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Comparison of sensor fusion methods for an SMA-based hexapod biomimetic robot

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ABSTRACT

This paper compares the performances of different sensor fusion algorithms in a shape memory alloy (SMA)-based hexapod biomimetic robot, SMABOT IV. The algorithms considered include a Kalman filter that minimizes the estimation error variance, an H_∞ filter that minimizes the worst-case estimation error, and a robust mixed Kalman/H_∞ filter that allows for uncertainties in both the system and measurement matrices. The sensors installed on the robot include an inertial measurement unit and an electric compass sensor for inertial guidance. In addition, a stride-length-estimation algorithm for an SMA-based legged robot was proposed to establish the legged odometry of the robot. Allan variance analysis is employed to identify the noise sources of inertial sensors, and the calculated variance values are used to design the parameters of the Kalman filter algorithm. Finally, experimental results of two-dimensional navigation are presented, and the performances of three sensor fusion algorithms are compared. The results indicate that after identifying the noise characteristics of inertial sensors, the Kalman filter provides the best performance.

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1. Introduction

Robots have been developed and researched for centuries, and they are now gradually being introduced into our daily lives. More and more engineers are focusing on studies of biomimetic robots, whose actuation mechanism, exteriors, motions, behaviors, or communication modes are designed by mimicking animals. In addition, biomimetic legged robots [1–8] can imitate the motion of insects and legged animals to achieve high mobility on rough terrain, and they can play an important role in rescue missions.

The actuation sources of biomimetic legged robots are classified into three types: motor [1,3,7], pneumatic [2,6], and artificial muscle [4,5,8]. Artificial muscle is the smallest and lightest type, and hence is very useful in building small insect-like robots. In this study, a hexapod biomimetic robot (SMABOT IV) based on a shape memory alloy (SMA) actuator was used as the plant for testing the performance of three sensor fusion algorithms.

The inertial measurement unit (IMU) (e.g., comprising accelerometers and gyroscopes) is self-contained and functions based only on physical laws of motion, which makes navigation systems based on IMUs inherently robust to interference. An IMU provides good high-frequency information but poor low-frequency data due to long-term system drift [9]. The inertial navigation system (INS) estimates velocity and position by integrating and double integrating the acceleration data from the IMU, respectively, which results in the unbounded estimation error increasing over time [10,11]. This shortcoming can be overcome if the IMU is corrected periodically based on information obtained from other sensors such as a global positioning system (GPS) [12], a leg-pose sensor [13], a vision system [14], or a range sensor [15]. The present study employed an electric compass sensor and estimated legged odometry as the aiding sensing devices.

There are many reports in the literature on the use of sensor fusion in mobile vehicles [14,16–18]. However, few studies have considered legged robots, especially SMA-based legged robots. We proposed an estimation algorithm for legged odometry based on temperature, which is a crucial characteristic of SMAs. The estimated legged odometry is used as one of the measurements in the sensor fusion processes.

The Kalman filter has been widely used in INS state estimation [8,12–16,19,20]. It combines all available measurement data with prior knowledge about the sensing device and the system to produce an optimal state estimation that statistically minimizes the error [21,22]. Nevertheless, uncertainty is always present in a real system, meaning that an exact model of a system and measurements are not available. Furthermore, the statistical characteristics of the process and measurement noise are difficult to determine. Accordingly, a robust filter (the H_∞ filter) was specifically designed to tolerate the uncertainty. Unlike the Kalman filter, which minimizes the variance of estimation error under the assumption that the statistical properties of the noise are known, the H_∞ filter minimizes the worst-case estimation error without making any assumption about the noise characteristics [8,23,24].

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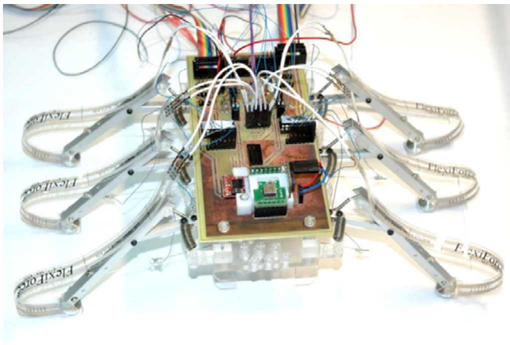

Fig. 1. SMABOT IV, a SMA-based hexapod robot with the IMU module, compass sensor and step touch sensors.

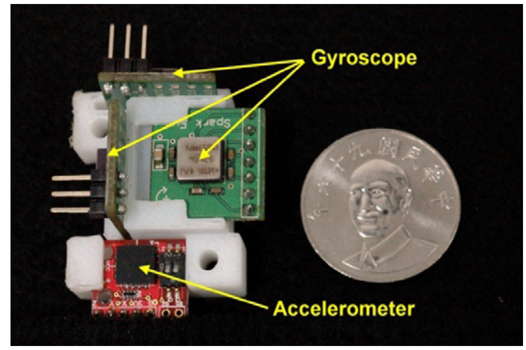

Fig. 2. IMU module containing a triaxial accelerometer and three rate gyroscopes.

Moreover, robust mixed Kalman/H_∞ filtering allows for uncertainties in the system and measurement matrices, provides a bound for the worst-case estimation error, and ensures that the variance of the state estimation error remains within acceptable bounds [8,25–28]. In the present study, the characteristics of the noise as obtained by Allan variance analysis [29–34] were used to design the parameters of the Kalman filter. Moreover, the parameters of the implemented H_∞ filter were designed according to the magnitude of sensor noise. Finally, the robust mixed Kalman/H_∞ filter was implemented with uncertainties in the system and measurement matrices, and the performances of the three filters were evaluated.

The paper is organized as follows. Section 2 introduces the SMABOT IV robot used as the plant for the sensor fusion processes. The sensors and the stride-length estimator for the SMA-based legged robot are described in Section 3. The sensor fusion algorithms are presented in Section 4. Section 5 describes the use of Allan variance analysis to compute the noise characteristics of the sensors. Experimental results and a comparison of the estimation performances of the proposed sensor fusion algorithms are presented in Section 6. Finally, conclusions are drawn in Section 7.

2. SMABOT IV

Fig. 1 shows the SMABOT IV, which is an SMA-based hexapod biomimetic robot [8]. The SMA actuator is an artificial muscle driven by the temperature [4]. Each leg of SMABOT IV is actuated by two SMA actuators to perform motions with two degrees of freedom. Each SMA actuator can produce a force of 300 gw. The robot has a size of 14 cm × 25 cm × 6 cm and weighs 290 g. Its maximum power consumption is about 25 W. The average speed when moving with a tripod gait is 30 cm/min.

3. Sensors

3.1. Inertial measurement unit

The IMU for the INS of the robot comprises a triaxial accelerometer to provide linear acceleration and three rate gyroscopes to provide the angular rate. Fig. 2 shows the self-made strap-down IMU module [8]. The gyroscopes are arranged mutually perpendicularly to form a sensor triad. Each gyroscope (ADXRS300, Analog Devices) is a single-chip yaw-rate gyroscope with a maximum rate limit of ±300°/s. The triaxial accelerometer (MMA7260Q, Freescale Semiconductor) has a selectable acceleration range from ±1.5 g to ±6.0 g. The measured value incorporates the gravity acceleration needed to be compensated for. The outputs of the accelerometer and gyroscope are analog voltage signals that are recorded by a multifunction data acquisition card (±5 V full-scale range, 12-bit resolution; PCI-1711, Advantech). Both the accelerometer and gyroscope are MEMS-based with signal conditioning, which result in a small IMU module (35 mm × 30 mm × 15 mm).

The IMU module was calibrated by following a previously proposed procedure [19]. Calibration parameters such as sensitivity matrix S_k, orthogonalization matrix T_k, misalignment matrix M_k, and bias vector $\vec{b}_k$ were computed. Then, the triaxial sensor module can be represented as

$$\vec{y}_k = S_k T_k M_k \vec{u}_k + \vec{b}_k, \tag{1}$$

where the subscript k represents types of sensors (e.g., g: gyroscope or a: accelerometer), $\vec{u}_k$ is the measurement vector, and $\vec{y}_k$ is the output vector, from which the input vector estimated is computed.

3.2. Electric compass sensor

The compass module shown in Fig. 3 (HM55B, Hitachi) is a dual-axis magnetic field sensor that provides digital directional information. The absolute orientation provided by this exteroceptive sensor can be used to compensate for the cumulative integration drift error from the gyroscope. The measurement principle of the compass sensor involves each of its two axes (the X-axis and the Y-axis) reporting the strength of the magnetic field parallel to it. The heading of the compass sensor can then be calculated as

$$\theta_{\text{compass}} = \tan^{-1}\left(\frac{-Y_c}{X_c}\right), \tag{2}$$

where θ_{compass} denotes a clockwise angle from north to the X-axis of the compass sensor, and X_c and Y_c denote the strengths of the magnetic field measured on the X- and Y-axes of the compass sensor, respectively. The output of the compass sensor is affected by its inclination, and hence the sensor output must be compensated by two orientation parameters, the roll and pitch angles, which refer to rotations about the X- and Y-axes, respectively. The roll and pitch angles of SMABOT IV can be estimated by the Y- and X-direction gyroscopes, respectively. The readings of the compass sensor can be transformed into the horizontal plane using the following equations [35]:

$$\begin{aligned} X_h &= X_c\cos(\phi) - Y_c\sin(\phi)\sin(\rho) - Z_c\sin(\phi)\cos(\rho) \\ Y_h &= Y_c\cos(\rho) + Z_c\sin(\rho), \end{aligned} \tag{3}$$

where ϕ is the pitch angle and ρ is the roll angle. The heading can then be computed from (2) by replacing (X_c, Y_c) with (X_h, Y_h). Only X- and Y-axis measurements are available in the HM55B compass module; the Z-axis measurement Z_c can be estimated using the following equation based on the principle that the resultant vector of X, Y, and Z has a constant norm:

$$Z_c = \sqrt{B_E^2 - X_c^2 - Y_c^2}, \tag{4}$$

where B_E is the strength of the earth's magnetic field in Taipei, Taiwan (45 μT).

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