ANALYSIS OF NASA BEARING DATASET OF THE UNIVERSITY OF CINCINNATI BY MEANS OF HJORTH'S PARAMETERS

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ABSTRACT

Hjorth's parameters are statistical time-domain parameters used in signal processing and introduced by Bo Hjorth in 1970. These parameters are Activity, Mobility and Complexity. They are related to the variance of the signal and of its subsequent derivatives. They are commonly used in the analysis of electroencephalography (EEG) signals for feature extraction, but also in the tactile signal analysis in robotic area. In this paper, Hjorth's parameters are applied to vibration signals for fault detection in ball bearings. In particular, an open-access dataset is used, those data cover a complete lifetime of a set of four bearings. They were run to failure under constant load and running conditions. The robustness of the dataset has been proven by a recent analysis proposed by Gousseau et al., who assessed that only two of the three datasets available are consistent and can be used for bearing diagnosis. Hjorth's parameters clearly identify the time when a damage occurs and its evolution in the time-domain. An intuitive explanation is given in the text to justify the good results obtained in the detection of fault on the outer race, inner race and rolling elements of the bearing. Hjorth's parameters can be easily computed with a minimum of computational resources, suggesting their use in real-time application for condition monitoring of ball bearings.

KEYWORDS: Hjorth's parameter, bearing, diagnostics

1. INTRODUCTION

With respect to the last decades, today the condition monitoring and diagnostics of mechanical components is a need for every maintenance center in Industry, despite the product developed or services offered by the company. A sudden break in production line has costs of missing product that abundantly exceed the costs of the component itself. As a consequence, the condition monitoring techniques have been developed so far in the literature, for the most common components such as gearboxes [1], ball bearings [2] and rotating shafts [3]. This paper focuses on the condition monitoring of ball bearing, i.e. on the early detection of incipient damage in the components the bearing is made of. In particular, a ball bearing is made of an inner race integral with the rotating shaft, an outer race integral with the fixed frame, rolling elements that link together the two races and a cage that keep the rolling elements equispaced in their seat. The most used diagnostics technique consists in the signal processing of the vibration signal acquired by an accelerometer placed near the bearing [4]. Incipient fault induces cyclic impacts of the rolling elements that could be collected and analyzed. The periodicity of impacts is highlighted in frequency domain, despite the need of a Signal-to-Noise ratio enhancement to reduce mechanical or electric noise [5]. So far [6], thousand of papers on condition monitoring appeared in Literature proposing from simple statistical parameters [7] to complex cyclostationary indexes [8]. These papers have their foundations on the mechanical behaviour of a faulted bearing and its dynamic analysis, or on the characteristics of the expected vibration signal [9]. More recently, machine learning techniques came into play powerfully [10]. Machine learning techniques take into account raw data or a set of features from both healthy and faulted bearings, determining a similarity between a test dataset and the reference ones. As drawback, these techniques require historical data, that are not available so frequently. The model-based and data-driven approaches could be combined to offer a quick diagnostics service and reliable maintenance of the algorithms [11]. This paper focuses on the application of simple statistical values for the diagnostics of ball bearing: the Hjiorth's parameters. They are statistical time-domain parameters used in

signal processing and introduced by Hjorth and Elema-Schönander in 1970 [12]. These parameters are Activity, Mobility and Complexity. They are related to the variance of the signal and of its subsequent derivatives. They are commonly used in the analysis of electroencephalography (EEG) signals for feature extraction [13], but also in the tactile signal analysis in robotic area [14]. In this paper, Hjorth's parameters are applied to vibration signals for fault detection in ball bearings. In particular, an open-access dataset is used, those data cover a complete lifetime of a set of four bearings [15]. They were run to failure under constant load and running conditions. The results shows that Hjort's parameter could early detect an incipient fault on different parts of a ball bearing. The small computational efforts needed, suggests their use in real-time application for condition monitoring of ball bearings or as a feature array for machine learning techniques.
The paper is structured as follows: Section 2 introduces the mathematical definition of the Hjorth's parameters both in time and frequency domain. Section 3 shows the results on open-access experimental dataset and Section 4 draws conclusions.

2. MATHEMATICAL THEORY OF HJORTH'S PARAMETERS

In this section, the mathematical theory of Hjorth's parameters is developed. These parameters are initially defined in the time domain, but could be transferred to the frequency (spectral) domain also. Finally, a dynamic relationship correlating the parameters both in the time and in the frequency domain is obtained.

2.1. Time domain analysis

Let us consider a generic vibration signal $y = f(t)$ (e.g. displacement, velocity or acceleration) defined in the time domain t. The variance $\sigma^2(y)$ of a vibration signal y represents a measure of the dispersion or variability of the signal about its mean value, in the form [16]:

$$\sigma^2(y) = \overline{y^2} - (\bar{y})^2 \tag{1}$$

where $\overline{y^2}$ is the mean square value (i.e. the mean power) of the signal [16]:

$$\overline{y^2} = \lim_{T\to\infty} \frac{1}{T} \int_0^T y^2(t)dt \tag{2}$$

$\bar{y}$ is the mean value of the signal [16]:

$$\bar{y} = \lim_{T\to\infty} \frac{1}{T} \int_0^T y(t)dt \tag{3}$$

and T is the signal acquisition period.
It should be noted that, for a vibration signal y presenting mean value $\bar{y}$ equal to zero, the variance $\sigma^2(y)$ is equal to the mean power $\overline{y^2}$ of the signal, i.e. to the square of the root mean square value *RMS(y)* of the signal itself, which is defined as [16]:

$$RMS(y) = \lim_{T\to\infty} \sqrt{\frac{1}{T} \int_0^T y^2(t)dt} \tag{4}$$

Moreover, the square root of the variance $\sigma^2(y)$ is called standard deviation $\sigma(y)$ of the signal y, in the form [16]:

$$\sigma(y) = \sqrt{\overline{y^2} - (\bar{y})^2} \tag{5}$$

After introducing the previous statistical quantities, now we can start defining Hjorth's parameters in the time domain. Hjorth's parameters [12] are statistic time-domain parameters adopted in the vibration signal processing that are related to the definition of variance $\sigma^2(y)$ and are calculated on the basis of the vibration signal amplitude y, its time-derivative (velocity in the following) $\dot{y} = dy/dt$ and its two-times derivative (acceleration in the following) $\ddot{y} = d^2y/dt^2$ [17].
The first Hjorth's parameter is called *Activity*. The Activity of a vibration signal is defined as the variance of the vibration signal amplitude y:

$$Activity(y) = \sigma^2(f(t)) \quad [y] \tag{6}$$

where the dimensions of the Activity parameter are the same of the vibration signal considered.
The second Hjorth's parameter is called *Mobility*. The Mobility of a vibration signal is given by the square root of the ratio between the Activity of the vibration signal velocity $\dot{y}$ and the Activity of the vibration signal amplitude y (i.e. the square root of the ratio between the variances of vibration signal velocity $\dot{y}$ and amplitude y):

$$Mobility(y) = \sqrt{\frac{Activity(\dot{y})}{Activity(y)}} = \sqrt{\frac{\sigma^2(df(t)/dt)}{\sigma^2(f(t))}} \quad [t^{-1}] \tag{7}$$

where the dimensions of the Mobility parameter are expressed as a ratio per time unit.
The last Hjorth's parameter is called *Complexity*. The Complexity of a vibration signal is denoted by the ratio between the Mobility of the vibration signal velocity $\dot{y}$ and the Mobility of the vibration signal amplitude y (i.e., the ratio between the square root of the ratio between the variances of vibration signal acceleration $\ddot{y}$ and velocity $\dot{y}$ and the square root of the ratio between the variances of vibration signal velocity $\dot{y}$ and amplitude y):

$$Complexity(y) = \frac{Mobility(\dot{y})}{Mobility(y)} = \frac{\sqrt{\frac{\sigma^2(d^2f(t)/dt^2)}{\sigma^2(df(t)/dt)}}}{\sqrt{\frac{\sigma^2(df(t)/dt)}{\sigma^2(f(t))}}} \tag{8}$$

It must be underlined that the Complexity is a dimensionless parameter. Moreover, from (6-8), it should be observed that the Activity, Mobility and Complexity parameters are time-related, as the Activity is associated to the variance of the vibration signal amplitude y, the Mobility is related to the variance of the vibration signal velocity $\dot{y}$ and the Complexity is connected to the variance of the vibration signal acceleration $\ddot{y}$ in the time domain t.

2.2. Frequency domain analysis

The generic vibration signal $y = f(t)$ previously defined in the time domain t can be transferred to the frequency (spectral) domain ω, in the form $y = F(\omega)$, by means of the Fourier transform [16]:

$$F(\omega) = \int_{-\infty}^{+\infty} f(t)e^{-j\omega t}dt \tag{9}$$

where the corresponding inverse Fourier transform is:

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{+\infty} F(\omega)e^{-j\omega t}d\omega \tag{10}$$

and the complex conjugate of the Fourier transform is:

$$F^*(\omega) = \int_{-\infty}^{+\infty} f^*(t)e^{j\omega t}dt \tag{11}$$

Let us introduce the power spectrum function $S(\omega)$, which is defined as the product of the Fourier transform $F(\omega)$ and its complex conjugate function $F^*(\omega)$:

$$S(\omega) = F(\omega)\cdot F^*(\omega) = \int_{-\infty}^{+\infty} f(t)\cdot f^*(t)dt \tag{12}$$

where the contribution of the phase $j\omega t$ in the frequency domain ω is not taken into account.
Starting from the definition of the power spectrum function $S(\omega)$ (12), the generic spectral moment m_n of order n can be written in the form [12]:

$$m_n = \int_{-\infty}^{+\infty} \omega^n \cdot S(\omega)d\omega \tag{13}$$

Since the trace of a generic vibration signal defined in the frequency domain is always symmetric with respect to the zero frequency value, then all odd-order spectral moments can be statistically assumed equal to zero and therefore, in the following, only even-order spectral moments will be taken into consideration.

Starting from (13), the spectral moment m_0 ($n = 0$) in the frequency domain ω is equal to:

$$m_0 = \int_{-\infty}^{+\infty} S(\omega) d\omega \tag{14}$$

which represents the total power in the frequency domain.
Hjorth's parameters are transferred from the time to the frequency domain on the basis of energy (i.e. power) considerations. Specifically, it is assumed that the total power of the vibration signal y in the frequency domain (14) is equal to its mean power in the time domain (2) as computed in the signal acquisition period T, in the form:

$$\int_{-\infty}^{+\infty} S(\omega) d\omega = \frac{1}{T} \int_{t-T}^{t} f^2(t) dt \tag{15}$$

where the time equivalent of the frequency function $S(\omega)$ is the square of the time function $f(t)$.
From (15), by taking into account (1,2,6,14), it is found that, in the hypothesis of signal mean value $\bar{y} = 0$ (3), the spectral moment m_0 in the frequency domain is equal to the variance of the vibration signal amplitude in the time domain, $m_0(\omega) = \sigma^2(f(t))$, i.e. to the Hjorth's parameter Activity (6):

$$Activity(y) = m_0(\omega) \tag{16}$$

Since the Activity parameter is directly correlated to the signal mean power (variance σ^2) in the time domain (6) and to the signal total power (spectral moment m_0) in the frequency domain (16), then a bearing fault can be eventually detected in the presence of a suddenly increasing value of the Activity during its operational life.
In the same manner of (14,15), the spectral moment m_2 ($n = 2$) in the frequency domain ω is:

$$m_2 = \int_{-\infty}^{+\infty} \omega^2 \cdot S(\omega) d\omega = \frac{1}{T} \int_{t-T}^{t} (\frac{df(t)}{dt})^2 dt \tag{17}$$

where the time equivalent of the frequency function $S(\omega)$ multiplied by the squared frequency ω^2 is the square of the first derivative of the time function $f(t)$.
From (17), it is found that the spectral moment m_2 in the frequency domain is equal to the variance of the vibration signal velocity in the time domain, $m_2(\omega) = \sigma^2(df(t)/dt)$, i.e. to the activity of the signal velocity, in the form Activity $(\dot{y}) = m_2(\omega)$.
Therefore, the square root of the ratio between the spectral moments m_2 and m_0 is equal to the Hjorth's parameter Mobility (7):

$$Mobility(y) = \sqrt{\frac{m_2(\omega)}{m_0(\omega)}} \tag{18}$$

The Mobility parameter gives a measure of the relative average velocity of the signal amplitude changes in the time domain (7), i.e. the variance of the power spectrum along the frequency axis in the frequency domain (18); therefore, there is a direct correlation between Activity and Mobility parameters, and again a bearing fault can be eventually detected in the presence of a suddenly increasing value of the Mobility during its operational life.
Finally, the spectral moment m_4 ($n = 4$) in the frequency domain ω is:

$$m_4 = \int_{-\infty}^{+\infty} \omega^4 \cdot S(\omega) d\omega = \frac{1}{T} \int_{t-T}^{t} (\frac{d^2 f(t)}{dt^2})^2 dt \tag{19}$$

where the time equivalent of the frequency function $S(\omega)$ multiplied by the frequency at the fourth power ω^4 is the square of the second derivative of the time function $f(t)$.
From (19), it is obtained that the spectral moment m_4 in the frequency domain is equal to the variance of the vibration signal acceleration in the time domain, $m_4(\omega) = \sigma^2(d^2 f(t)/dt^2)$, i.e. to the activity of the signal acceleration, in the form Activity $(\ddot{y}) = m_4(\omega)$.
Moreover, the ratio between the square root of the ratio between the spectral moments (m_4, m_2) and the square root of the ratio between the spectral moments (m_2, m_0) is equal to the Hjorth's parameter Complexity (8):

$$Complexity(y) = \frac{\sqrt{m_4(\omega)/m_2(\omega)}}{\sqrt{m_2(\omega)/m_0(\omega)}} \tag{20}$$

As regards the Complexity parameter, a bearing fault can be eventually detected if its value goes down to nearly the minimum value of the function, that is the unity. This is due to the fact that the value of the Complexity is minimum only if the vibration signal is a pure sine function in the time domain or a discrete frequency in the spectrum. De facto, when a bearing is damaged, a suddenly decrease of the Complexity parameter value arises.
In addition, from the previous equations, it was proven that the Hjorth's parameters, i.e. Activity, Mobility and Complexity, can be expressed both in the time domain t and in the frequency domain ω: this specific property will be used in the following in order to obtain a dynamic equation relating these three parameters.

2.3. Hjorth's parameter dynamic relation

The dynamics of a generic mass-spring-damper system with one degree of freedom is described by the second-order derivative equation in the time domain [16]:

$$m\ddot{x}(t) + c\dot{x}(t) + kx(t) = 0 \tag{21}$$

where (m, c, k) are the mass, damping and stiffness of the system, respectively.
A general solution of equation (21) can be written in the exponential complex form [16]:

$$x(t) = X_0 e^{j\omega t} \tag{22}$$

where $x(t)$ is the displacement of the system, with $X_0 > 0$ and $j \in \mathbb{C}$ $(j^2 = -1)$.
The first and second time derivatives of solution (22) are:

$$\dot{x}(t) = \frac{dx(t)}{dt} = X_0 j\omega e^{j\omega t}, \quad \ddot{x}(t) = \frac{d\dot{x}(t)}{dt} = -X_0\omega^2 e^{j\omega t} \tag{23}$$

where $\dot{x}(t)$ and $\ddot{x}(t)$ are the velocity and acceleration of the system, respectively.
Let us consider the acceleration $\ddot{x}(t)$ as reference vibration signal, in the form $y = \ddot{x}(t)$ (the vibration signal y is assumed to be acquired by accelerometers): from definition (6), it is found that the Hjorth's parameter Activity is equal to the variance of acceleration $\ddot{x}(t)$.
By substituting (22-23) into (21), the following equation in the frequency domain is obtained:

$$-m\omega^2 + cj\omega + k = 0 \tag{24}$$

The first and second time derivatives of equation (21) give the higher-order derivative equations in the time domain:

$$m\dddot{x}(t) + c\ddot{x}(t) + k\dot{x}(t) = 0 \tag{25}$$

$$m\ddddot{x}(t) + c\dddot{x}(t) + k\ddot{x}(t) = 0 \tag{26}$$

In particular, equation (26) correlates acceleration $\ddot{x}(t)$ with its first time derivative $\dddot{x}(t)$ (referred to as *jerk*) and second time derivative $\ddddot{x}(t)$ (called *snap*).
Moreover, within the fourth-order time derivative equation (26), by taking into account the previous definitions (6-8), the Activity, Mobility and Complexity parameters can be noted, which are associated to the acceleration $\ddot{x}(t)$, jerk $\dddot{x}(t)$ and snap $\ddddot{x}(t)$ terms, respectively.
The third and fourth time derivatives of solution (22) are:

$$\dddot{x}(t) = \frac{d\ddot{x}(t)}{dt} = -X_0 j\omega^3 e^{j\omega t}, \quad \ddddot{x}(t) = \frac{d\dddot{x}(t)}{dt} = X_0\omega^4 e^{j\omega t} \tag{27}$$

where $\dddot{x}(t)$ and $\ddddot{x}(t)$ are the jerk and snap of the system, respectively.
By substituting (23,27) into (26), the following equation in the frequency domain is found:

$$m\omega^2 - cj\omega - k = 0 \tag{28}$$

By comparing equations (26,28), it can be found that, within equation (28), the Activity, Mobility and Complexity parameters are related to the terms $-k$, $-cj\omega$ and $m\omega^2$, respectively, i.e., the Activity and Mobility terms are concordant (negative sign) while the Complexity term is discordant (positive sign): the dynamic relation among the Hjorth's parameters established in equation (28), which confirms the mathematical results previously obtained in the time and frequency domains, will be eventually validated by investigating the experimental results of the vibration signals for fault detection in ball bearings from the NASA Bearing Database of the University of Cincinnati [15].

3. EXPERIMENTAL VERIFICATION

The NASA Bearing Database of the University of Cincinnati [15] consists of three distinct datasets, each of which is related to a specific test-to-failure experiment on a bearing testrig. At the end of each experiment, the health status of the bearings is checked. Table 1 summarizes the different failure times for each test and the different faults detected at the end of each experiment. Gousseau et al. [18] previously analyzed the three datasets available proving inconsistency for bearing diagnosis of data in Dataset 3: therefore, this last dataset will not be considered in this paper.

Table 1 – Test characteristics

	Number of accelerometers	Test Time	Announced damages at the end of the test
Dataset 1	8	49680 min 34 days 12h	Bearing 3: inner race Bearing 4: rolling element
Dataset 2	4	9840 min 6 days 20h	Bearing 1: outer race
Dataset 3	4	44480 min 31 days 10h	Bearing 3: outer race

3.1. Experimental setup

The bearing test rig consisted of four bearings placed along the same shaft. The shaft was driven at constant velocity (*2000 rpm*) by an AC motor connected to the shaft itself through a rubber belt. The radial load of *26690 N* was applied to the shaft and the bearings by a spring mechanism. The bearings were lubricated through an oil circuit system that regulated the temperature and the flow ratio of the lubricant. All four bearings were Rexnord ZA-2115 with a double row of rolling elements, their parameters are given in Tab. 2. PCB 353B33 High Sensitivity Quartz ICP accelerometers were installed on the housing of each bearing. In Dataset 1, for each bearing two accelerometers were installed in radial directions, orthogonal to each other; in Dataset 2, only one accelerometer was installed for each bearing. The lifetime of the bearings was evaluated in 100 million revolutions. The failures were detected only after the bearings exceeded the expected lifetime. A thermocouple was placed on the outer race of each bearing to record the temperature and to monitor the lubrication circuit. In order to diagnose the bearing failures, a magnetic plug was installed in the oil feedback pipe to collect debris. The test was stopped when the value of accumulated debris exceeded a predefined threshold. Vibration data were collected every 10 minutes with time recording of 1 second. The sample frequency declared is *20 kHz* but, as shown in [18], the real sample frequency seams to be *20.48 kHz*.

Table 2 – Bearing characteristics

Rexnord ZA-2115 parameters	
Pitch diameter (mm)	71.5
Rolling element diameter (mm)	8.4
Number of rolling elements per row	16
Contact angle ($^\circ$)	15.17

In the next sections, Hjorth's parameters are computed for each record and for each dataset, according to definitions given in Section 2. The incipient detection of a faulted bearing is related to the trend behaviour of each Hjorth's parameter.

3.2. Dataset 1

In Dataset 1, there are two accelerometers for each bearing placed in radial directions but orthogonal to each other: one is placed along x axis and the other one is placed along y axis. The difference between signals along x and y axes is very low, probably for this reason in Dataset 2 the accelerometers are placed only along one axis for each bearing.

Dataset 1 does not present any continuous record. There is no information to know if is due to a stop of the motor or to a problem in the logging of the data. The Activity parameter, computed along the recording, shows a quasi-constant increment for all the bearings in the first four days (Fig.1). On the 9th day, a high increment affects Bearing 3, but the values go down to the previous ones after half a day. An increasing trend in the signal trace is clearly visible for Bearing 4 from the 25th day, while for Bearing 3 from the 31st day. Bearing 1 and Bearing 2 keep their values stable till the 33rd day. The increase after the 33rd day is due to an increment of the vibration energy produced by the fault Bearing 3 and Bearing 4 along the whole shaft.
As regards the Mobility parameter, Bearing 3 and Bearing 4 have an opposite behaviour (Fig.2). De facto, when Activity shows a damage, Bearing 3 is affected by a decrease in Mobility on the 31st day; on the contrary, when Activity shows a damage, Bearing 4 is affected by an increase in Mobility on the 23rd day.
The Complexity parameter (Fig.3) varies for Bearing 1, Bearing 2 and Bearing 4 in the first ten days. The values of Complexity for Bearing 1 and Bearing 2 are stable from the 11th day to the 26th day. The most evident and important variation takes place in Bearing 4, which presents a decreasing trend of Complexity from the 20th day. This datum is very significant because it allows to detect a fault: when the Complexity value reaches its minimum (about 1), the spectrum shows an increment of discrete frequencies and this means that there is a fault. Bearing 3 presents an evident decrease in Complexity on the 33rd day of the test and consequently even in this case it is possible to detect a fault.

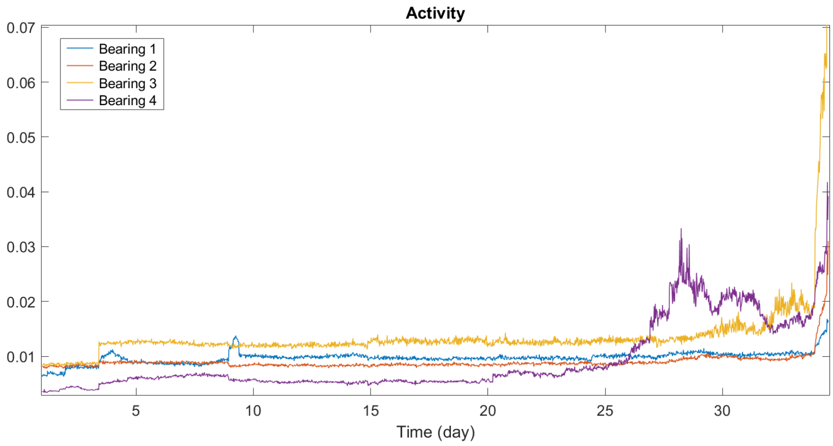

Figure 1 – Activity in Dataset 1.

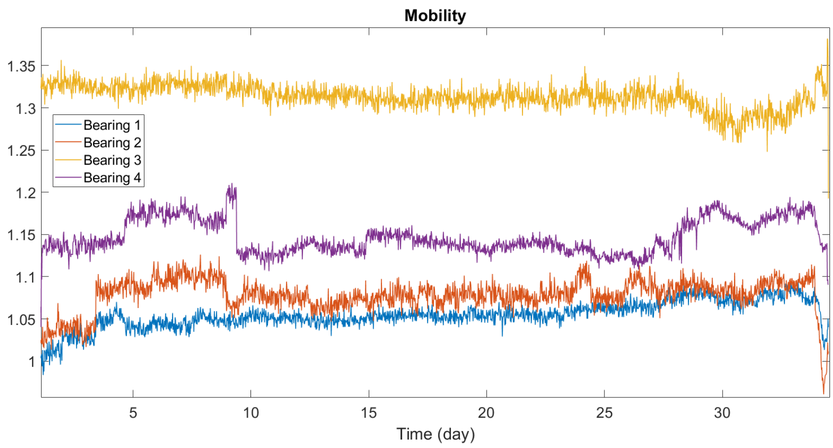

Figure 2 – Mobility in Dataset 1.

3.3. Dataset 2

Dataset 2 is the most analysed in literature [19, 20, 21, 22, 23, 24, 25]. The Activity parameter profile in the time of the four bearings of Dataset 2 is shown in Fig.4. In the first 3 days the Activity value of the four bearings is

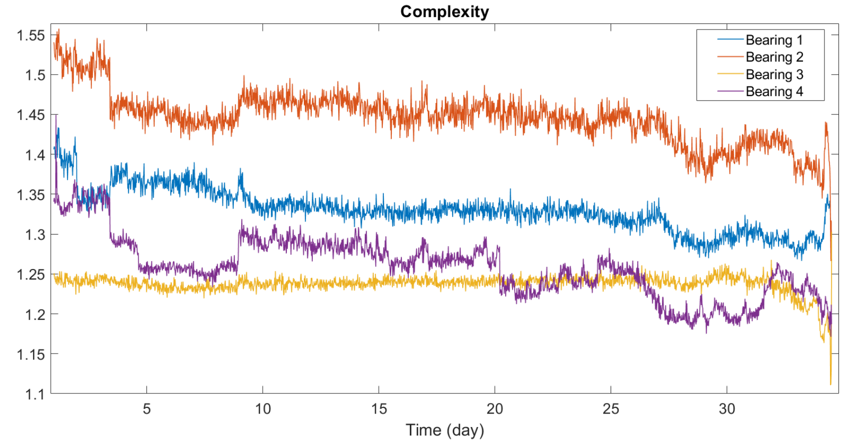

Figure 3 – Complexity in Dataset 1.

stable. On the 3.8th day, the Activity of Bearing 1 starts increasing while the other bearings continue being stable. On the 5th day, the Activity value of Bearing 1 decreases heavily, but during the same day it starts again increasing quickly till the stop of the machine. The Activity values of the other bearings start suffering from the variation of the system on the 5.3rd day. Mobility shows a unique behaviour for the four bearings (Fig.5). Bearing 2, Bearing 3 and Bearing 4 show a constant value till the 5th day, from the 6th day the Mobility values of these bearings start decreasing. The Mobility value of Bearing 1 is stable till the 3.8th day, subsequently it increases and on the 5th day it decreases for a few hours. Then it starts to increase again. Complexity shows constant values for all four bearings till the 3.8th day (Fig.6). At this time the Complexity of Bearing 1 starts decreasing and on the 4.7th day it reaches its minimum that is equal to 1.081. This trend is an evident factor of damage. The other three bearings do not suffer from the fault of Bearing 1 till the 5th day.

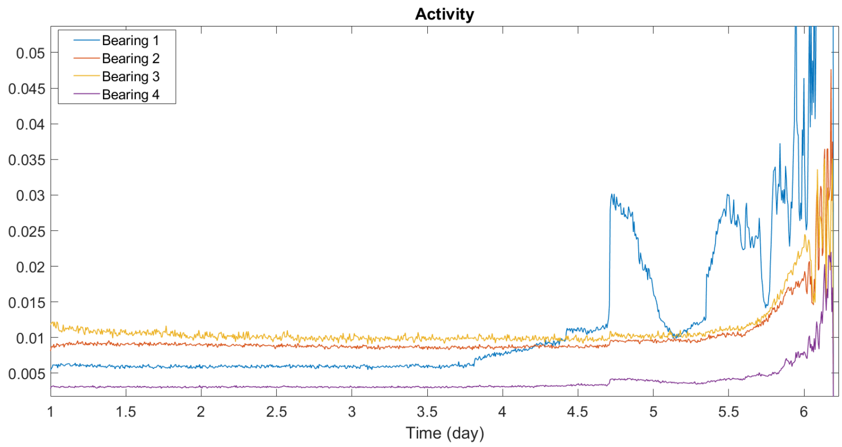

Figure 4 – Activity in Dataset 2.

4. CONCLUSIONS

In this work, signal vibration data from the Center for Intelligent Maintenance Systems of the University of Cincinnati are used to investigate the applicability of Hjorth's parameters to the diagnostics of bearings in stationary operative conditions. The vibration data result from a test rig that consists in a shaft and four bearings preloaded with a constant load, driven by an AC motor at constant velocity. The advantage of these data lies on the fact that they were recorded during the whole lifetime of the bearings, consequently they allow to study the time evolution of a damage until the machine stops.
Hjorth's parameters (Activity, Mobility, Complexity) are statistical time-domain features related to the vibrational signal and its first and second derivatives. The experiments recorded a different behaviour for each parameter. Ac-

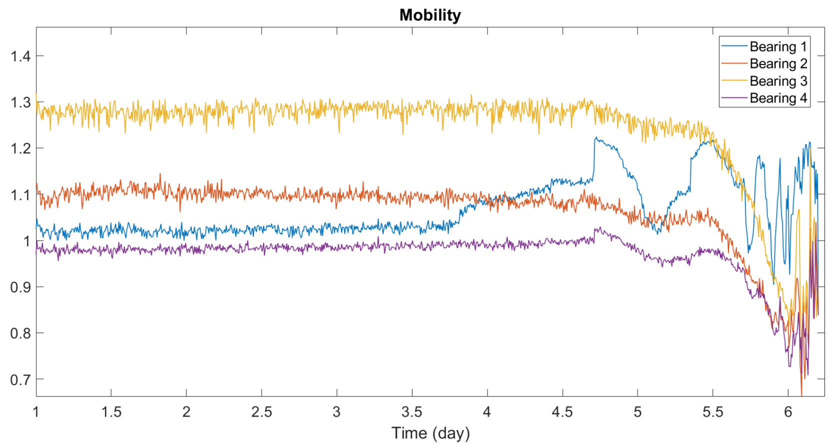

Figure 5 – Mobility in Dataset 2.

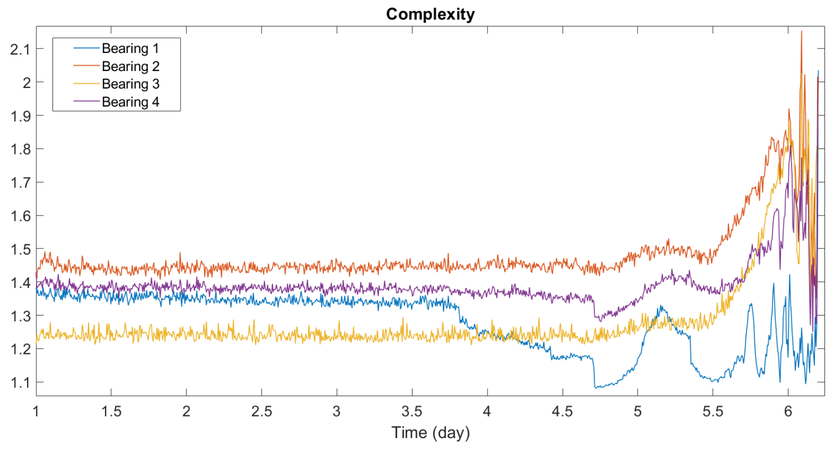

Figure 6 – Complexity in Dataset 2.

tivity presents an increasing trend in correlation with a bearing fault. Since Activity is directly related to the mean power of the signal, a damage in a bearing causes an increment in vibration first, then in the power of the signal. Mobility does not show a very clear behaviour in correlation with bearing damages: in some cases it presents an increasing trend and in other cases it presents a decreasing trend. This means that this parameter is not directly correlated with bearing damages. Complexity shows a decreasing trend in correlation with bearing faults, but Complexity is related to the integral of the signal spectrum along the frequency and it reaches its minimum value when the spectrum of the signal is discrete. Consequently, when a damage occurs, the frequency pertinent to the fault increases, while Complexity of the signal decreases. In conclusion Activity and Complexity show behaviours useful for the diagnostics of bearings in stationary operative conditions. They can be used to implement Condition Monitoring algorithms, but they can be also used as input features for Machine Learning algorithms.

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