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Robustness Estimation of Wireless MEMS Vibration Test under Harsh Environment

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Abstract

Robustness estimation is important issue to ensure stability, reliability, and precision of Wireless MEMS vibration test under harsh environment stressing. Although the robustness of vibration test is limited mainly by the embedded electronics and sensors, how to obtain precise and robust data by using energy effective and resources constrained wireless sensor nodes is still a problem. Paper uses the multivariate uncertainty statistics method to estimate robustness of online test data under harsh environment, and uses Fisher information distance to estimate transmitting robustness in its complication communication process. Experiments and simulation are designed to analyze the robustness and precise of wireless MEMS nodes in numerical value, results show estimation methods and model are effective.

***Keywords**: robustness, multivariate uncertainty statistics, Cramer-Rao lower bound, Fisher information distance*

1. Introduction

Measuring vibration is very essential in detecting and diagnosing any deviation from normal conditions. The advantage of MEMS accelerometers from conventional piezoelectric accelerometers are their size, easy installation, cost and so on.

In life cycle analysis, there are some qualitative experiments results for MEMS accelerometers in normal and harsh work situation. Ron Denton reported reliability results on MEMS accelerometers from field failure experience, the MTBF being around 2,000,000 hours (around 5*10-7h-1 for an exponential distribution of failures) [1]. Andover reported a failure rate of 1.75 ppm for MEMS accelerometers manufactured by MEMSIC [2].These results show that MEMS accelerometers are high reliability devices, with low failure rate. There have been several studies [3-6] addressing this issue for irradiation. COTS accelerometers have been shown to survive 1000 temperature cycles from -65°C to +150°C, as well as 30,000 mechanical shocks of 2,000G. But there are not enough test and analysis of its robustness.

Meanwhile, the MEMS sensors hold a great promise for the using of wireless smart vibration measurement based condition monitoring [7-14]. The robustness of the calibration procedure under harsh environment is crucial for the potential practical use of multi-sensor and single sensor devices. MEMS accelerometers applied in the paper are capacitive based MEMS accelerometers, it measure changes of the capacitance between a proof mass and a fixed conductive electrode separated by a narrow gap [15].

As the MEMS sensors of embedded electronics have two compensation means under harsh environment. One is environment compensation (system error); the other is noise signal filter which is stressed by harsh environment (random error and uncertainty). The paper is focused on the second problem. Robust statistic is shown to be useful to deal with the uncertain data in normal environment [16-20]. Based on this, paper supposes that the collect data under harsh environment contain "information" of test data. And the fisher information matrix and Cramer-Rao lower bound are applied to analyze robustness and precise of vibration sensor [21].

This paper addresses the problem of robustness estimation of wireless MEMS sensor working under harsh environment. In section II, The formulation of problem is introduced. In

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section III, the simulation method, experiment results and discussion will be present. In section IV, the conclusion is given.

2. Problem Formulation

There are two main problems in robustness analysis of wireless sensors under harsh environment (as shown in Figure 1). One is missing data processing in communication layer; the other is robust uncertainty analysis under harsh environment in physic layer.

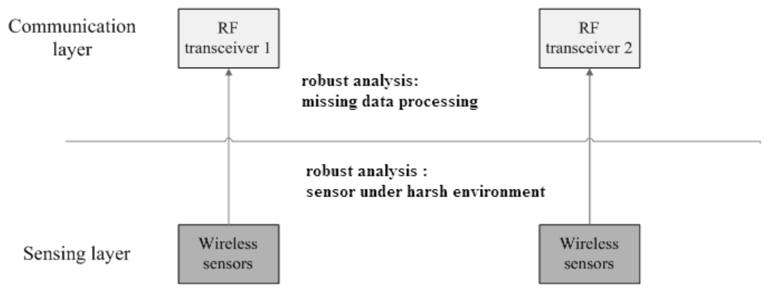


Figure 1. Two Layers of Wireless Vibration Sensor Robustness Analysis

2.1. Robust Estimation Problem of Vibration Test under Harsh Environment

The vibration signal model under harsh environment is shown as formula (1):

$$\Gamma_1(t) = f(t,T,H,...) + f'(t,T,H,...) \tag{1}$$

f(t,T,H,…) is certain test signal, f' (t,T, H,…) is uncertain signal come from harsh environment. Here Γ1(t) means only test vibration value, have not tested temperature, humidity, and other environment influence parameters.

In the test scenario, we test vibration, temperature, humidity and so on simultaneously, obtain Γ2(t,T,H,…) from formula (2).

$$\Gamma_2(t,T,H,...) = f(t,T,H,...) + f'(t,T,H,...) \tag{2}$$

To simplify the problem, here Suppose Γ2(t,T,H,…) has an empirical distribution, the qualitative robustness is essentially equivalent to weak continuity of Γ. As describe in formula (3)-(5).

Many of the most common test statistics and estimators depend on the sample (x 1. . . x n,) only through the empirical distribution function.

$$\Gamma_n = n^{-1} \sum \delta_{x_i} \tag{3}$$

Where δ_{x_i} stands for the pointmass 1 at x. That is,

$$\Gamma_n(x_1,..., x_n) = \Gamma(F_n) \tag{4}$$

If the limit in probability exists:

$$\Gamma(F) = \lim_{n \to \infty} \Gamma(F_n) \tag{5}$$

Then Γ is Fisher consistent, or (asymptotic robustness). Let:

$$y_i = \Gamma_{2,i}(t,T,H,...) \tag{6}$$

Then Cramer-Rao inequality is:

$$\begin{aligned} & e_i^{\,2} I_i \geq 1; and \\ & e_i^{\,2} = \int dy_i [(\hat{a}(y_i) - a)^2] \\ & I_i = I_i(a) = \int dy \left[\left(\left(\frac{\partial \ln p}{\partial a} \right)^2 p \right) \right] \\ & y_i = y_i(a, x_i) \end{aligned} \quad (7)$$

Where I is Fisher information [21], ‘p’ is distribution of ‘a’.

For Γ2 (t, T, H,…) has native component of uncertainty f’ (t, T, H,…), the robust estimation problem of vibration test under harsh environment is multivariate uncertainty robust statistics problem.

2.2. Robust Estimation Problem of Wireless Data Transmitting under Harsh Environment

In network transmitting, there are packet losing rate owing to attacks, environment influence, end of battery power and so on.

In the paper, wireless sensors losing packet stochastic processing is supposed to be Poisson processing.

The paper focuses on two robust estimation problems. One is robust estimations occurred in uncertainty different deployment place, the other is robust precise estimations of 10% uncertainty connectivity (or packet losing rate) in one node.

In the first situation, Fisher information distance D is defined to present different deployment status. As shown in formula (8).

$$D_F\,(p(x\,|\,\theta^1), p(x\,|\,\theta^2)) \equiv \min_{\theta_i} \int_{t_1}^{t_2} \left[\sqrt{(\frac{d\theta}{dt})^T [g_{ij}] (\frac{d\theta}{dt})} \right] dt \quad (8)$$

Suppose data transmitting probability of nodes in different deployment place is similar, the Kullback Leibler divergence is half of Fisher information distance.

$$D_F\,(p_1, p_2) \approx D_{KL}(p_1, p_2) + D_{KL}(p_2, p_1) \quad (9)$$

In the second situation, the location of missing data is defined to describe the relationship between precise (or CRLB) with missing data. Then:

$$\lim_{n \to \infty} CRLB_n(b) = c \quad (10)$$

b is location of missing data, n is number of transmitting data, c is const.

3. Methods and Simulation Analysis

To solve problems in section II, two hypotheses are introduced firstly, and then the robust uncertainty analysis of vibration test is proposed and simulated, in the end, based on the noisy uncertain signal model, robust estimation problem of wireless data transmitting is analyzed and simulated.

Hypotheses 1: the Packets losing during one period under uncertain interface is the Poisson stochastic process; and the Packets losing in different deployment is also the Poisson stochastic process.

Hypotheses 2: Harsh degree, or different environment information contain native test error information in Fisher information inequality. For example, the same MEMS chip, uncertainty and deviation of COS application have smaller value than it of industrial application; uncertainty and deviation of industrial application have smaller value than it of automotive electronics; and uncertainty of automotive application has smaller value than it of harsh applications.

3.1. The Vibration Test Design and Robustness Analysis under Harsh Environment

The first test is to verify the vibration signal model. Here we test vibration in different temperature, humidity, and in different place. Table 1 is temperature test data, Figure 2 shown test in hydroelectric station.

Table 1 presents test value of two MEMS vibration sensors in normal (20 º) and cold (-10º) temperature.

The first test is to verify the vibration signal model. Here we test vibration in different temperature, humidity, and in different place. Table 1 is temperature test data, fig.2 shown test in hydroelectric station.

Table 1 presents test value of two MEMS vibration sensors in normal (20 º) and cold (-10º) temperature.

So it is reasonable to use follow uncertain signal model under harsh environment like (3).

Table 1. Test Value of Two MEMS Vibration Sensors in Normal (20 º) and cold (-10º) Temperature

	x	**y**	**z**	**notes**
Normal temperature-	0.00g	0.06g	0.88g	
node No1	Rate 1/20	Rate 1/4	Rate 1/4	Vary data/all data
	Change 0.01g	Change 0.01g	Change 0.01g	Max-min value
Normal temperature-	0.05g	0.02g	0.92	
node No2	Rate 1/1.5	Rate 1/1.5	Rate 1/1.5	Vary data/all data
	Change 0.05g	Change 0.02g	Change 0.08g	Max-min value
Cold temperature-	0.01g	0.13g	0.92g	
node No1	Rate 1/20	Rate 1/4	Rate 1/4	Vary data/all data
	Change 0.01g	Change 0.01g	Change 0.02g	Max-min value
Cold temperature-	0.12g	0.16g	0.95	
node No2	Rate 1/1.5	Rate 1/1.5	Rate 1/1.5	Vary data/all data
	Vary 0.1g	Vary 0.08g	0.08g	Max-min value

Figure 2. Wireless vibration MEMS sensors in fields

$$F(x) = (1-\varepsilon)\cdot\Phi\left(\frac{x-\mu}{\sigma}\right) + \varepsilon\cdot\Phi\left(\frac{x-\mu_i}{k\cdot\sigma_i}\right) \quad (11)$$

$$\mu_i = \mu + \Delta\mu;$$

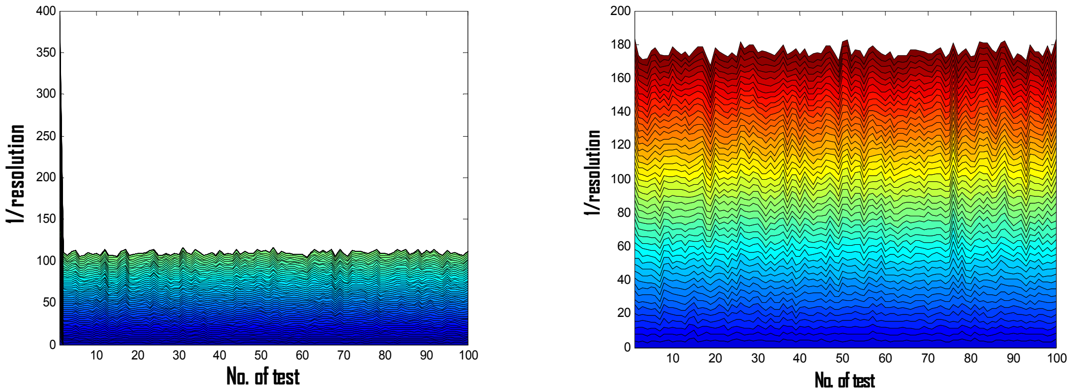
As the chance (or variety) measure is sub additive. That is, for any countable sequence of events $\Theta_1, \Theta_2, \cdots$, then have:

$$ch\{\bigcup_{i=1}^{\infty}\Theta_i\} \le \sum_{i=1}^{\infty} ch\{\Theta_i\} \quad (12)$$

Method 1: multivariate uncertainty robust statistics problem in worst case analysis, the every environment influence factor other than temperature, robust estimation can use formula (12), and meanwhile the resolving capability of robust statistics is inversely proportional to the harsh degree.

The simulation of method 1 is use (13) as normal robust statistics, use (11) as in robust harsh statistics. as shown in Figure 2

$$F(x) = (1-\varepsilon)\cdot\Phi(\frac{x-\mu}{\sigma}) + \varepsilon\cdot\Phi(\frac{x-\mu}{k\cdot\sigma}) \quad (13)$$



(a) An example resolving capability of robust statistics in normal environment

(b) An example resolving capability of robust statistics in harsh environment

Figure 3. (a) An example resolving capability of robust statistics in normal environment; (b) An example resolving capability of robust statistics in harsh environment

The CRLB of (13) had been proved to be (14):

$$CRLBc \approx (1+2\varepsilon)CRLG_G \quad (14)$$

Theory 1: the CRLBc' of uncertain signal model under harsh environment have value as shown in (15).

$$CRLB_{c'} \approx CRLB_c + (\Delta\mu_1'^2 + ... + \Delta\mu_n'^2) \quad (15)$$

Prove: suppose $\hat{\theta}$ is an estimation value of θ, the mean square error of $\hat{\theta}$ is $M^2(\hat{\theta})$.

$$M^2(\hat{\theta}) = E(\hat{\theta}-\theta)^2 \quad (16)$$

$$\begin{aligned} M^2(\hat{\theta}) &= E[\hat{\theta} - E(\hat{\theta}) + E(\hat{\theta}) - \theta]^2 \\ &= E[\hat{\theta} - E(\hat{\theta})]^2 + E[E(\hat{\theta}) - \theta]^2 \\ &+ 2E\{[\hat{\theta} - E(\hat{\theta})]\cdot[E(\hat{\theta}) - \theta]\} \\ &= \mathrm{var}(\hat{\theta}) + b^2(\theta) \end{aligned} \quad (17)$$

The formula (17) is true only $\hat{\theta}$ is asymptotic unbiased estimation.

$\mathrm{var}(\hat{\theta})$ satisfy:

$$\begin{aligned} &\mathrm{var}(\hat{\theta}) \geq 1/I; have\_CRLB\_value: \\ &CRLBc \approx (1+2\varepsilon)CRLG_G \end{aligned} \tag{18}$$

So the CRLBc' of uncertain signal model under harsh environment have value as shown in (15), the $(\Delta\mu_1{'}^2 + ... + \Delta\mu_n{'}^2)$ is come from $b^2(\theta)$

Method 2: multivariate uncertainty robust statistics problem in uncertain analysis tools.

Multivariate data analysis can include a large number of measured variables, even some variables overlap (it might be dependent). As shown in Figure 4.

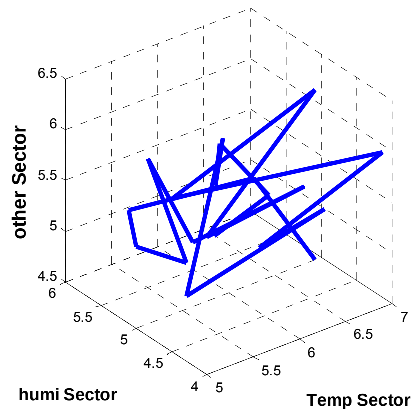


Figure 4. Factor Analysis in Multivariate Data Process

3.2. The Transmitting Data Test Design and Robustness Analysis under Harsh Environment

In test design, first is testing communication influenced by environment, for temperature influence the communication had been tested in research before, irradiation influence communication had been tested [27] (as shown in Figure5). Second is testing in communication protocol, how much packet loss rate can be accepted. Results show 10% packet loss rate is reasonable.

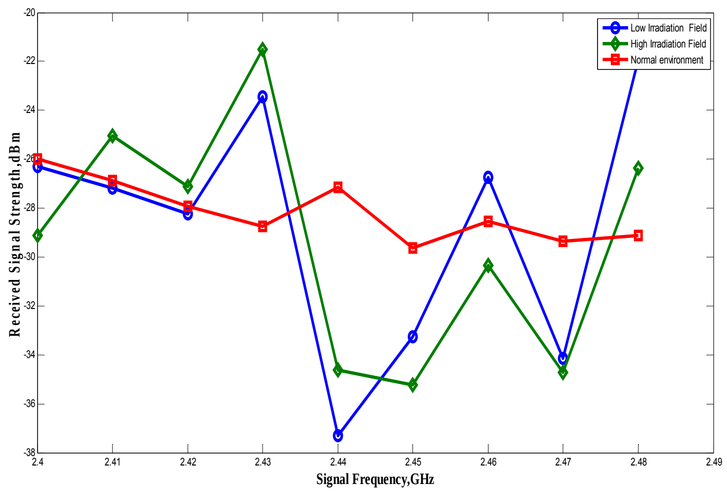


Figure 5. The Relationship between Nuclear Irradiation and Received Signal Strength at Different Frequency

Method 1: as periodic data has infinity number, so have Equation (19).

$$\overline{CRLB_n(b)} = c \qquad (19)$$

Suppose the Packets losing during one period under uncertain interface is the Poisson stochastic process; and the Packets losing in different deployment is also the Poisson stochastic process.

And suppose all acquired data transmit to the receiver.

Then use (13) as normal signal, (11) as robust signal, Figure 5 show Possion missing data is almost random, and the missing data increase uncertainty, the mean value almost has no change.

Method 2: Basically, Fisher information distance D (8)-(9) has similar meaning with cluster analysis of uncertain data (or to do cross-validation).

As shown in paper [28], reliable estimations of classifier accuracy using cross-validation techniques and finite-size data samples shows: the more accurate is a model induced from a small amount of real-world data, the less reliable are the values of simultaneously measured cross-validation estimates.

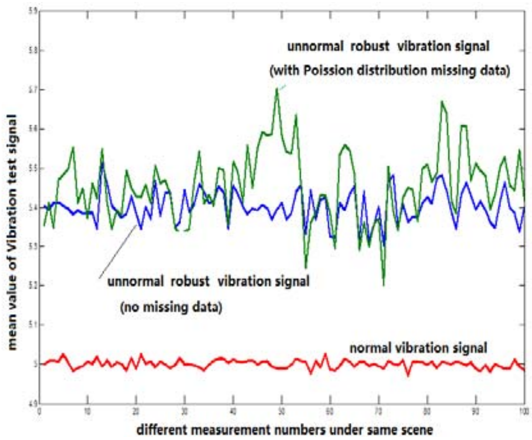


Figure 6. The Relationship between Robust Missing Signal and its Mean Value

4. Conclusion

This paper presents robustness analysis of wireless MEMS vibration sensors under harsh environment. In sensing layer,the robust uncertainty analysis of sensor shows the statistic resolution of test data is inverse proportional to the harsh degree, and the Fisher information is a function with harsh environment status. In communication layer, the mean value of test data influenced by Possion missing data is almost random, and the more missing data number increases the uncertainty value of test data, but the mean value has almost no change. It is also shown that Fisher information distance D has similar meaning with cluster analysis of uncertain data.

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