International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 2, February- 2013

Motion Estimation Using Sensors

Lakshmi Areekath

Vellore Institute of Technology

Abstract

Linear displacement estimation of a mobile device is useful in various real time applications, such as inertial navigation systems, video surveillance, video encoding etc. Present state of the art techniques perform the global motion estimation using image processing techniques, which requires complex computations and more power consumption.
Here, an attempt has been made to estimate the linear displacement of a mobile device using the in-built sensors. The in-built 3-axis accelerometer of mobile devices is employed to determine the linear displacement. Three different methods are used to convert acceleration to displacement. From the results we conclude that the in-built sensors can be used for linear displacement estimation of mobile devices.

1. Introduction

The recent advancement in the field of MEMS technology has led to a rapid growth in the inclusion of sensors in mobile devices. These devices consume only a fraction of the power used by the device and function in the background at all times. This has led to the development of applications that use the sensor readings.

Among the sensors the most widely used in mobile devices is the 3-axis accelerometer. The accelerometer is a hardware sensor that measures the acceleration force in m/s^2 that is applied to a device on all three physical axes (x (lateral), y (longitudinal), and z (vertical) axes.), including the force of gravity [2]. It is considered reliable for motion detection and consumes about 10 times less power than the other motion sensors.

In this paper we present three different approaches to determine displacement from accelerometer data. Unlike the previous experiments in which the accelerometer sensor is fixed on the device, here we use the in-built accelerometer in the Smartphone. The three approaches gives insight regarding the various degrees of accuracy that can be achieved through changes in the algorithm. Of the methods presented the first two have been dealt with in literature, while the third is a new step in the direction of motion estimation using accelerometer data alone.

The next section deals with the error sources associated with the conversion of accelerometer data into displacement data. Section 3 deals with the related work in this area, section 4 with the various methods adopted, section 5 with the results and discussion, followed by the conclusion.

2. Error sources

The accelerometer senses all kinds of acceleration. Its output consists not only of the desired motion data but also of other sources of acceleration. Thus the accelerometer data is generally noisy and requires a great deal of preprocessing before it is used. The two primary sources of noise in the received signal are irregular sampling rates and the noise inherent in discrete physical sampling of a continuous function [1]. The filtering out of noise is a difficult process esp. since it may result in loss of trajectory information. However the small amount of noise in the data can lead to severe drift in the derived displacement on double integration.

3. Related work

Related Work on Sensors-Assisted Applications: Some sensor-based work has been done in the areas of vehicle movement detection and computer vision. For example, the European patent application EP1921867 presented the idea of employing vehicle motion information provided by various sensors to improve coding efficiency of the video encoder [12]. The authors of [13] proposed a method for deploying mobile device cameras and inertial sensors for autonomous vehicle motion estimation. However, [12], [13] focused on detecting vehicle movement and vehicle-mounted mobile device cameras.

4. Adopted methods

Data acquisition consists of both the displacement and sensor data simultaneously of a mobile device. The displacement data is collected using image processing technique and sensor data using the Android APIs. The acquisition is performed after calibration of the device. Due to the implementation of the Android framework, its sampling mechanism is generally irregular.To regularize sampled values, the holes in the signal were interpolated via a process called data linearization

A. Time domain approach

According to the Laws of Physics, displacement, s, is obtained from the acceleration by

$$S = \int_0^T\!\!\int a(t)\, dt\, dt \qquad (1)$$

Since the signals are in digital domain, the integration is replaced by summation. To remove the low amplitude error from the acceleration signal, the mean from the signal. The signal is cumulatively summed once to get velocity. The mean of this signal is subtracted again from itself and cumulatively summed again to get the displacement. The mean value is subtracted again from the resultant signal. The drift in the plot is removed by subtracting the trend component from it.

B. Frequency domain approach

The mean is removed from the acceleration data. The Fast Fourier Transform of this data is determined. The integration is performed by dividing each element by the square of magnitude of the frequency band. The Inverse Fourier Transform of the resultant data is determined. The result is scaled.

C. Statistical approach using neural network

An artificial neural network is a mathematical model that consists of an interconnected group of artificial neurons. Neural network processes information using a connectionist approach to computation of input data. The neural network sometimes acts as an adaptive system that changes its structure during a learning phase. They are used to model complex relationships between inputs and outputs or to find patterns in data. Here the Levenberg-Marquardt Back Propagation algorithm [8], [9] is used to determine the relationship between the collected accelerometer and displacement data. The accelerometer data is divided into blocks of ten data each and these act as the input and the displacement data act as target values.

5. Results

On performing data processing in Matlab 2009b it is observed that the MSE values in the case of time and frequency domain approaches are 1.6602 m and 0.4869 m respectively. However in the statistical approach the MSE is 0.0000000535917 m and the regression value R is 0.999999999. These results can be attributed to the robustness of the NN model.

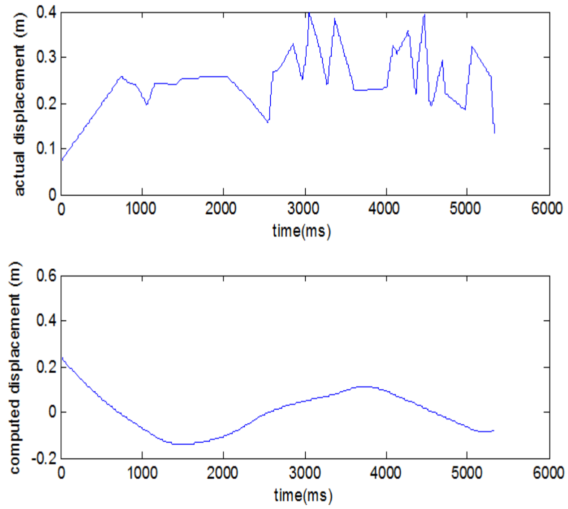

Figure 1. Results of time domain approach

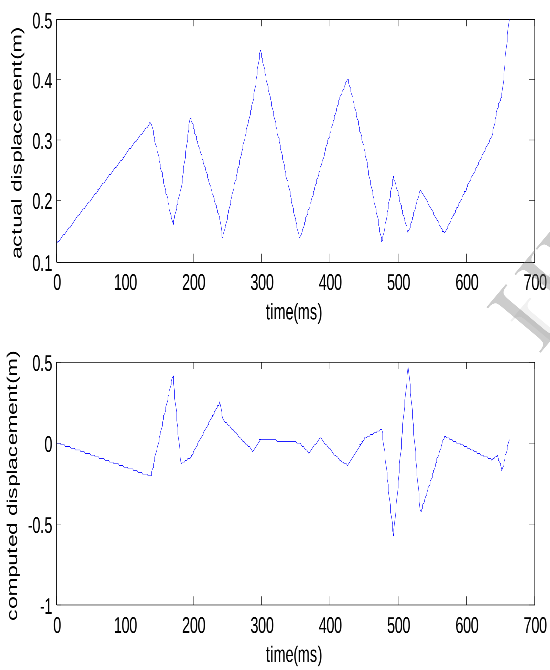

Figure 2. Results of frequency domain approach

6. Conclusion

The various approaches to displacement estimation resulted in different levels of accuracy. In the first two approaches the noise in the accelerometer data was converted into drift leading to larger error in the resultant signal. These methods are suited for trajectory or position estimation in Inertial Navigation Systems (INS). As regards to the third method using Neural Networks, the performance index of 0.0000000535917 MSE indicates high performance of the proposed model. Also this method achieves automatic synchronization of the sensor and displacement data unlike previous attempts that focused on manual synchronization. The practical implementation that uses in-built sensors is cost effective and consumes less power. In addition to all this since the sensor used is a basic accelerometer sensor, it can be implemented on a wide range of mobile devices. Currently the proposed model is tested for only a single device and along the z-axis. As further work, the data collection module can be extended to other devices and larger datasets to arrive at a more robust linear displacement estimation model.

7. References

[1] Xian Xueming Qian, “Global Motion Estimation and Its Applications,” School of Electronic and Information Engineering, Xian Jiaotong University, Xian, China

[2] Z. Chen, P. Zhou, and Y. He, “Fast Motion Estimation for JVT, document JVT-G016, Joint Video Team”, Pattaya, Thailand, 2003, pp. 7-14.

[3] A. M. Tourapis, “Fast ME in the JM Reference Software,” document JVTP026, Joint Video Team, Poznan, Poland, 2005, pp. 24-29.

[4] A. M. Tourapis, “Enhanced predictive zonal search for single and multiple frame motion estimation,” Proc. SPIE Conf. Vis. Commun. Image Process., vol. 4671, Jan. 2002, pp. 1069-1079.

[5] Xiaoming Chen, Member, IEEE, Zhendong Zhao, Ahmad Rahmati, Student Member, IEEE, Ye Wang, Member, IEEE, and Lin Zhong, Member, IEEE, “Sensor-Assisted Video Encoding for Mobile Devices in Real-World Environments.”

[6] Guangming Hong, Ahmad Rahmati, Ye Wang, Lin Zhong, “sensecoding: Accelerometer-Assisted Motion Estimation for Efficient Video Encoding”

[7] Y. Keller, A. Averbuch, “Fast Gradient Methods Based on Global Motion Estimation for Video Compression,” IEEE Trans. Circuits Syst. Video Technol., Vol. 13, No. 4, Apr. 2003, pp. 300-309.

[8] Hagan, M.T., Menhaj, M. (1994). “Training feed-forward networks with the Marquardt algorithm,” IEEE Transactions on Neural Networks, Vol. 5, No. 6, 1999, pp. 989-999.

[9] Kermani, B.G., Schiffman, S.S., Nagle, H.G. “Performance of the evenberg marquardt neural network training method in electronic nose applications,” Science Direct, Sensors and Actuators B: Chemical, Volume 110, Issue 1, 2005, pp. 13-22.

[10] Charrier, C., Lebrun, G., Lezoray, O. “Selection of features by a machine learning expert to design a color image quality metrics,” 3rd Int. Workshop on Video Processing and Quality Metrics for Consumer

Electronics (VPQM), Scottsdale, Arizona, 2007, pp.113-119.
[11] Kuryati Kipli, Mohd Saufee Muhammad, Sh. Masniah Wan Masra, Nurdiani Zamhari, Kasumawati Lias, Dayang Azra Awang Mat, "Performance of Levenberg-Marquardt Backpropagation for Full Reference Hybrid Image Quality Metrics"
[12] S. Martin and M. Ulrich, "Sensor assisted video compression," European Patent Application EP1921867, 2008.
[13] D. Strelow, and S. Singh, "Optimal motion estimation from visual and inertial measurements," in Proc. IEEE WACV, Dec. 2002, pp. 314-319.
[14] J.-M. Odobez and P. Bouthemy, "Robust multiresolution estimation of parametric motion models," J. Visual Commun. Image Represent., vol.6, no. 4, 1995, pp. 348-365.
[15] F. Dufaux and J. Konrad, "Efficient, robust, and fast global motion estimation for video coding," IEEE Trans. Image Process., vol. 9, no. 3,2000, pp. 497-501.
[16] A. Krutz, M. Frater, M. Kunter, and T. Sikora, "Windowed image registration for robust mosaicing of scenes with large background occlusions," in Proc. ICIP, 2006, pp. 353-356.
[17] R. Wang and T. S. Huang, "Fast camera motion analysis in MPEG domain," in Proc. ICIP, 1999, pp. 691-694.
[18] A. Smolic, M. Hoynck, and J.-R. Ohm, "Low-complexity global motion estimation from P-frame motion vectors for MPEG-7 applications," in Proc. ICIP, 2000, pp. 271-274.
[19] Y. Su, M.-T. Sun, and V. Hsu, "Global motion estimation from coarsely sampled motion vector field and the applications," IEEE Trans. Circuits Syst. Video Technol., vol. 15, no. 2, pp. 232-242, 2005.
[20] Y.-M. Chen and V. Bajic, "Motion vector outlier rejection cascade for global motion estimation," IEEE Signal Process. Lett., vol. 17, no. 2, 2010, pp. 197-200.
[21] S.Sapna, A.Tamilarasi and M.Pravin Kumar, "Backpropagation Learning Algorithm Based On Levenberg Marquardt Algorithm," CS & IT-CSCP 2012.