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Network of MEMS sensors for condition monitoring of industrial systems: accuracy assessment of features used for diagnosis

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***Abstract* – This paper analyses the effect of variability of metrological characteristics of a set of low-cost MEMS accelerometers on the calculation of typical features used in condition monitoring of automatic production lines. The knowledge of the contribution of the variability of sensor metrological characteristics to the final accuracy of features is expected to be interesting when networks of low-cost sensors are used or in cases the spread of their characteristics is high, due to a mass production without single calibration. The real variability of the sensor's characteristics has been experimentally evaluated according to a calibration of a set of 25 low-cost MEMS, carried out sensor by sensor. Digital sensitivity, signal-to-noise ratio and data rate variability of each sensor have been considered for analysis.**

Experimental data from an industrial test case has been processed comparing real data, by a high performance piezoelectric accelerometer, and modified ones, taking into account the variability of the above characteristics of MEMS.

The results show which features are more affected and which characteristics of MEMS are more influencing the features themselves.

Keywords – Accuracy; Digital MEMS; Sensors network; Condition monitoring.

I. INTRODUCTION

The most modern industrial realities aim to structure themselves as systems of collaborating computational entities which are in intensive connection with each other and with the physical world, providing and using, at the same time, large amount of data, and able to realize totally or partially autonomous operations, tuning, diagnosis and prognosis of devices, for improvement of efficiency, reliability and safety [1], [2], [3].

In this kind of industrial contexts, sensors and sensor networks cover a relevant role, because they provide information about physical processes which, ultimately, allows people or smart devices to make decisions [4].

The need of using a large number of distributed sensors, to monitor extensive and complex industrial systems, has led to a large diffusion of digital MEMS sensors, due to their ease of use, flexibility, low-cost and low-power consuming. However, some typical metrological attributes of measuring instruments, such as traceability and accuracy, should be guaranteed, to supply reliable measurement data from which to extract correct information about the system condition [5].

The use of networks of above sensors despite of many remarkable advantages needs to take into account some metrological topics, according to many recent literature references [6-7]:

- synchronization among sensors, in particular in dynamic applications [6];
- identification and control of the real operating conditions of embedded sensors [8];
- big data management, validation and uncertainty analysis in network systems [7];
- definition of specific metrological parameters (digitized sensitivity, …) [9, 10];
- remote self-calibration guaranteeing a satisfactory accuracy [11-14].

Some of these aspects refer to static characteristics, like sensitivity, time stability, signal to noise ratio, effect of interfering quantities, some other to dynamic ones, like frequency rate, frequency rate stability and so on.

Usually, condition information for the monitoring is synthetized into specific features, defined in the both time and frequency domains, able to define the status of the device for maintenance purposes and criteria are well known about choosing the most suitable features depending on the specific application [15-19]; some of them are sensitive to the variability of static characteristics of sensors, some other to the variability of dynamic ones, which are also related to the specific technology of sensors, which is a very fluid situation.

Furthermore, variability of metrological characteristics of sensors is not homogeneous, so that the features are differently affected from each other, depending on the characteristic influencing the feature itself [14]; as an example, the variability of the frame rate, that results not constant with reference to the same accelerometer and in the comparison among different accelerometers. This problem can impact, in particular, on the calculation of features in the frequency domain, like these based, for example, on the FFT of signals, that is a typical algorithm of data processing for CM.

Therefore, less information is available, based on in field applications, on the effect on features, due to the metrological characteristics of MEMS sensors, when single low-cost sensors or a network of such sensors is used.

According to the previous considerations, the aim of this paper is to analyse the effect of the variability of metrological characteristics of a set of sensors, on the calculation of typical features used in condition monitoring. The set of sensors taken into account is composed of 25 3-axis low-power digital MEMS accelerometers. Different condition monitoring applications will be considered, in order to get a more general idea about this effects.

The analysis starts from the issues of the calibration of the whole network, paying attention to the peculiarity of the digital acquisition and transmission system. Calibration data, will be also used to separate the different effects, like the influence of sensitivity or acquisition rate variability, according to the availability of accurate reference data.

The impact of all these elements on the calculation of the main features used for condition monitoring will be evaluated in terms of variability. The awareness about these effects can help in comprehensively evaluating the uncertainty of features and in understanding the resolution of CM techniques.

Section 2 will describe the methodology used to individuate the aspects of interest related to both static and dynamic characteristics and the way the influences of these effects are evaluated on a test case.

Section 3 shows the results with reference to a real test case; many features are taken into account.

Conclusions will end the paper, giving also an idea of future work.

II. MATERIALS AND METHODS

2.1 Materials

The digital MEMS accelerometer investigated in this work is a commercial ultra-low-power digital MEMS accelerometer (STMicroelectronics, model LSM6DSR [17]), connected to an external IC-board (STMicroelectronics, model 32F769IDISCOVERY [17]).

The output signals range $\pm 2^{16-1} = \pm 32768$ $\text{Decimal}_{16\text{-bit-signed}}$, where the digit unit is a signed 16-bit sequence converted into a decimal number. Then, the sensitivity of the digital MEMS accelerometer has to be expressed in linear units of $\text{Decimal}_{16\text{bit-signed}}/(\text{m}\cdot\text{s}^{-2})$. [10, 20-21]

A set of 25 MEMS accelerometers has made available by the manufacturer for a characterization study, and this made it possible to evaluate the variability of metrological characteristics within units and between units.

For each axis of each MEMS accelerometer, repeated tests have been carried out at the oscillation frequencies: 3, 6 and 10 Hz.

It is to be pointed out that the sensitivity of sensors in the range 10 to 1000 Hz has been considered constant, based on indication of previous experimental activity of calibration by a different calibration laboratory [20].

In order to estimate in the practical cases the influence of the metrological characteristics of MEMS on condition monitoring, the effect of these aspects will be evaluated with reference to a real industrial application.

A high performance cutting stage for non-woven tissue, described in [22], is considered as test-case. The system includes a revolving cylinder with sharp profiles and a non-driven roller, supported in a lubricated cradle, that exerts an elastic force against the first element, by means of a pneumatic system.

Piezoelectric accelerometers and other kind of sensors have been conveniently installed onto the cutting unit. In particular, the accelerometers signals acquired in a condition monitoring campaign have been considered in the present study.

The aim of condition monitoring, in this application, is to recognize the actual working status of the machinery among 4 different conditions, corresponding to 4 different levels of the knife wear, called '0', '1', '2', '3'. Condition '0' corresponds to a new unit; the subsequent conditions correspond to increasing levels of wear.

2.2 Methods

The methodology is according to the following steps:

- Evaluation of the metrological characteristics which are of interest for all the available MEMSs;
- modification of the real monitoring signals according to the variability of the metrological characteristic of interest;
- data processing of original and modified monitoring signals in order to evaluate features and their variability;
- comparison of the variability of features due to sensor characteristics with the variability of experimental data;
- comparison among different features.

2.2.1 Evaluation of MEMS characteristics

The following metrological characteristics have been evaluated:

a. Digital sensitivity

The processing method to evaluate the digital sensitivity is based on the FFT of the MEMS and the reference signals. The amplitudes of the spectrum in the range centred at the oscillation frequency and width ± 10%

of it, have been added up, in order to reduce the effect of variability of sampling rate. Then, the sensitivities are obtained by dividing the values thus calculated for MEMS (d_x, d_y, d_z) and reference ($a_{ref,x}$, $a_{ref,y}$, $a_{ref,z}$), respectively:

$$S_{xx} = d_x/a_{ref,x}$$
$$S_{yy} = d_y/a_{ref,y} \quad (1)$$
$$S_{zz} = d_z/a_{ref,z}$$

b. Signal-to-noise ratio (SNR)

The SNR in decibels relative to the sinusoidal carrier, has been calculated using a modified periodogram of the same length as the input. The modified periodogram uses a Kaiser window with β = 38. The result excludes the power of the first six harmonics, including the fundamental [23]. SNR, in particular, is defined as follows:

$$\mathrm{SNR} = 10 \cdot \log_{10}(\mathrm{powfund}/\mathrm{varnoise}) \quad (2)$$

where powfund is the power of the fundamental armonic, and varnoise is the variance of the noise, supposed to be normally distributed.

Then, from equation (2), it is possible to extract the variance of the noise (and the standard deviation by calculating the square root):

$$\mathrm{varnoise}=\mathrm{powfund} \cdot 10^{-\frac{\mathrm{SNR}}{10}} \quad (3)$$

c. Sampling rate

The data rate of each sensor is evaluated both as a mean value during the whole acquisition (~100 cycles) and during a single cycle of vibration. The variability of both values is also considered. In particular, the following methods have been considered:

- Method 1:

By means of the FFT of the data the first harmonic in the analysed cases has been evaluated. It is, in general, not coincident with the real oscillation frequency, due to differences between the actual and nominal sampling rates.

On the basis of this value, the real sampling rate can be obtained as follows:

$$sr_r = f_r \cdot sr_n / f_m \quad (4)$$

where:
f_m : measured oscillation frequency
f_r : real oscillation frequency (3, 6 or 10 Hz)
sr_n : nominal sampling rate
sr_r : real sampling rate

- Method 2:

The distance between peaks, that is the period of the sinusoidal signal, has been evaluated, in terms of number of points. The sampling rate in Hertz is obtained multiplying the measured period by the oscillation frequency (3, 6 and 10 Hz, in this case).

2.2.2 Evaluation of the effect of the metrological characteristics of MEMS on CM

The modification of real monitoring signals, provided by a piezoelectric sensor, according to the variability of the metrological characteristic of interest, has been realized as described in the following procedure:

- Evaluation of the sensitivity effect

The difference between nominal and real sensitivity produces an effect on the accelerometer signal, that can be estimated as follows:

$$\mathrm{modified\_signal} = \mathrm{signal} \cdot S_{meas}/S_{nom} \quad (5)$$

where:
signal: original accelerometer output of the piezoelectric sensor;
modified_signal: acceleration signal that, theoretically, we could obtain using a MEMS of the considered type with the nominal sensitivity provided by the manufacturer;
S_{nom}: nominal sensitivity of the MEMS sensors;
S_{meas}: average measured sensitivity, obtained by calibration.

- Evaluation of the noise effect

The standard deviation of the noise, evaluated by the signal-to-noise analysis of the data by the calibration, has been used to generate a normally distributed noise, which has been added to the original monitoring signal of the piezoelectric accelerometer.

- Evaluation of the sampling rate effect

The percentage variability of the sampling rate, estimated in the calibration phase, is applied to the sampling period of 10^{-4} s, used in the real case. This variability value is used as standard deviation of a normally distributed noise, that is added to the time vector. Then, the corresponding acceleration values are calculated with linear interpolation.

On the basis of data thus modified, the features have been calculated, and the differences with respect to those based on the original data have been estimated.

The evaluation has been carried out on data of 5 repeated tests, for each condition of the system, and the variability of the results has been considered.

III. RESULTS

3.1 Results of the calibration

3.1.1 Sensitivities

The average sensitivity at 10 Hz, for all the axes and all the accelerometers has been estimated to be 1693 $\mathrm{Decimal}_{16bit\text{-}signed}/(\mathrm{m \cdot s^{-2}})$. The variability of this value, considering a rectangular distribution, is evaluated as follows:

variability = $(S_{max}-S_{min})/(2\ \text{radq}(3))$ = 12 $\text{Decimal}_{16bit\text{-}signed}/(m \cdot s^{-2})$

where S_{max} and S_{min} are, respectively, the maximum and the minimum sensitivities calculated on the basis of repeated tests.

3.1.2 Real Sampling rate

The real sampling rate has been calculated, as described in Section II, using two different methods.

- Method 1:

If the FFT of data is examined, it can be seen that the first harmonic in the analyzed cases is not coincident with the oscillation frequency. The values are shown in Table1.

Table 1. Measured oscillation frequencies [Hz]

axis		3 Hz	6 Hz	10 Hz
X	mean	3.109	6.218	10.355
	st. dev.	0.025	0.049	0.092
Y	mean	3.111	6.221	10.359
	st. dev.	0.027	0.053	0.091
Z	mean	3.108	6.216	10.352
	st. dev.	0.026	0.052	0.087

This is due to the fact that the real sampling rate is not exactly equal to the nominal rate of 1660 Hz.

On the basis of these values, the real sampling rates are calculated by equation (4), and a mean sampling rate equal to 1602 Hz, with a standard deviation of 13 Hz, is obtained.

- Method 2:

The real sampling rate has been also estimated by means of Method 2, to validate the results of Method 1 and to evaluate the variability of the sampling rate for each accelerometer during the acquisition.

In fact, these values are variable from cycle to cycle, as can be seen in Fig. 1, with reference to the x-axis of the accelerometer 1. Mean and standard deviation of data obtained in the repeated tests at 3, 6 and 10 Hz are shown in Table 2.

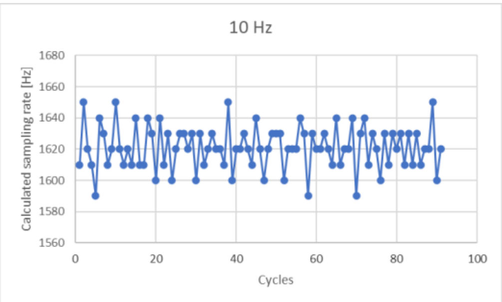

Fig. 1. Calculated sampling rate for the x-axis of the accelerometer 1, calculated cycle by cycle, at the oscillation frequency of 10 Hz.

Table 2. Mean and standard deviation of the sampling rate [Hz], calculated cycle by cycle, for accelerometer 1, x-axis.

	3 Hz	6 Hz	10 Hz
mean	1620	1621	1621
st. dev.	20	17	14

If the mean sampling rates are calculated for all the accelerometers, an overall average sampling rate equal to 1602 Hz, with a standard deviation of 13 Hz, is obtained, as for Method 1. It can be noticed that the behavior of axes x, y and z is very similar, due to the presence of a single clock on board.

The calculated mean sampling rate of 1602 Hz is affected by an error of 3.5% with respect the nominal rate, 1660 Hz.

If the variability of the sampling rate, calculated cycle by cycle for each accelerometer, is considered, a maximum standard uncertainty of 1.9% results on the sampling period.

If the variability of the sampling rate among sensors is considered, a standard uncertainty of 0.93% affects the sampling period.

Combining these contributions, an uncertainty of 2.1% for the sampling period is obtained.

3.1.3 Signal-to-noise ratio

The calculation of the signal-to-noise ratio on the calibration tests data, and of the standard deviation of noise, as described in the methodology section, provides a maximum value of 0.066 m/s^2.

3.2 Application of the calibration results to a real monitoring case

All the analyzed aspects should be taken into consideration when a net of MEMS sensors is used to monitor an industrial system. In particular, the effect of these aspects on the calculation of synthetic features for condition monitoring should be evaluated.

In order to estimate in the practical case the influence of the contributions evaluated in the previous paragraphs, they will be applied to a vibration signal acquired during the monitoring of a real industrial system.

A high performance cutting stage for non-woven tissue, described in Section II, is considered as test-case.

The acceleration signals, provided by a piezoelectric accelerometer installed on the system, have been analyzed.

Classical features have been considered and also features designed for this specific application, as, in particular: in the time domain, the mean of the peaks corresponding to the impacts of the knife (called peaks average); in the frequency domain, the percentage ratio of the power spectrum content for harmonics multiple of the principal frequency of impact with respect to the frequency spectrum on the whole (called band), or in specific bands of frequencies (band1, band2, band3). These features emphasize the relevance of phenomena corresponding to the periodic cutting action of the knife.

The effect on these features of the variability of the metrological characteristics of MEMS sensors has been evaluated as described in the methodology section.

The results are represented as percentage differences with respect to the features calculated on the basis of the original data, and the variability of these differences are represented as error bars in the graphs.

The obtained results are as follows:

- Sensitivity effect.

Features have been calculated on the basis of data modified for the effect of the sensitivity, and the differences with respect to the features based on the original data are estimated. Percentage differences are represented in Fig. 2.

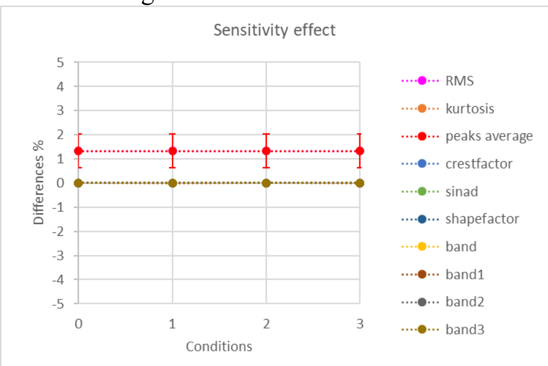

Fig. 2. Effect of sensitivity.

Fig. 2 shows that only the features RMS and peaks average (for these two features the points are overlapping) present differences with respect to the original case, due to a deviation of the mean sensitivity from the nominal value of about 1.3%.

Furthermore, in these cases, the variability of sensitivity produces a variability of the features that is not negligible, as shown by the error bars in the graph.

- Noise effect.

The addition of the MEMS noise on the real data doesn't produce significant variations on the considered features, as shown in Fig. 3.

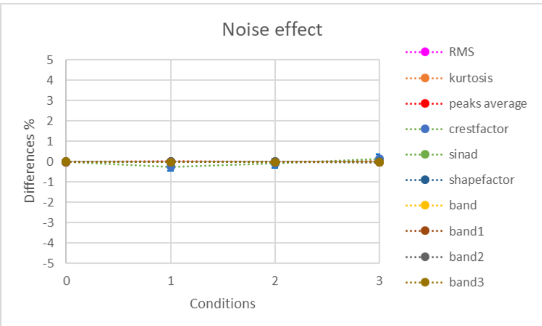

Fig. 3. Effect of noise.

- Sampling rate variability effect.

As said in Section 3.1.2, if the variability of the sampling rate, calculated cycle by cycle for each accelerometer, and the variability among sensors are combined, an uncertainty of 2.1% for the sampling period is obtained. This value of percentage uncertainty, applied to the sampling period of 10^{-4} s, set in the real application, is used as standard deviation of a normally distributed noise. This type of noise is then added to the time vector, and the corresponding acceleration values are calculated with linear interpolation.

Finally, features have been calculated on the basis of data thus modified, and the differences with respect to the features based on the original data are estimated. These results are shown in Fig. 4.

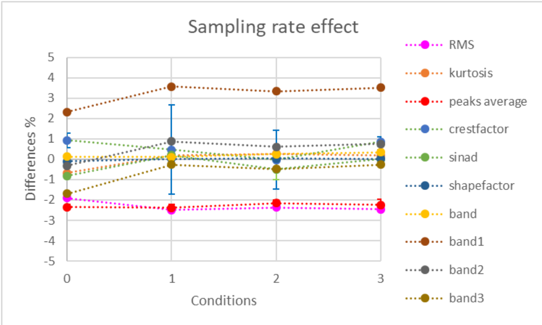

Fig. 4. Effect of sampling rate.

Fig. 4 shows that the effect of the variability of sampling rate is the most important, in particular on band1, RMS and peak average.

- Overall effect

If all the considered effects are combined, for each calculated feature, as root of the sum of squared differences, the maximum values in Table 3 are obtained.

Table 3. Combination of all the effects [%]

	Overall effect [%]
RMS	4.3
kurtosis	0.68
peak average	4.3
crest factor	0.93
sinad	0.82
shape factor	0.10
band	0.34
band1	3.6
band2	0.89
band3	1.7

It can be noticed that RMS, peak average and some features in the frequency domain are the most affected by the metrological characteristics of MEMS, previously analyzed, in the order of 4%.

IV. CONCLUSIONS AND OUTLOOK

This paper analyses the effect of variability of metrological characteristics of a set of low-cost MEMS accelerometers on the calculation of typical features used in condition monitoring of automatic production lines.

The real variability of the sensors characteristics has been experimentally evaluated by means the calibration of 25 MEMS accelerometers. Digital sensitivity, signal-to-noise ratio and sampling rate variability of each sensor have been considered for the analysis.

In order to estimate the influence of the metrological characteristics of MEMS on condition monitoring, the effect of these aspects has been evaluated with reference to a real industrial application.

The results show that some metrological characteristics of MEMS, in particular the variability of the sampling rate, can affect the features calculation, up to 4%.

Future work will be devoted to the investigation of other metrological characteristics of MEMS accelerometers, like stability and phase response, and their effect will be studied with reference to other kind of applications, remarkably different from each other, in order to highlight some more general considerations.

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