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An Adaptive Complementary Filter For Gyroscope/Vision Integrated Attitude Estimation

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Abstract

An attitude estimation algorithm which integrates gyroscope and vision measurements using an adaptive complementary filter is proposed in this paper. In order to make the filter more tolerant to vision measurement fault and more robust to system dynamics, fuzzy interpolator is applied. For recognizing the dynamic condition of the system and vision measurement fault, the cut-off frequency of the complementary filter is determined adaptively by using the fuzzy logic with designed membership functions. The performance of the proposed algorithm is evaluated by experiments and it is confirmed that proposed algorithm works well in the static or dynamic condition.

Key words: Adaptive complementary filter, Fuzzy logic, Gyro/Vision integrated attitude estimation

1. Introduction

According to development of the recent electro-mechanical technique, study on attitude estimation using micro electro-mechanical system (MEMS) based inertial sensors has been increased and its result is applied for various systems [1]. The inertial measurement unit (IMU) consists of three axis gyroscopes and accelerometers. The MEMS gyroscope measures angular rate of the system and the accelerometer measures specific forces of the system where IMU is mounted [2].

In conventional inertial sensor based systems, the computation of system's attitude is accomplished by integrating the angular rate obtained from the gyroscope [3]. However, because the gyroscope suffers from high drift and noise, attitude estimation by using gyroscope will deteriorate over time. On the other hand attitude derived from accelerometer does not diverge with time in the absence of motion acceleration. Thus, accelerometer can be used as a compensating sensor for correcting the drift of the gyroscope. In general case, data fusion algorithms are implemented to integrate two information sources from the gyroscope and accelerometer, respectively by using extended Kalman filter [4, 5] or complementary filter [6, 7, 8]. However, accelerometer cannot clearly distinguish inclination and acceleration. When the system operates in dynamic status, attitude estimation based on these methods will be less accurate.

In order to handle this problem, vision data is used to compensate the drift error of gyroscope in this paper. The vision data is obtained from stereo camera and attitude estimation error of vision based method does not diverge with time because it is not calculated via integration but rely

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on the recognition of feature points in dynamic situation. Although this method has long term attitude stability, the attitude estimation with vision data has features tracking error in dynamic situation. For reducing the effect of vision data disturbances on the attitude estimation, adaptive logic is required and one of algorithms is fuzzy logic [9, 10] which has a characteristic to represent prior knowledge as fuzzy rules, which can be used to identify the dynamic condition and the vision measurement fault. Thus, in this paper, an adaptive complementary filter is proposed using fuzzy logic which is used to automatically adjust the cut-off frequency according to dynamic states and the quality of vision measurement. Performance of the proposed algorithm is verified by comparing the convention method without fuzzy logic in experiments.

The rest of the paper is organized as follows. Section 2 introduces a brief description of the attitude estimation with MEMS gyroscope and vision data. In section 3, a complementary filter with fuzzy logic is explained. In addition, experiment and simulation results shown in section 4 and section 5 presents brief conclusions finally.

2. Attitude Estimation

In this section, attitude estimation methods using gyroscope and vision data obtained by stereo-camera are introduced. Each method have unique characteristics according to operating environment and the performance of attitude estimation can be improved by using the integration of two methods. In addition, it is important to select the appropriate coordinate for determining attitude of system. The navigation frame which refers to North-East-Down (NED) frame and the body frame are used as the reference and local frames, respectively. The gyroscope measurement is aligned with the body frame consisting of orthogonal axes where x-axis is in the direction of forward motion of the system, y-axis is in the transverse motion of the system,

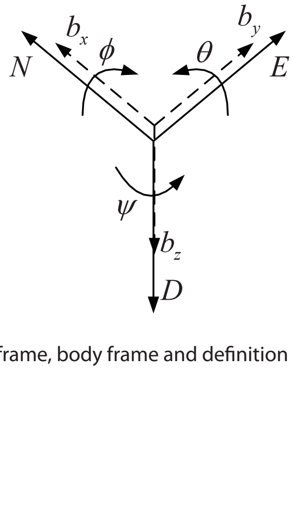

Fig. 1. Reference frame, body frame and definition of Euler angles

and z-axis in the down direction as shown in Fig. 1. The navigation frame and the body frame can be related by a sequence of rotations about Euler angles.

However, in this paper, it is assumed that the initial body frame is aligned with the initial reference frame as shown in Fig. 1, which is the result obtained through alignment process of the gimballed system. Alignment is the process whereby the orientation of the axes of a system is determined with respect to the reference axis in strapdown system or the gimbal is physically rotated until two of the body axes are level with respect to the reference axis in gimballed system. In many applications, it is essential to achieve an accurate alignment of a system within a period of time. However, in this paper, we are focusing on attitude estimation method instead of alignment.

2.1 Attitude Determination by Gyroscopes

Attitude estimation methods are classified as quaternion method, direction cosine matrix method, and Euler angle method. Among these, the Euler angle method which updates the Euler angles (roll, pitch, and yaw) uses the relationship between the body angular rotation rate and the derivative of the Euler angles as shown in Fig. 1. Euler angles have the advantages of being a more meaningful attitude expression than either the quaternion method or the direction cosine matrix method, which means that the user can recognize the attitude of the system intuitively. The update process of the Euler rotations of the body with respect to the chosen reference frame is expressed as [11]

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi/\cos\theta & \cos\phi/\cos\theta \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \tag{1}$$

where ω_i represents the angular rate of the i axis in the body frame. ϕ and ψ are three Euler angles, which represent the roll, pitch and yaw, respectively. The Euler angles can be obtained by directly integration of (1), given a known initial condition.

2.2 Attitude Determination by Vision Data

Attitude estimation method using vision data is based on the previous work [12]. The attitude estimation system shown in Fig. 2 by vision data consists of two infrared CCD cameras (VCC-S70) and infrared LEDs attached on the system, Matrox Meteor2-MC/4 frame grabber and a computer for the tracking algorithm. The vision data from two cameras is transmitted to the desktop computer and digitized to a resolution of 640x480 pixels. Fig. 3 shows the flow chart of the image processing algorithm [12]. Features (LED points) are extracted with the threshold and with the masking technique of the image plane. Then the 2-D point sets is obtained in the image plane. By using the epipolar line, the Hausdorff distance and the camera calibration information, the 2-D point sets of two images can be transformed to 3-D point sets. After the model indexing, 3-D point sets indexed with the model can be obtained. Finally, the attitude and the position of the system in body frame can be estimated by using the point sets. A more detailed image processing technique is introduced in the previous paper [12].

3. Adaptive Complementary Kalman Filter

The output of the previous section is two estimates of system's attitude from the gyroscope and the vision data, respectively. As already mentioned, in order to improve the estimation performance, data fusion is performed by using a complementary Kalman filter [6], which operates only on the errors in primary state variables and compensates for the disadvantage of each estimation result from gyroscope and vision data. Thus, this method provides relatively accurate attitude estimation compared to each output from the gyroscope and the vision data. Furthermore, in order to make the filter more robust to system dynamics error and more tolerant to vision measurement fault, the complementary Kalman filter applied by fuzzy logic is proposed in this paper. Fuzzy logic is designed to recognize the system dynamics status and the quality of the vision measurement and adjust the fading factor of the adaptive filter.

3.1 Conventional Complementary Filter

The high frequency response of the gyroscope is reliable, while its low frequency response is unreliable because of the

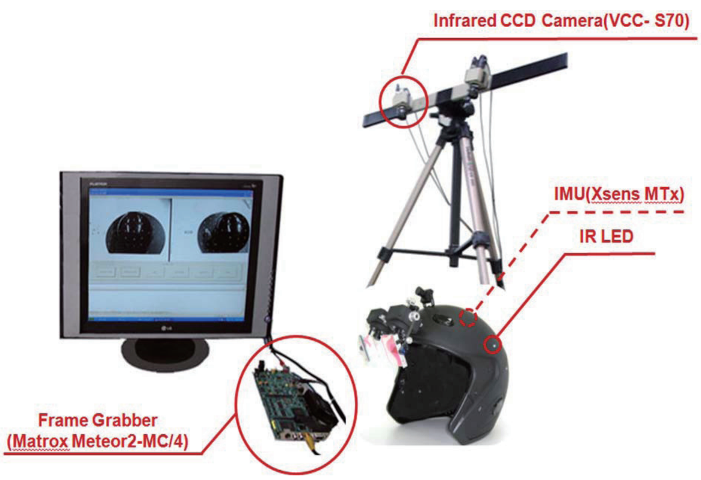

Fig. 2. Composition of the vision system [12]

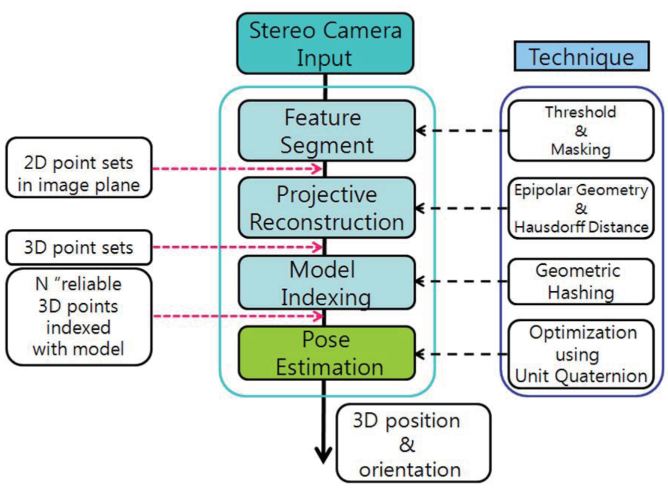

Fig. 3. The flow chart of the image processing for attitude estimation [12]

drift. In case of the vision data, it is drift-free, but it may be contaminated by tracking failures of feature points in the high dynamic motion. Thus, the measurements of vision and gyroscope have contrary characteristics that are suitable to combine each other by a complementary filter. The structure of the filter is shown in Fig. 4.

Gyroscope measurements are transformed from angular rates of body frame to Euler rates by (1) and ϕ_v is the attitude obtained from vision data. The complementary filter compares attitude from the integration of the Euler rate with the attitude angle from the vision data and the error between them is fed-back through a proportional and integral (PI) controller to compensate the gyroscope bias error, $\dot{\phi}_b$ [8]. The attitude result is expressed in Laplace form as follows

$$\hat{\phi} = \frac{1}{s}\left(\dot{\phi}_g - \dot{\phi}_b\right) = \frac{1}{s}\left(\dot{\phi}_g + K_P\left(\phi_V - \hat{\phi}\right) + \frac{K_I}{s}\left(\phi_V - \hat{\phi}\right)\right) \tag{2}$$

where K_P and K_I are a proportional gain and integral gain, respectively.

By rearranging (2), the attitude estimation values can be expressed as

$$\hat{\phi} = \frac{s^2}{s^2 + K_P s + K_I}\left(\frac{\dot{\phi}_g}{s}\right) + \frac{K_P s + K_I}{s^2 + K_P s + K_I}\phi_v \tag{3}$$

As shown in (3), the first transfer function refers to high-pass filter and the second one is low-pass filter. Thus, attitude can be estimated by integrating the attitude derived from the gyroscope through the high-pass filter and the attitude obtained from the accelerometers through a low-pass filter. The PI gains are related to the cut-off frequency of the filter and the damping ratio. Relations among PI gains, cut-off frequency and damping ratio are as follows:

$$\begin{aligned} K_I &= \omega^2 \\ K_P &= 2\zeta\omega \end{aligned} \tag{4}$$

where ω is the cut-off frequency and ζ is damping ratio which is fixed to 0.707 to provide a good transient response [8, 14].

The complementary filter using fixed cut-off frequency is difficult to satisfy acceptable performance in dynamic condition because attitude error caused by vision data disturbance is added to the filter. Thus, the cut-off frequency should be adjusted to improve the performance of the filter.

3.2 Fuzzy Logic for Adaptive Complementary Filter

In order to adjust the cut-off frequency by using a weighting factor, fuzzy logic [13] is applied to the complementary filter as shown in Fig. 5.

The input variables of the fuzzy logic for identifying system dynamics and vision measurement fault need to be defined. In the first, gyroscope measurement is relative to system movements, which can be used as an identification parameter of system dynamics. In terms of fault tolerance, normalized square error obtained by innovation information at present epoch can be used as detection parameter of vision measurement fault. Thus, the normalized square error and the absolute value of the gyroscope measurement are exploited as inputs of the fuzzy logic and they are expressed as

$$D_1(n) = \frac{e(n)^2}{C(n)} \tag{5}$$

$$D_2(n) = \left|\omega_x(n)\right| + \left|\omega_y(n)\right| + \left|\omega_z(n)\right| \tag{6}$$

where $D_1(n)$ is normalized square error, $C(n)$ is error variance which refers to $C(n)=E[e(n)^2]$, and $e(n)$ means one component of $\mathbf{e}(n) = \phi_V(n) - \hat{\phi}(n)$. This error value, $e(n)$ is a Gaussian random variable with zero mean and variance $C(n)$. As $e(n)$ is normalized by its covariance, $D_1(n)$ is a chi-square

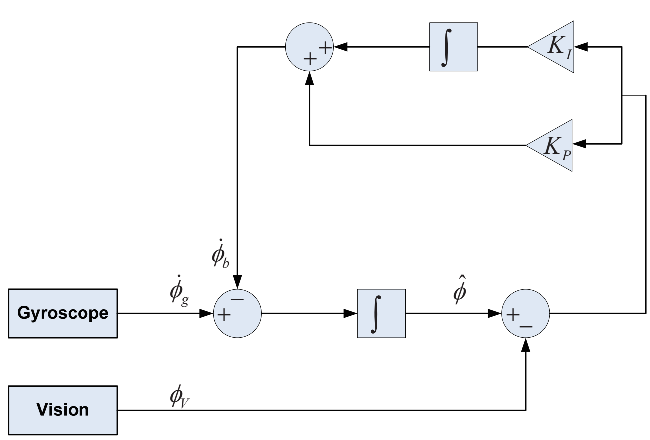

Fig. 4. The block diagram of the complementary filter

distributed random variable with n degrees of freedom, i.e., $D_1(n) \approx \chi^2(n)$. In order to monitor the quality of the vision measurement, chi-square test can be implemented with fuzzy logic. $D_2(n)$ denotes the motion grad in rotation which is used as criterion of system dynamics.

In order to design the membership functions of the fuzzy sets, both inputs of the fuzzy logic are classified as three grades, respectively and functions are shown in Fig. 6 and 7. As shown in these figures, L refers to Low, M represents medium, and H means high. In addition, F represents fault.

The output of the fuzzy logic consists of four singleton membership functions as follows:

$$\alpha(n) = \begin{cases} \alpha_1 & if\ \alpha(n) = S \\ \alpha_2 & if\ \alpha(n) = VS \\ \alpha_3 & if\ \alpha(n) = ES \\ 0 & if\ \alpha(n) = F \end{cases} \tag{7}$$

where $0<\alpha_3<\alpha_2<\alpha_1<1$, S represents small, VS is very small, ES is extra small, and F refers to fault status. By using the output of the fuzzy logic, the cut-off frequency of the complementary filter is adjusted as (8) and the output of the fuzzy logic is called weighting factor and is decided by (9).

$$\omega_c(n) = \bar{\alpha}(n)\omega_0 \tag{8}$$

$$\text{If } D_1(n) \text{ is } A_i \text{ and } D_2(n) \text{ is } B_i\text{, then } \alpha_i(n) = \alpha(n) \tag{9}$$

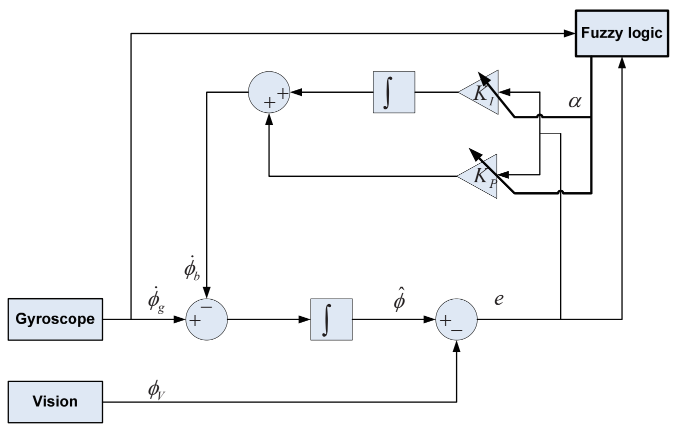

Fig. 5. The block diagram of the complementary filter with Fuzzy logic

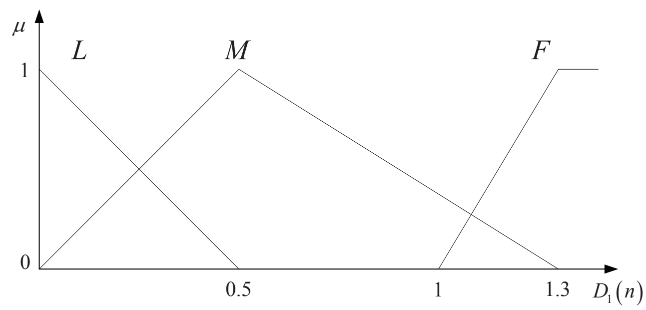

Fig. 6. Membership function of the normalized square error

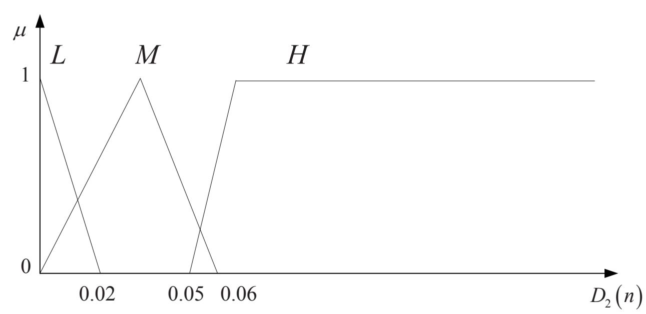

Fig. 7. Membership function of the motion grade

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In (8), ω_0 is nominal cut-off frequency. Equation (9) represents fuzzy rules of Takagi-Sugeno fuzzy logic which is commonly used and rather straightforward to understand. A_i and B_i are fuzzy sets in the antecedent, α_i is the output value of the fuzzy system corresponding to the i-th fuzzy rules written in table 1. In addition, $\bar{\alpha}(n)$ refers to the final value of the fuzzy logic and is expressed by the weighed average of the as follows:

$$\bar{\alpha}(n) = \sum_{i=1}^{9} \bar{\mu}_i \alpha_i(n) \tag{10}$$

where $\bar{\mu}_i$ is a normalized weighting factor which is expressed as

$$\bar{\mu}_i = \frac{\prod_{k=1}^{2} \mu_k^i}{\sum_{j=1}^{9}\left[\prod_{k=1}^{2} \mu_k^j\right]} \tag{11}$$

where μ_k^i is the output of the membership function in the case of k-th input and i-th fuzzy rule written in Table 1.

Finally, weighing factor should be selected according to dynamic status and vision measurement fault. If the system is experiencing severe dynamic motion, the attitude estimated from vision data has huge error due to tracking failure of feature points. In this case, smaller weighting factor should be used. A small weighting factor refers cut-off frequency is reduced and more reliability is given to the gyroscope. Otherwise, if the system is in low dynamic condition, then more weighting is put to the vision method. In addition, if normalized square error exceeds 1.3 (30 percent increase of the normalized square error compared to that of the expected value) regardless of dynamic condition, there is fault in vision data. Thus, in this case, zero weighting factor is selected as shown in table 1.

4. Experiments

This section describes simulation results and the off-line test with the real data. The experimental setup is shown in

Table 1. Fuzzy rules

Rule	$D_1(n)$	$D_2(n)$	$\alpha(n)$
1	L	L	1
2	L	M	S
3	L	H	VS
4	M	L	S
5	M	M	VS
6	M	H	ES
7	F	L	0
8	F	M	0
9	F	H	0

Fig. 8. The helmet model is on the rate table and the stereo camera system is placed beside the rate table. In order to estimate attitude of the helmet model, unique patterns of LEDs are implemented. In addition, a triple-axis rate table (Acutronic) is used as reference system and a triple-axis MEMS gyroscope (STIM 210) is used. Its bias instability is $0.5^{o}/h$, angular random walk is $0.15^{o}/\sqrt{h}$, and temperature gradients is $10^{o}/h$.

The performance evaluation is carried out by comparing with conventional complementary filter without the fuzzy logic. In addition, analysis on fault tolereance of filter is also performed in the simulation.

Figure 9 shows the attitude estimation result which is represented by the Euler angles. In this figure, the black line is the reference, the green line refers to the result of the conventional algorithm which has not fuzzy logic, the red line is the result of the proposed algorithm, and the blue line is the result when the only vision measurement is used. RMSE of the proposed algorithm is 0.4705, RMSE of the conventional algorithm is 0.5605 and that of vision data is 0.8822. As shown in the enlarged plot of Fig. 9 in Fig. 10, 11, and 12, the proposed algorithm shows the

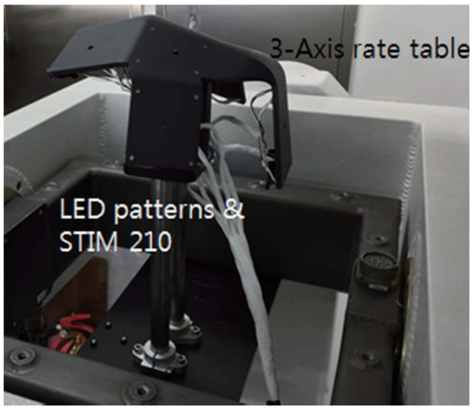

Fig. 8. Experimental setup

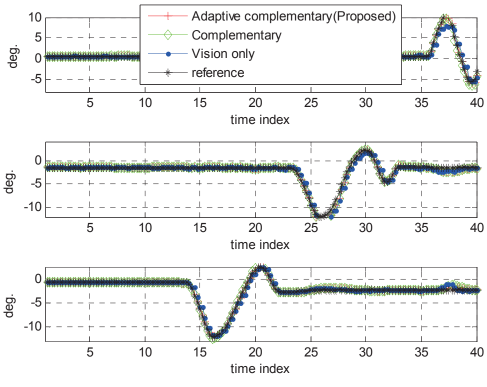

Fig. 9. Attitude estimation results (Top: roll angle, Middle: pitch angle. Bottom: yaw angle)

more accurate result than other methods. However, in some cases of dynamic motion (especially the attitude change at time index 33 in Fig.11), there is the performance reduction due to the response of the complementary filter which has sensitive response in dynamic situation. Mostly, its characteristic helps to improve the attitude estimate in a sudden change of attitude, but the characteristic occasionally causes an overshoot in normal condition as shown in Fig. 11. In order to reduce this effect on the estimation performance, the proportional gain and integral gain of the complementary filter should be reset according to the system response.

In Fig. 13, vision data faults caused by tracking failure of feature points are added at 18 time index and 28 time index. In addition, its effect lasts for 2 time index. The fault is modeled by a step-type fault which reflects characteristic of the vision data and its value is set to 5. Simulation results demonstrate the proposed algorithm performs well even under vision fault case because the proposed algorithm adjust the cut-off frequency according to the situation by using fuzzy logic. RMSE of the proposed algorithm is 0.4624, RMSE of the conventional algorithm is 0.6938 and that of vision data is 1.0846. In Fig. 14, it is confirmed that the cut-off frequency of the proposed algorithm (red dot line) is adjusted by the fuzzy rules in order to reduce the effect of the bias type fault in the vision data. Whereas the cut-off frequency of the adaptive complementary filter which have no fault detection rules in the fuzzy rules [8] does not change when the bias type fault occurs. In the case of dynamic situation (27~30 time index), both of the adaptive complementary filter adjust the cut-off frequency through the fuzzy rules (rule 1~6) in table 1.

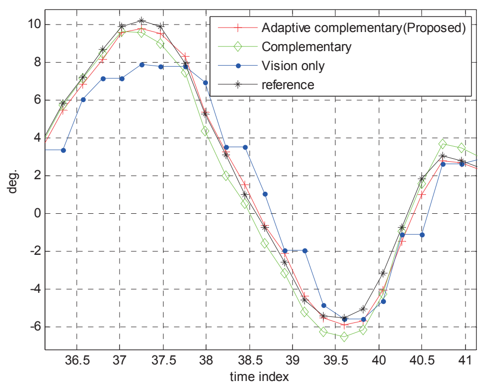

Fig. 10. Attitude estimation results 1 (enlarged roll angle)

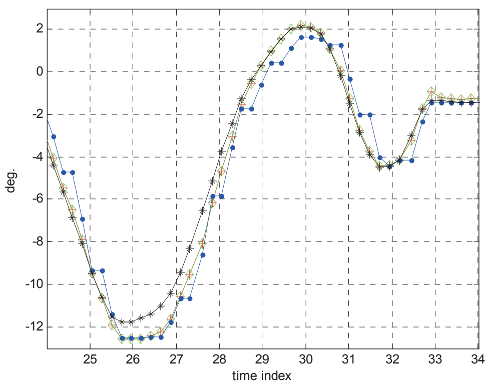

Fig. 11. Attitude estimation results 2 (enlarged pitch angle)

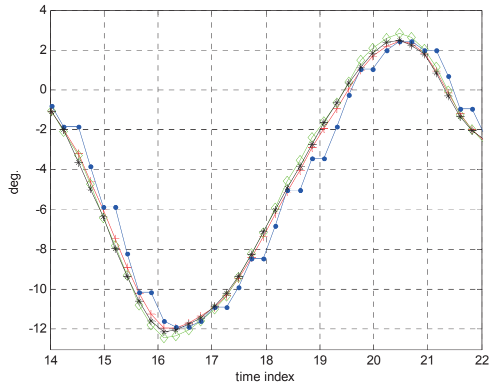

Fig. 12. Attitude estimation results 3 (enlarged yaw angle)

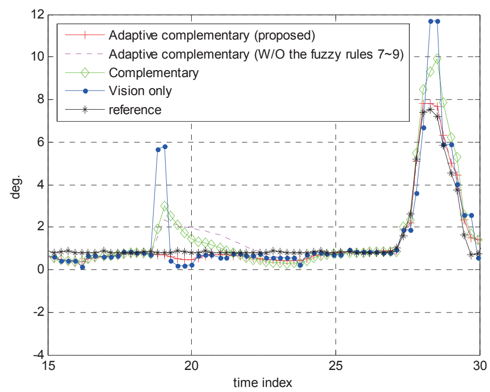

Fig. 13. Attitude estimation results with vision data fault

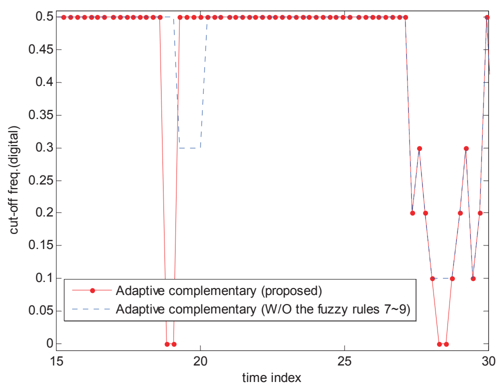

Fig. 14. Adjustment result of the cut-off frequency

5. Conclusions

An adaptive complementary filter using fuzzy logic has been proposed to estimate the attitude of the system using MEMS gyroscope and vision data obtained by stereo camera. The fuzzy logic is used to recognize dynamic status of the system and vision data fault by adjusting the cut-off frequency. In this way, it can make the filter more tolerant regarding vision data fault. The performance of the proposed algorithm is verified by simulations and its results show that the proposed attitude estimation method has better performance compared with conventional method.

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