Evaluation of a Low Cost Solid-State Accelerometer as a Distance Measuring Sensor for Vehicle Positioning System

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Abstract

This paper describes an evaluation of a low cost, solid state accelerometer as a distance-measuring device. Kalman Filter was applied to reduce random noise existing in the sensor. The random bias drift of the accelerometer was found to be 2.5mg. The accelerometer was moved back and forth eight times for a distance of 40cm with an acceleration of 10 m/s^2 and the distance error accumulated was +1.55cm. The bias drift rate due to temperature was 0.108μg/s when the accelerometer was placed at room temperature. The performance shows that the device is suitable for short duration distance measurement and may act as a complementary sensor to the GPS during signal blockage or between periodical absolute position updates.

1. Introduction

ITS (Intelligent Transport System) is an emerging field in which computer, communication, sensor and other technologies are applied to road transportation. It is aimed at reducing traffic congestion, improving traffic management, providing safety driving assistance, and facilitating both drivers and pedestrians.

Vehicle positioning technology is a fundamental and essential task in ITS. With the knowledge on the vehicle positions, tasks such as navigation, tracking, traffic management, route planning, information reference and driving record could become possible. Positioning technologies could broadly be divided into two main streams: relative positioning and absolute positioning. Absolute position means that the currently calculated position does not depend on the previous positions. Example of an absolute positioning system is the Global Positioning System (GPS). The advantage of this system is that there is no accumulation of drift error. However, GPS has the signal blockage problem and it has relatively low output rate. For a relative positioning system, dead reckoning method was employed to find the position. The angle and distance data are used to find the current position. One of the commonly used relative positioning system is Inertial Navigation System (INS). Dead reckoning positioning with gyros and accelerometers is called inertial navigation. The gyro measures the angular rate and the accelerometer senses the accelerations. Integration of angular velocity with time yields angle data. Distance data could be obtained by double integration of acceleration with time. INS is a self-contained device which requires no external electromagnetic signals. Thus, INS does not have the signal coverage problem found in GPS. Moreover, the data output rate of INS could be much faster than GPS. However, the disadvantage of INS is the bias drift problem. These errors would be accumulated and the accuracy deteriorates with time due to integration. Methods such as Kalman Filter are employed to reduce errors due to the random bias drift.

For urban area such as Hong Kong which has many high rise buildings, the use of GPS is difficult due to the signal blockage problem. Thus, INS should also be used for positioning. However, there must be some means to compensate for the accumulated position error. The combination of beacon signal, GPS, INS signal with the processing from Kalman Filter could be a viable solution.

A solid-state micromachined accelerometer has the advantage of small size, low cost and being self-contained. Compared to an odometer, a 3-axis accelerometer can sense three-dimensional movements while the former can only sense single-axis movements. Also, the data rate of an accelerometer can be much higher than that of an odometer. Moreover, an accelerometer is a self-contained device while an odometer must be fixed to the shaft of some wheels which could be inconvenient in some cases. Thus, this kind of accelerometer could be a viable solution as a short duration distance-measuring device.

An evaluation of an Inertial Navigation System (INS) consisting of a solid state gyroscope and an solid state accelerometer for a mobile robot can be found in [1]. An extended Kalman filter model for the thermal drift bias was built. Mostov [2] describes about systematic and random errors in an accelerometer. Methods are proposed to reduce the effect of random errors which includes proper modeling of the accelerometer and using feedback system. A software simulation of the mathematical model of an accelerometer is also suggested. In reference [3], Lobo, Lucas, Dias and Almeida describe about a prototype of an Inertial Navigation System consisting of a piezoelectric vibrating gyro, two silicon accelerometers, two clinometers and a magnetic compass. Robot arm was used to move the sensor in the experiments. A very detailed description of individual sensors and the system architecture are given. In reference [4], Lemaire talks about the use of an accelerometer for navigation purpose. The theory, implementation and usage of the ADXL202 accelerometer are given. Moreover, the future trend of using micromachined inertial sensors in vehicle and personal navigation system are talked about. An interesting description of inertial sensors such as solid state gyroscope and accelerometer is given by Verplaetse [5]. Also, some innovative applications of the inertial sensors are proposed such as intelligent camera, pen and shoe.

Below is an outline of this paper. The reduction of random noise of the accelerometer data using Kalman Filter is introduced in Section 2. In section 3, the accelerometer and the evaluation experiment setups are described. The evaluation methods and experimental results are covered in section 4. In section 5, discussions and conclusions are given.

2. Accelerometer Noise Reduction using Kalman Filter

Kalman filter is a commonly used method for random noise reduction and data fusion for positioning. In this method, statistical characteristics of a measurement model is used to recursively estimate the data. A brief introduction of KF is given below.

Kalman Filtering is a statistical technique that combines a knowledge of the statistical nature of system errors with a knowledge of system dynamics, as represented by a state space model, to provide an estimate of the state of a system. Any number of unknowns can be included in the states. In a navigation system, we are usually concerned with position and velocity. The state estimate is obtained using a weighting function called the Kalman gain, which is optimized to produce a minimum error variance. [6] A Kalman filter can be used to fuse measurements from multiple sensors and provide both an estimate of the current state of a system and a prediction of the future state of the system. The algorithm of KF is shown in Fig.1. [7]

For reduction of random noise of the accelerometer signal, a process model (Fig.2) with three integrators in cascade was used for processing a single axis of acceleration data. The system parameters are shown in Fig.3 and Fig.4. [8]. The power spectral density of the input white noise W is $1(m/s^2)^2/(rad/sec)$, and the sampling time Δt equals 1/206.6 s. The value of W was obtained after some experiments to provide better results.

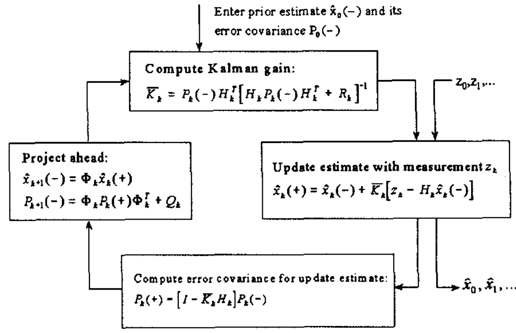

Fig.1. The Kalman Filter algorithm

Notation:
$\mathbf{x_k}$ is the system state
$\mathbf{z_k}$ is the measurement
$\mathbf{w_k}$ is the plant noise with its covariance $\mathbf{Q_k}$
$\mathbf{v_k}$ is the measurement noise with its covariance $\mathbf{R_k}$
"(-)" indicates the a priori values of the variables (before the information in the measurement is used).
"(+)" indicates the a posteriori values of the variables (after the information in the measurement is used).
$\bar{K}$ is the Kalman gain.
Φ_k is the transition matrix at time t_k
P_k is the error covariance matrix
H_k is the measurement matrix

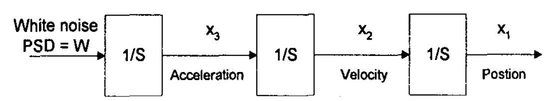

Fig.2. The process model of the accelerometer data for Kalman Filter

$$\phi_k = \begin{bmatrix} 1 & \Delta t & \Delta t^2/2 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 \end{bmatrix}$$

Fig.3. The state transition matrix for the Kalman Filter

$$Q_k = \begin{bmatrix} \frac{W}{20}\Delta t^5 & \frac{W}{8}\Delta t^4 & \frac{W}{6}\Delta t^3 \\ \frac{W}{8}\Delta t^4 & \frac{W}{3}\Delta t^3 & \frac{W}{2}\Delta t^2 \\ \frac{W}{6}\Delta t^3 & \frac{W}{2}\Delta t^2 & W\Delta t \end{bmatrix}$$

Fig.4. The error covariance matrix for the Kalman Filter

3 Experimental Setups for the Accelerometer Evaluation

3.1 The Accelerometer

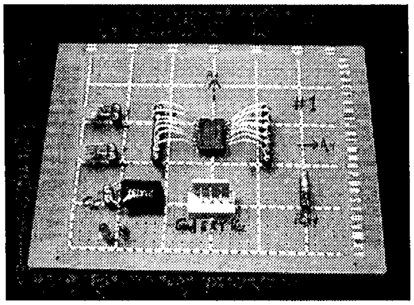

Fig.5. The accelerometer interface board

The accelerometer (interface circuit shown in Fig.5) that has been evaluated is ADXL202 produced by Analog Device. It is a low cost, low power, 2-axis micromachined accelerometer with a measurement range of ±2g (19.6m/s^2). It can measure both dynamic acceleration and static acceleration. The outputs are digital signals whose duty cycles are proportional to the acceleration in each of the two axes. [9] The output can be measured directly with a MCU timer system. This accelerometer is selected for evaluation as a distance measuring sensor due to its small size, low cost and acceptable performance.

3.2 The Data Acquisition Board

The microcontroller used in the data acquisition board is Motorola 68HC11F1. It has 512 bytes of EEPROM, 1024 bytes of RAM, an enhanced 16-Bit timer system, three Input Capture (IC) channels, an enhanced NRZ Serial Communications Interface (SCI). [10] The data acquisition circuit board is shown in Fig. 6.

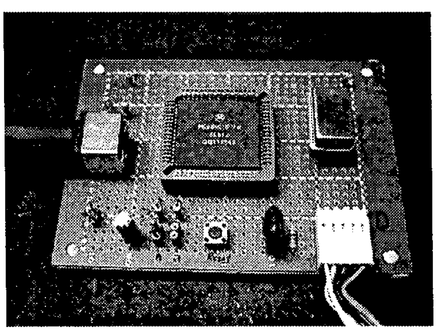

Fig.6. The data acquisition board with the microcontroller

The data output by the accelerometer is a 200Hz square wave whose duty cycle depends on the acceleration. Input Capture 1 (IC1) pin of the MCU was used to detect the signal from the accelerometer. The MCU would transmit the data to the PC via the Serial Communication Interface (SCI). A Visual Basic program was used at the PC to receive and save the data to the hard disk. A C program was written to process large amount of accelerometer data. The recorded data is downsampled by averaging the acceleration data within each downsampling period. The downsampled data was then stored in a file which could be plotted using MATLAB. For the results obtained, the data was averaged every twenty-five seconds to give a downsampled data.

3.3 The Sony Robot Arm

The robot arm used to move the accelerometer is a Sony SRX-410 High Speed Assembly Robot. It was designed for high assembling speed and high performance industrial applications. The system consists of the robot arm, a controller, a panel and a PC for programming the robot arm. Fig.7 shows a photograph of the accelerometer evaluation hardware setup. The block diagram of the experimental setup is shown in Fig.8.

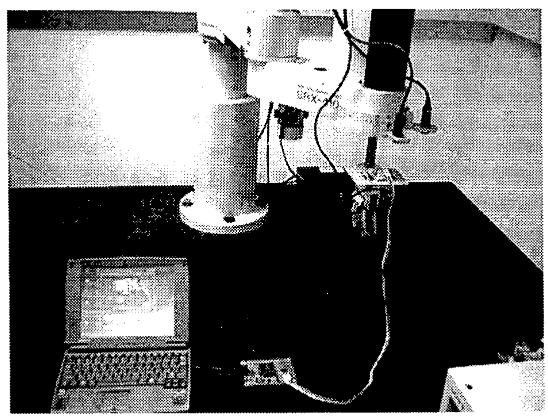

Fig.7. The accelerometer evaluation experiment hardware setup

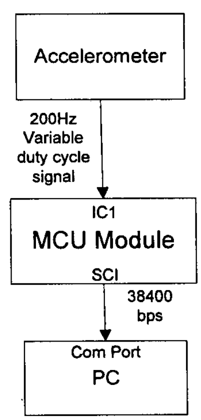

Fig. 8. Accelerometer data acquisition block diagram

4. Evaluation Methods & Experimental Results

4.1 Acquisition of 14-hour of Stationary Accelerometer Data

Fourteen hours of stationary accelerometer data was taken in order to study the effect of temperature on the bias drift. The recorded data occupied 81.3 Mbytes of hard disk space. The data was processed to give the acceleration readings which was then downsampled for plotting using MATLAB.

The duty cycle of the accelerometer output is proportional to the acceleration. The microcontroller was used to measure the duty cycle using the timer system. The timer counts was converted to ASCII and then sent to the PC for recording. The data was processed according to Fig.9.

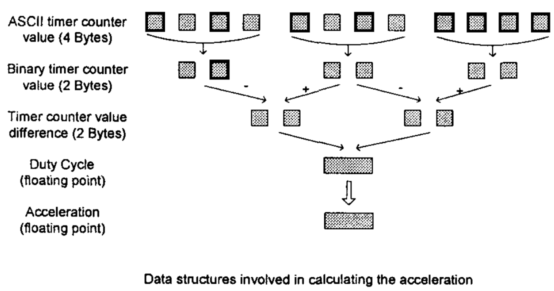

Fig 9. Data processing diagram for the acceleration data

Fig.10 and Fig.11 show the 14-hour of stationary acceleration data without and with Kalman filter processing respectively.

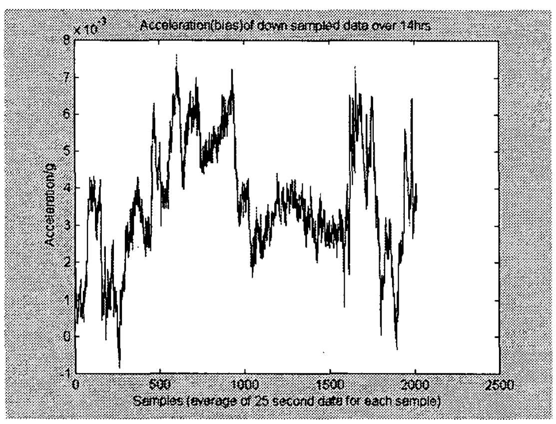

Fig.10. Stationary Acceleration data in 14 hours without Kalman Filter processing

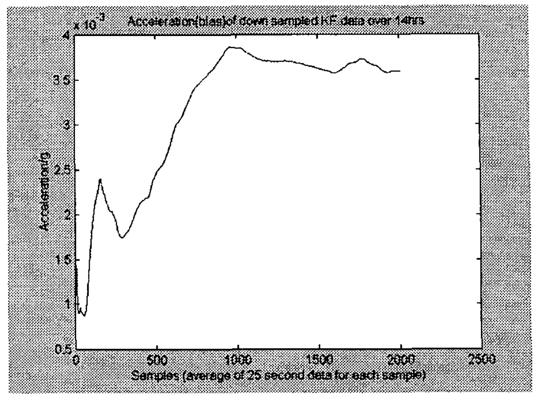

Fig.11. Stationary Acceleration data in 14 hours with Kalman Filter processing

4.2 Experiments Carried Out Using Sony Robot Arm

Experiments for accelerometer evaluation were carried out using the Sony Robot Arm. Twenty three sets of experiment with different velocity and acceleration combinations were done. The velocity ranged from 0 m/s to 1 m/s and the acceleration ranged from 0 m/s^2 to 10m/s^2. Two different sets of results with low and high acceleration is shown in the followings.

Figures 12-15 show the results of the experiment with acceleration at 10 m/s^2 which is high and with velocity at 1 m/s. The accelerometer was moved from left to right and vice versa for a distance of 40cm. Such motions were repeated for eight times. The acceleration was calibrated with a constant bias to reduce the zero offsets.

Fig.12 shows the acceleration data without Kalman Filter processing. This has resulted in a signal disturbed with random noises. A clearer shape of the signal obtained by using Kalman Filter is shown in Fig.13. The integrated velocity is shown in Fig.14 and the integrated distance is shown in Fig.15. The final distance was found to be +1.55cm while the actual final distance should be zero.

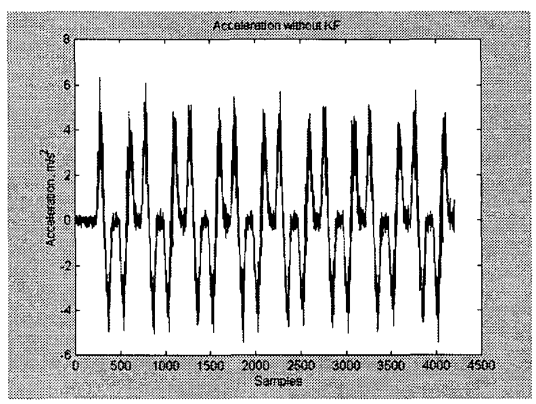

Fig.12. Acceleration results for acceleration of 10ms^{-2} and velocity of 1ms^{-1} without Kalman Filter processing

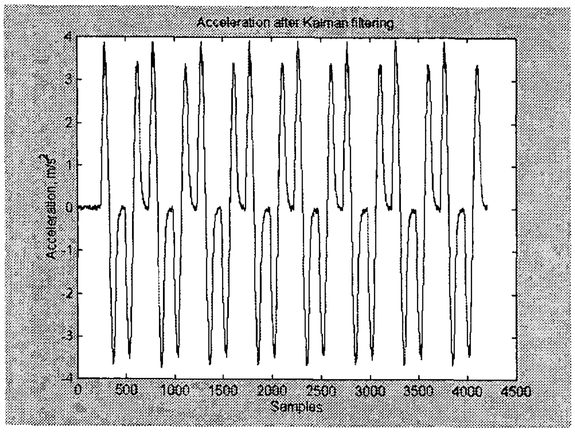

Fig.13. Acceleration results for acceleration of 10ms^{-2} and velocity of 1ms^{-1} with Kalman Filter processing

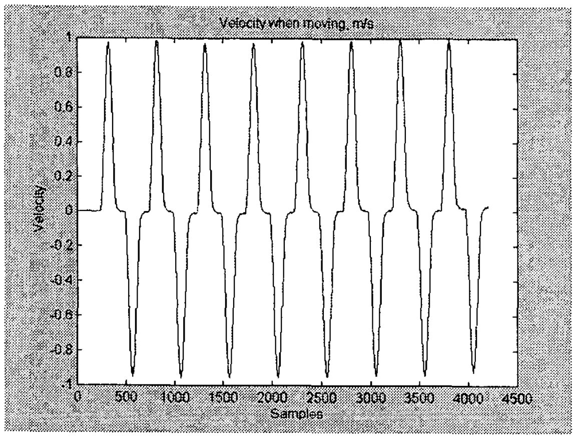

Fig.14 Velocity results for acceleration of 10ms^{-2} and velocity of 1ms^{-1}

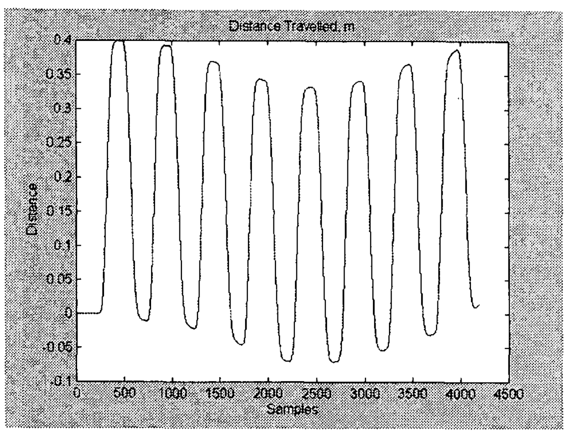

Fig. 15 Distance results for acceleration of 10ms^{-2} and velocity of 1ms^{-1}

Figures 16-19 show the results of the experiment with acceleration at 3 m/s^2 which is quite low and with velocity at 0.3m/s. The accelerometer was again moved from left to right and vice versa for a distance of 40cm. Such motions were repeated for three times. Figures 16 and 17 show the acceleration data without and with Kalman Filtering. Due to the random bias drift problem, the acceleration data was divided into regions for different bias reductions. The biases in the first seven regions were manually tuned to optimize the accuracy. The last six regions were not calibrated for comparison purpose. These calibrations also helped to estimate the random bias drift of the accelerometer. Fig. 18 shows the velocity which was calculated by integrating the acceleration data with time. Only the first two velocity cycles are calibrated with manually tuned acceleration biases. Fig. 19 shows the distance which was calculated by integrating the velocity data with time. Only the first two distance cycles are calibrated with manually tuned acceleration biases. This graph shows the affection of the random bias drift on the distance data after double integration of the accelerometer data.

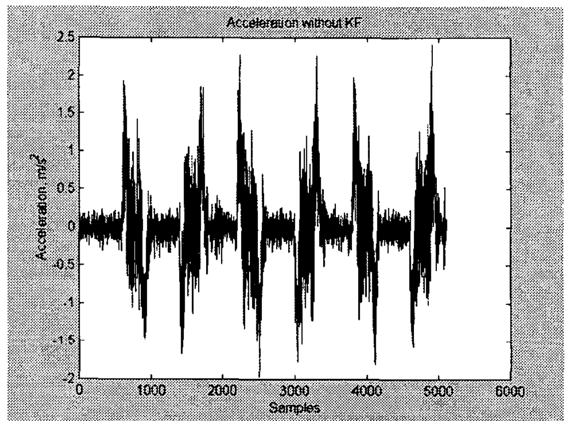

Fig.16. Data of acceleration at 3 m/s^2 without Kalman Filtering

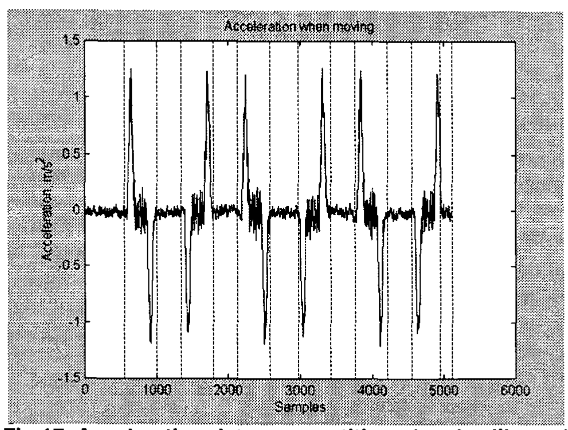

Fig.17 Acceleration data was partitioned and calibrated with different biases

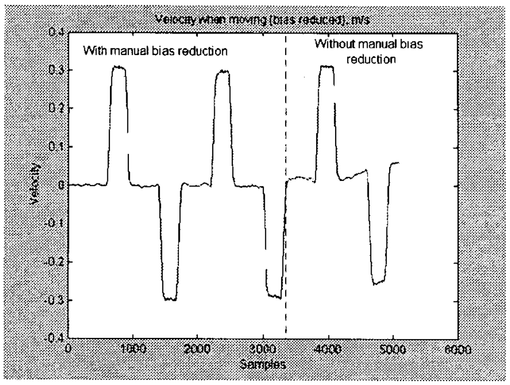

Fig.18. Velocity with and without manually tuned acceleration biases reduction (only first two velocity cycles are calibrated)

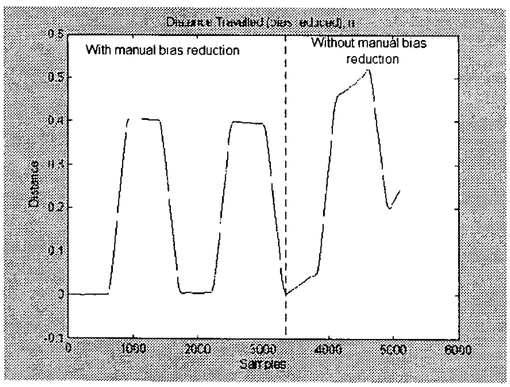

Fig.19. Distance with and without manually tuned acceleration biases reduction (only the first two distance cycles are calibrated)

5. Discussions & Conclusions

From the result shown in Fig.11, it is observed that the bias or zero offset of the accelerometer generally increased after powering up. After about seven hours, the bias settled down to fairly stable values. The results are due to the thermal bias drift of the accelerometer. The internal temperature of the sensor increases when it is warming up. The thermal bias drift rate when the accelerometer is placed at room temperature is found in this evaluation to be 0.108μg/s. If these bias drifts due to the temperature are not compensated, the results would be affected after operating for long duration. Compensation methods can be done by using low cost temperature sensing IC and crystal oven. [11]

The range of the biases deviations is about 2-3 mg which is fairly large. Better navigational grade accelerometer has about 0.1mg random bias drift. For a bias error of 2mg, the velocity errors built up in one minute is 1.178m/s. Moreover, the position error built up in one minute for a bias error of 2mg is 35.32m. Thus, if the random bias could be modeled properly, the accuracy in distance measurement can be greatly improved.

From the distance graphs of Fig.15, distortions are observed which were due to the random biases of the accelerometer. The random bias drift error is one of the major sources of the positioning error. When the acceleration is higher, the errors caused by the random bias are less significant.

The integrated final distance was found to be +1.55cm when the accelerations was 10 m/s^2 while the actual final distances should both be zero. Thus, the result is quite close to the ideal one. This good result was due to the relatively large acceleration imposed on the accelerometer. As the accelerometer can measure up to 2g which is 19.6133 m/s^2 of acceleration, the applied acceleration, 10 m/s^2 is relatively large. When compared with Fig.19, the distortions in distance measurement for higher accelerations are less. This means when the acceleration is higher, the errors caused by the random biases are less significant.

From the evaluation of the experiment results of the accelerometer, the performance of the accelerometer is acceptable as short duration distance measuring device. It could be combined with gyroscope and GPS to form a continuous integrated positioning system. Such a micromachined silicon accelerometer could be a self-contained sensor to give a low cost and small-sized distance-measuring device. Further research would be on the proper modeling of the accelerometer in order to reduce the effect of random bias drift. Moreover, the combination of GPS, digital compass, gyroscope and beacon signals with the accelerometer would be studied.

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