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Application of dispersion entropy to journal bearing hydrodynamic stability

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Abstract The article consists of two parts: analytical and experimental. The first part discusses the theory of signal analysis in nonlinear systems, particularly in the context of sliding bearings. The second part describes an experiment where a mechanical system achieves stable operation. Three types of signals reflecting different states of bearing operation are identified: unstable, transient and stable operation. The study showed that the value of DisEn (indicator) is related to the operating state of the bearing. This allows easier diagnosis of the bearing's condition and suggests the possibility of dispensing with a single sensor. In addition, a decrease in the difference between DisEn values for the *x* and *y* axes was noted in unstable operation.

Keywords: bearing, hydrodynamic stability, dispersion entropy, hydromonitoring.

1. Introduction

Modern design solutions require bearing nodes based on hydrodynamic plain bearings. The nonlinearity of their operating characteristics is driving the development of advanced algorithms for monitoring diagnostic signals to assess technical conditions and operating conditions. The unusual operating conditions of plain bearings require the use of innovative designs, materials and lubricants [1]. As a result, it becomes necessary to introduce innovative approaches to monitoring their condition.

The presence and severity of faults in rotating machines significantly impact their dynamics, leading to distinctive time series patterns in rotor vibrations. Analyzing these vibration signals provides a valuable method for detecting various types of faults in rotating machinery [2]. Given the nonlinear nature of rotating machines, the vibration time series often exhibit nonlinear behavior. As a result, nonlinear approaches are employed to identify fault-related features. Several nonlinear techniques have been developed for this purpose, reflecting the complex dynamics of rotating machinery. The Lyapunov exponent measures the rate of divergence of nearby trajectories in the system. It is used to quantify the system's sensitivity to initial conditions, providing insights into its chaotic behavior [3]. Fractal dimension is a measure of the irregularity and complexity of a signal. In the context of vibration signals, it helps characterize the intricate, self-repeating patterns associated with faults [4]. Teager-Kaiser Energy Operator enhances the detection of impulsive components in a signal, making it particularly useful for identifying sudden changes or anomalies in the vibration patterns related to faults [5]. Artificial Neural Network are employed to model the complex relationships within vibration data, allowing for the detection of fault-related patterns that may not be apparent through traditional methods [6]. Linear decimation involves systematically reducing the data points in a signal. This method aids in simplifying the analysis while preserving critical fault-related information [7]. Permutation Entropy-Based Methods is a measure of signal irregularity, providing insights into the complexity and disorder within the vibration time series [8]. Fuzzy entropy measures the uncertainty and randomness in a signal, making it suitable for capturing the unpredictable nature of fault-induced vibrations [9]. Multi-Scale Entropy approach involves analyzing the signal at multiple time scales, allowing for the detection of faults at different levels of complexity and frequency [10].

Claude Shannon extended Boltzmann's concept of entropy from thermodynamics to information theory, where it is used as a measure of uncertainty. The concept of entropy characterises the degree of irregularity or randomness in a time series. The higher the entropy value, the greater is the irregularity or randomness [11]. Approximate entropy and permutation entropy are two widely used in various scientific disciplines.

Approximate entropy and Permutation entropy have been widely used in a number of studies to diagnose and monitor the condition of rotating machinery. Approximate entropy has been used to detect cracks in a rotating shaft using signals from the cracked shaft obtained from numerical simulations of the rotor [12]. Rolling bearing damage diagnosis and service life prediction has been thoroughly discussed in the literature [13]. Additionally, rolling bearing damage detection based on real and simulated signals using Approximate Entropy and modal decomposition methods has been investigated [14]. Gearbox failure diagnosis, utilizing local mean decomposition, permutation entropy, and extreme learning machine techniques, is covered in another study [15]. Furthermore, Sliding Dispersion Entropy has been applied for damage diagnosis of diaphragm pump components [16] Another method called fuzzy dispersion entropy has been used to diagnose rolling element bearings [17].

Approximate entropy, although widely used, is characterised by unreliable results for short signals. Another pointed drawback of this method is the computational complexity that precludes its use in real-time applications, for the analysis of long signals [18].

In order to improve the method, a method called Entropy of dispersion (DisEn) was introduced for accurately determining the degree of uncertainty in time series. Studies have shown that DisEn, compared to existing methods, does not generate unreliable values for short signals, has less computational complexity, and exhibits low sensitivity to noise [19]. Rosteghi's research has also shown the impact of dimension embedding, class count, signal length and time delay in DisEn. In addition, the effects of additive noise, changes in the frequency and amplitude of signals, and changes from periodicity to non-periodic nonlinearity on DisEn were studied. These studies demonstrated the usefulness of DisEn for detecting changes in the nonlinear dynamics of vibration signals in rotating machinery.

The paper presents the application of DisEn to diagnose the operating condition of hydrodynamic plain bearings and is compared with a typical method of assessing operating stability.

2. Dispersion entropy

DisEn is derived from Shannon entropy and is used to measure anomalies quickly. The concept of symbolic dynamics stems from the simplification of measurements, a time series is transformed into a new signal containing only a few different elements. The study of signal dynamics is reduced to the analysis of a sequence of symbols, which may result in the loss of some detailed information, but preserves some invariant, solid features of the dynamics [20].

When all signal elements are assigned to a single class, the series becomes completely predictable, resulting in an entropy of zero. In contrast, when all possible dispersion patterns have a uniform probability distribution, all values of the series become independent and have a random distribution, resulting in a maximum entropy value. The best-known methods based on the entropy of symbols are Approximate entropy and PerEn, as well as the DisEn method used in this paper.

For a given one-dimensional signal of length N: $x = \{x_1, x_2, ..., x_N\}$, the DisEn algorithm involves 4 main steps [21]:

Step 1: At the beginning, x_j (j = 1, 2, ..., N) are assigned to c classes labelled from 1 to c. A number of linear and nonlinear approaches are used. Although the linear mapping algorithm is fastest when the maximum and/or minimum values of the time series are much larger or smaller than the mean/median value of the signal, most x_i are assigned to only a few classes. Therefore, we first use the normal distribution function to map x to $y = \{y_1, y_2, ..., y_N\}$ in the range from 0 to 1. We then use the linear algorithm to assign each y_j an integer from 1 to c using the formula $z_j^C = round(c \cdot y_j + 0.5)$, where z_j^C denotes the jth element of the classified time series. The rounding procedure involves adjusting the number to the nearest digit. This step can also be performed using other linear and nonlinear mapping techniques.

Step 2: Identify possible patterns or features. Each embedding vector mc_i^z embedding dimension m and time delay d is formed according to the equation $mc_i^z = \{z_{i+(c-1)\,d}, z_{i+(c-2)d}, \dots, z_i\}$, where i = 1, 2, ..., N – (m – 1)d. Each time series mc_i^z is mapped to a dispersion pattern Π^{m-1}, where $\Pi^{m-1} = \{v_0, v_1, \dots, v_{m-1}\}$. Where $v_0 = c_i^z$ oraz $V_j = c_{i+(m-j)d}^z - c_{i+(m-(j+1))d}^z$ dla $j = 1,2, \dots, m-1$. The number of possible dispersion patterns that can be assigned to each time series $z_i^{m,c}$ is c^m because the signal consists of m elements and each element can take one of the integers from 1 to c.

Step 3: Calculation of frequency of occurrence. Calculate the frequency of occurrence of each pattern or feature divided by the number of total observations. For each of the c, m potential scatter patterns, the relative frequency is obtained as follows:

$$p(\Pi_{v_0 v_1 \dots v_{m-1}}) = \frac{Number\{i | i \le N-(m-1)d, z_i^{m,c} \text{ has type } \Pi_{v_0 v_1 \dots v_{m-1}}\}}{N-(m-1)d}. \tag{1}$$

In fact, the expression $p(\Pi_{v_0 v_1 \dots v_{m-1}})$ shows the number of dispersion patterns $\Pi_{v_0 v_1 \dots v_{m-1}}$ to which $z_i^{m,c}$ are assigned, divided by the total number of embedding signals of embedding dimension m.

Step 4: Calculation of entropy. Based on Shannon's definition of entropy [11], the value of DE with embedding dimension m, time delay d and number of classes c is calculated as follows:

$$DE(x,m,c,d) = -\sum_{\Pi=1}^{c^m} p(\Pi_{v_0 v_1 \dots v_{m-1}}) \cdot \mathrm{n}(p(\Pi_{v_0 v_1 \dots v_{m-1}})) \quad (2)$$

In any entropy method, there is a need to select appropriate parameter values. There are three parameters in DisEn, namely the embedding dimension m, the number of classes c and the time delay d. Based on the study of the application of DisEn in the study of rolling bearings [19] for the study of the hydrodynamic stability of the sliding bearing operation, the parameters were selected:

- *classes* = 10 – theoretically, when c is too small, two amplitude values that are very far apart can be assigned to a similar class, while when c is large, a very small change can change their class, making the DisEn method sensitive to noise. Moreover, when m or c is too large, the computation time is high. In addition, if the embedding dimension m is large, it may cause the DisEn algorithm to be unable to observe small changes.
- *emb_dim* = 2 – *s*tudies have shown that when the embedding dimension m is small and the number of classes c is large, NDisEn leads to more reliable results. The longer the signal, the greater the stability of profiles based on NDisEn. Therefore, the study used m = 2.
- *delay* = 1 – the time delay d after exceeding the value of 4 makes the standard deviation of DisEn of the signals larger. In this study, a time delay of d = 1 was used.

3. Experiments on laboratory test stand

In order to conduct tests on the real signal, an experiment was designed. It was carried out on a laboratory test stand. Figure 1 shows the laboratory test stand, which consists of a speed-controlled electric motor, a coupling that connects the motor to a shaft that is supported by roller bearings at both ends. In the centre of the shaft is a plain bearing under test with two mounted eddy current sensors. The bearing used has a rubber lining with longitudinal grooves. This bearing, also known as a cutless or stern tube bearing or a water-lubricated bearing, is a type of marine bearing used to support rotating shafts in boats and ships. These bearings are commonly used in small watercrafts such as electric boats, as well as larger vessels, due to their reliability, durability, and low maintenance requirements. This is a commercial bearing designed to fit a 20 mm diameter shaft. The eddy current sensors act as distance sensors, allowing the trajectory of the shaft axis (orbit, trajectory of the centre of the shaft) to be directly tracked. A laser tachometer measures the speed of the shaft. The lubrication system works on the principle of closed circulation of water as a lubricant, with water supply and drainage to the bearing from a tank. Measurement data, such as the signal from the tachometer and the x and y displacements from eddy current sensors, are recorded using a measurement card with a sampling frequency of 4200 Hz and a 16-bit analog-to-digital converter.

The signal analysed in measurement systems using eddy current sensors is disturbed by inhomogeneities in the shape and physical properties of the shaft surface. In the literature, the disturbance associated with eddy current measurement is referred to as "runout". Mechanical runout and electrical runout can be distinguished [22]. Mechanical runout is related to imperfections in the shape of the shaft under test, i.e. surface roughness, corrugations, the presence of scratches, dents or other deformations. Electrical runout is related to magnetic inhomogeneities of the surface of the shaft under test. The lack of constant magnetic characteristics of the surface is the result of mechanical machining processes (e.g. turning). This machining creates residual stresses, which are the direct cause of the observed variation in electrical runout of the shaft surface. Due to mentioned interferences, the signal is filtered using a bandpass Butterworth filter. In the experiment, the analysis was carried out by observing the frequency corresponding to the rotor rotation and several of its harmonics from 0.3 to 2.4 of the rotational frequency. Diagnostic information about the stability of the journal bearing operation, which can be identified on the rotational trajectory. Proprietary software allows data recording, elimination of runout phenomenon, plotting of rotational trajectories of shaft axes. Calculations needed to determine DisEn were made after the completion of the experiment.

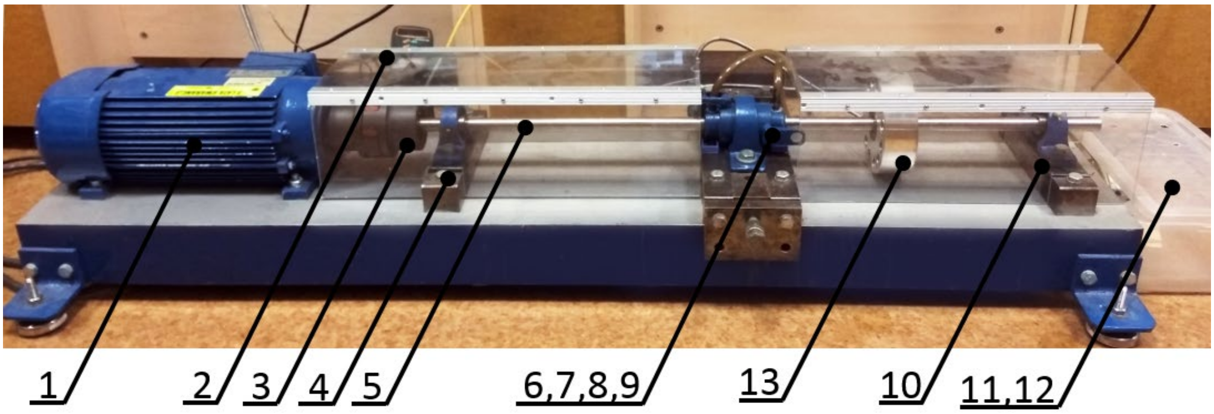

Figure 1. Test stand: 1 – motor with speed control system; 2 – non-contact digital laser tachometer; 3 – clutch; 4, 10 – rolling bearing; 5 – shaft; 6 – slipping bearing; 7 – bearing loading system; 8 – lubricant supply and discharge valves; 9 – eddy current sensors; 11 – pump forcing lubricant circulation; 12 – lubricant tank; 13 – rotor disc used for balancing.

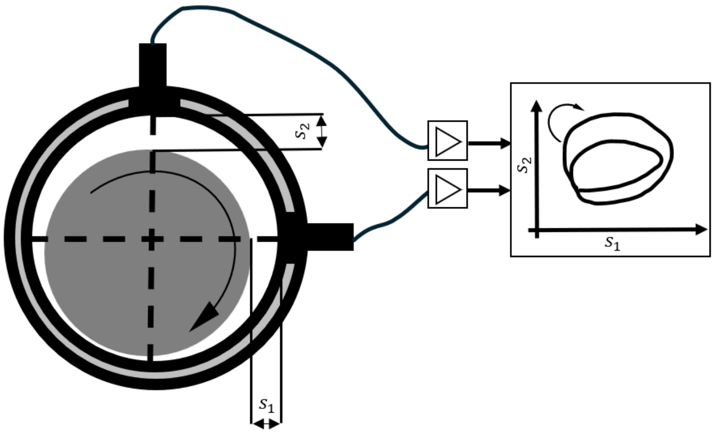

Figure 2. Vibration monitoring system of sliding bearing nodes.

During the experiment, the operation of a sliding bearing loaded with a force of 100 N in the horizontal plane at a rotational speed of 4304 RPM was recorded. This speed corresponds to the resonant frequency of the system under test. The resonance which was identified before the experiment. Prior to the measurements, the bench was set up to reach operating temperature to minimise the effect of temperature on the planned experiment. This is a speed closely related to the resonant frequency of the system under study. The tachometer signal and the displacement signal in the *x* and *y* axes of the shaft relative to the sliding bearing pan were recorded. The displacement signal comes from eddy-current sensors and is a standard signal used for slide bearing analysis. These are relative vibrations. This is in contrast to most machine diagnostic methods, which are based on analysing the signal from an accelerometer that records absolute vibrations. However, in machines equipped with journal bearings, such as hydrodynamic or hydrostatic bearings, relative vibration sensors are often utilised. These sensors detect the relative motion between components, such as the shaft and the bearing housing, providing insights into the dynamic behavior of the bearing system. Figure 3 shows the recorded signals during the experiment. The bearing ran unstably and after about 15 seconds it began to run correctly. In order to achieve such a course, a lubricant of increasing viscosity was fed into the bearing. The optimum viscosity of the lubricant depends on the load, speed, temperature, bearing design and the requirements for operational stability. A high viscosity grease can provide better separation between surfaces, which can be beneficial for bearings operating under high loads or low speeds. High viscosity can help maintain a lubricating film when high loads occur. A lower-viscosity lubricant may be preferred for bearings operating under high-speed conditions, where high viscosity can lead to greater friction resistance and heat generation.

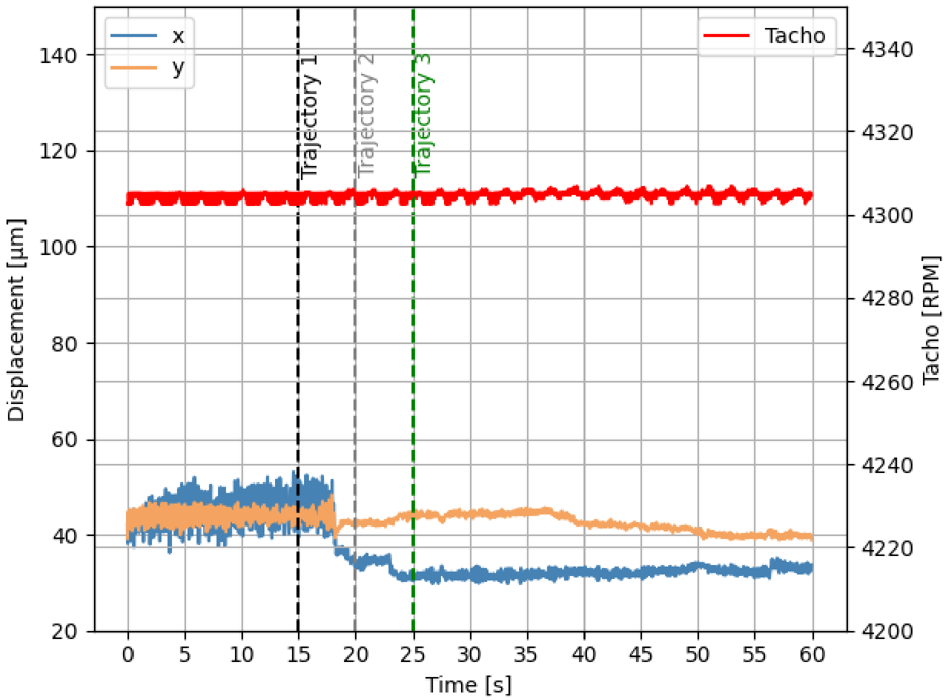

Figure 3. Signals from the tachometer and the shaft axis displacement signal in the *x* and *y* plane.

4. Identification of hydrodynamic states

Based on the recorded *x* and *y* signal, a series of rotational trajectories were obtained, one trajectory for every two rotations. The rotational trajectory is the primary method for evaluating the performance of a plain bearing at the stage of simulation studies for design purposes and at the stage of operation for evaluating the performance of a plain bearing [23]. As an example, three trajectories are shown, marked as trajectories 1, 2 and 3.

Figure 4 shows a typical *x* and *y* signal waveform and the trajectory determined from it, recorded up to the 15th second when the system was operating unstably. The characteristics of such a signal are high amplitude and irregularities within the signal. A characteristic feature of the Orbit plot for such operation is the non-overlapping of successive trajectories and phase markers of 0, 360 and 720 degrees. Typically, trajectories are also characterised by a larger spread.

Figure 5 shows a typical waveform of the *x* and *y* signal and the trajectory determined from it, recorded around the 20th second when the system begins to work more and more steadily but does not yet achieve stable operation. The characteristics of such a signal are a smaller amplitude of oscillation than in the case of an unstable state and decreasing irregularities in the signal. A characteristic feature of the Orbit plot for such operation is the partial overlap of successive trajectories and phase markers of 0, 360 and 720 degrees. In the analysed trajectory, the first and last phase markers overlapped.

Figure 6 shows a typical waveform of the *x* and *y* signal and the trajectory determined from it, recorded after the 25th second when the system begins to operate stably. The characteristics of such a signal are small amplitude of oscillation and high regularity of the signal. The characteristic of the Orbit plot for stable operation is the overlapping of successive trajectories and phase markers of 0, 360 and 720 degrees.

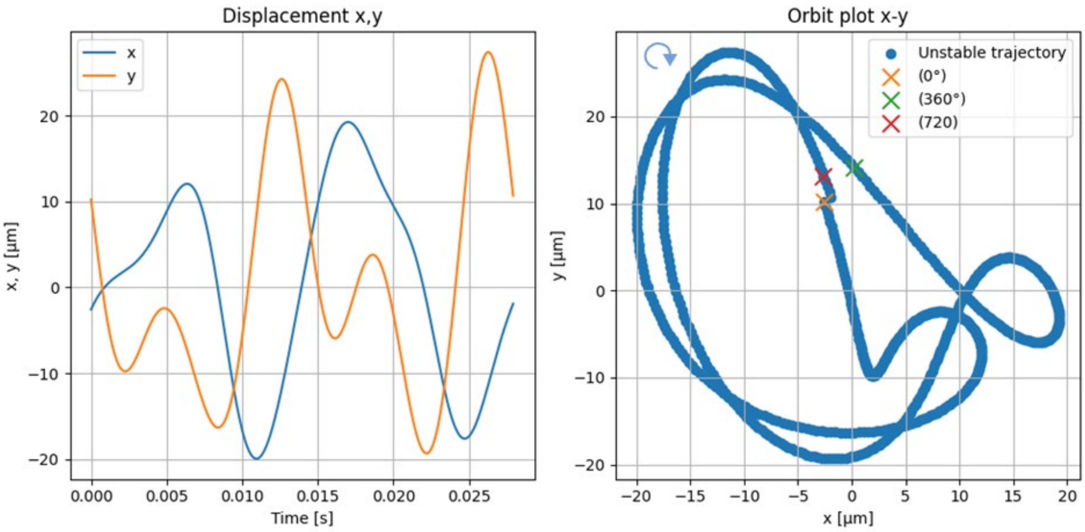

Figure 4. Unstable trajectory.

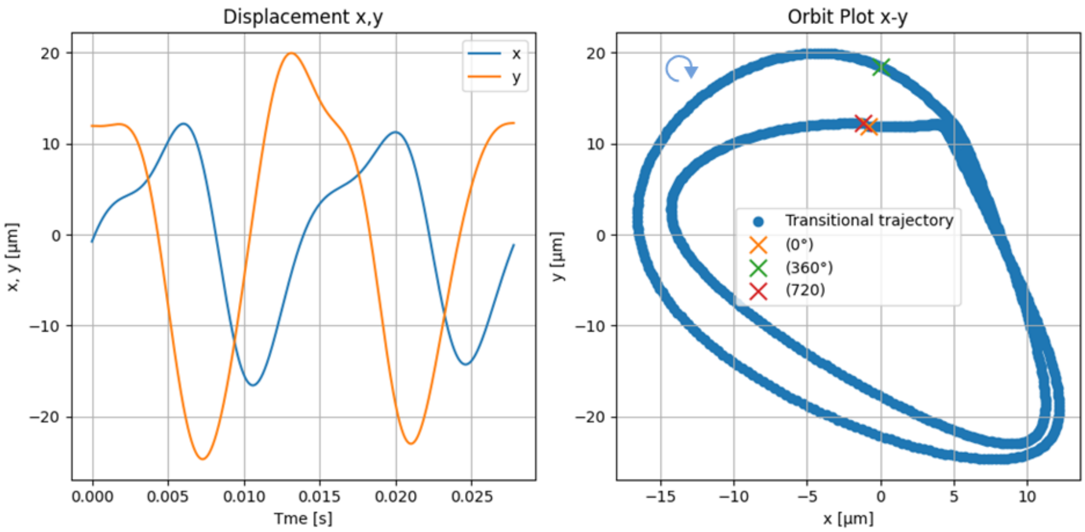

Figure 5. Transitional trajectory.

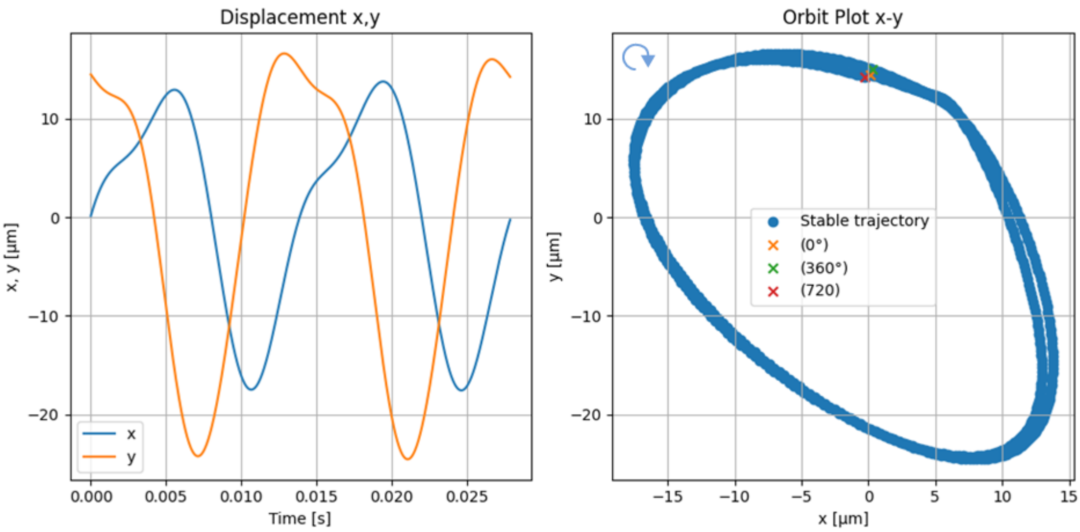

Figure 6. Stable trajectory.

5. Application of DisEn to assess the stability of plain bearing operation

Dispersion entropy is a measure of randomness or disorder in dynamic signals. In the context of analysing the trajectories of movement of the shaft relative to the bearing pan, the entropy of dispersion is an indicator that reflects the complexity of these trajectories. To facilitate the interpretation of DisEn, consecutive parts of the signal describing two complete rotations were analysed. Figures 4–6 and 7–9 show three example waveforms corresponding to an unstable, transient and stable trajectory. Figure 7–9 shows the signal along with the determined DisEn for both *x* and *y* signals. For each trajectory, the DisEn values analysed for the *x* signal (green), the *y* signal (red) were analysed separately, additionally the mean value of the dispersion values for the *x* and *y* axes (black) was calculated. According to theory, these signals are characterised by a variable value of DisEn. The conducted experiment shows that three trajectories can be characterised based on the value of DisEn. The first, unstable one is characterised by chaotic and unpredictable changes. In this case, the changes are very random and difficult to predict. The second, transient, is a type of trajectory in which a mixture of regular and random changes is observed. In this case, although there is a certain degree of regularity, there are also irregular patterns. The third, stable, is characterised by regular and repetitive changes. This is a type of trajectory in which there is limited variability, and the system is able to maintain itself under specific conditions.

A higher value of entropy of dispersion means that the signal has more variety or more random changes, suggesting greater randomness in the dynamics of this data. With a higher entropy of dispersion, changes in the signal displacement over time of a mechanical system may be more difficult to predict because they are more random or chaotic. This can suggest a less stable or more erratic behaviour of the system or phenomenon that the analysed signal describes. The dispersion entropy value alone does not provide a complete interpretive context and is dependent on the mechanical system and its operating parameters. When evaluating the entropy gain of dispersion, it is important to compare the entropy values for different trajectories. In the experiment presented here, the observed relationship of the state of the rotational trajectory to the value of DisEn. DisEn allows to characterize the operation of a sliding bearing, the higher the value of DisEn the less stable the bearing operates.

A noticeable difference of a few per cent, between the DisEn value depending on the operating condition of the bearing and its trajectory allows a single indicator to be obtained to describe the shape of the trajectory. Replacing the graphical interpretation of the trajectory shape with a single indicator allows for simple and repeatable implementation of an alarm in the event of a change in the trajectory shape. It was observed that the mean values of DisEn for the *x* signal and the *y* signals in the case of an unstable state are not only higher, but overlap. Additionally, a difference between the two appears in the stable state, which can also be an object of observation.

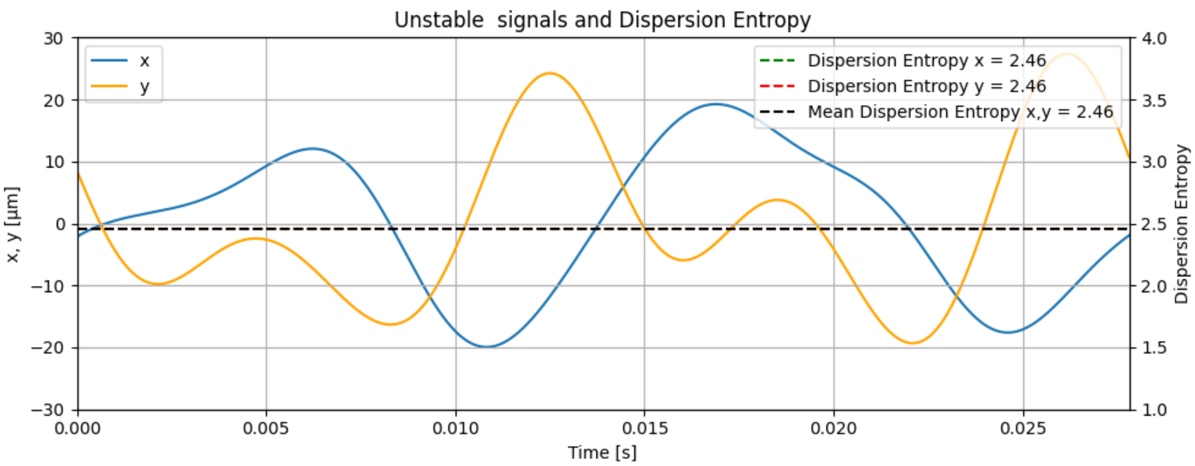

Figure 7. Dispersion Entropy for unstable signals.

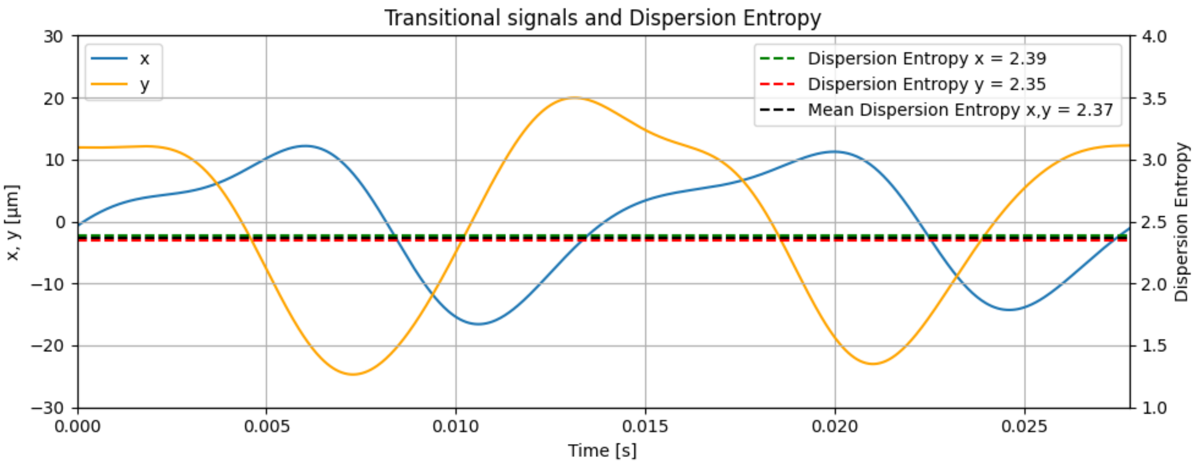

Figure 8. Dispersion Entropy for transitional signals.

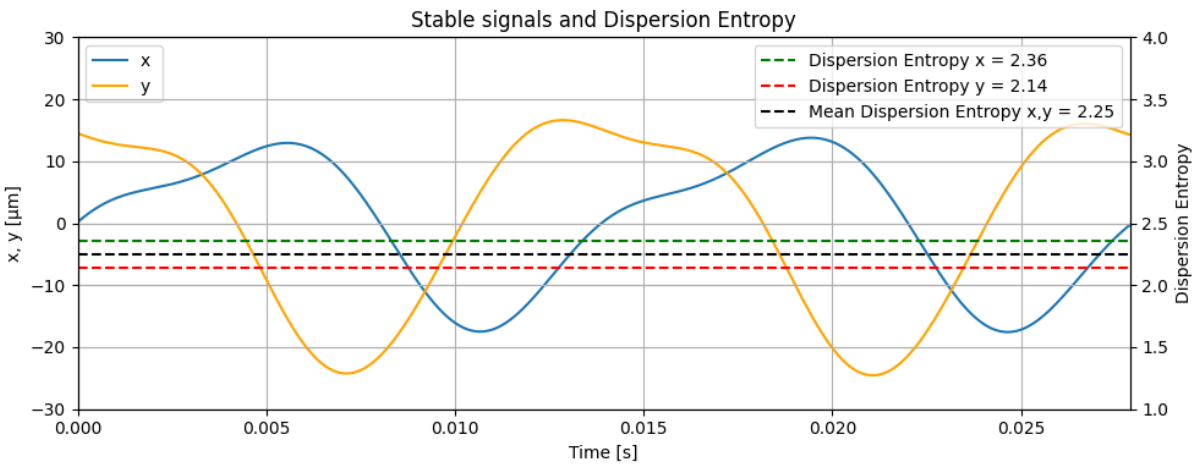

Figure 9. Dispersion Entropy for stable signals.

6. Conclusions

The article consists of two parts, first analytical and second experimental. In the first, the theory related to the analysis of signals resulting from the operation of nonlinear systems, which include the sliding bearing, is presented. The first part presents the existing application of DisEn in machine diagnostics and demonstrates the advantages that justify its use in sliding bearing diagnostics.

In the second part, based on the conclusions of previous research work related to the use of DisEn in data analysis, an experiment was designed in which the mechanical system gains stable operation at constant speed. From the signal, 3 parts were extracted which characterise the operating state of the sliding bearing as unstable, transient and stable. From these 3 signals, rotational trajectories were determined, which are the diagnostic symptoms in the classical analysis of sliding bearing operation. The trajectories corresponding to unstable operation of the sliding bearing showed different dynamics of signal variation, which directly led to an increase in the value of DisEn. The analysis of a single indicator value is much simpler than the analysis of rotational trajectories. The increase in DisEn corresponds to both x-axis and y-axis signals, which leads us to assume that a single sensor can be dispensed within the diagnostic system. A decrease in the difference between DisEn values for the x-axis and DisEn values for the y-axis was also observed for unstable operation. The analysis showed that it was possible to define the shape of the trajectory using the DisEn value. During the tests, individual trajectories for the various 3 operating states of the bearing were specified and the signal was clipped so that it described exactly two trajectories, which is standard procedure in journal bearing diagnostics. Both signals were also filtered in the same way and described with the same number of samples. The selected parameters were taken from previous studies using DisEn in machine diagnostics.

Further research on the usability of DisEn in machine diagnostics is planned, the problem of appropriate signal length in the ability to describe the phenomenon need further investigation. Research on the full signal describing the experiment using a sliding-window dispersion entropy indicates the instability of DisEn values depending on the length of the adopted measurement window and sampling frequency. The use of the DisEn indicator in bearing diagnostics is a promising and novel method. Further research and validation could lead to the widespread application of this technique in industry, which will translate into improved safety and efficiency in machine operation.

Additional information

The author declare: no competing financial interests and that all material taken from other sources (including their own published works) is clearly cited and that appropriate permits are obtained.

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