An ultra-low-power attitude angular estimation solution based on a single accelerator

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***Abstract*—An ultra-low-power attitude module is the ultimate target for the majority of Medical Engineering. In this paper, we present an ultra-low-power attitude angular estimation module solution, which integrates accelerator and zigbee chip. Firstly, different from common solutions, our angle module merely assists with an accelerator. Secondly, the attitude angles are derived from the gravity vector. Thirdly, considering the characteristics of the practical projects, some heuristic rules are used to further reduce the consumption. The working power of our module is only $3.43mW$, which is dramatically lower than other the state-of-the-arts solutions. Besides, massive experiments show that the lasting time is more than a week, which is always in the work state and persists in sending the data of attitude angles. Finally, in order to verify its actual performance in the application, we also deploy proposed solution in the sleep caring system of mental patients, especially for sleep. At the same time, we publish our demonstration video and source code with the aim of being a reference solution for researchers.**
Video - https://youtu.be/hgfoW1TdI8o
Source code - https://github.com/ZhuChaozheng/person_pose_estimator

Keywords*—*Ultra-Low-Power; Angular Estimation; Accelerometer; Gravity;Heuristic Rules

I. Introduction

In Medical Engineering, assisted medical devices dominate a bunch of markets, particularly, on the aspects of various wearable caring systems. All of them rely on a consistent technique, ultra-low-power, which not only diminishes the nurse's attention on maintaining the device power but to reduce the pain of patients during the process of switching the power supply. Meanwhile, the sensor of attitude angle plays a key role in plenty of medical applications, for instance, kinds of state estimation systems prefer to understand the status of patients and offer further caring plans. A number of mental patients suffer from great pressure in minds, So it is a common case for a patient to kill himself in silent sleep time. The caring system of mental patients, especially for sleep, is an urgent requirement for medical workers. While All of those must be with the dependency of ultra-low-power attitude angle estimation solution.

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Broadly speaking, the techniques of attitude angle can be divided into two classes, one is from vision, the other is from sensors. For vision, Q. Dang reviewed Deep Learning based 2D human pose estimation [1], which introduced the researches of attitude angle estimation in Deep Learning. As for the sensors, a lot of researchers spend their time on those practical solutions. T. Marcard proposed automatic 3D Human attitude angle Estimation from Sparse IMUs [2], which used the SMPL human body model and sparse IMU (only six IMUS) to solve multi-node attitude calculation based on IMU. Utilized massive sensors based on the SMPL model, like orientation measurements, acceleration measurements and anthropometric calculation, it got the human 3D attitude angle. H. Yinghao also presented a method of sensors, namely deep inertial poser: learning to reconstruct human pose from sparse inertial measurements in real-time [3]. Throughout this paper, he used six sensors with deep learning to reconstruct human pose. In his pipeline, a real-time 3D body estimation results with angle errors of 15.85 degrees were demonstrated by sending IMU sensors data into the LSTM network to predict SMPL body model parameters. To approach the requirements of patients, D. Looney offered a practical method of motion attitude angle detection [4]. During his work, the most valuable result was the wearable In-Ear Encephalography Sensor for Monitoring Sleep. Meanwhile, it could reach the accuracy of 78% according to the preliminary observations from Nap Studies [5], which used ear-EGG-sensor to detect patient's napping.

However, the existing attitude angle solutions have some problems. Literature [1] relied on the deployed cameras and was consisted of external observers, which brought the limit of activity range for engineering application. At the same time, Literature [1], [3] proposed the reasoning of neural networks needed plenty of computing capability, which caused significant power consumption. Literature [2] presented the multi-node attitude angle calculation based on IMUs didn't need to deploy external devices around patients in advance, but multi-node means that the sensors are as many as possible. Besides, it can't be ignored that a large number of real-time floating-point quaternion operations raised power consumption. In short, the external devices caused a limited environment, enormous computations led to heavy power consumption, and

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multiple devices broke out the complicated problem, further evolve to be unreliable.

Thus, we propose an ultra-low-power attitude angle solution based on the single accelerator which is free of gyroscope and sensor network.

1) Selecting the most suitable components, like accelerator and communication, for the ultra-low-power angle module.
2) Using the gravity vector calculation instead of the quaternion calculation, it reduces the pressure of system performance.
3) considering the characteristics of the practical projects, some heuristic rules are used to further reduce the consumption.

In the rest of the paper, we describe our system in Section 2 exhaustively, particularly, for the explanation of the resolution of the gravity vector. Then we present the evaluation results in Section 3. At the same time, we demonstrate a practical case with applying our module for sleep caring system of mental patients. Lastly, we end with conclusions in Section 4.

II. System Design

A. System Overview

The ultra-low-power attitude angular estimation solution consists of a hardware system, a corresponding algorithm of attitude angle, and some practical project tricks. As we all know, the design of a hardware system has a significant impact on power consumption. To provide a complete sensor module, this attitude angle estimation solution not only contains the sensor but the communication interface of Zigbee. Determined an available solution, we investigated a lot of relevant chip manufacturers, as shown in Figure 1. During this process, we technically did tradeoff between computing capability and power consumption. We only pick a low power three-axis accelerometer LIS3DSH rather than equip 6-axis accelerometer and gyroscope, which provides a sensitivity of up to $1mg/digit$ and the measurement range up to 16g. Compared with two components assembled in IMU (inertial measurement unit), one accelerometer definitely diminishes the power consumption.

As for the controller, STM32L053 microcontroller is selected to cater to the computation requirement. ZigBee (LRF215) is famous for ultra-low power transmission medium and used as the wireless communication interface in this solution. It uploads the data to the coordinator gateway that serves as a data forwarding gateway. In order to miniaturize the system, we choose CR2302 lithium-ion battery as the power supply of the whole system. At the same time, this module has a well-rounded power management system, which is the basis of reducing the power consumption of the system. While paying attention to the computing capacity for the gravity vector calculation, all of our targets is to pick the most matching components as lower power as possible.

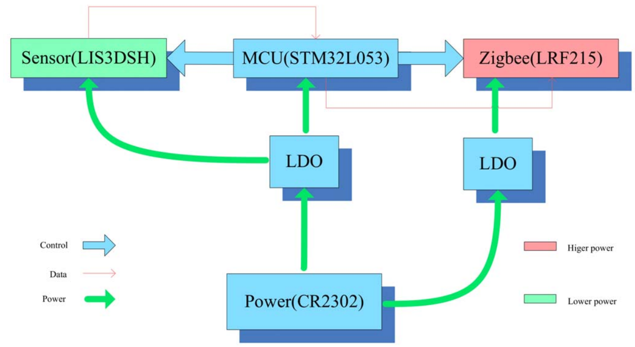

Fig. 1. The diagram of hardware system

B. Attitude Angle Estimation from Gravity

Before commencing deriving the equations of attitude angle estimation (AAE), we would like to introduce the concept of the body coordinate system and the inertial coordinate system. Generally, the measurement value of accelerometer is in the body coordinate system, while the real value of accelerometer is in the inertial coordinate system as the same as the gravity. Every sensor has various kinds of noise, we need to exactly model our accelerometer error [6] as equation (1).

$$a_m^B = S_a a^B + n_a + b_a \tag{1}$$

In this paper, we are going to carry out the accelerometer calibration with the state-of-arts Allan variance method [7]. During this process, the accelerometer is stationary, so the inertial coordinate system and the body coordinate system is consistent. Besides, S_a is often defined as a unit matrix, and both of the bias b_a and the expectation value n_a are also treated as the constant. For this moment, we have recovered the real value a^B with eliminating the Gauss noise and the bias.
For an object either remains at rest or continues to move at a constant velocity, the external force caused acceleration is equal to zero and negligible. In this case, the object only suffers from the gravity $g^B(0, 0, -9.81)$ in the inertial coordinate system, then the body coordinate system and the inertial coordinate system are the same ones. It can be described as equation (2):

$$a^B \approx g^B \tag{2}$$

However, it is clear that when rotation occurs, the body coordinate system will be no longer aligned with the inertial coordinate system as the initial status. It will be rotated on a certain angle in the body coordinate system, as shown in Figure 2. There exists a clear gap between the gravity direction and the z-axis of the body coordinate system. Supposing that the gravity vector mappings into the body coordinate system is (a_x^B, a_y^B, a_z^B) measured by the accelerometer and corrected by the Allan variance method, we can deduce the attitude angle of the object through the decomposed values of the gravity on the body coordinate system.

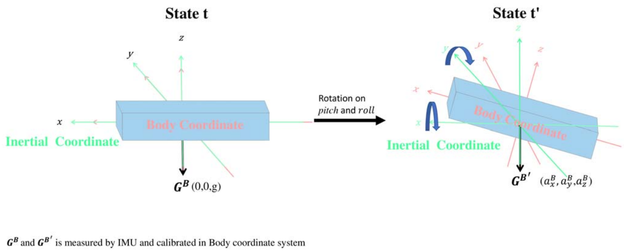

Fig. 2. Gravity in the body coordinate system

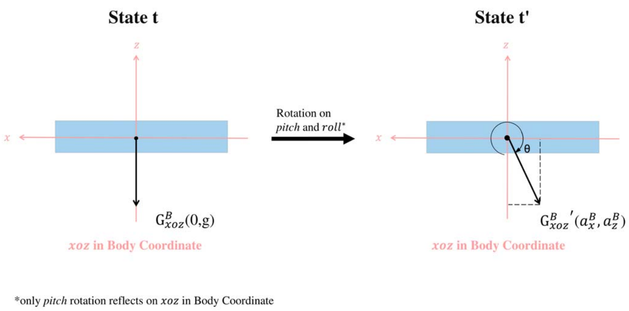

Fig. 3. Rotation facilitates the decomposition of the gravity on the xOz plane of the body coordinate system

For example, an object produces a counterclockwise rotation around the y-axis, while the gravity is going to be decomposed in the plane of xOz, as shown in Figure 3:

Obviously, according to the trigonometric function, the solution of is the following:

$$\theta = \arctan\left(\frac{a_x^B}{a_z^B}\right) \tag{3}$$

In fact, the $pitch$ angle refers to the rotation angle of an object around the y-axis of the inertial coordinate system, which is opposite to the rotation direction of the gravity vector, so the $pitch$ angle is the following:

$$pitch = -\arctan\left(\frac{a_x^B}{a_z^B}\right) \tag{4}$$

For the same reason:

$$roll = -\arctan\left(\frac{a_y^B}{a_z^B}\right) \tag{5}$$

Where the $roll$ angle refers to the rotation angle of an object around the x-axis of the inertial coordinate system. So far, we have already deduced the $roll$ and $pitch$ angle of an object, which rotates around the x-axis and y-axis, respectively. However, since the yaw angle is around the x-axis of the inertial coordinate system and always orthogonal to the gravity vector, it is unlikely to be affected by the gravity vector.

This algorithm substitutes the complex quaternion floating-point operation with a simple trigonometric function operation for an object that either remains at rest or continues to move at a constant velocity. Meanwhile, with the lookup table (LUT) or Taylor expansion, the calculation of the arctangent function is about to be avoided, which significantly reduces the computing complexity.

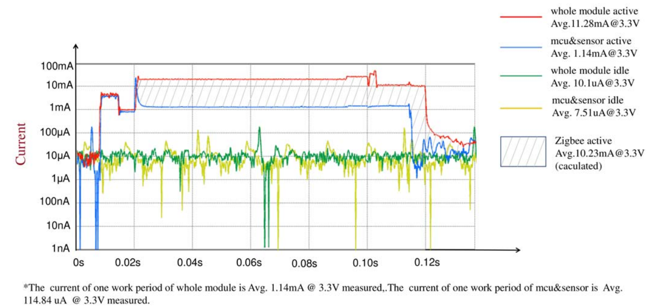

Fig. 4. The results of power consumption measurement

C. Heuristic Rules

Alternatively, we explored to apply some heuristic tricks in our solution. Considering that the typical case needs low-frequency attitude angle data rather than high-frequency data. Although if we set data frequency is 30Hz or higher, it can maintain a more accurate attitude angle. Unless used in high-frequency feedback motion in real-time, it is not necessary for other applications. Meanwhile, when setting the frequency is 0.01 or lower, it can further reduce the consumption by executing a series of sleep operations. However, this scene is only suitable for collecting inaccurate real-time data. According to the target of servicing the medical fields, we prefer to set the frequency is 0.5Hz after enormous tests on engineering projects.

III. Experiment

In order to evaluate the trust performance about our solution, we design and experience two kinds of tests. One is to measure the consumption data and compare with other similar solutions from professional measurement instruments. The other we design a demonstration application of sleep caring system of mental patients by applying this module.

A. Comparisons of Power Consumption

We tested the power consumption of the module with Energy Profiler from Silicon labs, obtaining the results as the Figure 4:

The power consumptions of the whole module are the red (active) and green (idle) in Figure 4, respectively. Cut the power supply of Zigbee, we record the sum power of the MCU and the accelerometer. It is too subtle to measure the power consumption of the sensor, but it is 0.0198mW from looking up the corresponding datasheet. Thus, the blue and yellow lines are directly considered as the active and idle status of the MCU, respectively.

Finally, we splite the mcu and sensors power consumption from the whole module, showing the results of the Zigbee

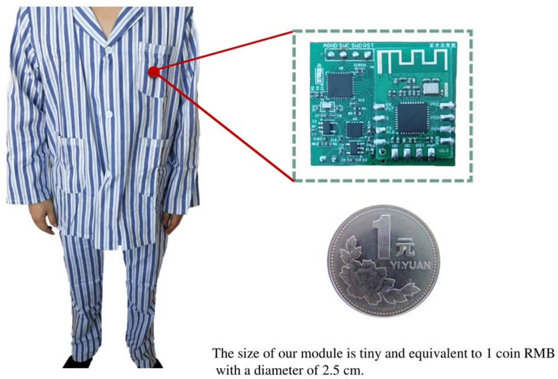

Fig. 5. Mental patients equipped with our system in his front pocket

module as the shadowed area. exhaustive power consumption showed in Table I.

TABLE I
EXHAUSTIVE POWER CONSUMPTION

Part	Active power (mW)	Idle power (uW)	Average (mW)
MCU	3.8	25.09	0.38342
Acceleration sensor	0.0198	active	0.0198
Zigbee	33.7592	8.61	3.02678
the whole module	37.57	33.70	3.43

Besides, we publish the data compared with other the state-of-the-arts solutions on power consumption, as Table II.

TABLE II
COMPARISON WITH THE STATE OF THE ART SOLUTIONS ON POWER CONSUMPTION

work	Average power consumption (mW)	Sensor power consumption (mW)	Features
DD-Fusion [8]	18.99	1.4	Using EEG and IMU
GesR-EEG [9]	5.1	4.1	Using EMG
VCC-CNN [10]	9	0.004	Based on CNN For visual context classification
ours	3.43	0.0198	Using gravity vector caculation

Obviously, AAE only cost 3.43mW and has the lowest power consumption comparing with other solutions.

B. Medical Application

As a solution toward engineering, we would like to test our module in sleep caring system of mental patients. As mental patients prefer to suicide in sleeping time, it is a vital task to care for the status of mental patients, especially sleep in a specific time. To verify the performance of the system, We select three kinds of different ages and genders of mental patients as the test samples, as Figure 5.

The accuracy of the system is 99.1%, and its battery life is 10 days. This is an awesome standard in majority fields. For more information, please visit https://youtu.be/hgfoW1TdI8o. From the above experiments, AAE has a good tradeoff in accuracy and battery life within a low volume for Medical Engineering.

IV. Conclusion

We designed an ultra-low-power attitude angular module solution based on the resolution of the gravity vector, which only used one accelerometer to detect attitude angle, and an embedded Zigbee worked as the communication interface for a complete sensor module. The method of decomposing the gravity vector dramatically diminished the power consumption of the system. Finally, massive evaluations about its overall performance showed that this module worked continuously for more than 10 days with stably output the angle data through the Zigbee network, and its volume is only 31.2mm*27.3mm. An alternative experiment that sleep caring system of mental patients is an awesome application for our module. In the future, we hope to extend this module solution to the behavior recognition of more interesting species, such as cats, dogs and so on.

Acknowledgment

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