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A new fuzzy logic-based adaptive complementary filter algorithm for UAV Attitude Estimation

İHA tutum tahmini için yeni bir bulanık mantık tabanlı uyarlanabilir tamamlayıcı filtre algoritması

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Abstract

Micro Electro-Mechanical System (MEMS) Based Inertial Measurement Units (IMU) are widely used for attitude estimation in unmanned aerial vehicle (UAV) systems owing to their small, light weight and cost effectiveness. On the other hand, it has some disadvantages that influence performance, such as noisy output, low sensitivity, poor accuracy, and bias stability. Also, MEMS-based IMU sensors (accelerometers and magnetometers and gyroscopes) cannot provide adequate navigation solutions as a standalone system. Different sensor fusion techniques have been proposed in the literature to obtain reliable attitude estimation. However, most of these fail in situations such as nonlinear measurement models, nonlinear process dynamics, and long-range navigation. This article presents a new fuzzy rule-based complementary filter (CF) that combines magnetic field, angular velocity and acceleration measurements from low-cost MEMS-based IMU sensors to achieve a more robust attitude estimation in a UAV under dynamic motion. The proposed approach adjusts the cut-off frequency of the CF to the optimum value according to the variable dynamic motion of the system. Thus, the problem of constant cut-off frequency is eliminated and a more robust attitude estimation is achieved even with the varying movements of the system. Both real experiments and numerical simulations confirm the validity of the presented method.

Keywords: Attitude estimation, Inertial measurement unit, Fuzzy Logic, Complementary filter, Real time experiments.

Öz

Mikro Elektro-Mekanik Sistem (MEMS) Tabanlı Atalet Ölçüm Birimleri (IMU), küçük, hafif ve maliyet etkinliği nedeniyle insansız hava aracı (İHA) sistemlerinde tutum tahmini için yaygın olarak kullanılmaktadır. Öte yandan, gürültülü çıkış, düşük hassasiyet, zayıf doğruluk ve önyargı kararlılığı gibi performansı etkileyen bazı dezavantajları vardır. Ayrıca, MEMS tabanlı IMU sensörleri (ivmeölçerler ve manyetometreler ve jiroskoplar) bağımsız bir sistem olarak yeterli navigasyon çözümleri sağlayamaz. Güvenilir tutum tahmini elde etmek için literatürde farklı sensör füzyon teknikleri önerilmiştir. Ancak bunların çoğu, doğrusal olmayan ölçüm modelleri, doğrusal olmayan süreç dinamikleri ve uzun menzilli gezinme gibi durumlarda başarısız olur. Bu çalışma, dinamik hareket altındaki bir İHA'da daha gürbüz bir tutum tahmini başarmak için düşük maliyetli MEMS tabanlı IMU sensörlerinden alınan manyetik alan, açısal hız ve ivme ölçümlerini birleştiren yeni bir bulanık kural tabanlı tamamlayıcı filtre sunmaktadır. Önerilen yaklaşım, sistemin değişken dinamik hareketine göre tamamlayıcı filtrenin kesme frekansını optimum değere ayarlar. Böylece sabit kesme frekansı sorunu ortadan kaldırılır ve sistemin değişen hareketlerinde bile daha sağlam bir tutum tahmini elde edilir. Hem gerçek deneyler hem de sayısal simülasyonlar, sunulan yöntemin geçerliliğini doğrulamaktadır.

Anahtar kelimeler: Tutum tahmini Atalet ölçüm birimi, Bulanık Mantık,, Tamamlayıcı filtre, Gerçek zamanlı deneyler.

1 Introduction

The use and development of unmanned aerial vehicles (UAVs) has become a popular topic in areas such as military field surveillance and control, monitoring and recovery of natural disasters, monitoring and mapping of agricultural areas [1-2]. For this reason, researchers and scholars focused on the development of UAVs, which are increasingly used in different fields. Within the scope of military applications, UAVs are used in various fields such as electro-optical information gathering, ammunition supply, radar deception and jamming. The fact that UAVs offer a lower cost solution than manned aircraft makes them more preferable in military applications.

Many problems arise in the development of a small, inexpensive, and lightweight UAV system [3-4]. Robust and effective state estimation in the attitude and direction reference system (AHRS) is the primary requirement for micro-UAVs to locate and track on the map [5]. Therefore, one of the most important challenges of developing a micro-UAV is to design a robust, efficient and accurate navigation system. For the control and navigation of micro-UAVs, the vehicle's attitude angles must be known. Although these angles can be measured with an inertial navigation system (INS), classical MEMS technologies offer more suitable solutions in micro-UAVs. Recently, MEMS-based IMUs consisting of (3-axis) accelerometer (AM), gyroscope (GS) and magnetometer (MM) sensors have widely used for attitude estimation of many different systems [6-9]. The most important reason for choosing these sensors is that they are light, cheap and have low power consumption. However, MEMS-based IMU sensors are noisier and less sensitive than mechanical and optical sensors. Therefore, they cannot provide an efficient measurement when estimating the attitude of the system. This situation attracted the attention of researchers and led to

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various studies on the development of a robust and simple AHRS algorithm [10-14].

The MEMS gyroscope sensor computes the angular ratio of the system, the MEMS accelerometer sensor measures the gravitational acceleration, and the MEMS magnetometer sensor estimates the Earth system's magnetic field direction [15]. Systems with inertial sensors are usually used to estimate the attitude of the system by integrating measurements obtained from the gyroscope sensor [16]. Since the noise error in the measurements is also integrated over time, a noise error called drift error occurs. Therefore, attitude estimation using only gyroscope sensors degrades over time. MM and AM sensors can be used to compensate for the drift error of the gyroscope sensor. Since the attitude estimation calculated using these sensors is not calculated through integration, it does not deviate over time when there is no motion acceleration in the system. However, these sensors are sensitive to the motion acceleration in the dynamic state of the system. In addition, measurements taken with MM sensors are affected by the noise of electronic or ferromagnetic equipment in the environment [3]. Although the attitude of the system calculated by MM and AM sensors is stable in the long time, the attitude estimation made with these sensors contains high frequency noise error in dynamic state.

Considering that it is difficult to obtain an efficient and robust result in attitude estimation using a single sensor, many sensors fusion algorithms related to the approach of fusing different sensors for more accurate attitude estimation have been suggested. Complementary filters using frequency filtering features in linear systems [17-19] and extended Kalman filters (EKFs) are known as the most widely used algorithms [20-22]. Even though attitude estimation can be made with higher accuracy with the Kalman filter algorithm, its high computational complexity and inability to solve nonlinear problems make it difficult to implement [23]. On the other hand, the complementary filter algorithm has low computational complexity and can solve nonlinear problems, making it easy to implement of the algorithm [24]. Therefore, the complementary filter (CF) approach is preferred in embedded systems that do not involve computational complexity and require low energy consumption [25]. The CF is known as a sensor fusion algorithm that integrates measurements taken from the MM and AM sensors with the angular velocity measurement from the GS sensor and reduces the gyroscope drift error [26]. Using this algorithm, the roll and pitch angles of a system are computed by fusing the GS and AM measurements, and the yaw angles are computed by fusing the GS and MM measurements [27].

The constant-gain CF algorithm is suitable for navigation systems in micro-UAVs with limited sensor resources. However, the micro-UAV attitude estimation accuracy is low with this algorithm during dynamic motion. There are some recent contributions, though limited, that focus on adapting filters to improve the accuracy of micro-UAV attitude estimation under various dynamic conditions. For example, Duong et al. [28] proposed gradient descent based complementary filter with fuzzy tuning for attitude estimation with MEMS IMU. The AM and GS measurements were evaluated with Mamdani FIS in the study. Poddar et al. [29] introduced the adaptive nonlinear complementary filter with PSO support for attitude estimation. Measurements from AM, MM and GS sensors were used in the study. Zhang et al. [30] proposed the Second Estimator of the Optimal Quadrature Complement filter model. MARG sensors named MTi-3 were used in the study. Hwang et al. [31] presented the adaptive nonlinear complementary filter model. Measurements from MEMS's inertial sensor and external optical sensor were combined to describe the Helmet attitude Tracking System. Zheng et al. [32] presented a nonlinear complementary filter model. In the study, attitude estimation was made using AM, GS, and MM sensors as well as camera images as an extra external sensor. Zhu et al. [33] designed a novel Mahony Complementary Filtering Based on Allan Variance algorithm. Measurements from AM, MM and GS sensors were used in the algorithm. Bao et al. [34] developed an adaptive complementary filter based on Deep Q-learning Network. In the study, attitude estimation was made using AM, GS, and MM sensors as well as polarization sensors.

As can be seen from the literature review, some studies used AM, GS and MM sensors for attitude estimation, while some studies used AM and MM or AM and GS sensors. In some studies, attitude estimation was made with an algorithm developed for the nonlinear complementary filter.

However, none of the proposed attitude estimation techniques offer an adaptive system for linear complementary filter combining magnetic field, angular velocity, and acceleration measurements from low-cost MEMS-based IMU sensors. This work presents an adaptive new fuzzy logic based complementary filter that allows fusion of accelerometer, gyroscope, and magnetometer measurements from MEMS-based IMU sensors to achieve more robust attitude estimation under dynamic motion. The CF is preferred owing to some of its features, such as having less computational complexity, using a high-pass filter to minimize measurement noise, and taking into account possible drift errors. The proposed adaptive CF presented here has also been validated with real-time data obtained from a calibrated test environment capable of providing roll, pitch and yaw motions in the TUBITAK MAM Test Center laboratory.

2 Attitude estimation

In this section, attitude estimation methods computed using accelerometer, gyroscope and magnetometer sensors are discussed in detail. The sensor used for each method has certain advantages according to its structure. To control the position of the system on the map, the proper coordinate frame must be selected. In the study, the North-East-Down frame system is used as the reference and body frames for the attitude estimation of the system.

The navigation frame consists of orthogonal axes, where x-axis is in the direction of roll motion, y-axis aligns of the pitch motion, and z-axis is line with the yaw motion of the system.

The transformation from a body frame to navigation frame can be defined by using three using method which are Euler angle method, quaternion method, and direction cosine matrix method. In this paper, Euler angle method is used to show the attitude of the system moving in the reference frame.

2.1 Attitude estimation from gyroscope

Using a triaxial gyroscope at time t in the sensor frame, the measured angular rate for each of the axes can be represented as: [35]:

$$\omega_t^m = \omega_t + b_{\omega,t} + e_{\omega,t} \tag{1}$$

where, $e_{w,t}$ is considered zero-mean Gaussian noise, $b_{\omega,t}$ is the time varying offset term by low frequency error fluctuations, w_t is the actual angular rate, and ω_t^m is the measured angular velocity signal.

The pitch, yaw and roll rate obtain from the GS sensor measurement with respect to the body frame are defined as q, r and p, respectively, and are related to the derivative of Euler angles. The correlation between the gyroscope measurement and the derivative of the roll, pitch and yaw Euler angles can be defined as follows [36]:

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} \dot{\emptyset} \\ 0 \\ 0 \end{bmatrix} + R_x \begin{bmatrix} 0 \\ \dot{\theta} \\ 0 \end{bmatrix} + R_x R_y \begin{bmatrix} 0 \\ 0 \\ \dot{\varphi} \end{bmatrix} \tag{2}$$

which yields,

$$\begin{bmatrix} \dot{\emptyset} \\ \dot{\theta} \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\emptyset\tan\theta & \cos\emptyset\tan\theta \\ 0 & \cos\emptyset & -\sin\emptyset \\ 0 & \sin\emptyset\sec\theta & \cos\emptyset\sec\theta \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{3}$$

where, R_y and R_x denotes rotation matrices for y and x axis respectively. In addition, r, q and p denote the angular velocity of the z, y and x axis, respectively. $\dot{\varphi}$, $\dot{\theta}$ and $\dot{\emptyset}$ are Euler angles, which denote system yaw, pitch, and roll angle, respectively. These angles are acquired by integrating the aforementioned equations, which generally include gyroscope sensor errors such as measurement errors in the low frequency.

2.2 Attitude estimation from accelerometer

Accelerometer measurement from MEMS-based IMU sensor can be represented as [37]:

$$\begin{aligned} a_m &= R_b^n(q)^T(a_t - g) + a_{bt} + a_n \\ &= \dot{v}^b + \omega \ x \ v^b - R_b^n(q)g + a_{bt} + a_n \end{aligned} \tag{4}$$

where, a_n is assumed to be the zero mean white noise, a_{bt} is the offset error caused by high frequency error, g and $v^b$the gravitational acceleration and the linear acceleration in the navigation frame, respectively. a_m is the measured accelerometer signal.

Under stationary or low motion conditions $(\dot{v}^b, \omega \approx 0)$ the acceleration measured from (4) can be estimated as [38]:

$$a_m = \begin{bmatrix} a_{mx} \\ a_{my} \\ a_{mz} \end{bmatrix} \approx -R_b^n(q)g = \begin{bmatrix} |g|\sin\theta \\ -|g|\sin\varphi\cos\theta \\ -|g|\cos\varphi\cos\theta \end{bmatrix} \tag{5}$$

The accelerometer sensor can be used as a pitch sensor in a steady state system, and roll ($\emptyset$) and pitch (θ) angles can be obtained using the gravity vector affecting the system. The following equations are used to calculate pitch and roll angles [39]:

$$\begin{bmatrix} \emptyset \\ \theta \end{bmatrix} = \begin{bmatrix} atan2\left(\dfrac{a_{my}}{a_{mz}}\right) \\ atan2\left(\dfrac{a_{mx}}{\sqrt{a_{my}^2 + a_{mz}^2}}\right) \end{bmatrix} \tag{6}$$

where, a_{mz}, a_{my} and a_{mx} represent the linear acceleration caused by the gravitational force in the z, y and x axis, respectively.

Given that the system is in steady state, the linear acceleration terms gradually approach zero. The attitude estimation calculated using equation (6) gives more accurate results in stationary or low-level dynamic movements of the system. If the system is in a circular motion for a long the accelerometer sensor measures both the gravitational acceleration acting on the system and the centrifugal forces acting on the system due to the earth's rotation. Therefore, the attitude estimation of the system computed using only the accelerometer sensor is of low accuracy. The attitude of the system, calculated using accelerometer and gyroscope sensor measurements, gives more accurate results at low level system movements. However, the accelerometer sensor causes measurement errors in high dynamic movements of the system due to high frequency noises [40].

2.3 Attitude estimation from magnetometer

The yaw angle of the system is estimated by magnetometer measurements. The measurement of the 3-axis magnetometer sensor can be expressed as follows [41]:

$$m_m = R_b^n(q)^T \cdot \bar{H} + m_n$$
$$m_m = R_b^n(q)^T \cdot \begin{bmatrix} H\ \cos(\varphi_{inc})\cos(\varphi_{dec}) \\ H\ \cos(\varphi_{inc})\sin(\varphi_{dec}) \\ H\ \sin(\varphi_{inc}) \end{bmatrix} + m_n \tag{7}$$

where, φ_{inc} is the inclination angle of the Earth's magnetic field, φ_{dec} is the declination angle, H is the magnitude of the magnetic induction, $\bar{H}$ is the magnetic field vector of Earth, m_n stands for the white Gaussian noise, and m_m denotes is the measured magnetic field [41]. H, φ_{inc}, and φ_{dec} parameters vary with geodetic location and time [39].

The yaw angle of the moving system can be found after the angles $\emptyset$ and θ, which are calculated when estimating the attitude. The mathematical expression used to calculate the yaw angle can be represented as follows [35]:

$$\varphi = \tan^{-1}\left(\frac{m_x\sin\emptyset - m_y\cos\emptyset}{m_x\cos\theta + m_y\sin\theta + m_z\sin\theta\cos\emptyset}\right) \tag{8}$$

where, m_z, m_y, and m_x define the magnetic field evaluated along z, y and x axis, respectively.

The relationship between IMU sensors (accelerometer, gyroscope, and magnetometer) and attitude estimation is discussed in detail above. In the next section, the working principle of the CF algorithm will be introduced using these sensors.

3 Complementary filter

The CF is a commonly used sensor fusion algorithm in reliable attitude estimate due to its low computational complexity. Gyroscope measurements have high accuracy at stationary or low dynamic motion, but low performance due to drift error. Although accelerometers and magnetometer measurements have low accuracy in high frequency motion of the system, measurement errors in the sensor do not integrate over time. This means the sensor measurements are more accurate when the system is stationary condition or moving with low dynamics [42].

Given the advantages of sensors having complementary frequency responses, it would be appropriate to use a CF algorithm to fuse the measurements from sensors. Thus, the accuracy of the system's attitude estimation can be increased. The idea of the algorithm is to first apply a low pass filter for measurements from the accelerometer sensor and secondly a high pass filter for measurements from the gyroscope sensor. Then it fuses measurements to calculate the pitch and roll angle. In addition, the measurements of the magnetometer and gyroscope sensors are likewise fused to calculate the yaw angle.

Figure 1 demonstrates the basic structure of the complementary filtering algorithm. The x_1 and x_2 are input signals containing high frequency and low frequency noises, respectively. These signals are filtered through low and high pass filtering and free from these noise errors. Considering that $G(s)$ be a low-pass filter, then $\bar{G}(s) = 1 - G(s)$ becomes a high-pass filter transfer function. Here $s = \sigma + j\omega$ represents the complex variable in frequency domain. Using the Laplace transform method, the output of the complementary filter can be stated as [43]:

$$\hat{x} = x_1 * G(s) + x_2 * \bar{G}(s) \tag{9}$$

In attitude estimation, x={∅,θ,φ} is used to denote the system's roll, pitch, and yaw angle, respectively. $\dot{x_g} = \{\dot{\emptyset}, \dot{\theta}, \dot{\varphi}\}$ shows the attitude estimated by gyroscope measurement, while $x_a = \{\emptyset_a, \theta_a, \varphi_a\}$ shows the attitude estimated by accelerometer or magnetometer measurement. A classical complementary filter algorithm can be stated as [44].

$$\hat{x} = a\left(\int \dot{x_g}\, dt\right) + (1 - \alpha)x_a \tag{10}$$

The gain parameter α, which determines the weighting factor of the attitude angle estimated by the gyroscope measurement, is between [0, 1].

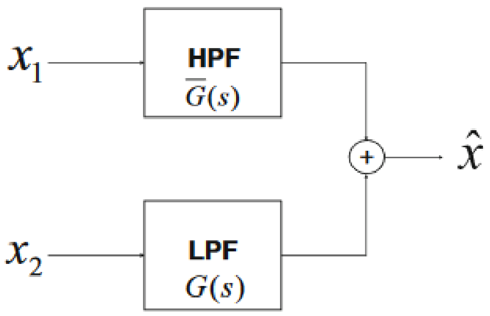


Figure 1. Basic structure of traditional constant-gain complementary filter

4 Adaptive complementary filter strategy

The CF is mainly designed to combine accelerometer, gyroscope and magnetometer measurements using their beneficial behavior at different frequencies. Therefore, a high-pass filter is applied for low-frequency noise to accelerometer and magnetometer sensor measurements. A low-pass filter is used for high-frequency noise to the gyroscope measurement. The output of the filters is fused to estimate the angle of the system. During the stationary and low dynamic movement of the system, the cut-off frequency of the CF can be easily obtained, and so the system's attitude can estimate accurately. In contrast, the complementary filter structures that have a constant cut-off frequency cannot be accurately estimated the system attitude in case of strong acceleration or rotation due to accumulated measurement errors.

Fuzzy logic unit is used to make decisions about the states of unstable or imprecise systems. In contrast the conventional machine language logic theory, fuzzy logic unit uses membership degrees ranging from 0 to 1. Also, in fuzzy logic unit, non-numerical expressions such as low, medium, and high are used to expression of rules and situations.

The fuzzy logic unit can be explained in three successive steps:

a) Fuzzification - Fuzzification is the process of identifying certain features in numerical or crips values and converting them to fuzzy values.

b) Fuzzy logic rule base - The process is to execute rules to compute fuzzy output functions. In order to best express the behavior of the system, fuzzy inputs are interpreted with a set of rules.

c) Defuzzification - The process is used to defuzzify fuzzy output functions to get numerical values as output. Inputs are converted into crips values that can be read and used by the system according to the established rules. [45]

In the scope of this study, an adaptive complementary filter developed with fuzzy logic unit is proposed to make more accurate and robust attitude estimation of the constant-gain complementary filter against rapid acceleration and maneuvering movements of the vehicle. The fuzzy logic unit is designed to define the dynamics of the vehicle and adjust the cut-off frequency of the filter under changing vehicle motion. Figure 2 shows the fuzzy logic based adaptive gain complementary filter algorithm structure.

The most common types of fuzzy rules found in the literature are Mamdani and Sugeno type models [46 - 47]. The method of producing output from fuzzy inputs is the main difference between them. The Sugeno type FIS uses a weighted average to compute the net output, while Mamdani uses the defuzzification technique of the fuzzy logic unit output with the output membership functions of the FIS. On the other hand, the Sugeno method has less computational complexity than the Mandami type FIS. The Sugeno type FIS was chosen because it gives a computationally efficient output, which is a fixed or linear (weighted) mathematical expression.

Sugeno based fuzzy logic unit is used to adaptively adjust the cut-off frequency of the high and low pass filter according to the measurements taken from the inertial sensors under variable vehicle dynamics. The input variables of the fuzzy logic unit system for distinguishing vehicle dynamics need to be defined firstly. The inputs of the fuzzy logic unit are the values of certain forces and angular velocities measured by the gyroscope, accelerometer and magnetometer sensors. The inputs of the fuzzy system which are defined as;

- $D_1 = \|\dot{y}_a(t)\| = \sqrt{\dot{y}_{ax}(t)^2 + \dot{y}_{ay}(t)^2 + \dot{y}_{az}(t)^2}$
- $D_2 = \|\dot{y}_m(t)\| = \sqrt{\dot{y}_{mx}(t)^2 + \dot{y}_{my}(t)^2 + \dot{y}_{mz}(t)^2}$
- $D_3 = |y_g(t)|$
- $D_4 = |\dot{y}_g(t)|$

where $\dot{y}_a(t)$ defines rate of change in accelerometer measurements, $\dot{y}_m(t)$ denotes the rate of change in magnetometer measurements, $y_g(t)$ describes gyroscope measurements and $\dot{y}_g(t)$ presents rate of change in gyroscope measurements. The mentioned measurements are related to the directional axis of the sensor.

Accelerometer and gyroscope measurements are used for stationary and dynamic situations since magnetometer measurement is not required for pitch and roll angle estimation. Likewise, magnetometer and gyroscope measurement are used for yaw angle estimation.

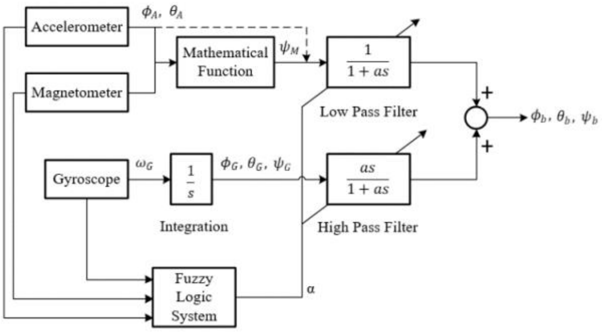


Figure 2. Basic Structure of the Proposed Adaptive Gain Complementary Filter

The proposed fuzzy logic unit scheme for distinguishing the stationary or dynamic state and determining the cut-off frequency is given in Table 1. Here, stationary, dynamic, and rotation are abbreviated as S, D, and R, respectively.

Table 1 Rule Basis of Fuzzy Logic

Conditions	D_1	D_2	D_3	D_4	$\mu(t)$
S or no R	low	N/A	low	low	1
D motion	N/A	N/A	high	N/A	0
D motion	high	N/A	N/A	N/A	0
D motion	N/A	N/A	N/A	high	0
No magnetic disturbance	low	low	N/A	low	1
Moving disturbance	high	high	N/A	high	0

In the proposed rules for determining the cut-off frequency in Tables 1, the last column gives the output expression according to the inputs of the generated fuzzy logic unit, where μ is valued in the range of [0,1].

Using the output of the system, the constant-gain complementary filter structure is made adaptive-gain. How to cut the frequency setting between the system output ω_{high} and ω_{low} is computed by applying the weighting factor (μ) as described in (11),

$$\omega_c = \mu\omega_{high} + (1-\mu)\omega_{low} \tag{11}$$

If μ =1 then ω_c =ω_{high}. This indicates that the measurements from the accelerometer sensor are more robust for the system's attitude estimation.

System entries in a fuzzy logic unit table are represented as high and low. The membership function (12) is a function that can be expressed logically by converting qualitative system inputs such as high and low to the value (μ) between [0, 1]. It can also be distinguished according to parameters. Figure 3 shows the membership function used for fuzzy logic unit inputs.

Examining the rule table, it is clear that the system is considered to be in a stationary or low dynamic motion when all the inputs are in the qualitatively small condition. Therefore, it is valid to assume μ=1 for this case.

$$\mu(t) = \prod_{i=1}^{4}(1-\mu_i(t)) \tag{12}$$

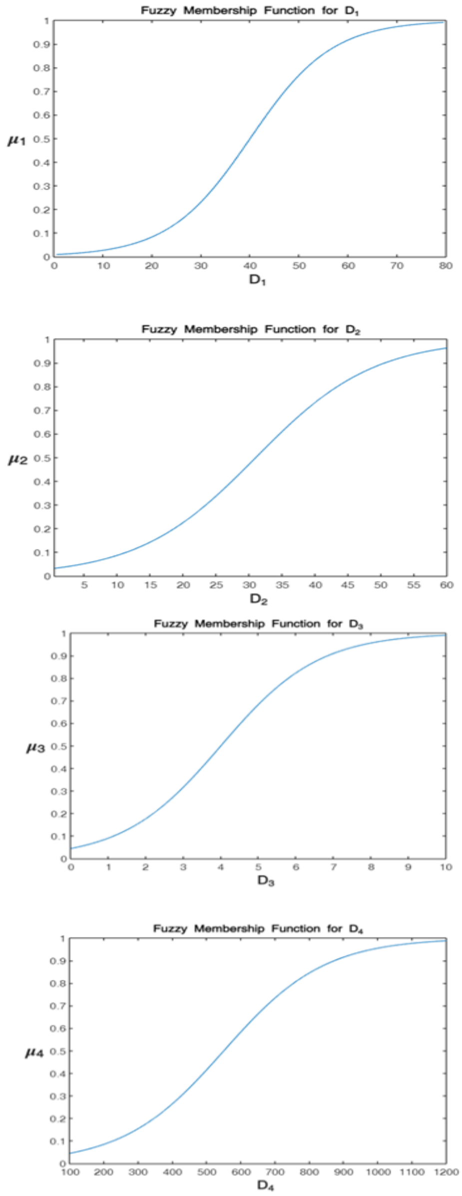


Figure 3. The fuzzy logic unit membership function

5 Experiments and Simulation Results

In this section, firstly the simulation result of the developed algorithm was demonstrated. The developed algorithm was compared with the constant-gain complementary filter and reference motion. Then, in order to prove the simulation results, the attitude data of the system were collected from a real-time experimental environment. The data were applied to the constant-gain complementary filter and the developed algorithm. The performance evaluation of the developed algorithm was made by comparing it with the constant-gain CF.

MATLAB simulation environment was used for performance validation and evaluation of proposed algorithm. An IMU sensor model was created that can adjust both sensor distortions (i.e. bias and scale factors) and sensor stochastic properties. The simulator was used in order to improve algorithms before used real time experimental apparat. The algorithm performance results obtained in the simulation was expressed below.

An experimental apparatus (in TUBITAK MAM Research Center) shown in Figure 4 was used to validate the performance of the complementary filter and the proposed algorithm with real sensor data. In the test environment shown in Figure 5, roll, yaw, and pitch movements were applied to the MPU9250 9-DOF IMU sensor that connected to the Arduino microcontroller.

Figure 4. Real time experimental test assembly

A data acquisition system was set up to process of the measurements from the sensors. The microcontroller was collected raw data from the accelerometer, magnetometer, and gyroscope sensors. The sensor data was saved in a file directory on the microcontroller. Then the data file was imported into MATLAB for validation and evaluation of algorithms.

Fuzzy logic input values were determined to model the motion of the system. The fuzzy logic inputs produced the output value according to the specified rules. The algorithm cut-off frequency was adjusted by passing the fuzzy logic output values through the weight function. In order to determine the range of the cut-off frequency, stationary and dynamic motion was applied to the system. Then, Fast Fourier Transform (FFT) was applied to the measurements taken from the accelerometer and gyroscope sensors in both motion states. In this study, the sampling frequency was taken as 100 Hz for FFT process. The upper and lower cut-off frequencies were determined as ω_{high} = 4.83 Hz and ω_{low} = 0.3418 Hz, respectively. The cut-off frequency was changed between these limits with respect to the inputs of the fuzzy logic unit. The constant-gain complementary filter, ω_C = 2.2441 Hz, which is the middle of the lower and upper cut-off frequency values, was chosen. In order to compare the performances of the algorithms, the root mean square error (RMSE) value of the Euler angles (rolling, pitch and yaw) was computed.

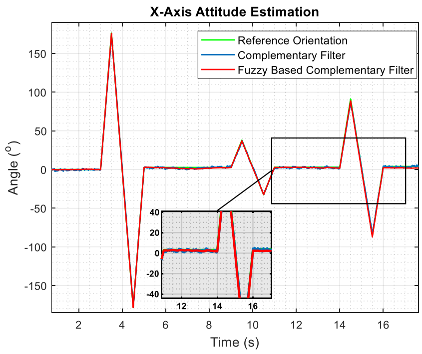
Figure 5 (a) shows the attitude estimation simulation results represented by Euler pitch angles. In this figure, the green line shows the reference motion, the blue line denotes the result of the constant-gain complementary filter algorithm, and the red line indicates the result of the algorithm proposed with the fuzzy logic-based approach. According to the first simulation results, while the RMSE value of the proposed algorithm was calculated 0.4263, the RMSE value of the constant-gain complementary filter algorithm was calculated 0.8252.

Figure 5 (b) and (c) demonstrate the simulation result of Euler roll and yaw angles, respectively. According to the simulation results of the Euler roll angle, while the RMSE value of the proposed algorithm was calculated 0.9861, the RMSE value of the constant-gain complementary filter algorithm was calculated 1.5334. Finally, while the RMSE value of the proposed algorithm of the Euler yaw angle was calculated 2.0371, the RMSE value of the constant-gain complementary filter algorithm is 4.2743.

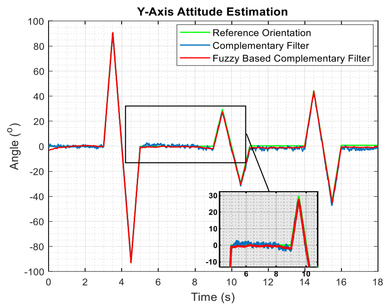
The error values of roll, pitch and yaw angles in terms of RMSE for CCF and FTCF are listed in Table 2.

Table 2 Root Mean Square Error (RMSE) for CCF and FTCF

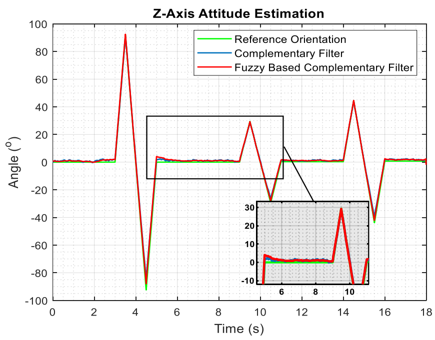
Algorithm	RMSE pitch (deg)	RMSE roll (deg)	RMSE yaw (deg)
CCF	0.8252	1.5334	4.2743
FTCF	0.4263	0.9861	2.0371



(a)



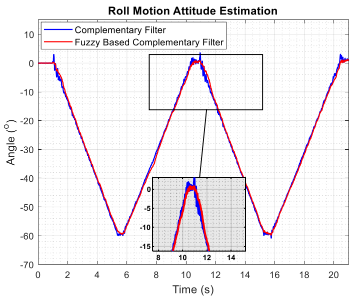
(b)



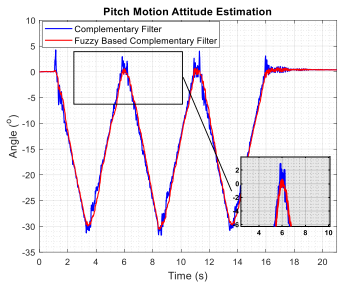
(c)

Figure 5. The simulation results of Euler (a) roll, (b) pitch, and (c) yaw motions

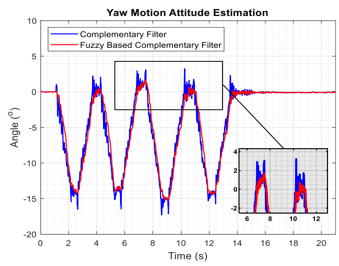
As can be seen from the results, the algorithms show close performance in the stationary motion situations of the system in the simulation environment. But, attitude errors occurred in the constant-gain complementary filter algorithm when the system was in dynamic motion. The reason why the accuracy of the constant-gain complementary filter is relatively low is because the gain is constant. Therefore, in the proposed method, the filter gain is designed to be adjustable over time to improve the accuracy of the attitude estimation.



(a)



(b)



(c)

Figure 6. Experimetal result of (a) roll (b) pitch (c) yaw movements with test setup

system is under low dynamic motion, the cut-off frequency have high value within the specified frequency limits. This means that the measurements get from the accelerometer sensors have more reliable when estimating the system's attitude. Conversely, during high dynamic motion of the system, the cut-off frequency of the algorithm takes values close to the cut-off frequency expressed as low. The simulation results show that the proposed algorithm gives better results than the constant gain complementary filter, especially in dynamic movements of the system. Because, the proposed algorithm adjusts the cut-off frequency according to the system motion using fuzzy logic.

Studies were carried out in the test apparatus to prove the results of the simulation environment. The test setup containing the IMU was rotated around the X, Y, Z axis. Then measurement data were collected using the microcontroller. The test setup initially performed a roll motion ranging from -60 to 0 degrees, starting from the zero roll and tilt position. Figure 6 (a) shows the result of the roll motion test.

Figure 6(b) shows the -30 to 0 degree motion result of the test setup for pitch motion. Figure 6(c) shows the result of the test setup moving in the z-axis at an angle of deviation ranging from -15 to 0 degrees.

Considering all the test outputs, it appears that the proposed filter has a position angle error of less than 1 degree compared to the reference motion. This indicates that the proposed fuzzy-based adaptive complementary filter is more stable than the constant-gain complementary filter in especially dynamic situations.

6 Conclusions

The attitude estimation problem of the UAV, which takes into account some weaknesses such as noisy output, poor accuracy, low sensitivity and bias stability affecting MEMS based inertial sensor measurements under dynamic motion, is solved by adapting the complementary filter using a fuzzy logic unit

In order to validate the proposed algorithm and evaluate its performance, the MATLAB simulation environment, which can simulate IMU measurements in random motion, was used. An IMU sensor model was created in the simulator that can adjust both sensor distortions (i.e. bias and scale factors) and sensor stochastic properties. This simulator has been used to validate and improve algorithms before working with real data. The performance of the fuzzy-based adaptive complementary filter algorithm, whose verification and development has been completed, is tested on a real test system with the roll, yaw and pitch motion data received from the MPU9250 9-DOF IMU sensor connected to the Arduino microcontroller. The simulation and real experimental results shows that the proposed fuzzy-based algorithm significant advantages compared to the traditional complementary filter. The new approach has been shown to provide a reliable attitude estimation using low-cost MEMS inertial sensors for many applications.

7 Author contribution statements

In the scope of this study, Author 1 and Author 2 contributed equally to the creation of the idea, its design, the literature review, the evaluation of the results obtained, the analysis of the results, and the checking of the spelling and content of the article.

8 Ethics committee approval and conflict of interest statement

There is no need to obtain permission from the ethics committee for the article prepared. There is no conflict of interest with any person/institution in the article prepared.

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