligned} Prob\,\{\alpha(k)=1\} &= E\,\{\alpha(k)\} = \bar{\alpha} \\ Prob\,\{\alpha(k)=0\} &= 1 - E\,\{\alpha(k)\} = 1-\bar{\alpha} \end{aligned}$$

First of all, the filter is initialized with the following assumptions for the state estimate $x(0)$ and the error covariance matrix $P(0)$

$$\hat{x}^{+}(0) = E\,[x(0)] \tag{2}$$

$$P^{+}(0) = E\left[\left(x(0)-\hat{x}^{+}(0)\right)\left(x(0)-\hat{x}^{+}(0)\right)^{T}\right] \tag{3}$$

Then, the following time update equations are used to propagate the state estimation and covariance for every measurement $k \in \{1, 2, \cdots, \infty\}$:

1. Calculation of the sigma points from the initial conditions (2) and (3)

$$\begin{aligned} \hat{x}^{(i)}(k-1) &= \hat{x}^{+}(k-1) + \tilde{x}^{(i)}, \quad i = 1, 2, \cdots, 2n \\ \tilde{x}^{(i)} &= \left(\sqrt{nP^{+}(k-1)}\right)_{i}, \quad i = 1, 2, \cdots, n \\ \tilde{x}^{(n+i)} &= -\left(\sqrt{nP^{+}(k-1)}\right)_{i}, \quad i = 1, 2, \cdots, n \end{aligned} \tag{4}$$

2. Transformation of these sigma points using Equation (1)

$$\hat{x}^{(i)}(k) = f\left(\hat{x}^{(i)}(k-1), u(k-1), k-1\right) \tag{5}$$

3. Combine the $\hat{x}^{(i)}(k)$ vectors to obtain the prediction of the state estimate

$$\hat{x}(k) = \frac{1}{2n}\sum_{i=1}^{2n}\hat{x}^{(i)}(k) \tag{6}$$

4. As the process noise is addictive and independent, the predicted error covariance is given as

$$P(k) = \frac{1}{2n}\sum_{i=1}^{2n}\left(\hat{x}^{(i)}(k)-\hat{x}(k)\right)\left(\hat{x}^{(i)}(k)-\hat{x}(k)\right)^{T} + Q \tag{7}$$

Finally, implement the following measurement update eauations:

1. Updating the sigma points with the predicted mean and covariance

$$\begin{aligned} \hat{x}^{(i)}(k) &= \hat{x}^{+}(k) + \tilde{x}^{(i)}, \quad i = 1, 2, \cdots, 2n \\ \tilde{x}^{(i)} &= \left(\sqrt{nP(k)}\right)_{i}, \quad i = 1, 2, \cdots, n \\ \tilde{x}^{(n+i)} &= -\left(\sqrt{nP(k)}\right)_{i}, \quad i = 1, 2, \cdots, n \end{aligned} \tag{8}$$

2. Transformation of each of the predicted points through measure equation

$$\hat{y}^{(i)}(k) = \alpha(k)h(\hat{x}^{(i)}(k), k) \tag{9}$$

3. Combine the $\hat{y}^{(i)}(k)$ vectors to obtain the predicted measure

$$\hat{y}(k) = \frac{1}{2n}\sum_{i=1}^{2n}\hat{y}^{(i)}(k) \tag{10}$$

4. Since the measurement noise is also addictive and independent, the covariance of the predicted measurement is as follows:

$$P_{y}(k) = \frac{1}{2n}\sum_{i=1}^{2n}\left(\hat{y}^{(i)}(k)-\hat{y}(k)\right)\left(\hat{y}^{(i)}(k)-\hat{y}(k)\right)^{T} + R \tag{11}$$

5. Estimate the covariance between $\hat{x}(k)$ and $\hat{y}(k)$

$$P_{xy}(k) = \frac{1}{2n} \sum_{i=1}^{2n} \left(\hat{x}^{(i)}(k) - \hat{x}(k)\right) \left(\hat{y}^{(i)}(k) - \hat{y}(k)\right)^T \tag{12}$$

6. The measurement updates are performed as follows:

$$K(k) = P_{xy}(k) P_y^{-1}(k) \tag{13}$$

$$\hat{x}^+(k) = \hat{x}(k) + K(k)\left(\alpha(k) y(k) - \hat{y}(k)\right) \tag{14}$$

$$P^+(k) = P(k) - K(k) P_y(k) K^T(k) \tag{15}$$

where $y(k)$ is the measurement.

Remark 2.1. *Stochastic variable $\alpha(k)$ is used to indicate the effects of randomly varying arrival of measurement data. That is, if $\alpha(k) = 1$, then no measurement data lost in the system, and if $\alpha(k) < 1$, part or all of the measurement data are lost.*

Remark 2.2. *The choice of the covariance matrices Q and R has affect on the quality of the state estimation. However, according to the existing technical literature, the analytical guidelines which ensure proper settings of matrices do not exist. In this paper, the trial and error procedure is used. Therefore, a future subject of this study is to develop an optimization procedure, such as the genetic algorithm, to set the covariance matrices Q and R to ensure the optimal settings of UKF parameters.*

Remark 2.3. *Note that no explicit calculation of Jacobians is necessary to implement this algorithm, which reduces the complexity and errors associated with finding the Jacobians of a complex system and also allows the filter to be applied to a wide scope of system formulations.*

3. Greenhouse Climate Control Dynamics.

The dynamic changes in the greenhouse are determined by differences in energy and mass contents between inside and outside air. In a greenhouse, the state climate can be represented by two variables, namely, inside air temperature, and absolute humidity. A simplified greenhouse climate model adequate for control purposes describes the dynamic behavior of the state variable with the following energy balance and water vapor balance equations [28].

3.1. Energy balance.

The greenhouse air energy balance is affected by energy supply and energy losses. The former is due to an artificial heating system (E_h) and heat load imposed by solar radiation (E_s) and the latter is due to transmission through the greenhouse cover (E_c), forced ventilation (E_v), and fog system (E_f). This balance can be written as follows:

$$\frac{dT_{in}}{dt} = \frac{1}{C_0}\left(E_h - E_c - E_v - E_f + E_s\right) \tag{16}$$

in which,

$$E_h = Q_{heater}, \quad E_s = S_i, \quad E_v = \frac{V_R C_0}{V_T}\left(T_{in} - T_{out}\right)$$

$$E_c = UA\left(T_{in} - T_{out}\right), \quad E_f = \lambda Q_{fog}$$

where T_{in}/T_{out} is the inside/outside air temperature, C_0 is the thermal capacity, Q_{heater} is the heat provided by the greenhouse heater, S_i is the intercepted solar radiant energy, V_R is the ventilation rate, UA is the heat transfer coefficient of enclosure, λ is the latent heat of vaporization, Q_{fog} is the water capacity of the fog system, and V_T is the temperature active mixing air volume.

3.2. **Water vapor balance.** The water vapor balance is calculated by the following formula, modified according to [29], in which the soil evaporation rate and the condensation rate at the inner face of the greenhouse cover are neglected:

$$\frac{dw_{in}}{dt} = \frac{1}{V_H}\left(Q_{fog} + E(S_i, w_{in}) - V_R\left(w_{in} - w_{out}\right)\right) \tag{17}$$

where w_{in}/w_{out} is the inside/outside humidity, $E(S_i, w_{in})$ is the evapotranspiration rate of the plants, and V_H is the humidity active mixing air volume.

In summer operation, Q_{heater} is set to zero. It is also worth noticing that, the evapotranspiration rate $E(S_i, w_{in})$ is related to the intercepted solar radiant energy through the following simplified relation:

$$E(S_i, w_{in}) = \alpha\frac{S_i}{\lambda} - \beta_T w_{in} \tag{18}$$

where α is an overall coefficient to account for shading and leaf area index and β_T is an overall coefficient to account for thermodynamic constants and other factors affecting evapotranspiration (i.e., stomata, air motion).

3.3. **Dynamic model of the greenhouse climate control systems.** In paper [11], considering that the conditions of operating the ventilation-cooling are rather dominated by solar radiation alone (i.e., $\beta_T = 0$), the term $\beta_T w_{in}$ can be neglected. Supposing $\alpha' = \alpha(\lambda V_H)^{-1}$, normalizing the control variables through these equations $V_{R,\%} = V_R/V_R^{\max}$, $Q_{fog,\%} = Q_{fog}/Q_{fog}^{\max}$, $\lambda' = \lambda Q_{fog}^{\max}$, $V' = V_H/Q_{fog}^{\max}$, and defining the inside temperature and humidity as the dynamic state variables, x_1 and x_2, respectively, the ventilation rate and the water capacity of the fog system as the control (actuator) variables, u_1 and u_2, respectively, the intercepted solar radiant energy, the outside temperature, and the outside absolute humidity as the disturbances, $z_i(t)$, $i = 1, 2, 3$, and $y = x_1^2 + x_2^2$, Equations (16) and (17) can be put in the following state-space form:

$$\begin{cases} \dot{x}_1 = \dfrac{1}{C_0}\left(z_1 - \lambda' u_2\right) - \dfrac{u_1}{t_v}\left(x_1 - z_2\right) - \frac{UA}{C_0}\left(x_1 - z_2\right) \\ \dot{x}_2 = \dfrac{1}{V'}u_2 + \alpha' z_1 - \dfrac{u_1}{t_v}\left(x_2 - z_3\right) \\ y = x \end{cases} \tag{19}$$

where parameter t_v represents the time needed for one air change the sampling period.

The UKF algorithm is designed for the discrete time system. So we should discretize the above continuous-time model to apply the algorithm. In this paper, the nonlinear 3-order Runge-Kutta algorithm is applied to discretize the model (19) with a proper simulation step (1s).

Remark 3.1. *It should be pointed out that if some international standards are used to protect the systems against the external environment, such as IP 55, IP 65, etc., and a good maintenance is performed, then the influence of system noise can be neglected. In this case, the UKF algorithm can be removed.*

4. **Simulation Results.** In the simulation, the greenhouse model parameters described in (19) are as follows [11]:

$$\begin{aligned} &C_0 = -324.67\ min\ W\ {}^oC^{-1}, \quad UA = 29.8\ W\ {}^oC^{-1}, \quad t_v = 3.41\ min \\ &\lambda' = 465\ W, \quad \alpha' = 0.0033\ g\ m^{-3}\ min^{-1}\ W^{-1}, \quad 1/V' = 13.3\ g\ m^{-3}\ min^{-1} \end{aligned}$$

The UKF was designed for the state estimation problem, and has been applied in nonlinear control applications requiring full-state feedback [30]. In this paper, we use a

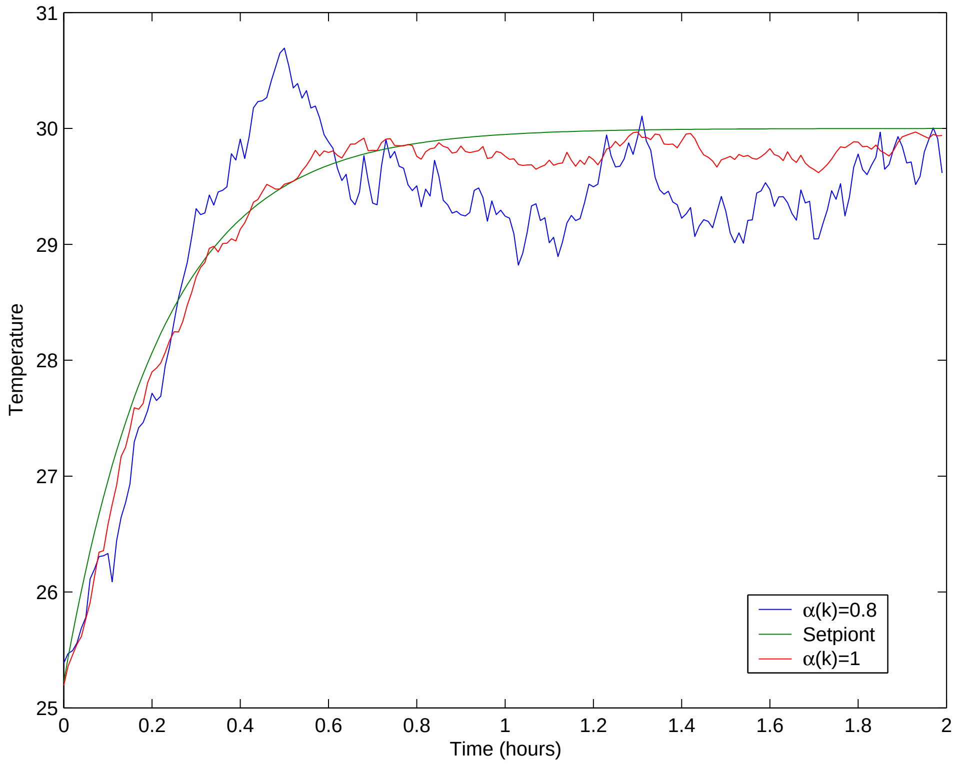

FIGURE 1. Temperature response in greenhouse

nonlinear control technique proposed in [11] to control the above model, and put emphasis on the estimation performance of the state from the noisy measurement.

Assume $\alpha(k) = 0.8$, and the Gaussian white noise $w(k)$ and $v(k)$ are added to both the process and measurement equations to simulate the real situation

$$E[w(k)] = \begin{bmatrix} 0 & 0 \end{bmatrix}^T, \quad E[v(k)] = \begin{bmatrix} 0 & 0 \end{bmatrix}^T$$
$$Q = diag\left(\begin{bmatrix} 10^{-6} & 10^{-6} \end{bmatrix}\right) \quad R = diag\left(\begin{bmatrix} 0.5 & 0.5 \end{bmatrix}\right)$$

This paper tries to describe a kind of filtering technique for the practical application at greenhouse climate control system to estimate the temperature and humidity. Simulation results are illustrated from Figure 1 to Figure 2, which show the results of the temperature and humidity estimation by UKF with and without measurement loss, respectively.

By comparison from Figure 1 to Figure 2, it can be seen that the UKF algorithm without considering missing measurement gives a more accurate and smoother estimation than the one with measurement loss.

5. **Conclusion.**

This paper presents a derivative-free nonlinear filtering technique to the state estimation problem for greenhouse climate control systems. It has been shown that the UKF algorithm without considering missing measurement achieves a better level of accuracy than the one with measurement loss. This simulation result will be very useful for further study of state estimation of greenhouse climate control systems with communication constraints.

Acknowledgments. This work was supported in part by the National Natural Science Foundation of China (Grant No. 60974001, 61104121), and the Engineering and Physical Sciences Research Council, UK (EP/F029195).

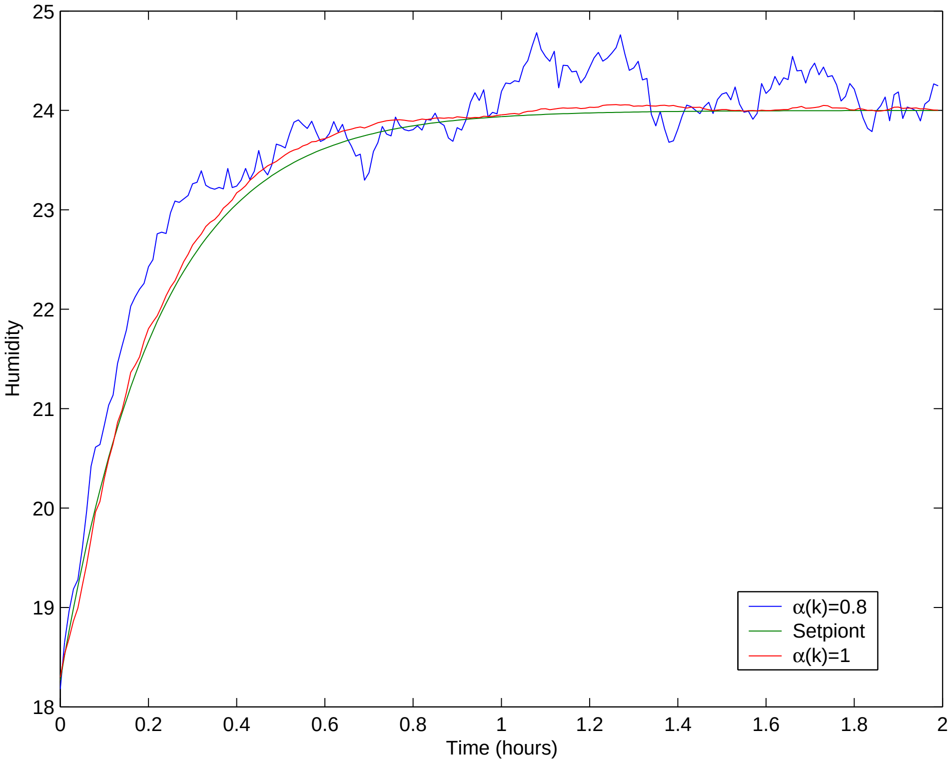

FIGURE 2. Humidity response in greenhouse

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