

# 전기제어 설비의 출력 안정화를 위한 가우시안 접근법

## A Gaussian Approach in Stabilizing Outputs of Electrical Control Systems

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**Abstract** - Sensor readings always have a certain degree of randomness and fuzziness due to its intrinsic property, other electronic devices in the circuitry, wires and the rapidly changing environment. In an electrical control system, such readings will bring instability in the system and other undesired events especially if the signal hovers around the threshold. This paper proposes a Gaussian-based statistical approach in stabilizing the output through sampling the sensor data and automatic tuning the threshold to the range of multiple standard deviations. It takes advantage of the Central limit theorem and its properties assuming that a large number of sensor data samples will eventually converge to a Gaussian distribution. Experimental results demonstrate the effectiveness of the proposed algorithm in completely stabilizing the outputs over known filtering algorithms like Exponential smoothing and Kalman Filter.

**Key Words** : Sensor, Threshold, Standard deviation, Actuators, Gaussian distribution

### 1. Introduction

Recent advancement in micro controller and their cheap availability has led to the development of embedded control systems for almost all real-life applications [1]. Their presence is everywhere from electrical, industrial, military, education, transportation, business, agriculture to home applications [2-5]. Sensors and actuators are critical components in electrical control systems, where the output of sensors is programmed to trigger the actuators when a specified threshold is crossed.

The output of a sensor is a result of observing a physical phenomenon and converting them into a suitable electrical signal. Those signal always have a certain degree of randomness or fluctuations which appears in the output as some noise level added to it. It is because of the intrinsic property of sensors, other electronic components throughout the circuitry and other environmental reasons [6-9]. In many cases, a simple low pass filter, or certain digital filtering algorithm can be used to smooth out such noisy signals to a

great extent [10, 11]. However, in the case of high bandwidth sensors, filtering limits the ability to measure high-frequency physical changes in the environment since their bandwidth is narrowed down. Moreover, filtered signals are not 100% smooth and contain randomness just like the original signal. Even with those filtering method, if the signal hovers around the threshold, it would bring huge instability in the system's output. Especially in the applications which require higher resolution, chances of instability in the output is even higher.

In this paper, we propose a Gaussian-based threshold tunable algorithm for stabilizing the actuators through sampling sensor data and automatically tuning the threshold. We establish a hypothesis that probability density function (PDF) of any random sensor reading can be modeled by the Gaussian distribution. The key technique presented in this method is manipulating the preset threshold for the stable operation of actuators since two or more threshold for the same action cannot exist simultaneously in the digital world. And the question of how much the threshold should be tuned to cover the entire signal is addressed with the modeling of sensor data using Gaussian distribution. By taking it into account, 99.73% of sensor data will fall under the three standard deviation ( $\sigma$ ) range. The algorithm will keep track of the state of the system and tune the threshold to the  $3\sigma$  range once the signal reaches the threshold. At this point, no matter how much the signal fluctuates, the state of the output will remain constant. It

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will tune back from the  $3\sigma$  to the original threshold only when the signal crosses below the  $3\sigma$  range. As a result, there is always the stability in the output independent of the level of noise or any randomness in the sensor data. Chapter 3 gives detail realization of the proposed algorithm and explain the working concept in the detail. Chapter 4 compares the proposed method with other filtering methods: Exponential smoothing and Kalman filter, and shows its effectiveness over those methods.

### 2. Related Work

Most of the published work focuses on noise reduction for sensor data acquisition using either analog circuit techniques or digital filtering techniques. M. Aamir et al. reports noise reduction techniques in the embedded system where the investigation of hardware and layout techniques can provide concrete solutions [12]. Similarly, F. Reverter reported analog circuit techniques which can help in interfacing sensors directly to microcontrollers without the use of signal conditioning circuit [13]. This method can help in reducing noise caused by surrounding electronic devices. Other noise cancellation techniques for single and double sensor were also reported where canceling signal is generated by measuring noise field [14, 15]. V. Y. Mendeleyev et al. designed an optical sensor for reducing the influence of intensity fluctuations on output stability [16]. The analysis of the stabilization principle is performed assuming that the contribution of the intrinsic noise of the detectors and electronics to the output of the sensor is negligible in comparison to that of the light source's intensity fluctuations. K.H. Eom et al. presented improved Kalman filtering method to reduce noise and obtain correct data in the multi-sensing environment [17]. P.H.G. Mani et al. reported on integration testing of sensors and actuators with embedded processing component. It focuses on sensor and actuator fault detection which can critically impact the system performance [18]. Other papers reported issues in sensor anomaly detection in wireless sensor networks [19-21] and false alarm reduction methods [22].

### 3. Gaussian-based Threshold Tunable Algorithm

As we discussed in previous chapters, sensor data always have a certain degree of randomness and fuzziness due to various factors associated with it. The probability density function (PDF) of such sensor measurements can be modeled by a Gaussian distribution. Gaussian distribution is

by far the most accurate PDF model to quantify uncertainty or random variables when making inferences as it is based on Central Limit Theorem (CLT). Mathematically the proposed algorithm can be expressed as

$$y = fp(x), \text{ tracker} \tag{1}$$

where  $y$  is the output of the system which is the function of the probability of the random Gaussian variable  $x$ , and the Boolean variable tracker which stores the previous state of the system. Here  $p(x)$  can be expressed as

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{x-\mu^2}{2\sigma^2}\right] \tag{2}$$

$$p(|X-\mu| \leq \sigma) = 0.6828 \tag{3}$$

$$p(|X-\mu| \leq 2\sigma) = 0.92452 \tag{4}$$

$$p(|X-\mu| \leq 3\sigma) = 0.9973 \tag{5}$$

where  $\mu$  is the mean (expected value),  $\sigma$  is the standard deviation and square of the standard deviation,  $\sigma^2$  being the variance. The probability that a random variable  $X$  lies in an interval is given by equation (3), (4) and (5).

#### 3.1 Proposed algorithm

In this section, we explain the realization of our proposed algorithm and show how it works in stabilizing the outputs without any filtering. Setting thresholds is very crucial in any control systems. In embedded control systems, microcontrollers are programmed to set the threshold for the operation of actuators [23]. We especially take the example

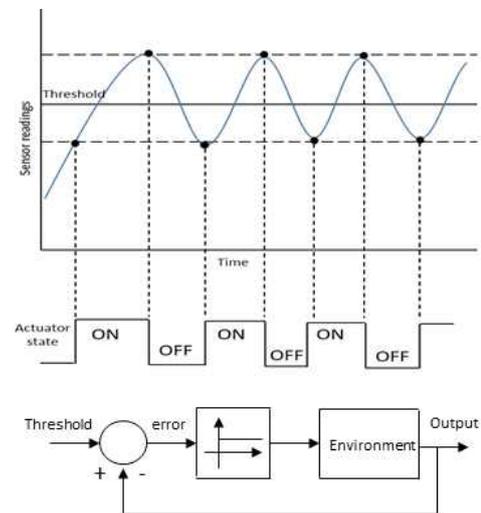


Fig. 1 Bang-bang/Hysteresis type control

in Bang-bang or Hysteresis control type (see Fig. 1) systems.

In general cases, irrespective of the level of noise, a single threshold will ensure smooth operation of the actuators. Suppose in a normal environment, readings of a temperature sensor triggers a motor when a specified threshold is reached. It turns on if the signal crosses above the threshold and turns off if the signal goes below the threshold. However, if the signal stays around the threshold, it will bring instability in the operation of the motor. The frequent change in the state eventually will bring mechanical failure in the motor.

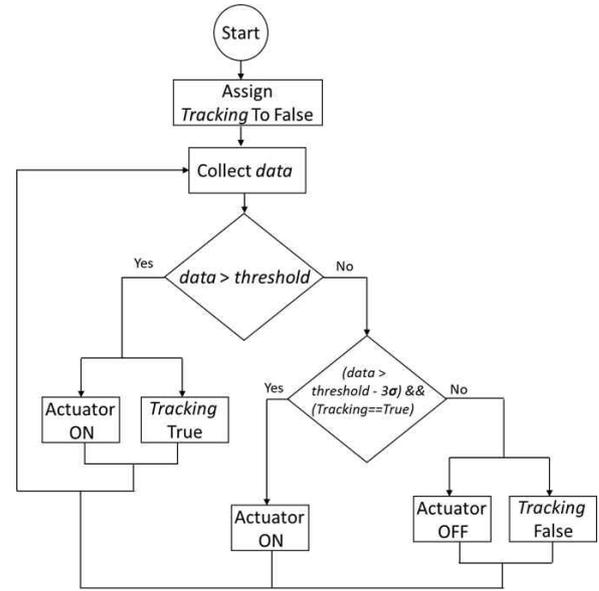
Many practical methods do exist to prevent such events from occurring. Some of them include reading the sensor data only at certain time intervals or introducing delays in reading the signals. Other methods include tracking the threshold where signals will be ignored for a specified time once the threshold is reached. These type of methods are useful especially in environmental monitoring and control where continuous data is not of much importance. However, in other applications where the instantaneous response is required per observation, such methods may not be helpful.

**Algorithm 1** Threshold Tuning

```

1: Begin: Determine threshold;
2: Read n samples from the sensor at  $t=0$  to  $t=n$ ;
3: Compute  $\sigma$  from n samples;
4: Assign a Boolean variable Tracker to FALSE
5: Start Loop
    #Condition 1
    if (current sensor reading > threshold)
        do Actuator → ON
        do Tracker → TRUE
    #Condition 2
    else if ((current sensor reading > (threshold -  $3\sigma$ ))
AND (Tracker → TRUE))
        do Actuator → ON
    else do Actuator OFF
        do Tracker FALSE
6: End
    
```

Here, Algorithm 1 shows the working procedure of the Threshold tuning algorithm. The working concept of the algorithm is also shown in flowchart in the Fig. 2. In step 1, a threshold is determined and assigned to the variable threshold. In step 2 and 3, n number of samples are read from the sensor to calculate the standard deviation  $\sigma$ . In step 4, a Boolean variable Tracker is assigned a FALSE or 0



**Fig. 2** Flowchart representation of the Algorithm1

value initially. This Boolean variable will be assigned TRUE value only if the signal reaches the threshold. This will help in determining whether the signal has crossed the threshold or not. In step 5, the system loop begins, and Condition 1 is checked first. If the sensor reading reaches the threshold, the actuator will be triggered ON, and the Tracker variable will be assigned TRUE simultaneously. Activation of Condition 1 leads to the activation of Condition 2 immediately where the previous status of the actuator will be maintained. Once the signal is below  $3\sigma$  range, the actuator is triggered OFF, and the Tracker variable will be assigned FALSE. This creates a stable zone for the signal from the original threshold to the  $3\sigma$  range.

**3.2 Dynamic Threshold tuning**

Readings of sensor data in single sensing and multi-sensing environment often different. The measurement data of the multi-sensing environment has more noise and disturbances than the single sensing environment [17]. Even the sensors of the same type manufactured by same vendor company drift slightly when actual measurements are done [9]. To address these problems we added a feature to the Algorithm 1, i.e. dynamically tuning the threshold every loop.

Algorithm 2 represents dynamic threshold tuning algorithm. The only difference between this algorithm and Algorithm 1 is, it computes the standard deviation every time a new sample is taken. A new  $3\sigma$  range is set every time the loop runs.

**Algorithm 2** Dynamic threshold Tuning

```

1: Begin: Determine threshold;
2: Assign a Boolean variable Tracker to False
3: Start Loop
   Read current sample from the sensor and Store;
   Compute and update  $\sigma$  in every loop;
   if (current sensor reading > threshold)
       do Actuator  $\rightarrow$  ON
       do Tracker  $\rightarrow$  TRUE
   else if (current sensor reading > (threshold -  $3\sigma$ ))
       AND (Tracker  $\rightarrow$  TRUE)
       do Actuator  $\rightarrow$  ON
   else do Actuator  $\rightarrow$  OFF
       do Tracker  $\rightarrow$  FALSE
4: End
    
```

## 4. Experiments and Discussions

### 4.1 Actuator output with known methods

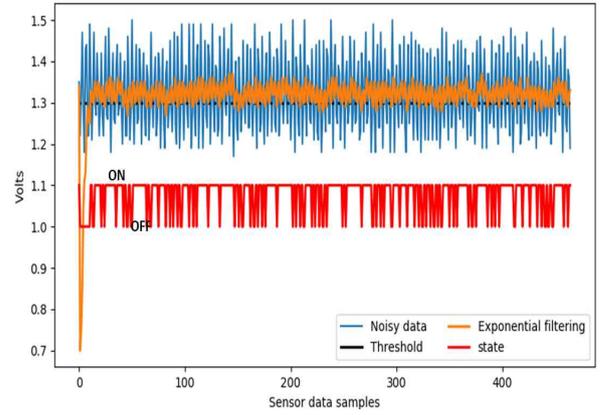
In this section, we compare our method with other known methods: Exponential smoothing and Kalman filter, in the actuator stability criteria. Exponential smoothing method smooths the noisy readings from the sensor and acts as a low-pass filter. Equation (6) and (7) shows the mathematical expression of the Exponential smoothing method:

$$s_0 = x_0 \quad (6)$$

$$s_t = \alpha \cdot x_t + (1 - \alpha) \cdot s_{t-1}, 0 < \alpha < 1 \quad (7)$$

where  $s_t$  represents sensor data at time  $t=0$ ,  $\hat{x}_t$  represents the best estimate of the data and  $\alpha$  is the smoothing factor. The value of  $\alpha$  close to zero will have a greater smoothing effect but less responsive to the recent changes, whereas value closer to 1 will have lower smoothing effect but more responsive to the recent changes. The value of the estimator  $s_t$  will be updated every time the sensor makes a new reading.

Figure 3 shows the application of the Exponential smoothing algorithm at  $\alpha = 0$ . For the experimental purpose, we used a microcontroller board based on ATmega32u4 providing 16 MHz clock speed and 10 bit ADC. The algorithm successfully managed to smooth the signal and filter the high frequencies. However, it was not able to reduce the frequent changes in the state of the output. Another common yet



**Fig. 3** Application of Exponential smoothing algorithm

complex algorithm is Kalman filter which has a wide range of application including sensor signal processing. It is based on a state-space approach where it optimally estimates the states of the model containing statistical noise with known parameters [24].

$$\bar{x}_k = F_{k-1} \bar{x}_{k-1} + G_{k-1} u_{k-1} + W_{k-1} \quad (8)$$

$$y_k = H_k \bar{x}_k + v_k \quad (9)$$

The state dynamics and output equations are described by equation (8) and (9) respectively. Here,  $x$ ,  $y$ ,  $u$ ,  $w$ ,  $v$ ,  $F$ ,  $G$ ,  $H$  represents state vector, output vector, input vector, process noise vector, measurement noise vector, system matrix-state, system matrix-input and observation matrix respectively. These equations can further be divided into two groups:

a. Time update equations

$$\hat{x}_{k/k-1} = \hat{x}_{k-1} \quad (10)$$

$$P_{k/k-1} = P_{k-1} + Q_{k-1} \quad (11)$$

b. Measurement update equations

$$K_k = \frac{P_{k/k-1}}{P_{k/k-1} + R} \quad (12)$$

$$\hat{x}_{k/k-1} = \hat{x}_{k-1} + K_k (Z_k - \hat{x}_{k/k-1}) \quad (13)$$

$$P_k = (I - K_k) \cdot P_{k/k-1} \quad (14)$$

Here, equation (10) and (11) represent the time update equations and (12), (13) and (14) represent the measurement update equations.  $Q$ ,  $R$ ,  $K$  and  $Z$  represents process noise covariance, measurement noise covariance, Kalman gain and

measured value respectively. Figure 4 shows the application of Kalman filter algorithm. For our experiment in sensor signal processing the parameters of Kalman filter are assumed as follows:

- i.  $x$  is the sensor output voltage,
- ii.  $F = 1$ ; meaning the sensor reading does not vary instantaneously,
- iii.  $G = 0$ ; meaning there is no control input and
- iv.  $H = 1$ ; meaning the output voltage is only observable.
- v.  $R$  is the variance of the sensor reading

Estimating  $Q$  and  $R$  is very challenging and often require complex calculations [17]. We arbitrarily assigned a very small value of  $1 \times 10^{-4}$  to  $Q$ , whereas  $R$  was the variance of the sensor reading calculated after taking 50 samples. It successfully managed to get rid of the noise and estimate the signal. However, it could not reduce the frequent changes in the state of the output satisfactorily. It is because filtered signals are not 100% smooth and they also hover around the threshold just like the original signal.

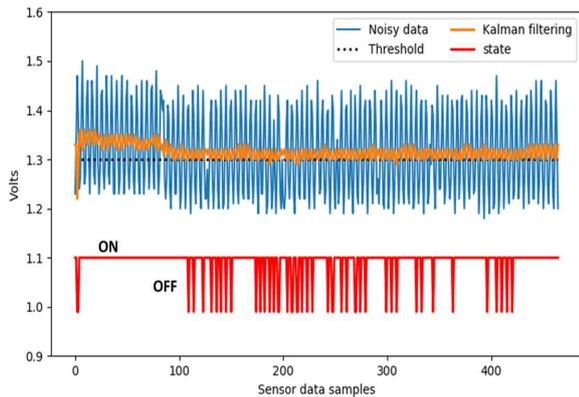


Fig. 4 Application of Kalman Filter algorithm

#### 4.2 Actuator output with the proposed method

The proposed method controlled the threshold based on the measurement of the probability of the random Gaussian variable. We empirically found that the observed series of sensor measurements indeed converged to Gaussian distribution when the sufficiently large number of samples were taken. We took 2000 sample readings of a light sensor (CdS photo sensor) in an illuminated room of 500 lux. With the total power supply of 5 V, the  $\mu$  of sensor readings was 1.33 V with the  $\sigma$  being 0.12. The maximum and minimum value observed was 1.71 V and 0.96 V respectively. Operating

frequency of the sensor was observed to be approximately 120 Hz.

Figure 5 shows the extraction of the sensor data using an oscilloscope. Figure 6 shows sensor readings in using an embedded computer (ATmega32u4) where  $1\sigma$ ,  $2\sigma$  and  $3\sigma$  range cover approximately 68%, 95% and 100% of the data. Figure 7 shows PDF of the collected sensor data fitted to Gaussian distribution.

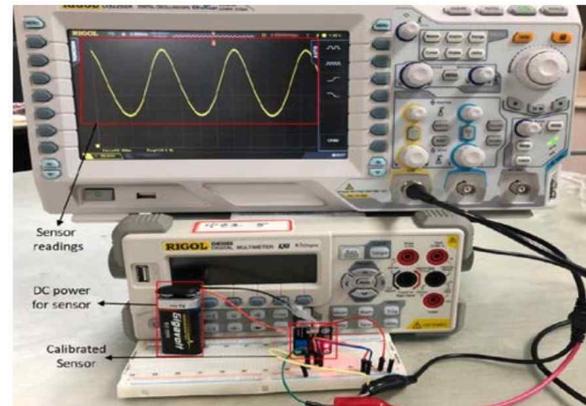


Fig. 5 Data acquisition with the analog method

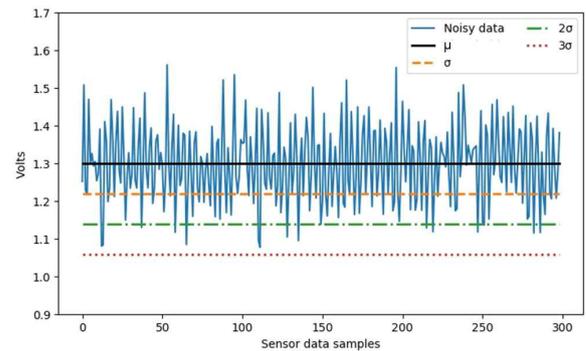


Fig. 6 Data acquisition with the digital method

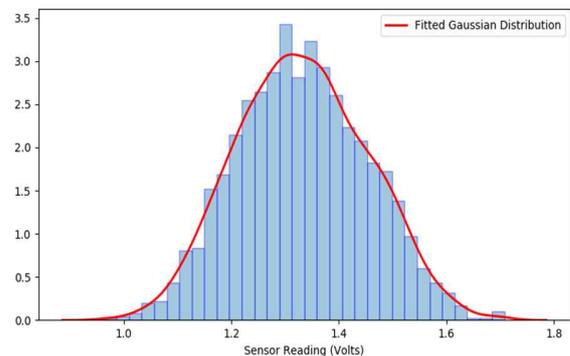


Fig. 7 PDF of the collected sensor data

As shown in Figure 7 we manipulated the environment for the experimental purpose to demonstrate the usefulness of the algorithm. In a normal environment, the output of the system is completely stable irrespective of any level of noise as shown in Figure 8. Once the signal is at the threshold the actuator status is ON, and it keeps on maintaining the same status till the signal is at the  $3\sigma$  range. Once it goes below the  $3\sigma$  range, the actuator status is OFF. Now after this, even if the signal crosses above  $3\sigma$  range its status would not change to ON. This brings great stability to 99.7% to the output of a control system. In addition to that, unexpected events can be avoided, life of the actuators can be prolonged, and maintenance cost can be reduced as well.

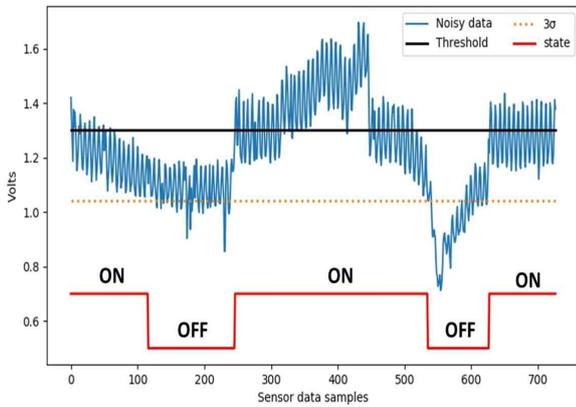


Fig. 8 Application of the proposed algorithm in the manipulated environment

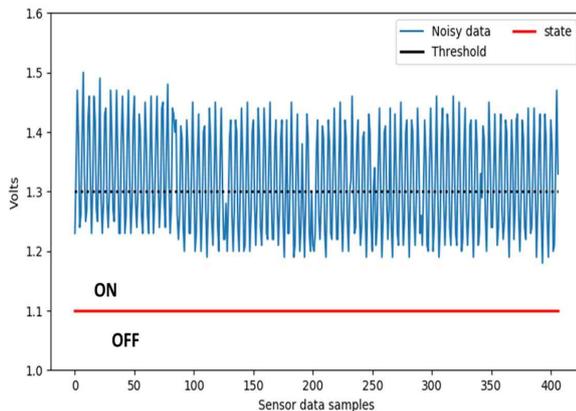


Fig. 9 Application of the proposed algorithm in the normal environment

### 4.3 Discussions

The average stability using Exponential smoothing

algorithm, Kalman filter and the proposed algorithm was approximately 50%, 70% and 99.7% respectively. Our initial hypothesis before beginning the experiment was all the data of the readings of sensors in an uncontrolled environment would converge to a Gaussian distribution. However, not all sensors exactly converge to the Gaussian distribution and the shape of the distribution of those sensors are somehow complex. A Gaussian distribution is merely an approximation of such complex probability distributions. Also, the variance of a filtered signal is much less than a raw sensor signal. The algorithm proposed in this paper can be applied to a filtered signal. The '3σ range' can be made much narrower with the cost of increase in computation time.

Robust quantitative approach can also be adopted for outlier detection if it is of high importance. The  $3\sigma$  rule may break down at the contamination level greater than 10%. Other statistical outlier detection rules like the Hampel identifier can be used which breaks down at the contamination level greater than 50% [25].

$$Contamination = \frac{no.of\ outliers}{no.of\ samples} \tag{15}$$

The threshold level  $\mu \pm 3\sigma$  can be changed to  $\pm 3S$  and S can be expressed as

$$S = \frac{median|x_i - \tilde{x}|}{0.6745} \tag{16}$$

where  $x_i$  is the sample data,  $\tilde{x}$  is the sample median and the whole numerator part of the equation (16) is the median absolute deviation (MAD) i.e. median of the absolute deviations from the data's median.

### 5. Conclusion

Electrical control facilities deploy sensors and rely on their measurements and data acquisitions. Our work mainly focused on designing an algorithm capable of manipulating the preset threshold for the stable operation of the actuators. We modeled the random variables of the sensor readings by the Gaussian distribution. And by taking advantage of the properties of the distribution, we tuned the threshold to  $3\sigma$  range covering 99.73% of the signal. We also discussed the possibility of the proposed algorithm in the multi-sensing environment using dynamic tuning of the threshold. Finally, we used Exponential smoothing algorithm, and Kalman filtering for the same purpose and, experimentally found our method performed better. With the

application of the proposed algorithm, complete stability can be achieved in any Bang-bang or Hysteresis type control system.

### 감사의 글

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