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Complementary Filter for Orientation Estimation:

Adaptive gain based on dynamic acceleration and its change

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***Abstract*—An attitude and heading reference system that comprises a low-cost inertial measurement unit and a magnetometer is often inaccurate during highly dynamic motion. To mitigate sensor errors, we used a well-known complementary filter. The basic objective in using this filter was to compensate for the drift in the gyro by using the accelerometer and magnetometer as an assistance component. This paper presents the design of an adaptive mechanism to adjust filter gain using a fuzzy logic controller. We hypothesize that dynamic acceleration and change in dynamic acceleration can be used as inputs for the controller. The controller thus produces two adaptive gains for use as filter gains. The experimental result shows that the estimated angle has a good trend until a specific time, i.e., until the influence of the gyro-drift causes estimated angle divergence.**

Keywords—orientation; AHRS; complementary filter; adaptive gain

I. INTRODUCTION

We developed a shoe-type measurement device for measuring gait information such as step length, width, and pressure distribution [1-3]. The device, shown in Fig. 1, consists of an inertial/magnetic measurement unit (IMMU), a wireless module, pressure sensors, and ultrasonic receivers/transmitters. To improve the orientation (bank, elevation, and heading) and position estimation, we design a filter to fuse the IMMU sensor.

Attitude and heading reference systems (AHRS) are typically used to determine orientation and heading. AHRS consists of an accelerometer, gyro, and magnetometer that provide a three-component inertial attitude solution without position and velocity. The attitude solution provided by the gyro is therefore prone to being unbounded, to bias, and to random-walk errors [4]. The accelerometer measures roll and pitch by leveling to correct the gyro-unbounded error. The magnetometer is used to correct the gyro-derived heading. The tool used to blend the high-frequency characteristics of the gyro and the low-frequency characteristics of the accelerometer is an estimator. The estimator's algorithm evolved along two major paths: Kalman filter and complementary filter [5]. This paper focuses on the complementary filter for orientation estimation.

The choice of an optimal filter gain value, unfortunately, depends on the application or the motion to which the sensor module is subjected. As an example, in [6], the author compared angular rate measurements against a threshold value as one of the parameters to determine the filter gain value in a gait application. In [7], the author used dynamic acceleration to determine acceleration level in unmanned aerial vehicle applications.

This paper presents a method for choosing the filter gain adaptively by combining dynamic acceleration and the change in dynamic acceleration as inputs for the controller. The aforementioned adaptive gain is the output of the fuzzy logic controller (FLC) in the simulation study. Adaptive gain K_1 will be the filter gain for the gyro component, and the second adaptive gain K_2 will be the filter gain from the assistance component, which is provided by the accelerometer and magnetometer. The intended application is to track foot orientation on a shoe-type measurement device; therefore, our experimental data are sourced from a real pendulum-like and IMMU sensor.

The rest of this paper is organized as follows: Section II describes the system at a glance, including the complementary filter and fuzzy logic mechanism in our design. Section III describes the experiment and simulation results. In section IV, we present our conclusions.

II. SYSTEM CONFIGURATION, COMPLEMENTARY FILTER, AND CONTROLLER DESIGN

A. System Configuration

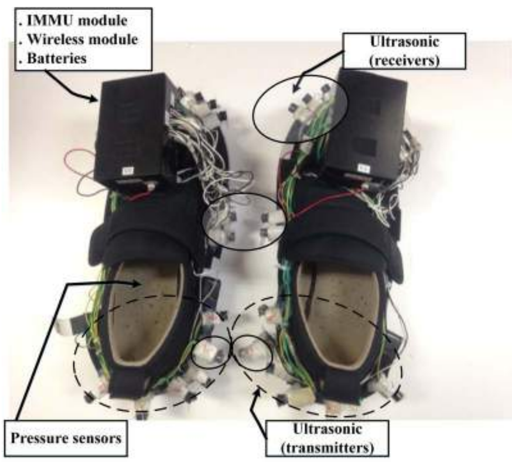


Fig. 1. Shoe-type measurement device.

As shown in Fig. 2, the time derivative of the Euler attitude is expressed in terms of the angular rate using (1) [8]

$$\dot{\omega} = \begin{bmatrix} \dot{\emptyset} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & sin\emptyset\ tan\theta & cos\emptyset tan\theta \\ 0 & cos\emptyset & -sin\emptyset \\ 0 & sin\emptyset\ /cos\theta & cos\emptyset/\ cos\theta \end{bmatrix} . \omega \quad (1)$$

where $\emptyset$, θ, and ψ are roll, pitch, and yaw angle, respectively.

In the assistance component block, roll and pitch may be determined without knowledge of gravity using (2) and (3), respectively

$$\emptyset = \text{arctan2}(-a_y, -a_z) \quad (2)$$

$$\theta = \arctan\left(\frac{a_x}{\sqrt{a_y^2 + a_z^2}}\right) \quad (3)$$

where a_x, a_y, and a_z are the acceleration components of the accelerometer. The magnetic heading measurement is as shown in (4).

$$\psi = \text{arctan2}\begin{pmatrix} -m_y cos\emptyset + m_z sin\emptyset, \\ m_x cos\theta + m_y sin\emptyset sin\theta + m_z cos\emptyset sin\theta \end{pmatrix} \quad (4)$$

where m_x, m_y, and m_z are the magnetic field components of the magnetometer.

B. Complementary Filter Design

Ideally, the complementary filter blends sensors such that the total transfer function H(s) = 1, which means that no additional dynamics are introduced. If θ(s) is the input, the relationship is identical to that in [9]:

$$\theta(s)\ H(s) = \theta(s) \quad (5)$$

If $G_i(s)$ is the dynamic response of each component, design filter $F_i(s)$ and its relation to H(s) is

$$H(s) = \sum_{i=1}^{n} G_i(s)\ F_i(s) = 1 \quad (6)$$

A pair of filters for the gyro component ($F_g(s)$) and the assistance component ($F_a(s)$)

$$sF_g(s) + F_a(s) = 1 \quad (7)$$

is such that the pair of first-order filters are

$$F_g(s) = \frac{\tau}{\tau s + 1} \quad (8)$$

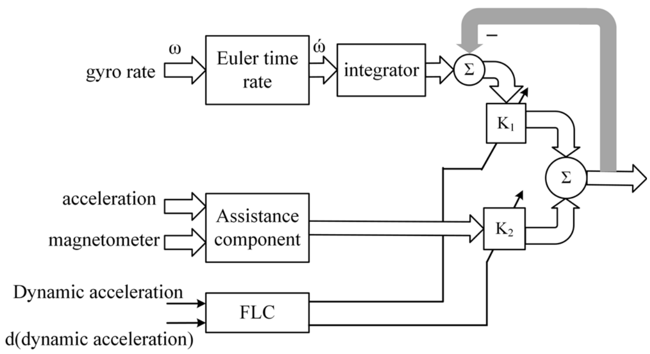


Fig. 2. Block diagram of the adaptive gain complementary filter.

$$F_a(s) = \frac{1}{\tau s + 1} \quad (9)$$

Filter gains K_1 and K_2 are adjusted by the output of the FLC. A block diagram of the complementary filter and the controller is shown in Fig. 2.

Fig. 3 shows our method for maintaining $K_1 + K_2 = 1$ using an intuitive strategy. Each FLC output is divided by the total value of those controller outputs, i.e.

$$K_1 = \frac{K_1'}{K_1' + K_2'} \quad (10)$$

$$K_2 = \frac{K_2'}{K_1' + K_2'} \quad (11)$$

C. Controller Design

The purpose of the controller is to calculate K_1' and K_2' based on fuzzy inference rules. The fuzzy controller block has two input variables, i.e., dynamic acceleration (α_k) and change in dynamic acceleration ($d\alpha_k$), which is modeled in (12) and (13), respectively. The dynamic acceleration is the absolute of the norm of acceleration minus gravitation (g).

$$\alpha_k = |\ \|a\| - g| = \left|\sqrt{a_x^2 + a_y^2 + a_z^2} - g\right| \quad (12)$$

$$d\ (\alpha_k) = \alpha_k - \alpha_{(k-1)} \quad (13)$$

The input variable α_k has five membership functions decided intuitively based on experimental data from the real pendulum, i.e. P_1, P_2, P_3, P_4, and P_5. The second input also has five membership function variables, i.e. NL, NS, ZE, PS, and PL. We also defined two outputs K_1' and K_2', each with five membership functions, i.e. NL, NS, ZE, PS, and PL. Figs. 4(a) and 4(b) show the fuzzy membership function for the inputs as well as for the output described in Figs. 5(a) and 5(b). The design of the fuzzy rule base outputs are shown in Tables 1 and 2, respectively.

III. Experimentation

A. Design

As stated earlier, we designed the filter for tracking foot orientation so that our experimental data is sourced from a real pendulum-like and sensor experiment. An IMMU sensor consists of an accelerometer (±16 g), a gyro (±1500 deg/s), and a magnetometer (±0.9 Ga), these was installed adjacent to the electromagnetic motion tracking system receiver (Fastrak®) on the free-swinging pendulum.

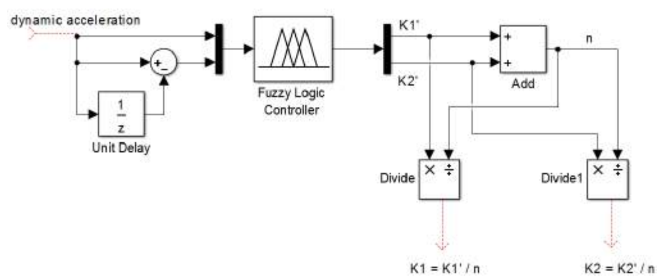


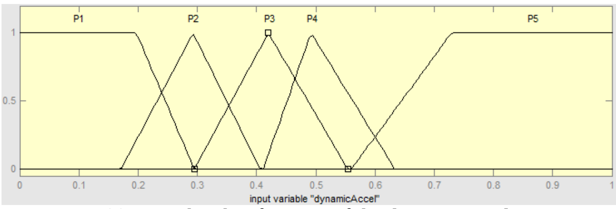
Fig. 3. K_1' and K_2' substitution values.

To validate the experimental result, we used Fastrak Polhemus® as the reference by recording the roll, pitch, and yaw angles of the pendulum movement. Sensor data were transmitted to the PC wirelessly, but the Fastrak attitude data were transmitted to the PC via a cable using an RS232 protocol. A MATLAB data acquisition program recorded data from the IMMU and the Fastrak on the same routine.

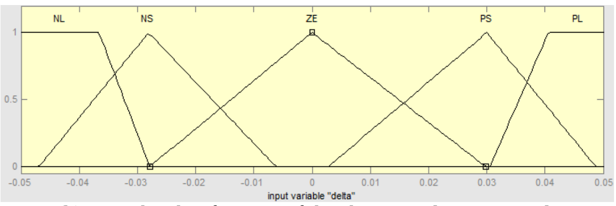
We used the conventional right-handed coordinate frame, i.e., the thumb is the x-axis (pointed forward), the first finger is the y-axis (pointed right), and the second finger is the z-axis (pointed toward the center of the earth). In this experiment, the sensor movement is on the x–z plane. We focused on the pitch angle as the y-axis acted as the pivot of the movement. However, the pendulum movement was sometimes sheer, giving roll and yaw angles. Fig. 6 shows the experimental apparatus.

B. *Experimental Result*

Figs. 7, 8, and 9 compare the data of the roll, pitch, and yaw estimations using the Fastrak as the reference. The horizontal axis represents the sample number; the vertical axis indicates the degree of roll, pitch, or yaw. Fig. 10 shows the filter gain value during simulation.

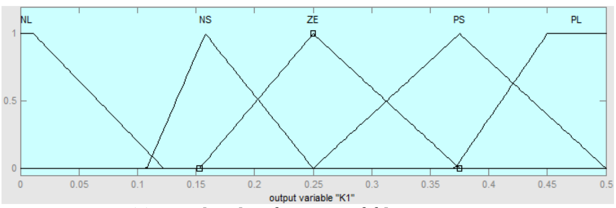


(a) Membership function of the dynamic acceleration

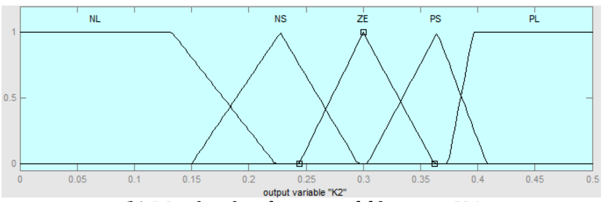


(b) Membership function of the change in dynamic acceleration

Fig. 4. Input membership function.



(a) Membership function of filter gain K_1'



(b) Membership function of filter gain K_2'

Fig. 5. Output membership function.

TABLE I. RULE BASE OF FILTER GAIN K_1'

		α_k				
		P_1	P_2	P_3	P_4	P_5
$d(\alpha_k)$	NL	NL	NL	NS	NS	ZE
	NS	NL	NS	ZE	ZE	PS
	ZE	NL	NS	ZE	ZE	PS
	PS	NS	ZE	ZE	PS	PL
	PL	ZE	PS	PS	PL	PL

TABLE II. RULE BASE OF FILTER GAIN K_2'

		α_k				
		P_1	P_2	P_3	P_4	P_5
$d(\alpha_k)$	NL	ZE	NS	NS	NL	NL
	NS	PS	ZE	ZE	NS	NL
	ZE	PS	ZE	ZE	NS	NL
	PS	PL	PS	ZE	ZE	NS
	PL	PL	PL	PS	PS	ZE

C. *Discussion*

We conducted the experiments on the x–z plane; therefore, the dominant angle was pitch (elevation), ranging between −35 and 35 degrees, as shown in the Fig. 8(a). The trend of the estimated pitch angle is similar to the reference up to 300 data samples. A pendulum sheer movement can also be seen on the x-axis, ranging from −10 to 10 degrees (Fig. 7(a)). In addition, the sheer movement on the z-axis caused a yaw angle ranging from −20 to 20 degrees, as shown in the Fig. 9(a).

In Fig. 7, we observe that the roll angle is well estimated up to 100 data samples, but the next divergence is in the range −40 to 40 degrees; this holds true for the yaw angle as well, where divergence occurs with time. We surmise that our fuzzy rule base determination process was less than optimal; therefore, the filter gain was not balanced. The tendency for divergence was dominated by the effect of the gyro drift angle estimation. We

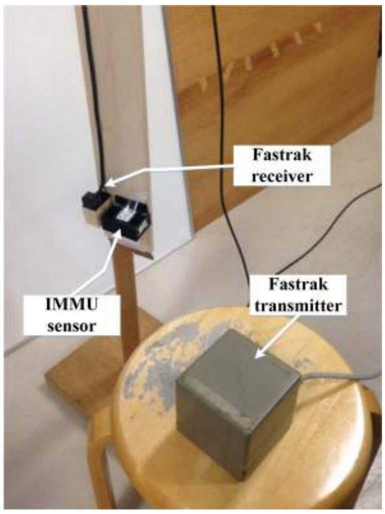


Fig. 6. Experimental apparatus and its installation.

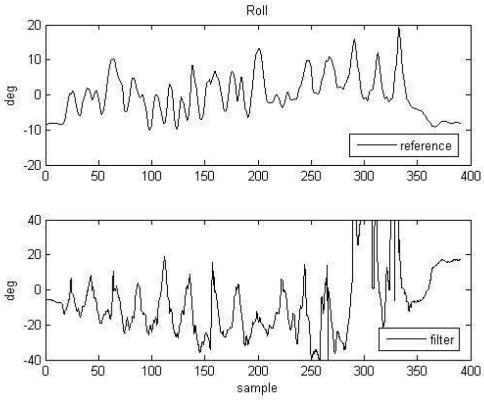


Fig. 7. The result of roll angle.

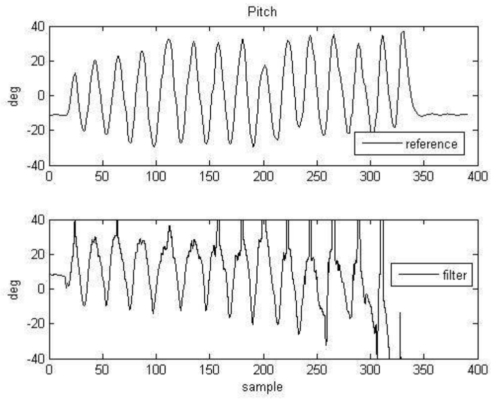


Fig. 8. The result of pitch angle.

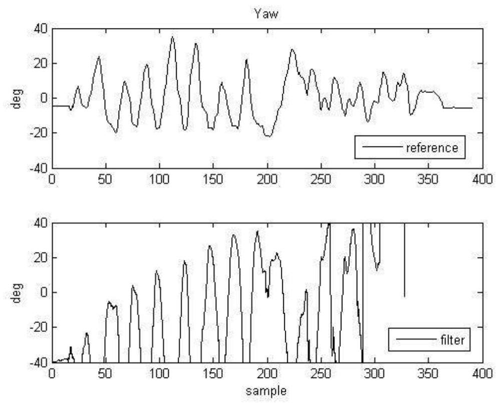


Fig. 9. The result of yaw angle.

can observe from Figs. 7−9 that the divergence started from sample 250. Fig. 10, where K_1 begins to increase at sample 250, confirms this observation. An increase in K_1 indicates that the primary influence to the estimator result was from the gyro-drift.

The next design will require improvements, especially to the fuzzy rule-base determination. In addition, further observations of the sensor outputs are necessary, particularly for special applications such as foot orientation tracking. A new parameter for the filter input must also be determined.

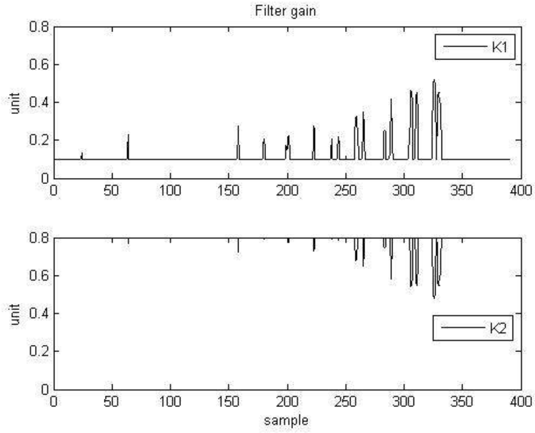


Fig. 10. Filter gain value.

IV. CONCLUSION

We designed an adaptive-gain complementary filter using a fuzzy logic controller. The experiment was performed with dynamic movement using a pendulum-like apparatus. The correct orientation trend was obtained, particularly in the pitch angle. However, a divergence trend was observed in the estimated angles as the filter gain increased; the gyro-drift began to dominate the estimation with time. In the future, we will focus on evaluating the fuzzy rule-base process and identifying new parameters as inputs.

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