Title:

Signal processing and power issues in acquisition of vibration data by MEMS accelerometers

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ABSTRACT

Micro-Electro-Mechanical Systems (MEMS) sensors offer multiple advantages over conventional sensing devices. These advantages often include smaller size and weight, reduced power consumption, integration of signal conditioning circuits directly on the chip, and reduction in cost for the sensor and system as a whole.

The concept of sensor networks is often considered as a possible way to collect data from a group of territorially distributed sensors, and as a perfect candidate for tasks of structural health monitoring. A single sensor node usually possesses a limited amount of power that has to be spent efficiently on powering of the sensors, computational tasks and wireless data transmission. In this paper we present a comparative study summarizing performance of several analog-to-digital converters and MEMS accelerometers from various manufacturers. The testing was performed on the platform of Wireless Intelligent Sensor and Actuator Network (WISAN). The goal of the comparison is to establish reliable estimates on the resolution, accuracy and power consumption of various data acquisition devices and sensors utilized in an ultra-low-power application.

INTRODUCTION

Many methods of Structural Health Monitoring (SHM) utilize vibration information to detect and locate damage. The extent to which vibration data is

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used depends on a specific methodology. Reviews of vibration-based damage detection methods based presented by Friswell and Penny [1] and Farrar at al. [2] list a variety of vibration damage detection methods.

Examples of vibration damage detection methods include detection changes in the natural frequencies of a structure, such as in an earlier work by Cawley and Adams [3] or Salawu [4]. Vibration information can also be used in conjunction with model updating methods, such as in papers by Fritzen et al. [5] and Wang et al. [6]. Analysis of changes in mode shapes due to damage represents yet another subgroup of modal methods. A representative work is a paper by Pandey et al. [7] describing a method for locating cracks by observing changes in curvature mode shapes, as well as papers by Farrar and Jauregui [8], and Kim et al. [9], etc.

All these various damage detection methods exhibit different sensitivity to the accuracy of vibration acquisition. For example, methods based on natural frequencies are far more tolerant to noise in the vibration signal than mode shape based methods [1, 10]. Individual sensitivity of a given damage detection method to the accuracy of vibration acquisition requires careful selection of an appropriate sensor that can provide needed precision and selection of the appropriate signal processing methods and data acquisition equipment.

Micro-Electro-Mechanical Systems (MEMS) accelerometers have been considered by many as perfect sensors for applications of structural health monitoring. MEMS advantages over conventional sensors include smaller size and weight, reduced energy consumption, integration of signal conditioning circuits directly on the chip, and potential reduction in cost for the sensor and system as a whole.

The concept of a sensor network has recently gained serious attention from researchers, where several inexpensive low-power nodes perform monitoring of structural health [11-16]. Utilization of a sensor network in structural health monitoring brings up the issue of supplying power to the sensors and the sensor nodes themselves. The limited battery energy has to be efficiently split between the sensors and signal conditioning circuitry, computational tasks and wireless data transmissions. Therefore, the sensor network framework brings together two major considerations: accuracy of vibration acquisition and power required to acquire the data.

In this paper, we present a comparative study, summarizing static performance of several MEMS accelerometers from various manufacturers utilized as sensing elements for Wireless Intelligent Sensor and Actuator Network (WISAN, [16]). The goal of the comparison is to establish reliable estimates on the resolution and accuracy of various sensors utilized in an ultra-low-power application, where energy consumption by sensors and signal conditioning circuits is as important as precision of measurements.

CONTRIBUTING FACTORS

Considering the accuracy of vibration data acquisition by a sensor node, it is possible to identify two major contributing factors: inherent accuracy of the sensor and accuracy of analog-to-digital conversion. The inherent accuracy of the sensor is a parameter defined by the internal structure, sensing methods and manufacturing process used by the maker of the device. The accuracy of analog-to-digital conversion is defined by the Effective Number Of Bits (ENOB) of the Analog-to-Digital Converter (ADC) which primarily depends on internal noise of the ADC, internal noise of the signal conditioning circuitry, and noise that digital circuitry creates on the power supply lines. The latter factor is extremely important for networked sensor nodes, where digital and analog circuitry is tightly packed together and little can be done to alleviate the problem.

The effective number of bits of an ADC is also a factor of the conversion methodology. A Successive-Approximation Register (SAR), the most often used type of ADCs, is normally manufactured for resolutions of 8-16 bits and sampling frequencies up to millions of samples per second. High-resolution 20-24bits ADCs are often built using Sigma-Delta (SD, 1-bit) conversion principle. These ADCs are usually limited to a few hundred samples per second.

Energy consumption of the data acquisition subsystem of a sensor node is primarily defined by the energy consumption of the sensor, energy consumption of the signal conditioning circuitry and energy consumption of the analog-to-digital converter. Energy consumption of a sensor is a parameter defined by the manufacturer. Minimization of energy consumption by a sensor through power cycling is possible, but this option is not reviewed in this paper.

The energy consumption of the analog-to-digital converters depends on a particular device model and principle of operation. In this paper we will consider 3 different micro-power ADCs from Texas Instruments. Successive approximation register ADCs (ADS8325 and internal ADC of MSP430F149) consume energy only during signal sampling and conversion times and spend the majority of the time in sleep mode. On the other hand, to achieve the highest resolution, a sigma-delta ADC has to stay continuously powered all the time.

THE TEST PLATFORM

A custom-made test platform (Figure 1) based on a WISAN sensor node was built to accommodate 6 different accelerometer models from different manufacturers.

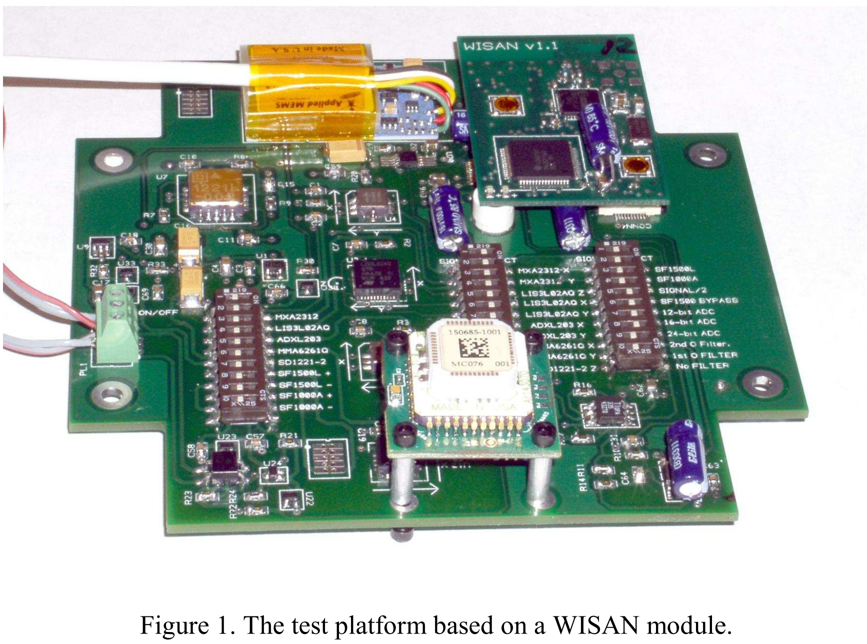

Figure 1. The test platform based on a WISAN module.

Table I. Parameters of the tested accelerometers.

Manufacture, accelerometer model	Range, G	Nominal noise floor, $\mu g\sqrt{Hz}$	Supply voltage, V	Supply current, mA	Typical power consumption, mW
MEMSIC, MXA2312	±2.0	200	2.7-5.25	4.9	14.7 at 3V
Analog Devices, ADXL203	±1.7	110	3-6	0.7	2.1 at 3V
Freescale, MMA6261Q	±1.5	300	2.7-3.6	1.2	3.6 at 3V
Silicon Designs, SD1221-2	±2.0	2	5	10	50 at 5V
STMicro, LIS3L02AQ	±2.0	50	2.4-5.25	0.85	2.45 at 3V
Applied MEMS, SF-1500L	±3.0	0.3	±6 - ±15	10	120 at ±6V

The accelerometer models and their key characteristics are listed in Table I. The test board was implemented as a two-layer design with a ground plane to minimize noise in the electronic circuits. The boards contains low noise linear voltage regulators that convert ±6V battery power into +3V and +5V supplies for digital and analog electronics and sensors. Three different analog-to-digital converters represent different precisions and principles of operation, summarized in Table II. ADS1216 and ADS8325 are stand-alone ADCs from Texas Instruments, while MSP430F149 is a microcontroller at the core of WISAN with a built-in 12-bit ADC. The switches on the test board allow flexible configuration and routing of sensor signals to ADCs. All ADCs were set to sample the incoming signal at 100Hz rate.

Table II. Parameters of the tested ADCs.

ADC	Conversion principle	Nominal number of bits, bits	Manufacturer-specified ENOB at 100Hz, bits	Maximum sampling rate, sps	Supply voltage, V
ADS1216	Sigma-Delta	24	≈20	780	2.7-3.3
ADS8325	SAR	16	13.8	100,000	2.7-3.6
MSP430F149	SAR	12	-	200,000	2.7-3.3

MEASURING ENOB OF THE ADC CONVERTERS

The goal of this test was to establish true ENOB of the digital-to-analog converters. The resolution of digitized sensor data cannot be higher than the resolution of the ADC, establishing the limit on the accuracy of the acquired vibration data. Dynamic testing of the ADCs is necessary to assess their performance, where the input signal is provided by a function generator.

The IEEE-STD-1241 [17] gives a standard procedure based on sine-wave curve fitting to test the performance of the ADCs. Different algorithms have been developed using this standard. The four parameter sine wave testing [18] is an iterative algorithm that estimates the frequency of the input sine wave using an interpolated DFT and fits a sinusoid of the nearest amplitude, phase, frequency and offset. These parameters help in determining the rms error of the input signal and provide the Signal to Noise Ratio (SNR). The Effective Number of Bits (ENOB) is calculated as,

$$ENOB = (SNR - 1.76)/6.02 \tag{1}$$

In our experiments we utilized an HP-3314A function generator, which supplied a sinusoid with the amplitude of 1.5V and offset of 1.5V (1.25V for

ADS1216) and frequency of 2Hz to the ADCs. The four parameter sine wave testing algorithm and formula (1) were used to compute the effective number of bits. The results of these experiments showed virtually identical ENOB about 10 bits for all three ADCs. The reason for such behavior was due to the fact that ENOB of the signal generator itself was limited to 10 bits, therefore the quality of the digitized signal was determined by the quality of the incoming sinusoid and not by the ADCs.

To alleviate the limitation of the signal generator, a method presented by Simões et al. [19] was utilized in ADC testing. This method allows determination of ENOB for analog-to-digital converters driven by signal sources of lower resolution than the ADC. Due to noise present in the signal generator, the input sinusoid signal can be represented as $s'(t) = A\sin\omega t + n(t)$, where $n(t)$ is assumed to be white noise of variance σ_n^2. Therefore, the SNR of the digitized waveform is

$$SNR_{MSD} = 10\log\frac{\sigma_S^2}{\sigma_{ADC}^2 + \sigma_n^2}, \tag{2}$$

where σ_{ADC}^2 is the variance of all noise associated with the ADC.

For most signal sources, parameter σ_n^2 is proportional to the amplitude of the signal. With change in amplitude of the input signal, σ_n^2 changes while σ_{ADC}^2 remains unaffected. Thus, reduction in the input signal amplitude by a factor k changes the signal to noise ratio as,

$$SNR_{MSD} = 10\log\frac{\sigma_S^2/k^2}{\sigma_{ADC}^2 + \sigma_n^2/k^2}. \tag{3}$$

The above equation may be rewritten as,

$$10^{-SNR_{msd}/10} = k^2 \times 10^{-SNR_{ADC}/10} + 10^{-SNR_{src}/10}, \tag{4}$$

where, SNR_{MSD} is measured SNR, SNR_{ADC} is SNR of the ADC, and SNR_{src} is SNR of the source.

Taking several measurements with different values of k, it is possible to construct a linear regression from (4) in the form $y = a + bx$, where $y = 10^{-SNR_{MSD}/10}$ and $x = k^2$. Parameters a and b of the regression represent true SNR values (and, thus, ENOB values) of the source and the ADC

$$SNR_{ADC} = -10\log(b) \tag{5}$$

$$SNR_{SRC} = -10\log(a) \tag{6}$$

The testing was conducted by this method by supplying various input amplitudes to the ADCs, recording 30-second waveforms, applying the four parameter sine wave testing method to obtain SNR_{MSD}, calculating values of x and y, performing a linear regression, computing the SNR_{ADC} and SNR_{src} with subsequent calculation of $ENOB_{ADC}$ and $ENOB_{src}$. The testing was performed in configuration with and without a 2nd order anti-aliasing filter. The tests were repeated 5 times with averaging of the results. Results of the testing are summarized in Table III, showing values of $ENOB_{ADC}$ and $ENOB_{src}$ as well as the correlation coefficient R and the P value.

As results show, the ENOB value of the signal generator was indeed around 10 bits. Due to noise, the ENOB values of the ADCs are lower than the nominal values, with the best results shown by ADS1216.

Table III. Summary of the ADC testing.

ADC configuration		$ENOB_{ADC}$, bit	SNR_{ADC}, db	$ENOB_{src}$, bit	R	P
ADS1216	No filter	15.79	96.84	10.21	0.99984	<0.0002
	2nd order filter	16.05	98.43	10.18	0.99309	<0.0001
ADS8325	No filter	12.21	75.29	9.13	0.93421	0.00206
	2nd order filter	12.01	74.06	10.07	0.99912	<0.0001
MSP430	No filter	11.41	70.47	9.31	0.99273	<0.0001
	2nd order filter	11.58	71.47	9.92	0.99949	<0.0001

ENERGY CONSUMPTION BY ADC

Energy consumption by an ADC in a senor node can be comparable or even more than energy consumption by a sensor. In this paper we consider only micro-power ADCs, better suited for applications in sensor networks.

An SAR ADC consumes most energy during sampling and conversion times and very little in shutdown mode between conversions. In general, per sample energy consumption by an SAR ADC sampling data at a frequency *f* can be expressed as

$$E = (T_{SAMPLE} + T_{CONVERT})P_{ACT} + \left(\frac{1}{f} - T_{SAMPLE} - T_{CONVERT} \right) P_{SLEEP} \quad (7)$$

where T_{SAMPLE} is the sampling time, $T_{CONVERT}$ is the conversion time, P_{ACT} is power consumption in active mode (assuming equal power consumption during sampling and conversion), P_{SLEEP} is power consumption in sleep mode.

The sampling time for ADS8325 is fixed and is 6 clock cycles (1Mhz clock), while the sampling time for MSP430F149 is programmable and was set to 256 clock cycles (8Mhz clock) or 32µs to accommodate taking measurements both from accelerometers and from built-in temperature sensor. The conversion time for ADS8325 is fixed and is 16 cycles of 1Mhz clock, conversion time of MSP43-F149 is 13 cycles (8 Mhz clock). Typical consumption by ADS8325 is 2.25mW in active mode and 0.3µW in sleep mode. Typical power consumption by the built-in ADC of MSP430F149 with internal reference is 3.6mW in active mode and about 3µW in sleep mode. Given these values, energy spent per sample at 100Hz is 52.5nJ for ADS8325 and 151nJ for MSP430F149.

To achieve the maximum accuracy, a Sigma-Delta ADC should remain powered at all times. Sleep mode is possible, but in most cases it will lower the ENOB value. Therefore, for a continuously active SD ADC, the energy consumption per sample can be expressed as

$$E = P_{ACT} / f \quad (8)$$

Typical power consumption of ADS1216 in the utilized configuration is about 0.483mW. Therefore, per sample energy consumption is 4.83µJ.

SENSOR NOISE FLOOR

The noise floor measurement of different sensors was performed in a seismically quiet environment, away from vibrating sources. The goal of testing was to demonstrate how actual SNR_{ADC} (directly related to ENOB) of the ADC converters compares to the SNR values acquired in noise floor measurements. The testing was conducted in configuration with the second order filter tuned at 20Hz cut-off frequency and sampling frequency of 100Hz. The results of testing are given in Table IV.

Table IV. SNR values from the noise floor measurements, db.

	SF1500L	SD1221	LIS3L	ADXL203	MMA6621	MXA2312
ADS1216	-113.81	-103.91	-102.84	-86.38	-78.97	-82.75
ADS8325	-79.51	-91.916	-91.16	-74.72	-71.99	-76.47
MSP430	-74.89	-80.22	-84.87	-73.64	-71.02	-74.76

CONCLUSIONS

A few observations can be made from the presented results.

First, an important insight on measurement accuracy can be made comparing results presented in Table III and Table IV, where measured noise floor SNR (Table IV) produces better values than SNR_{ADC} maximally achievable by an ADC (Table III). The reason for such behavior is in the fact that noise floor measurement utilizes only a small portion of the full ADC (and sensor) range and therefore cannot be an accurate predictor for the full-range performance. This fact provides strong motivation for performing dynamic characterization of the sensor-ADC path to establish true resolution and accuracy of vibration acquisition devices.

Second, we observed at least an order of magnitude difference in the energy consumption on per sample basis of the SD and SAR ADCs. While SAR clearly wins from the power consumption perspective, an SD ADC may be a better choice for high precision applications. For example, an ADS1216 is better paired with an accurate accelerometer like SF-1500L, while an ADS8525 will adequately perform with a less precise accelerometer such MMA6621.

Third, at the current state of commercially available technology increasing effective resolution of a vibration acquisition system comes at a premium of increasing the power consumption both by the sensors and by the analog-to-digital converters. Practical selection of sensors and ADC converters for utilization in tasks of vibration acquisition should follow the minimal requirements posed by the damage detection method and strike a balance between accuracy and energy consumption.

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