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Research Article

ACOUSTIC CAMERA AS A TOOL FOR IDENTIFYING MACHINERY AND EQUIPMENT FAILURES

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ABSTRACT
Sound and noise are as old as humanity itself. They have accompanied civilization, evolution, and development for centuries. Music and speech represent not only the key elements of human life but also unpleasant feelings of noise that have always been an integral part of human existence. As industrial development has required more energy, powerful machinery, and equipment, there have been still noisier machines. Traffic has grown quickly due to the number and speed of vehicles. For that reason, an acoustic camera is used for the dynamic visualization of machinery and equipment noise as it analyses the sources of noise in details. Subsequently, qualified measures are introduced based on the results of the analysis. The paper considers launching another application. According to the proposed methodology, its use in identifying machinery and equipment failures and their maintenance is proved. The experiment was performed on a four-wheel lawn mower. The primary focus was on the identification of failures using an acoustic camera. The previous method allowed to quickly, precisely and efficiently identifying the failures in two out of five tested machines.

Keywords: failure, maintenance, visualization, acoustic camera

INTRODUCTION

Technical diagnosis is considered to be one of the main methods to reach high effectiveness related to preventive maintenance of machinery and equipment in production. For that reason, there is a range of diagnostic methods used to determine a state of equipment, e.g., diagnostic without dismantling as one of the most popular methods nowadays. The method mentioned allows observing a state of a machine during its normal operation without involving any down time, and therefore, we can observe an increasing trend in using the method mentioned. Failures were identified by different methods, e.g., in [1, 15, 16]. In this paper, the Artificial Neural Network (ANN) introduced a system that was used to solve the problem of intelligent diagnosis of bearing knock faults in Internal Combustion (IC) engines. Namely, ball bearings are integral elements in most rotating manufacturing types of machinery. While recognizing defective bearing is quite straightforward, discovering the source of defect requires advanced signal processing techniques. Also, the paper [2] includes a proposal of an automatic bearing defect diagnosis method based on the Swarm Rapid Centroid Estimation (SRCE) and Hidden Markov Model (HMM). Moreover, other diagnostic methods were used in the paper [3]. Based on the facts in the paper, bearings are not only critical components in induction motors but the bearing failure is one of the most common failure modes in these motors.

Economic losses caused by bearing failures can be prevented by implementing health monitoring and fault diagnosis of bearings and unscheduled maintenance as well. The paper mentioned introduces trace ratio linear discriminant analysis (TR-LDA) that could be used for dealing with high-dimensional non-Gaussian fault data for dimensionality reduction and fault classification. Furthermore, the paper [4] used the method that studies the most significant statistical-time features estimated from vibration signal. Subsequently, it uses an equivalent of the curvilinear component analysis, and thus a nonlinear manifold learning technique for compression and visualization of the feature behaviour. The latter enables to interpret the underlying physical phenomenon. Stochastic resonance (SR) has been proved to be an effective way to detect a weak signal submerged in heavy background noise. The improvement of the SR approach to enhance the effectiveness of weak signal detection through a circuitry system addresses the paper [5]. Based on the presented experimental facts about noise, we are able better to understand the correlation between noise in an apparatus and its reliability. The main advantages of noise measurements could be considered that the tests are less destructive. Noise as a diagnostic tool is presented in [6]. Also, a diagnostic system detecting vibration and acoustic emission is used in the paper [7]. A vibration model of rolling element bearings in a rotor-bearing system for fault diagnosis is introduced in the paper [8]. Rolling element bearings are often used in rotary machinery, but they also represent fragile mechanical parts. Hence, accurate condition monitoring and fault diagnosis for them plays a major role in ensuring machinery's reliable running. Timely diagnosis and early intervention of bearing faults are desirable, but the early fault detection is easily submerged in noise. Mentioned noise diagnostic is proposed in paper [9, 14]. An original approach for detection and localization of faults occurring in Direct Current (DC) machine was suggested in the article [10]. There was described a system for diagnosing DC machines. The system performed an analysis of the acoustic signals of DC machine. The objection of the paper [11] is to estimate the leakage detection level in the case that these methods are used for diagnosing single leakages under steady-state operating pipeline's conditions. Technical diagnostic using vibroacoustic signals deals paper [12, 13].

The sound is a mechanic undulation that is accompanied by oscillation of particles in space. The oscillation results in an uneven arrangement of particles, i.e., some places contain more and some fewer particles. The previous arises from a direction of movement. In the case of large assembly of particles, a higher density can be observed. Following the previous fact, based on the thermodynamic, acoustic pressure increases. Namely, a sound wave means that density and pressure changes periodically in time and different places as well. Specifically, in one place there is the maximum particle density, while elsewhere it is happening in a different time.

The previous is confirmed as follows:

$$\xi = \xi m \sin(2\pi f \left(t - \frac{x}{c}\right)) \tag{1}$$

where: ξ – deviation of a single particle in a dimension "x" for a given time unit "t"
ξm – maximum deviation (typical for sound intensity)
f – sound frequency
t – time
x – dimension
c – speed of sound propagation

Velocity change due to movement of particles is represented as follows:

$$v = vm \cos(2\pi f \left(t - \frac{x}{c}\right)) \tag{2}$$

where: v – velocity
v_m – velocity amplitude (vm = ξ_m.2πf)

Subsequently, we are able to compute acoustic pressure:

$$\mathrm{p} = pm \sin\left(2\pi f (t - \frac{x}{c})\right) \tag{3}$$

where: P_m – $\rho_0 c v_m$, if ρ_0 = the average density of dimension
P_m – pressure amplitude

Intensity of sound corresponds to energy passing through a surface over time as follows:

$$\mathrm{I} = \frac{1}{2}\,\rho_0 c v m^2 = \frac{1}{2\,\frac{p_{m^2}}{\rho . c}} \tag{4}$$

The speed of sound also depends on the properties of dimension. Specifically, it reaches 340 meters per second in the air (20°C) while it is more in the water, i.e., 1440 meters per second.

Although the primary use of an acoustic camera is a dynamic visualization of sound propagation, the aim of the paper is to show and prove its wider use, i.e., the identification of machinery and equipment failures. Indeed, a consumer plays the key role regarding maintenance machinery and equipment as he can determine the length of using his products with maximal utility. For that reason, it is a regular maintenance that could help to extend the lifespans of machinery and equipment. Particularly, an acoustic camera could shorten a time needed for the identification of failures invisible in normal operation. Thus, the analysis of our paper is focused on a four-wheel lawn mower widely used in households.

Economic methods of Investment Projects Evaluation (cost project selection criteria).

The cost criteria are usually not listed in financial literature as they do not evaluate a project concerning cash flow, i.e., they evaluate a project concerning investment and operating costs. Therefore, they have appeared predominantly in various technical and engineering publications. In fact, this method compares annual costs of comparable variants of investment projects, i.e., mainly the same scale of production, which ensures the investment variant, and the same price. The variant with the lowest annual average costs is considered to be the most appropriate one.

Annual average costs are represented as follows:

$$V{=}J.i{+}O{+}R$$

where: R – annual average costs of the variant,
O – annual amortization,
i – required (expected) rate of return in %,
J – investment costs (similar to capital expenditure),
V – other annual operating costs (i.e., total operating costs – amortization).

The coefficient of required rate of return represents minimal required rate of return (respectively the average cost of company's capital) that has to be ensured by a project.

We consider two variants of investment project (two different lawn mowers) that ensure the same performance requirements.

The lawn mower I. – a purchase of the two-wheel lawn mower in the price of 100 €. Its service lifespan is estimated for four years. Estimated annual labour costs are 30 €, material consumption is 20 €, other costs are 10 €. Linear amortization is considered.

The lawn mower II. – a purchase of the two-wheel lawn mower in the price of 150 €. Its service lifespan is estimated for four years. Estimated annual labour costs are 10 €, material consumption is 20 €, other costs are 10 €. Linear amortization is considered.

The required rate of return in the case of both projects is deemed to be 10%. Annual average costs in the case of the lawn mower I. are 95 € and 92.5 € regarding the lawn mower II. The most suitable and viable project is the lawn mower II. based on the comparison of these two options regarding annual costs. The previous is also valid, even though the project requires higher investment costs. Moreover, the second project results in greater savings in other operating expenses compared to the growth of amortization and required rate of return.

Following our results above, an early diagnosis of potential machinery and equipment failures (including acoustic diagnostics) can ensure cost savings on their repair and maintenance, and thus mitigate average annual costs of machinery, leading to an efficient allocation of investments.

MEASUREMENT METHODOLOGY

The measurement was conducted gradually on the five four-wheel lawn mowers of the same type from different producers, with different performance parameters, different lifespan, and condition of use. The measurement using an acoustic camera was carried out in two ways:

a) Static measurement of the noise source. Regarding an engine of lawn mowers working at maximum speed, we analysed: acoustic spectrum of the emitted sound, spectrogram, and acoustic images of dominant frequencies.
b) Measuring the noise source while cutting grass as a standard activity (see Fig. 1). Related to these measurements, we evaluated: acoustic spectrum, spectrogram, a sound film, and acoustic images of dominant frequencies.

Subsequently, based on the spectrograms, a sound film and acoustic images of dominant frequencies, we could clearly identify any failures/defects and/or non-standard behaviour of the lawn mower.

RESULTS

The method of static measurement using an acoustic camera was considered to be only slightly effective while identifying failures of tested machines. The second method, i.e., lawn mower track in front of an acoustic camera, was more suitable for the effective results. The measurement was conducted at the distance of 3.3 meters from the start of an acoustic camera track (see Fig. 1). Fig. 2 shows the spectrum of emitted noise of the lawn mower AL – KO PowerLine 4600 BR. As a result, dominant frequencies are in

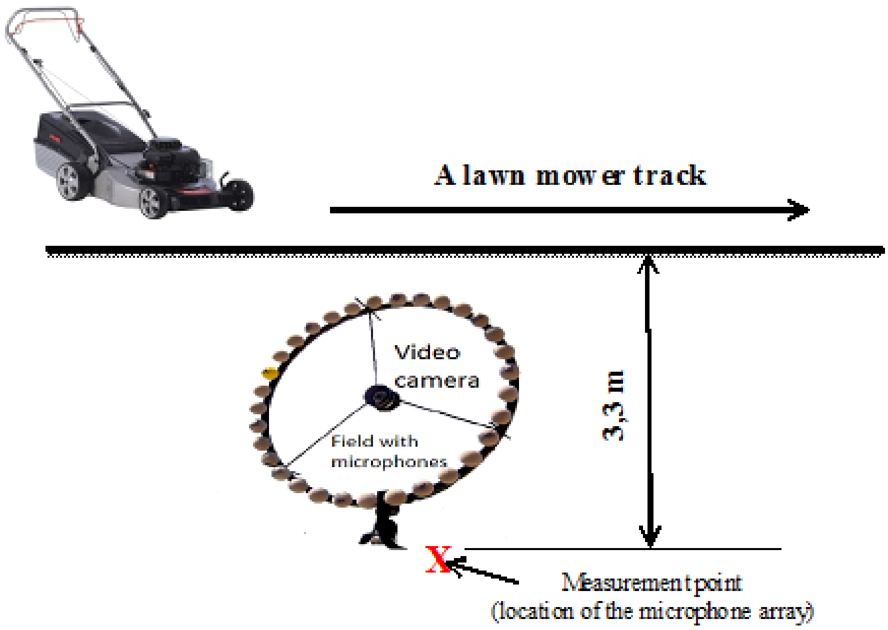

Fig. 1. The scheme of a lawn mower track using an acoustic camera

the low frequencies, i.e., to 250 Hz. Subsequently, the spectrogram of emitted noise was generated as is shown in Fig. 3.

Following our results from the spectrogram, the frequency 5000 Hz results in emitting a high level of noise having an impulse character with a time between impulses about 40 ms-1 (labeled as an ellipse in Fig. 3). However, these impulses disappear in the overall noise, so an observer will not find out any problem with a lawn mower. Also, the acoustic image of the dominant frequency 5000 Hz was generated to indicate the source of sound propagation (see Fig. 4).

Based on the acoustic image and conducted analysis, the noise of this frequency is caused by a failure of a lawn mower. Detailed analysis showed the seal failure on the cylinder head of the engine, and thus compression gas leak that is a clear failure of the tested lawn mower. Times between impulses (see Fig. 3) are proportional to the speed of the crankshaft of the engine in a lawn mower.

Also, we tested the lawn mower AL – KO 52 BR Comfort. Fig. 5 shows the spectrogram of emitted noise of the lawn mower. Following our results from the spectrogram, dominant frequencies are in a range of the low frequencies, i.e., to 250 Hz. Subsequently, the spectrogram of emitted noise was generated as is shown in Fig. 6.

Following our results from the spectrogram, the frequencies 270 Hz and 1150 Hz to 1250 Hz result in a high level of noise. Also,

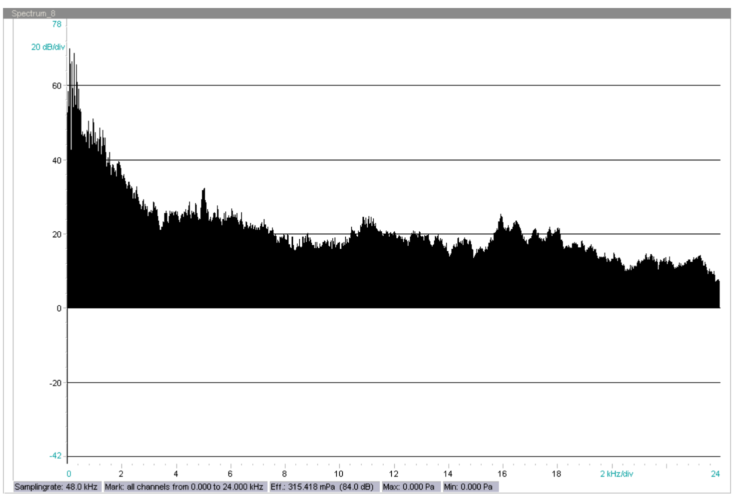

Fig. 2. The spectrum of emitted noise of the lawn mower

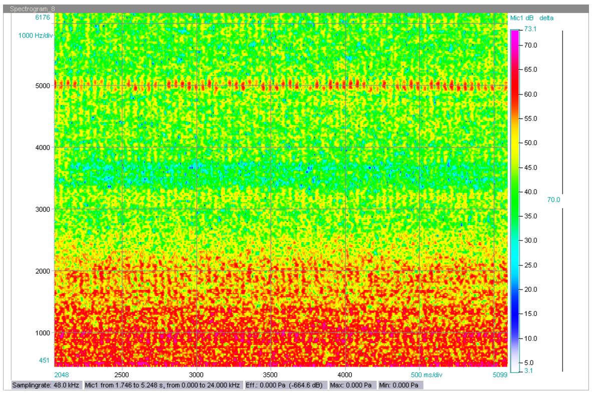

Fig. 3. Spectrogram of emitted noise

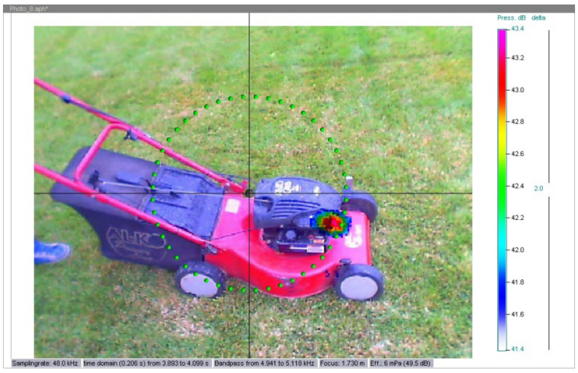

Fig. 4. The acoustic image of the dominant frequency 5000 Hz

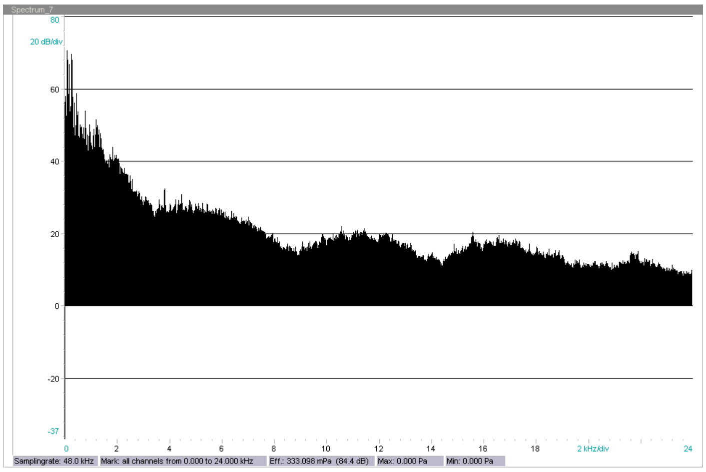

Fig. 5. The spectrum of emitted noise of the lawn mower

the noise is evenly spread from the source of noise, which is the lower part of the engine. Subsequently, the acoustic image of the dominant frequency 270 Hz and 1150 Hz to 1250 Hz was generated to indicate the source of sound propagation (see Fig. 7).

Based on the acoustic image and conducted analysis, the noise of this frequency is caused by the resonant cover since the centre of the source noise moves in time to the lawn mower body.

DISCUSSION

The measurements have demonstrated the ability to identify the machinery and equipment failures based on the visualization noise sources. According to the detailed analysis, each failure manifests with a different spectral composition of noise. Spectrograms show tonal parts, time-dependent acoustic events proportional to the conditions of tested machines. One of the most important findings is the ability of the precise identification of noise sources. Particularly, there should be found a non-standard part of the sound on the spectrogram, mark it and then create acoustic images.

The entire identification process is characterized by:

- **Short measuring time** – a few seconds, respectively several tens of seconds in the complicated cases.
- **Fast data processing and measurement evaluation** – the identification takes several minutes in the case of repeated measurements and is dependent on the operator's experience and computer performance.
- **Unambiguous identification of failures** – the authors identified the failures quite accurately. In practice, the database of spectrograms, spectra, respectively acoustic images corresponding to a particular failure is created by repeated measurements. The previous will make possible to streamline the entire maintenance process.

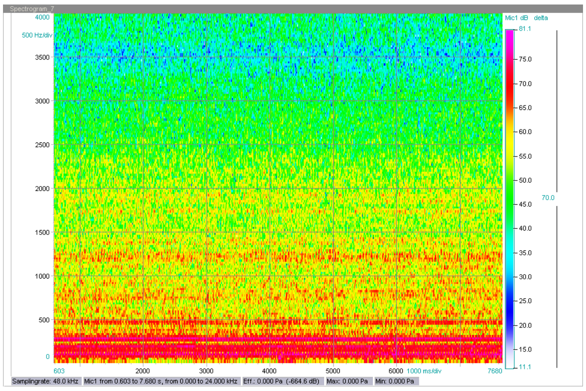

Fig. 6. Spectrogram of emitted noise

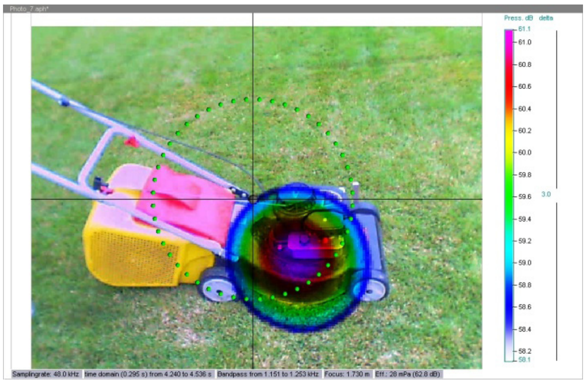

Fig. 7. The acoustic image of the dominant frequency 1150 to 1250 Hz

CONCLUSION

Nowadays, the market has offered a number of acoustic cameras and specialized, custom-formed microphone arrays, which can be used to identify failures. However, the only drawback regarding the method is a relatively high price of equipment that makes this method applicable only to larger amounts of the identified equipment, i.e., larger operations. The authors conducted a whole range of measurements using an acoustic camera. The findings support the fact that the acoustic camera is a perspective tool in the area of predictive maintenance as it enables early identification of machinery and equipment failures often without down time, i.e., its full operation (production lines, technological operations, transport equipment). Based on the changes in the spectral composition of the sound, it is even possible to track an emerging failure, and thus estimate the time when it is necessary to perform maintenance.

The benefits of this non-contact method can be used at a variety of devices, even at greater distances, where there is no risk to health.

For faster identification of faults or its prediction, it is necessary to create a database of samples with frequency characteristics of individual faults, in addition to experience, which in the future may reduce costs and speed up this fault detection technology.

Diagnosis of acoustic camera faults has a great future ahead, not only in the diagnostics of machinery and equipment, but also in other sectors, such as construction, where other methods have been used.

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