Developing Integrated MEMS Products for Medical and Industrial Markets

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ABSTRACT

Aims: As the trend in technology is shifting toward smaller and more compact devices with requirements for more accurate measurement systems, new sensors and components enabling this trend are also being brought to market. Micro electromechanical sensors (MEMS) and devices utilizing these components are finding new applications in mobile and hand-held devices, mobile robotics and navigation. Inertial sensors have been shown to be subject to a number of different error sources such as temperature and integration drifts and other biases mostly caused by the sensitivity of the sensors as well as by external disturbances [1-5]. However, due to recent advances in MEMS technologies, these errors are better controllable.

Study Design: This paper describes recent developments in the field of MEMS with proof-of-concept devices for a variety of sensing applications. Our recent research has focused on monitoring of human vital signs and displacement tracking of controlled and free-hand motions.

Results: In this study, we demonstrate that current commercial off-the-shelf MEMS based inertial measurement units (IMU) can be used as such with appropriate signal processing both in medical and industrial applications.

Conclusion: Our proof-of-concept device has been used in basic human vital signs detection, such as tremor and respiration. Other tests were performed to verify the suitability of the sensor in demanding industrial applications with high accuracy requirements for rotation and displacement.
Keywords: Micro electromechanical systems; sensors; inertial measurement unit; accelerometer; gyroscope; magnetometer; barometer.

1. INTRODUCTION

In line with the trend of technology requiring smaller and more compact measurement systems and devices, the enabling sensors are shifting toward smaller and more accurate components. Micro electromechanical sensor (MEMS) and integrated measurement unit (IMU) based applications are thus increasing rapidly. Many areas are currently equipped with such sensors and units, including mobile and hand-held devices, mobile robotics and vehicle navigation. The products on the market in these different segments are game controllers [1], mobile phones, portable medical devices [2-6] and motion detectors [2-5]. The basic interest for using these sensors is based mostly on the low cost, miniature size, and usually light weight together with fast response compared to traditional, externally referenced sensors [2]. Especially inertial sensor based motion detection has been an increasing topic of research recently. In inertial motion sensing, the most commonly used sensors are accelerometers, gyroscopes and magnetometers. The inertial sensors are however subject to a number of different error sources such as integration and temperature drifts [1-2,7-10] and other biases caused by the sensitive structure of the sensors. However, with recent advances in sensor technologies new applications in motion detection and displacement tracking are appearing rapidly [2-3,6,11-13]. Recently MEMS technologies have been integrated into the medical device industry and industrial applications. As the growing megatrend in life sciences is personalized medicine with connected health, much emphasis has been put in this field. MEMS based devices also enable the use of wireless gateways from the device to the monitoring systems [3].

The objective of this research was to evaluate the overall performance and suitability of inertial MEMS technologies toward reliable medical device and industrial applications. The topics of interest were vital signs monitoring and motion tracking especially in industrial applications. Thus, the objective of this research was to provide an understanding of MEMS based IMUs in two major categories of industry that are increasingly using these enabling technologies.

2. METHODOLOGY

The applications and proof-of-concept (POC) devices that are presented in this paper were equipped with a state-of-the-art IMU sensor, the ADIS 16480 (Analog Devices, Norwood, MA, USA). This sensor Fig. 1 is a ten degree of freedom (DOF) inertial MEMS sensor with dynamic orientation output. It consists of a ±10g triaxial accelerometer, a triaxial gyroscope with ±450°/s dynamic range and 6°/h in-run stability, a ±2.5 gauss triaxial magnetometer and a pressure sensing barometer. With relatively small dimensions (47 mm x 44 mm x 14 mm), extended Kalman filter (EKF) [14] and broad operating temperature range (-40°C to +85°C), it is a complete sensor package that can be used in a variety of different application testing. In the applications, also the evaluation board (ADIS-EVAL) was used for convenient data transfer to the computer for analysis.

Although the ADIS device was manufactured for applications in automotive navigation and large scale industrial robotics, it seemed to be adequate for POC testing in such medical device applications as the detection of human respiration and hand tremor. As an industrial application, the sensor was also used for controlled movement detection of hand held
motions. The basis for each POC was the scientific evaluation of algorithm development and performance analysis enabling Monte Carlo method [8].

Fig. 1. The used sensor (1) and the evaluation board (2) to which the sensor was attached. This sensor device was enclosed in a plastic container as seen in Fig. 2

2.1 Industrial Applications

2.1.1 Controlled movement detection

The overall accuracy of motion detection was performed in laboratory conditions using a 6 DOF industrial robot as presented in Fig. 2. (Motoman, XRC, Yaskawa Electric Corporation, Kitakyushu, Japan). The controlled testing was done in two test cases, the first for detecting planar movement on a triangular path, and the second for detecting angular accuracy of the sensor device over a 90 degree angular motion.

Fig. 2. The robot setup for the 90 degree angular motion detection with the sensor attached to the tip of the wrist
2.1.1.1 Triangular path

The sensor was attached to the tip of the robot which was set to drive a triangular path with 200 mm adjacent legs and the hypotenuse linking the legs. In motion detection, the envelope detector was used to track the movement and stable position. At each node, a two second stable position was programmed to the robot software. After detecting correct movements, the accelerometer signal was first integrated to receive the velocity at each stage and after second integration the displacement. Fig. 3 illustrates the path driven with the orientation of each acting triaxial accelerometer indicated.

![Fig. 3. The path driven is illustrated with the axis motion at each stage represented with colors](image)

First, the accelerometer data on gravity was converted into m/s² form. Then, envelope detection was applied to find the periods of movement from the accelerometer and gyroscope data. If the sensor was detected to be motionless, the accelerometer and gyroscope offsets were analyzed and stored for the next time interval. If the sensor was in motion, the gained acceleration data was updated using the data from the motionless stage. This included also the application of rotation matrix data from the stationary stage for compensating orientation changes. Finally, also the position was updated using the gained accelerations and current offsets. From these results, the velocity and displacement for each axis were calculated using Equations (1) and (2). The total displacement was calculated using (3). The update rate used in these experiments was 2460 Hz.

\[
v(t) = \int a(t) = a\Delta t + v_0
\]

\[
s(t) = \int \int a(t) = \int v(t) = \frac{1}{2} a\Delta t^2 + v_0\Delta t + s_0
\]

\[
S(t) = \sqrt{s(t)^2_x + s(t)^2_y + s(t)^2_z},
\]

where subscript '0' denotes the result of a previous time domain, 'x', 'y' and 'z' denote each axis, 't' is the time interval, 'v' denotes the linear velocity and 'a' is the linear acceleration.
2.1.1.2 90 Degree angular motion

In the angular movement detection experiments, the sensor device was attached to the tip of the robot. The robot wrist was programmed to execute a 90 degree angular movement around the shaft of the wrist and the displacement, angular motion and repeatability were detected Fig. 4. The linear displacements were calculated using (1), (2) and (3), the rotational accuracy around each axis using (4) and total accuracy using (5).

\[
\theta(t) = \int \omega(t) \, dt + \theta_0
\]

\[
\theta(t) = \sqrt{\theta(t)^2 + \theta(t)^2 + \theta(t)^2},
\]

where subscript ‘0’ denotes the result of a previous time domain, ‘x’, ‘y’ and ‘z’ denote each axis, ‘t’ is the time interval, ‘\(\omega\)’ denotes the angular velocity and ‘\(\theta\)’ is the angular acceleration.

![Fig. 4. The experimental testing illustrated with each axis representation. The motion was such that the device was set to move about the Y-axis](image)

2.2 Medical Applications

There are several simultaneous bodily functions present at all times. We investigated how the different functions can be resolved from the basic data gained from the accelerometers and gyroscopes. Furthermore, the purpose was to evaluate to what extent these functions blur the detection of the motions, especially the hand movements.

2.2.1 Human respiration

The respiration was detected by holding the device on the subject’s chest for a duration of 2 minutes while recording the output data from all sensors. The algorithm was based on Fast Fourier Transformation (FFT) and smoothening of the power spectrum to detect the respiration. The respiration was verified by comparing the gained power spectrum to the reference values of the detected respiration rate. This experiment shows that with relatively simple algorithms, the respiration can be detected using a MEMS device.
2.2.2 Hand tremor detection

Detection of hand tremor was performed by the subject holding the sensor device in his hand while the output of the accelerometers was recorded for durations of 2 minutes. Testing was done in the following manner: The device was held steady with the subject’s hand supported on a table. Then the subject lifted his hand from the table to approximately 30 cm from the table top and held it there steady but unsupported. Finally, the subject placed his hand back on the table to a stable position. Basic FFT methods with envelope detection were used for obtaining the hand tremor data and after that, adaptive filtering was used in compensating for it.

3. RESULTS AND DISCUSSION

This research concentrated on a relatively wide range of scientific experiments. On the one hand the results pertain to human vital signs monitoring and on the other hand to industrial applications. The objective was to detect a variety of key features from small motions to fast movements in robust applications. Furthermore, we investigated whether by optimizing the algorithms a number of different kinds of motion detection could be achieved with a common MEMS platform.

3.1 Industrial Applications

3.1.1 Controlled movement detection

The robotic movements were detected to be identical between the movement and rest periods. Thus, it was relatively straightforward to find the different stages of the motion. It was also found that the displacement detection and the repeatability were accurate. The overall accuracy of displacement detection was approximately 5 mm over a length of approximately 68.2 cm at 7.5 cm/s velocity. The total duration of the experiments was 19 seconds.

3.1.1.1 Triangular path

Fig. 5 contains the analyzed data of the triangular path experiments.

3.1.1.2 90 degree angular motion

From Fig. 6, it is evident that in rotational motions, the angular accuracy is notably high at within 1º, while the displacement accuracy has noticeable deviation being approximately 25 mm at the end of the 20 second experiment. Most of the deviation was detected to be caused by the vibrations in the robot itself rather than resulting from the sensor device quality errors. By tuning the filtration and detection algorithms, this issue could be reduced so that the final position displacement error was reduced to within one centimeter.

3.1.2 Free-hand movement detection

In free-hand experiments, the sensor device was moved inside an open box with 200 mm vertices. It was noted that in these experiments the algorithm needed some modifications, because of the nature of hand movements compared to the robotically controlled motions. Free-hand motions caused significantly less distortions and vibrations, so in detecting these
motions, the movement detector needed to be adjusted to clearly more sensitive detection parameters. After tuning the algorithm, we detected errors in the magnitude of approximately 5 mm in these experiments.

Fig. 5. The motion detection by the accelerometers of the sensor device is shown in (A). The different stages of movement are detected when the motion data exceeds the threshold limit highlighted in red. (B) Shows the velocity data integrated from corrected accelerations. (C) Illustrates the integrated position tracking from (B) including all axes with the black line as the result during the experiment. The negative time periods in (B) and (C) indicate the steady position prior to the robotic motion.

Fig. 6. The results of the sensor device in angular motion detection with overall displacement (A) and angular movement detection (B). Clearly, the angular motion using the gyroscopes has high accuracy (B), while external robot based vibrations cause slight deviation in displacement throughout the testing (A).
3.2 Medical Applications

3.2.1 Human respiration

The detected human respiration is illustrated in Fig. 7. The peak with the lower frequency corresponds to the whole cycle of respiration, that is, from one inhalation to the next inhalation. The higher frequency peak, being double, corresponds to the inhalation-or-exhalation frequency.

![Graph showing analyzed accelerometer signal with detected respiration rate. The two peaks indicate the respiration rate as the frequency of the respiratory cycle (first peak) and the frequency of either inhalation or exhalation (second peak).]

**Fig. 7.** The analyzed accelerometer signal with detected respiration rate. The two peaks indicate the respiration rate as the frequency of the respiratory cycle (first peak) and the frequency of either inhalation or exhalation (second peak)

3.2.2 Hand tremor detection

The results in Fig. 8 show a clear peak at both ends of the experiment indicating the vertical movements. In between the peaks, the hand tremor is seen as unstable signal noise, out of which the tremor was detected at 9 Hz. The experiment was done to verify that hand tremor can be detected accurately using accelerometers as seen in the left column. The data was used in further analysis of hand movements by applying an adaptive filter method (right column) which compensated for the subject’s hand tremor in other movement detections.
Fig. 8. The output of the accelerometer (raw data and compensated data) is shown in (A). (B) Correspondingly illustrates the movement detection of the sensor (according to paradigm described in text). In (C) the frequency of the hand tremor is detected at 9 Hz. For each set of results the left column contains the raw data after FFT analysis and the right column the results after adaptive filtering.

3.3 Summary of the Results

From the industrial applications perspective, this study centered on analysis of robotically assisted motions. Thus, gyroscopes were notably accurate in rotational motions while accelerometer based motion tracking was accurate in translational motions. In rotational motions, the translational tracking based solely on accelerometers deviated strongly with respect to time. Translational tracking along a planar path was within 5 mm, while in rotational motions the accuracy was roughly a magnitude of 5 times lower at 25 mm.

Respiration was observed to be easily detectable from the measurement data. The current sensor installation is not optimal for monitoring of heart beats as they are not adequately discernible. Of tested human motions, the hand tremor was observed to be very prominent. In preliminary testing it was found that the tremor easily masked the subtle movements of the sensor. Fortunately, the spectral properties of the tremor were readily discernible from typical hand movements.

The results for human respiration indicated that it can be accurately detected using accelerometers. The detection of hand tremor was based on FFT power spectrum analysis in an exercise in which the POC device was held free hand and unsupported. The results showed that tremor could be detected using data obtained from accelerometers analyzed with relatively basic algorithms. Furthermore, by applying an adaptive filter method, the subject’s hand tremor could be compensated.

Essentially this research shows that in the fields of medical device development and industrial applications, some completely separate error sources need to be detected and understood. One such major error concern, especially specific for medical applications,
involves reliability. When applying MEMS technologies to medical devices, it is vital that the device produces accurate and reliable detection. Especially when using the sensors in instruments, the movement may be minute and the requirement for reliable drift compensation is even more challenging. Some specific sources of error in industrial applications come from the external operation conditions. In these applications, temperature and environmental conditions are great challenges for reliable operation. Also, possible external magnetic fields and unstable circumstances produce challenges and major sources of error.

According to the literature, the major error sources in MEMS based applications are drifts from the sensors themselves and those caused by integration errors [1,7-11]. Other important concerns involve calibration for which reason externally referenced sensors (laser, optical camera, robust body design) are often used as back-up. The third main source of errors is algorithm based. Thus, algorithm development plays a major role in the analysis of MEMS based applications. Algorithm development requires substantial amounts of time and effort especially in detection of movements in the magnitude of millimeters. However, by successful analysis, new breakthrough applications may be achieved with MEMS technologies.

4. CONCLUSIONS AND FUTURE WORK

This paper presents a recent proof-of-concept device and research topics that enabled the use of MEMS based IMUs. The results show that with the used IMU sensor, respiration and hand tremor can be detected using accelerometers, and that by using a triaxial accelerometer together with a triaxial gyroscope, motions can be detected at displacement accuracies within 5 mm over a range of 680 mm. Major error sources specifically in medical and industrial applications were also covered, showing that algorithm development requirements may be substantially different in various use cases.

In the fields of medical device development and industrial applications, some completely separate error sources need to be detected and understood. However, as MEMS technologies are improving in accuracy and reliability, a huge market potential is also becoming more evident. This has also opened the research for miniaturizing the MEMS sensors through enabling nano technologies [15]. As the global trend in life sciences is personalized medicine with connected health, our future work in the life sciences field deals with new applications for medical devices and human vital signs monitoring. We will also research other fields of industrial applications including a topic involving both fields, namely motion detection with inertial sensors.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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