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MOTION CAPTURE WITH MEMS SENSORS

Abstract. **The object of this article** is the registration and analysis of human movements based on sensors. This paper presents a comparison of the basic methods of data processing from inertial micromechanical sensors to collect data a device was implemented that captures movements. As result the device uses the motion data from accelerometer and gyroscope to calculate the motion trajectory: the angle of rotation and acceleration. The data is read by the microcontroller, after which it is filtered and processed by one of the filters (Complementary, Kalman), and finally transferred to a computer for further analysis and display. **The purpose of the article** is to compare several methods of data processing from microelectromechanical. **The results obtained:** device was developed, obtained data that can be used to characterize the methods and analyze their work in the system. **Conclusions:** In the course of the study, a device was developed for collecting and processing data from MEMS sensors, which showed the effectiveness of the complementary filter in comparison with the Kalman filter in real-time systems with limited computing power. Real results confirmed that the results of the complementary method using less computational resources are not far behind the more costly Kalman filter without the use of auxiliary sensors, like a digital compass.

Keywords: MEMS; MCU; gyroscope; accelerometer; motion detecting; Complementary filter; Kalman filter.

Introduction

Problem statement. The problem of recording the movement of human limbs includes the task of accurately tracking and analyzing the movements of various parts of the body during various actions. There are various approaches to capture human limb motion, including optical computer vision (CV), inertial measurement sensors (IMU), and electromyography (EMG). Each of these methods has advantages and disadvantages, and the choice of technique depends on the specific application and the accuracy and precision required.

Optical motion capture systems use cameras to track the position of a person's limbs using computer vision algorithms. Additionally, this technology can use markers attached to the object's limbs for greater stability. These systems are highly accurate and can capture detailed motion data, but are typically expensive and require a controlled environment with minimal interference.

They can also be affected by changes in lighting conditions or occlusion in the scene. Computer vision methods can also be more susceptible to noise and errors than gyroscope sensors, especially if the camera is not stabilized or if there are moving objects in the scene.

IMUs are sensors that are attached to limbs and measure acceleration, angular velocity, and magnetic field strength to detect changes in an object's orientation and rotation. These sensors can be used in a wide range of environments and are relatively inexpensive, but they can suffer from drift and noise, which can affect measurement accuracy. Gyro sensors are generally more accurate than computer vision methods for detecting rotation and are less susceptible to noise or errors. However, gyroscope sensors are less flexible than computer vision methods because they are designed specifically to detect rotation and cannot detect other types of motion.

The EMG approach measures electrical activity in limb muscles and can be used to determine limb movement. This method is noninvasive and can be used in a variety of situations, but it may have interference and may not provide as accurate or detailed information about limb motion as optical or IMU-based approaches.

So computer vision techniques can be more flexible and can detect a wider range of motion, but they can also be computationally expensive and more sensitive to noise and errors. Gyro sensors are more accurate for detecting rotation, but are less flexible and subject to drift over time. The choice of method will depend on the specific requirements of the application and available resources.

IMU sensors are most suitable in case of tracing separate human body parts, the final result can be small device, that connects to different limbs to precisely track motions [1].

Main material

IMU sensors. One of the types of IMU sensors is a digital gyroscope, it is a device that measures the angular velocity, or the rate at which an object's orientation changes over time. It is used in various applications such as navigation, robotics and virtual reality. The last one could help in areas of human-computer interaction. The main principle of operation of a digital gyroscope is the Coriolis effect. When an object rotates, a force acts on it that is perpendicular to the direction of its motion. This force is known as the Coriolis force. This force arises due to the fact that different points of the rotating surface move at different speeds, in other words, the Coriolis effect can be considered as a force felt by all objects that move along the surface of a rotating object. In a digital gyroscope, this force is measured using a vibrating structure known as a MEMS (Micro Electro-Mechanical System) sensor. The MEMS sensor consists of a test mass suspended from a spring. As the gyroscope rotates, the Coriolis force causes the test mass to vibrate in a direction perpendicular to the plane of rotation. Capacitive sensors located at the edges of the reference mass detect vibration.

As the test mass moves (Fig 1, 2), the capacitance between the test mass and the sensors changes, producing an electrical signal proportional to the speed of rotation.

Fig. 1. Normal sensor status

Fig. 2. Sensor status under force

Hardware. Comparison of algorithms requires data from sensors, and to obtain data, a device was developed that tracks the movements of human limbs, which includes boards with a microprocessor and inertial micromechanical sensors.

The STM32F401CCU6 microcontroller was chosen as the central computing module, and the MPU-6050 microelectromechanical sensor as a gyroscope and accelerometer.

The STM32F401CCU microcontroller is a microcontroller from STMicroelectronics' STM32F4 series, which is based on the ARM Cortex-M4 processor core. It has a clock speed about 84 MHz, 512 KB of Flash memory, and 96 KB of SRAM. But mostly STM32F401CCU is suitable for our purpose, because it provides several features:

- I2C bus for MEMS sensor connection;
- USB bus to transfer data to the computer;
- FPU(floating point unit) to speed up calculating mathematical formulas.

Additional advantages are its low cost and high availability.

The MPU-6050 is a 6-axis sensor that conveniently combines a gyroscope and an accelerometer in a small package, which makes it possible to use single physical connection and collect data over common I2C bus. MPU-6050 is also suitable to this project due to its low cost and ease of use [2].

As already mentioned, the sensor is connected to the microcontroller via the I2C bus (Fig 3), since the SDA and SCL lines are open drain, which means that they can only sink current, but not give it away, so 4.7 kΩ pull-up resistors are used.

The USB bus is used to transfer prepared data for further processing and visualization using virtual serial port technology (Fig 4), which represents UART (universal asynchronous receiver-transmitter) protocol over USB.

The circuit also receives power from the USB port when connected to a computer, the linear regulator lowers it from 5 volts to 3.3 volts, which is acceptable for the microcontroller and sensor.

Complementary filter. Another problem in the way of motion capture is the methods of processing data received from sensors, since in fact these data are noisy digitalized signals that are not related to each other in any way. To calculate the rotation angle, was used a complementary filter, which combines the gyroscope and accelerometer data together to obtain a more accurate estimate of the object's orientation. The gyroscope provides high frequency angular velocity measurements and the accelerometer provides low frequency gravity measurements [3]. To implement the complementary filter, the algorithm needs to calculate an orientation using the gyroscope data. This can be done using the trapezoid integration algorithm; the trapezoidal rule is a numerical integration method that can be used to estimate the value of an integral by approximating the area under a curve. In the context of integrating raw data from a gyroscope, the trapezoidal rule can be used to estimate the object's orientation over time:

$$\theta[N-1]=\theta[0]+\sum_{i=1}^{N-1}\left(\left(w[i]+w[i-1]\right)\cdot\frac{\Delta t}{2}\right), \qquad (1)$$

where θ[0] is the initial value of the angle (usually zero); θ[*N*-1] is the calculated end value of the angle; *w*[0], *w*[1], ..., *w*[*N*-1] – sequence of *N* samples of angular velocity; Δt – time delta.

A simple representation of a given formula in a C programming language is shown in Listing 1.

```
#define SAMPLE_TIME 0.01
// Function to integrate the gyroscope data using
the trapezoidal rule
double integrate_data(double *gyro_data, int
num_samples)
{
    double area = 0.0;
    for (int i = 1; i < num_samples; i++) {
        double avg = (gyro_data[i] + gyro_data[i-
1]) / 2.0;
        area += avg * SAMPLE_TIME;
    }
    return area;
}
```

Listing 1. Estimation the object's orientation over time

Now it is important to process raw data from the accelerometer and get its orientation, it can be done with atan2 function. This function is a mathematical function that calculates the arctangent of two arguments, y and x, given as atan2(y, x). It returns the angle between the positive x-axis and the point (x, y) in the Cartesian plane, measured in radians (Fig 5):

$$\theta = arctg\left(y/x\right). \qquad (2)$$

Its representation in code is shown in Listing 2.

```
#define RAD_TO_DEG 57.295779513082
double pitch = atan2(accel_x_raw, accel_z_raw)
* RAD_TO_DEG;
```

Listing 2. Representation in formula code (2)

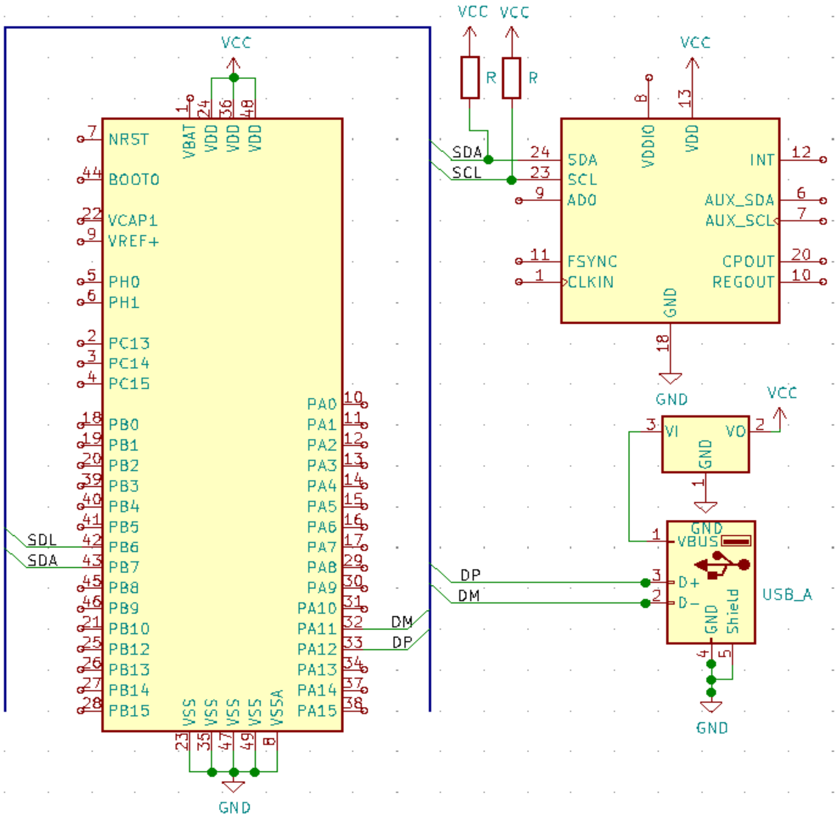

Fig. 3. Connection circuit of the microcontroller, sensor, and USB port

Fig. 4. Diagram of the data pipeline

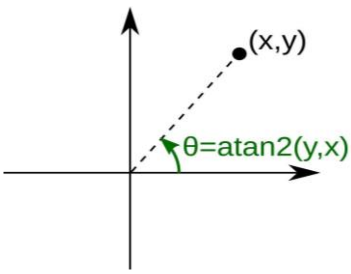

Fig. 5. Angle θ between the ray to the point (*x*, *y*) and the positive *x*-axis

Then it is possible to proceed to the calculation of the filter itself with this value. The filter is a weighted average of the two scores, where the weights are chosen to balance the accuracy and stability of the filter (Fig 6, G(s) represents the transfer function for the low-pass filter, whereas G¯(s) is the transfer function of the high-pass filter, such that G(s) + G¯(s) = 1.). The basic idea is to use the gyroscope value to correct for drift in the accelerometer estimate and use the accelerometer estimate to correct high frequency noise in the gyroscope estimate (Fig 7).

In the result of the filters work the estimate of the object's orientation will be more accurate [4].

On Fig 6 and 7:

$$orientation = \left(orientation_{gyroscope} * coef\right) + (orientation_{accelerometer} * (1 - coef)),$$

where $orientation_{gyroscope}$ is a gyroscope orientation, $orientation_{accelerometer}$ is an accelerometer orientation, $coef$ is a weighting factor from 0 to 1 that determines the balance between gyroscope and accelerometer estimates.

Red line is gyroscope values, blue is accelerometer values, green is a result.

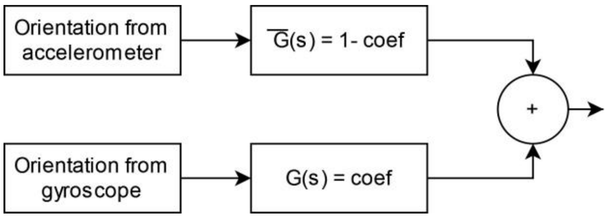

Fig. 6. Basic structure of Complementary Filter.

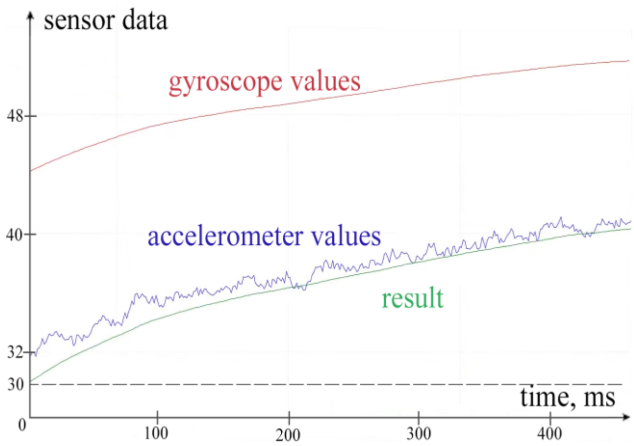

Fig. 7. Complementary filter result

Over time, the gyroscope values will begin to drift due to noise and bias in the sensor data. The complementary filter will detect this drift and slowly put more weight on the accelerometer estimate, resulting in a more accurate estimate of the object's orientation. In addition, this approach shows a good result when hitting the device (Fig. 8).

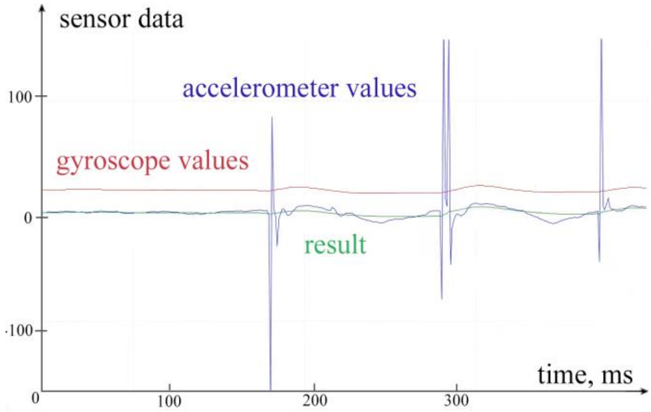

Fig. 8. Result of Complementary filter with hits

Main disadvantage. This method of calculation is poorly applicable for calculating the angle of rotation along the Z-axis, since its calculation will require the projections accel_angle_x and accel_angle_y, and in this case, they are almost equal to zero.

When x and y are both zero, the point (x, y) is located at the origin of the Cartesian plane. At the origin, the direction of the vector (x, y) is undefined since it has no direction. Therefore, it is not possible to determine the angle between the positive x-axis and the point (x, y) using atan2 when x and y are both zero.

$$\operatorname{atan}2(y,x)=\begin{cases}\operatorname{arctg}(y/x), & \text{if } x>0;\\ \operatorname{arctg}(y/x)+\pi, & \text{if } x<0\ \&\ y\geq 0;\\ \operatorname{arctg}(y/x)-\pi, & \text{if } x<0\ \&\ y<0;\\ +\pi/2, & \text{if } x=0\ \&\ y>0;\\ -\pi/2, & \text{if } x=0\ \&\ y<0;\\ \text{undefined}, & \text{if } x=0\ \&\ y=0;\end{cases} \quad (3)$$

So that is why, the calculation of this angle is not possible or will be performed with a large error. Calculation of the desired angle should be made only by the value of the gyroscope, without filtering (Fig. 9).

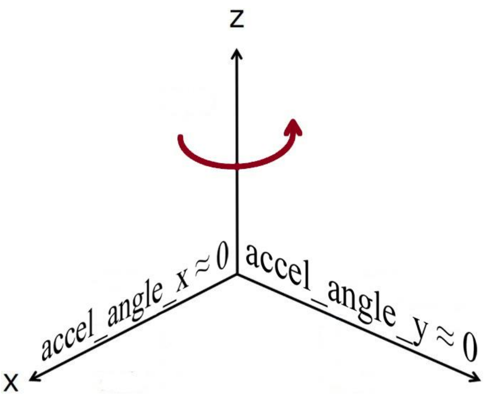

Fig. 9. Axes projection demonstration

In addition, to obtain a more accurate angle of rotation along the Z-axis, an alternative is to use an auxiliary magnetometer module - a digital compass.

Magnetometer module can provide the raw magnetic field data, which are measurements in the X, Y, and Z directions. By calculation and subtraction the magnetic declination angle from the inclination angle, the Z-axis rotation angle can be obtained.

Kalman filter. Another filter that can be reviewed and compared to complementary filter is Kalman filter. It is a mathematical algorithm that estimates the state of a system by combining noisy measurements and a model of the system dynamics. It is commonly used in many applications, including navigation, control systems, and signal processing.

The main idea of the Kalman filter is to recursively update an estimate of the state of the system based on two sources of information: measurements from sensors and predictions from a mathematical model of the system. The filter maintains two key components: a state estimate and a covariance matrix.

The state estimate is a vector that represents the best guess of the current state of the system, based on all available information up to the current time. The covariance matrix is a measure of the uncertainty or error in the state estimate [5].

The Kalman filter operates in two stages: the prediction stage and the update stage. In the prediction stage, the filter uses the mathematical model to predict the state of the system at the next time step, based on the current state estimate. This prediction is then used to calculate the covariance matrix for the predicted state [6].

In the update stage, the filter uses the actual measurement data to correct the predicted state estimate and covariance matrix. The Kalman filter calculates the Kalman gain, which is a weighting factor that determines how much to trust the predicted state estimate versus the measurement. The measurement is then used to update the state estimate and covariance matrix, which are then used in the next prediction stage.

The Kalman filter is designed to handle noisy or incomplete measurements, and it is able to incorporate new measurements as they become available, continuously refining its estimate of the system state. By using both the mathematical model and the actual measurements, the Kalman filter is able to provide a more accurate and robust estimate of the system state than either of these sources alone (Fig 10).

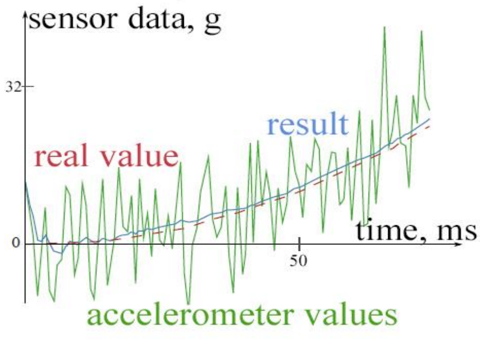

Fig. 10. Kalman filter result

Red line is original coordinate, green is sensor values, and blue Kalman filter is result.

Complementary filter and Kalman filter are both used for sensor fusion in order to improve the accuracy of the sensor readings. However, they differ in their underlying algorithms, complexity, and computational requirements (Table 1).

Complementary filter is a simple algorithm that combines the readings from an accelerometer and a gyroscope to estimate the orientation of an object. It is easy to implement and requires less computational power than a Kalman filter. However, it may not be as accurate as a Kalman filter, especially in the presence of noise or other sources of error.

Table 1. Comparison of method

	Complementary filter	**Kalman filter**
Algorithm complexity	Simple, easy to implement	More complex, requires more computational resources and expertise to implement
Accuracy	Low accuracy, particularly in noisy environments	High accuracy
Sensor fusion ability	Limited to combining data from two sensors, typically an accelerometer and a gyroscope	Can fuse data from multiple sensors, such as accelerometer, gyroscope, magnetometer, and GPS, allowing for more accurate tracking and compensation for various external factors
Real-time performance	Real-time processing is possible	Real-time processing is possible but can be limited by the complexity of the algorithm and the available computational resources
Robustness	Less robust to sudden changes and noise	More robust to sudden changes and noise due to its ability to estimate the noise and uncertainty in the system

Kalman filter, on the other hand, is a more complex algorithm that uses a mathematical model of the system and the sensor measurements to estimate the state of the system.

It is able to handle more complex systems and can incorporate multiple sensors and other sources of information to improve the accuracy of the estimate. However, it requires more computational power than a complementary filter and can be more challenging to implement.

In general, a complementary filter may be suitable for simple applications where accuracy is not so critical as performance, while a Kalman filter may be more appropriate for more complex systems where accuracy is critical and more computational power is available. It is also possible to use both filters in combination to take advantage of their strengths and improve overall accuracy.

DSP and DMP. It is also necessary to note several approaches that can speed up work with data and even increase the accuracy of the calculation result.

The first approach is to use a digital signal processor (DSP), which is a specialized microprocessor designed to process digital signals in real time. Unlike general-purpose microprocessors, DSPs are optimized for signal processing, which typically involves performing a lot of mathematical operations on data samples such as processing vectors or matrix.

Their special hardware functions can significantly speed up the processing of raw data from MEMS sensors, e.g. multiply floating point numbers in one cycle.

Also, DSPs usually have a specialized memory architecture that allows them to access data quickly and efficiently, and moreover DSPs often have multiple processor cores that allow them to process different signals from gyroscope, accelerometer and magnetometer in parallel.

Another type of hardware accelerator is a digital motion processor (DMP), besides of DSP, motion processor are embedded in MEMS sensors and are able to fuse the data from these sensors to provide more accurate measurements of the device's orientation, motion, and position in space. Such component is often integrated into microcontrollers or microprocessors and used in motion detection applications such as smartphones, smart watches, and game controllers [7].

DMP is designed to offload some processing tasks from the main processor, such as sensor data combining and motion processing, and provides more accurate and reliable motion detection capabilities. In other words, DMP is already a full-fledged replacement for motion detection algorithms for MEMS sensors, which is implemented in hardware as a coprocessor.

Conclusions

For the tasks of processing "raw" data for tracking, the complementary filter and the Kalman filter are effective tools that provide a means to accurately estimate the state of the system based on noise measurements.

They are particularly useful for motion tracking systems that include multiple sensors, such as gyroscopes, accelerometers, and magnetometers, because they can efficiently combine measurements from these sensors to obtain a more accurate representation of the system's motion.

They can be used for a wide range of motion tracking applications, including gait analysis, sports performance monitoring, and rehabilitation [8].

However, the effectiveness of filters in motion tracking systems depends on careful parameter setting and model selection. The parameters of the Kalman filter must be chosen to balance accuracy and sensitivity, and the model used must accurately represent the dynamics of the monitored system. Overall, the choice between Complementary filter and Kalman filter depends on the specific application and the available resources. Complementary filter is a simple and efficient algorithm that can be useful for applications where real-time performance [9] and simplicity are important, such as in simple robotic systems or basic motion tracking.

On the other hand, Kalman filter provides higher accuracy and more robustness to noise and sudden changes, making it more suitable for complex and high-precision applications, such as aerospace and autonomous vehicles.

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Захоплення руху за допомогою датчиків MEMS

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Анотація. Предметом дослідження даної статті є реєстрація та аналіз рухів людини за допомогою датчиків. У даній роботі представлено порівняння основних методів обробки даних інерційних мікромеханічних датчиків. Для збору даних було реалізовано пристрій, що фіксує рухи. У результаті пристрій використовує дані руху з акселерометра та гіроскопа для розрахунку траєкторії руху: кута повороту та прискорення. Дані зчитуються мікроконтролером, після чого фільтруються та обробляються одним із фільтрів (додатковим, Калмана) і, нарешті, передаються на комп'ютер для подальшого аналізу та відображення. **Метою статті** є порівняння кількох методів обробки даних з мікроелектромеханічних. **Отримані результати:** розроблено пристрій, отримані дані, які можна використовувати для характеристики методів та аналізу їх роботи в системі. **Висновки:** У ході дослідження було розроблено пристрій для збору та обробки даних від датчиків MEMS, який показав ефективність комплементарного фільтра порівняно з фільтром Калмана в системах реального часу з обмеженою обчислювальною потужністю. Реальні результати підтвердили, що результати додаткового методу з використанням менших обчислювальних ресурсів ненабагато поступаються дорожчому фільтру Калмана без використання додаткових датчиків, таких як цифровий компас.

Ключові слова: мікромеханічні датчики; мікроконтролер; гіроскоп; акселерометр; детектування руху; додатковий фільтр; фільтр Калмана.