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Improvement of UAV Attitude Information Estimation Performance Using Image Processing and Kalman Filter

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영상처리와 칼만필터를 이용한 UAV의 자세 정보 추정 성능 향상

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Abstract In recent years, researches utilizing UAV for military purposes such as precision tracking and batting have been actively conducted. In order to track the preceding flight, there has been a previous research on estimating the attitude information of the flight such as roll, pitch, and yaw using images taken from the rear UAV. In this study, we propose a method to estimate the attitude information more precisely by applying the Kalman filter to the existing image processing technique. By applying the Kalman filter to the estimated attitude data using image processing, we could reduce the estimation error of the attitude angle significantly. Through the simulation experiments, it was confirmed that the estimation using the Kalman filter can estimate the posture information of the aircraft more accurately.

Key Words : Military, UAV, Image Processing, Kalman Filter, Flight Attitude Estimation

요 약 최근에 정밀 추적이나 타격 등의 군사 목적으로 UAV를 활용하는 연구가 매우 활발하게 진행되고 있다. 앞서가는 비행체를 추적하기 위해 후방에서 촬영한 영상을 활용하여 롤, 피치, 요와 같은 그 비행체의 자세 정보를 추정하는 기존의 연구가 진행되었다. 본 연구에서는 기존의 영상처리기법을 이용한 연구에 칼만 필터를 적용함으로써 자세 정보를 더욱 정밀하게 추정하는 방법을 제시한다. 영상처리를 사용해서 추정한 비행 자세 데이터에 칼만 필터를 적용함으로써 기존의 방식에서 발생했던 자세 각도의 추정오차 범위를 크게 줄일 수 있었다. 시뮬레이션 실험을 통해서, 칼만 필터를 적용할 경우 비행체의 자세 정보를 더욱 정확하게 추정할 수 있음을 확인할 수 있었다.

주제어 : 군사, 무인비행체, 영상처리, 칼만 필터, 자세정보 추정

1. Introduction

Recently, UAV has been utilized not only for military usage but also for the whole industry, and studies for utilizing UAV more efficiently are continued[1-5]. When an UAV is flying in the air measuring and controlling the current operating state and flight attitude of the UAV is a very important issue

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in military application[6]. In recent years, researches have been conducted to measure the flight attitude information of the UAV using an INS / GPS system using a MEMS IMU for attitude control[7]. However, in the case of submerged flight such that a large number of UAVs fly in a certain area along a specific leading UAV, it is necessary to perform a mission in which a posterior UAV estimates the attitude information of the leading UAV, then a concrete and effective attitude estimation method is needed.

Recently, there has been a study on mission flight that estimates the attitude information of the preceding flight and follows the previous flight based on the information by Paul and others[8]. This study was to estimate the attitude information of the preceding flight by analyzing the image information taken from the camera mounted on the following flight body. Image and statistical processing such as color space segmentation[9,10], template matching[11], edge detection[12], corner detection[13], virtual horizon line detection[14], and linear regression[15] were used. As a result, it was a study to estimate Euler angles such as roll, pitch and yaw by using image processing. The problem with this method is that the estimated angle is more than 21 degrees in the case of the roll, and the possibility of tracking failure based on the posture estimation becomes very high. To improve this, Kalman filter[16] was applied to the attitude data estimated by image processing. The Kalman filter is a recursive filter that traces the state of a linear dynamics system that contains noise, and proceeds with optimal statistical prediction of the current state based on measurements taken over time. In this paper, we propose an advanced system that improves the attitude estimation performance by using the tracking characteristics of the Kalman filter.

2. Estimation of UAV Attitude Information

2.1 System Architecture

The system proposed by Paul and others is a system that uses a camera mounted on a rear aircraft to photograph an advanced flight object and estimate the flight attitude information of the flight object through image processing. In this study, Kalman filter is applied to the attitude data estimated by this system, so that the estimated attitude information can be calculated more stably and precisely. The overall system structure is shown in Fig. 1, and the operation sequence is as follows.

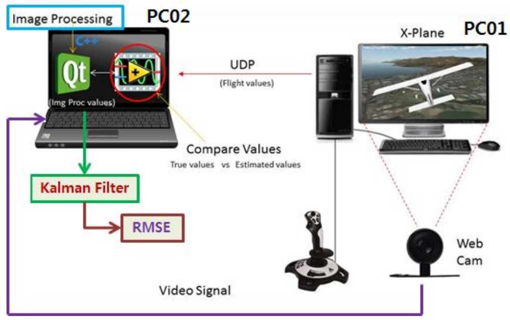


Fig. 1. Overall Structure of the Proposed System

1. In PC01, the flight simulator X-Plane[17] is used to create the preceding flight, and the actual flight data is transmitted to the PC02 while executing the flight.
2. Then, take a picture of the PC01's display screen with the camera, and transfer the recorded movie to PC02 through the UDP communication.
3. The PC02 analyzes consecutive images of the video and estimates the attitude information of the preceding flight.
4. Apply a Kalman filter to estimate flight attitude data that efficiently adapts to unclear changes in the estimated attitude data.
5. Experiments are conducted to compare the simulated flight data with the flight attitude data estimated through the Kalman filter.

2.2 Attitude Estimation

The overall configuration of the flight attitude information estimation system proposed by Paul and others is shown in Fig. 2, and the process of estimating roll, pitch, and yaw angles is as follows.

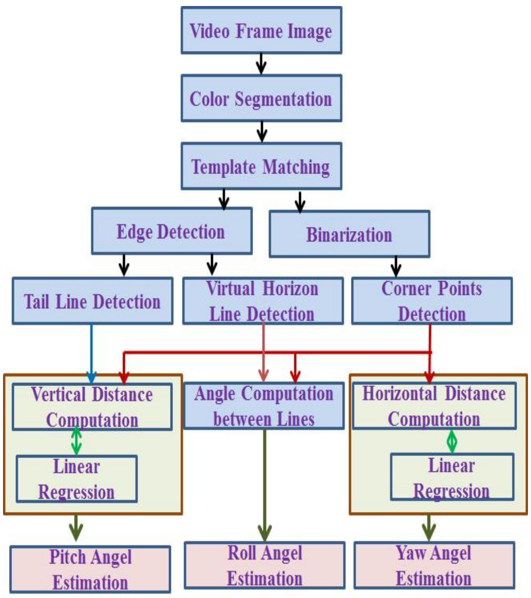


Fig. 2. Block Diagram of UAV Attitude Estimation System Proposed by Paul and others

1. Take a picture of the flight scene of the leading vehicle using a camera mounted on a following vehicle Then, an individual frame of the moving picture is applied to the estimation system.
2. Use the color segmentation technique to detect the area of the flying object.
3. Template matching technique is used to accurately detect objects by comparing them with forward flying objects.
4. Detect the edge from the matched object and binarize the image.
5. Detect a virtual horizontal line while detecting the tail line of the aircraft based on the detected edge information. Then, corner points are detected from the binarized image.
6. Calculate the vertical distance from the detected tail line information and corner point information. Then, the angle between the lines is calculated from the virtual horizontal line and the corner point information. Also, the horizontal distance is obtained from the corner point information.
7. Apply linear regression from the calculated vertical distance data, and estimate the pitch angle using the result and the vertical distance value.
8. Estimate the roll angle using the angles calculated between the lines.
9. Also estimate the angles based on the calculated horizontal distance values and the linear regression results calculated from them.

Based on the experimental results of the roll, yaw, and pitch angles, which are the attitude information of the preceding flight, through the estimation process as shown in Fig. 2 composed of Paul et al., the flight information generated by the X-Plane simulator and the flight information estimated by image processing and linear regression are compared. For the roll angle, an error of up to 21 degrees occurred, and a mean error of 9 degrees was measured except for the instantaneous peak due to a sudden change of direction. In the case of yaw angle, a mean error of 7 degrees and 2 degrees was generated, respectively. In case of pitch angle, an error of 2 degrees and 1 degree was measured respectively.

An error of about 5 to 7 degrees in the flight attitude estimation is an estimated value that is likely to fail continuous tracking. Therefore, it is necessary to reduce this error to a much lower degree. In this paper, we would solve this problem by applying Kalman filter.

3. Improvement of Attitude Estimation by Kalman Filter

3.1 Kalman Filter

The Kalman filter is a filter developed by Rudolf E. Kalman in the early 1960s and is a signal processing algorithm that estimates the optimal value by using past data and current measurements to remove the noise contained in the measured values.

Prediction Phase

$$x_k = A \cdot x_{k-1} + B \cdot \mu_k + w_{k-1}$$
$$z_k = H \cdot x_k + r$$
$$P_k = A \cdot P_{k-1} \cdot A^T + Q_s$$

Update Phase

$$g_k = \frac{P_{k-1} \cdot H^T}{H \cdot p_{k-1} \cdot H^T + r}$$
$$\hat{x}_k = x_{k-1} + g_k(z_k - H \cdot \hat{x}_{k-1})$$
$$P_k = (1 - g_k \cdot H) \cdot P_{k-1}$$

A : Prediction matrix
B : *Control matrix*
P : Covariance matrix (uncertainty)
H : *Sensors readings matrix*
Q_s : State noise covariance
x_k : *current state matrix*
x_{k-1} : *previous state matrix*
u_k : *control signal*
w_{k-1} : *white noise of process*
z_k : *current observed values matrix*
r : *accuracy of instruments(sensors)*

Fig. 3. Process of Kalman Filter

The goal of Kalman filter is to estimate the optimal current state from accumulated historical data and the best data currently available. The Kalman filter adopts a method of repeatedly performing time update (prediction) and measurement update (correction) as shown in Fig. 3. The time update is a step of estimating a current value based on previous data, and the measurement update is a step of correcting a current measurement value using the estimated value. In this paper, we apply the Kalman filter to the estimated roll, pitch, and yaw values through image processing to achieve robust estimation with less error.

3.2 Application of Kalman Filter

3.2.1 System Implementation

In order to improve the attitude estimation performance, the Kalman filter was applied to the flight attitude estimation algorithm proposed by Paul et al. The overall configuration of the proposed system using Kalman filter is shown in Fig. 4 and the process is as follows.

1. Initialize the Kalman filter in PC01's flight attitude estimation main system.
2. Take off the Cessna 172SP unmanned aerial vehicle from the X-Plane simulator installed on PC02 and fly it with the joystick.
3. Start communication with the flight attitude estimation system using UDP.
4. Take a picture of the flight scene of the Cessna unmanned aerial vehicle using an external camera (assuming it is mounted on a following aircraft).
5. Estimate Cessna's flight attitude using image processing and linear regression from the captured images.
6. Apply a Kalman filter to the estimated flight attitude data using image processing and linear regression and earn the predicted data.
7. Compare the original attitude data that generated from the X-Plane simulator with the estimated data from Kalman filter.

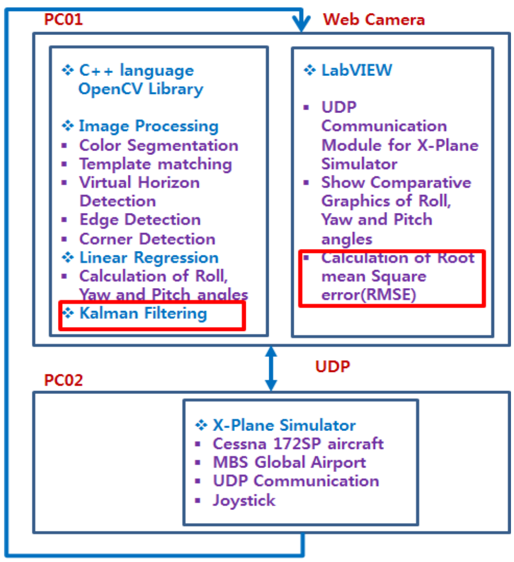


Fig. 4. Overall Configuration of The Proposed System using Kalman Filter

3.2.2 Kalman filter Processing

Fig. 5 shows the software configuration that performs Kalman filter processing using C ++ and OpenCV library.

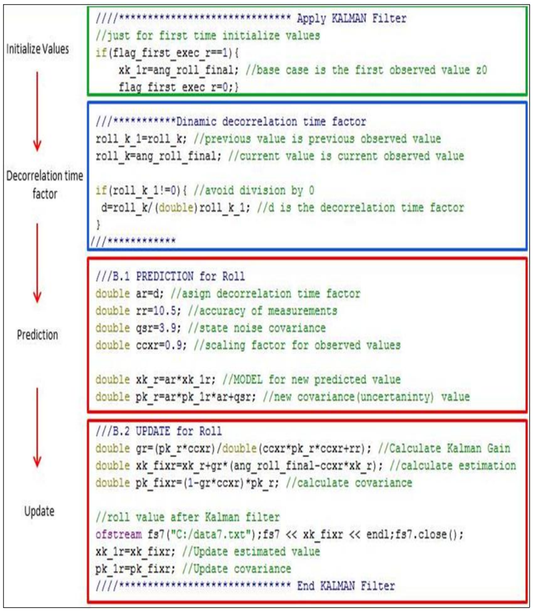


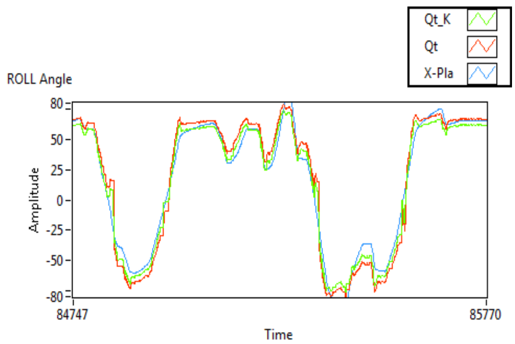
Fig. 5. Software Configuration that Performs Kalman Filter Processing

In order to operate the Kalman filter, the first previous predicted value x_{k-1} is initialized with the first data estimated through image processing and linear regression. The covariance value P_{k-1} is initialized to 1 and then replaced with the new value from the second iteration. And other fixed initial values necessary for Kalman filter operation are initialized by using fine tuning test values determined in the constructed system to minimize RMSE[18]. Then, the posture data of the unmanned aerial vehicle estimated through image processing and linear association based on the camera image is applied to the Kalman filter and the posture estimation is performed in real time by repeating the prediction and updating process.

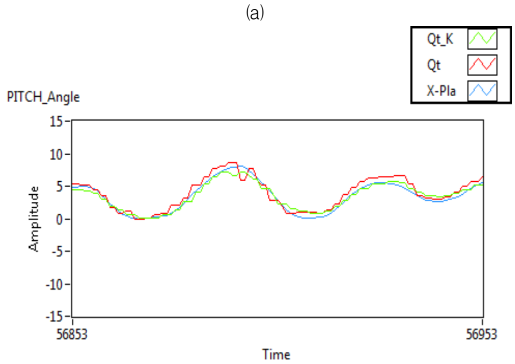
4. Experiments and Results

4.1 Attitude Information Estimation

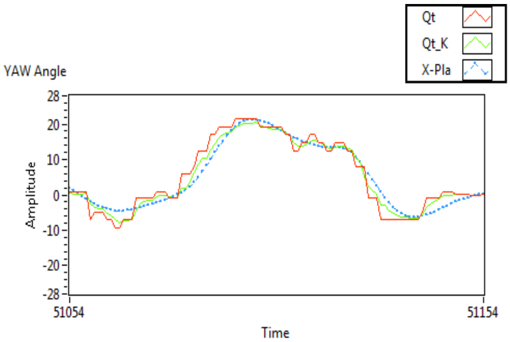
The real-time operation experiment was performed by linking the unmanned aerial vehicle posture estimation system with the Kalman filter constructed in Section 3 with the camera and X-Plane simulator. Based on the flight attitude data generated during the operation of the unmanned aerial vehicle Cessna generated by the X-Plane simulator, the estimated data from the image processing and the linear association are compared with the estimated data through the Kalman filter. Fig. 6 (a) shows roll angle, (b) pitch angle, and (c) yaw angle, respectively. In the figure, the blue line represents the attitude data generated by the X-Plane, and the red line represents the data estimated through image processing and linear association. And the green line shows the estimated data from the Kalman filter. The mean and maximum error values for the estimated data are shown in Table 1. When the Kalman filter is used, the roll angles are improved by 6.1 and 3.8 degrees. For the pitch angle, the attitude estimation performance improved by a maximum of 0.6 degrees and a mean of 0.3 degrees, and a maximum of 4.2 degrees and a mean of 0.8 degrees for the yaw angle.



(a)



(b)



(c)

Fig. 6. Mean and Maximum Error Values for The Estimated Before and After Kalman Filter Processing

Table 1. Comparisons among the Measured and the Estimated Data

	Image Processing		Kalman Filtering		Improved	
	Mean	Max	Mean	Max	Mean	Max
Roll	9.1	21.3	5.3	14.2	3.8	6.1
Pitch	1.1	2.3	0.8	1.7	0.3	0.6
Yaw	2.4	7.3	1.6	3.1	0.8	4.2

4.2 RMSE Measurements

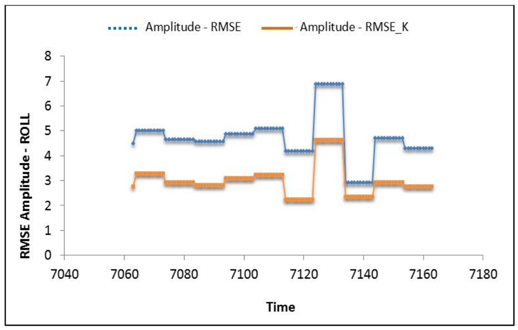
The aim of this study is to more precisely estimate the flight attitude of the leading unmanned aerial vehicle using a camera mounted on the following unmanned aerial vehicle. In order to verify the estimated performance, RMSE(Root Mean Square Error or RMSD(Root Mean Square Deviation) measure is used[18]. RMSE or RMSD is expressed as the square root value of the second sample moment relative to the difference between the predicted value and the observed value by the model, as in the following equation (1).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(p_i - o_i)^2}{N}} \tag{1}$$

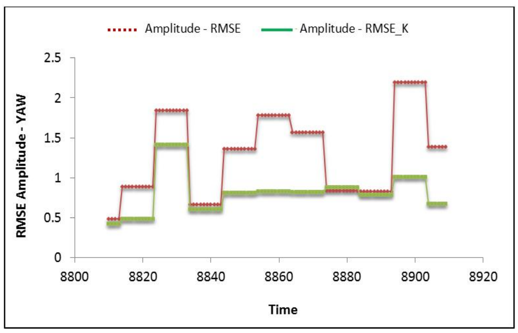
where N is sample size, p_i is a predicted value, and o_i is an observed value.

A RMSE value of 0 indicates that there is no difference between the two values, and the lower the value, the better the estimation performance is. Therefore, RMSD is a measure of accuracy. As the time progresses, the RMSEs of the image processing result and the Kalman filter processing result are measured and compared in order to examine the error variation with the real-time flight data generated from X-Plane.

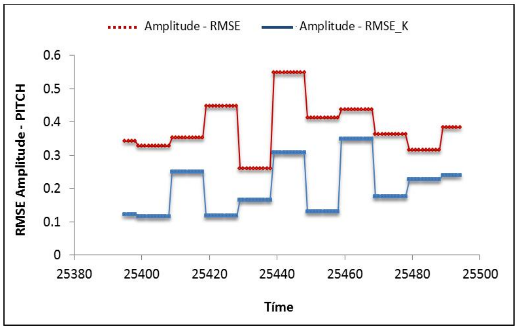
Fig. 7 shows the comparison of RMSE measurement results after image processing and Kalman filter processing about the estimated roll angles, (b) pitch angles, and (c) yaw angles, respectively. And Table 2 presents the mean and maximum RMSE values for the three attitude angles. It can be seen from the table that the estimate passed through the Kalman filter is more accurate than both the average and maximum values than the image processing estimates. By applying the Kalman filter as shown in Table 2, it is possible to improve the accuracy by 42% by the average and 35% by the maximum.



(a)



(b)



(c)

Fig. 7. Comparison of RMSE measurement results after image processing and Kalman filter processing

Table 2. Comparison of Mean and Max RMSE Values for Three Attitude Angles

RMSD	Image Processing		Kalman Filtering	
	mean	max	mean	max
Roll	4.8	6.9	2.8	4.5
Pitch	1.2	2.2	0.7	1.4
Yaw	0.4	0.54	0.2	0.35

5. Conclusion

In this paper, Kalman filter is added to the existing system estimated by using image processing to improve the estimation performance of the flight attitude estimation system of the proceeding unmanned aerial vehicle proposed by Paul and others. The estimation error of the flight attitude data estimated through the added Kalman filter can be reduced by 35% to 47% with much higher accuracy in all three of the roll, pitch, and yaw for the simulation attitude data generated in real time from the X-Plane simulator. In the future, we intend to realize the unmanned aerial vehicle posture estimation system through the improvement of camera and estimation system, and the experiment on actual unmanned aerial vehicle.

REFERENCES

[1] E. N. Barmpounakis, E. I. Vlahogianni & J. C. Golias.(2016). Unmanned Aerial Aircraft Systems for transportation engineering: Current practice and future challenges. *International Journal of Transportation Science and Technology, 5(3),* 111-122.
DOI : 10.1016/j.ijtst.2017.02.001

[2] J. P. Lee, J. W. Lee & K. H. Lee. (2016). A Scheme of Security Drone Convergence Service using Cam-Shift Algorithm. *Journal of the Korea Convergence Society, 7(5),* 29-34.
DOI : 10.15207/jkcs.2016.7.5.029

[3] H. J. Mun. (2016). Countermeasure to Underlying Security Threats in IoT communication. *Journal of IT Convergence Society for SMB,* 6(2), 37-44.
DOI : 10.22156/cs4smb.2016.6.2.037

[4] K. O. Park & J. K. Lee. (2017). A Countermeasure Technique for Attack of Reflection SSDP in Home IoT. *Journal of Convergence for Information Technology, 7(2),* 1-9.
DOI : 10.22156/cs4smb.2017.7.2.001

[5] K. B. Kim, G. M. Geum & C. B. Jang. (2017). Research on the Convergence of CCTV Video Information with Disaster Recognition and Real-time Crisis Response System. *Journal of the Korea Convergence Society, 8(3),* 15-22.
DOI : 10.15207/jkcs.2017.8.3.015

[6] Y. B. Sebbane. (2016). *Smart Autonomous Aircraft: Flight Control and Planning for UAV*. New York: CRC Press.

[7] Y. Wang, J. Mangnus, D. Kostic, H. Nijmeijer & S. T. H. Jansen. (2011). Vehicle State Estimation Using GPS/IMU Integration. *2011 IEEE SENSORS Proceedings* (pp. 28-31). USA : IEEE.
DOI : 10.1109/icsens.2011.6127142

[8] Q. Paul, J. H. Hyeon, Y. H. Moon & S. W. Ha. (2017). A Study on Attitude Estimation of UAV Using Image Processing. *Journal of the Korea Convergence Society, 7(5),* 29-34.
DOI : 10.22156/CS4SMB.2017.7.5.137

[9] H. D. Cheng, X. H. Jiang, Y. Sun & J. Wang. (2001). Color Image Segmentation: Advances and Prospects. *Pattern Recognition, 34(12),* 2259-2281.
DOI : 10.1016/s0031-3203(00)00149-7

[10] W. S. Hwang & M. R. Choi. (2016). Convergence Research of Low-Light Image Enhancement Method and Vehicle Recorder. *Journal of the Korea Convergence*

Society, 7(6), 1-6.
DOI : 10.15207/jkcs.2016.7.6.001

[11] J. C. Yoo & C. W. Ahn. (2013). Template Matching of Occluded Object under Low PSNR. *Digital Signal Processing, 23(3),* 870-878.
DOI : 10.1016/j.dsp.2012.12.004

[12] L. Ding & A. Goshtasby. (2001). On the Canny Edge Detector. *Pattern Recognition, 34(3),* 721-725.

[13] J. Cui, J. Xie, T. Liu, X. Guo & Z. Chen. (2014). Corners Detection on Finger Vein Images using the Improved Harris Algorithm. *International Journal for Light and Electron Optics, 125(17),* 4668-4671.
DOI : 10.1016/j.ijleo.2014.05.026

[14] P. Mukhopadhyay & B. B. Chaudhuri. (2015). A Survey of Hough Transform. *Pattern Recognition, 48(3),* 993-1010.
DOI : 10.1016/j.patcog.2014.08.027

[15] S. M. Ross. (2017). Introductory Statistics: Chapter 12 - Linear Regression. USA : Academic Press. 519-584Y. I. Kim. (2017). An Oral Health Promotion Behavior Model for Adolescents. *The Korean Journal of health service management, 11(2),* 129-142.

[16] G. Welch and G. Bishop. (2001). *An Introduction to the Kalman Filter*. SIGGRAPH. ACM, Inc..

[17] Laminal Research. (2017). *How X_Plane Works. X-Plane*. http://www.x-plane.com/desktop/how-x-plane-works/

[18] Wikipedia. (2018). *Root-mean-square deviation.* https://en.wikipedia.org/wiki/Root-mean-square_deviation.

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