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IMPLEMENTATION OF WAVELET SCALOGRAMS FOR AUDIO SIGNAL ANALYSIS

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ABSTRACT

In the past few decades, wavelets have found an important place in many fields due to their nature and advantages compared to other algorithms. When the focus is on signal processing, wavelets can be used as an algorithm for de-noising, frequency analysis, feature analysis, etc. The spectrogram is one of the most common visual representations of the signal in the frequency domain when the Fourier transformation is used. Wavelets have their algorithm for signal representation in the frequency domain, and it's called scalogram due to the nature of the scaling properties of the wavelet function.

This paper explores the application of the Continuous Wavelet Transform (CWT) for generating and analyzing scalograms. Audio signals from different direct current (DC) motor sounds are used as test data to demonstrate the effectiveness of this approach. All implementations and analyses are carried out using MATLAB software. The results highlight the advantages of wavelet-based analysis in capturing time-frequency characteristics that may not be easily observed with traditional Fourier-based methods.

Keywords: wavelets, frequency analysis, scalograms, continuous wavelet transform, direct current motor sounds.

INTRODUCTION

The development of technology in the modern era has enabled significant advancements in signal analysis and processing, particularly in the field of audio processing. One of the most intriguing approaches in this domain is converting audio signals into visual representations, which offer new possibilities for visualization and further analysis. This method of interpreting signals allows researchers to identify the frequency and time-domain characteristics of sound in an intuitive and informative way. The conversion of audio signals into images and further processing using wavelets has become a significant area of research and application. This interdisciplinary field enables the visualization and analysis of audio signals in a way that provides unique insights into their frequency characteristics.

One of the most powerful tools used for this purpose is wavelet transformation. Unlike traditional methods such as the Fourier transform, wavelet transformation enables simultaneous analysis of signals in both the time and frequency domains, providing more precise information about the signal's structure. The application of this method results in spectrograms and scalograms, which visually represent the dynamics of the signal across different frequency ranges.

The objectives of this paper are: first, to provide the reader with a thorough understanding of the process of converting audio signals into images (scalograms), and second, to demonstrate how these images can be further analyzed and processed to extract key information. Through practical examples in MATLAB, specific implementations and results will be presented.

This study aims to contribute to the understanding of the complexity of audio signals through visualization and analysis, providing readers with tools for further research and application in various fields, from audio engineering to medical diagnostics. The goal of this paper is to emphasize the importance of visualizing audio signals for a deeper understanding of their characteristics.

For the purpose of this paper, various audio sounds from direct current motors are used. All sounds are recorded in the laboratory and the production hall. Some of the important characteristics of these motors are: input voltage from 12V to 13V, no load speed (rotation per minute) about 80, maximum output power from 18W to 25W, approximate dimensions 16 x 13.5 x 4.5cm. Due to the paper's length, only representative examples are used for this paper.

The paper is organized into four sections including introduction and conclusion. The second section provides relevant background theoretical information. The third section presents a time and frequency analysis of DC motor sounds. The fourth section gives the results of the analysis of wavelet-based scalograms.

WAVELETS

Wavelets are fundamental mathematical tools that can be used for signal and image analysis and processing (Graps, 1995). In the context of signal analysis, wavelets enable the understanding and representation of complex signals through localized functions that expand in time or frequency. This approach allows for efficient detection and analysis of various signal characteristics, such as changes in frequency, amplitude, or shape (Damnjanović et al., 2020).

In image processing, wavelets are used to separate different scales and details of an image, which is useful in applications such as image compression, noise reduction, and edge detection (Kingsbury, 1999). The advantage of wavelets over traditional methods like the Fourier transform lies in their ability to provide better time-frequency localization, which is crucial for analyzing rapidly changing signals or images with varying levels of detail (Sifuzzaman et al., 2009). By using wavelets, it is possible to efficiently perform multichannel analysis, allowing for improved pattern recognition and feature extraction in both signals and images.

In its simplest form, a wavelet represents a wave function of limited duration whose average value is zero (Damnjanović et al., 2019). Wavelets have been developed to enhance existing signal-processing algorithms and address certain limitations. Basic wavelet $\psi(x)$, the so-called "mother wavelet" is defined as:

$$\psi_{a,b,}(x) = \frac{1}{\sqrt{a}}\psi(\frac{x-b}{a}), a > 0, \quad (1)$$

where a is the scaling parameter and b is the translation parameter. Selection of the parameters is the most difficult task in the wavelet function, and it depends on the shape and complexity of the wavelet function (Damnjanović et al., 2021).

All wave transformations can be considered forms of time-frequency representation for continuous (analog) signals, making them similar to harmonic analysis. The Continuous Wavelet Transform (CWT) uses wavelets that enable signal analysis in continuous time, decomposing the signal into localized functions in time and frequency (Guido et al., 2020). This approach is similar to Fourier analysis but allows for better time-frequency localization. CWT is defined by the inner product of the function (f) and the basis "mother" wavelet $\psi_{a,b}(x)$:

$$CWT_f(a,b) = (f, \psi_{a,b}) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(x)\psi^*\left(\frac{x-b}{a}\right)dx, \quad (2)$$

Today, there are numerous wavelets used in various fields of signal analysis, image processing, and mathematics. Some of the fundamental types of wavelets include: Haar, Daubechies, Coiflets, Symlet, Biorthogonal, Reverse biorthogonal, Meyer, Morlet, etc (Damnjanović et al., 2018).

Scalograms

The scalogram is a graphical representation of the time-frequency content of a signal, obtained using the wavelet transform, which enables signal analysis at different time scales and frequencies (Rioul and Vetterli, 1991). Unlike the spectrogram, which relies on the Short-Time Fourier Transform (STFT) and fixed window sizes for analysis, the scalogram uses wavelet functions with variable-sized windows. This approach provides high temporal resolution for rapid changes in the signal (high frequencies) and high-frequency resolution for slower oscillations (low frequencies), making it particularly useful for analyzing non-stationary signals (Bolos and Benitez, 2014).

In a scalogram:

- The horizontal axis represents time, allowing insight into when specific signal features appear.
- The vertical axis shows scale, which can often be converted to frequency for easier interpretation.
- The color intensity or shading indicates the signal energy at a given scale at a particular time, visualizing how the signal's energy evolves over time.

The wavelet transform, which underlies the scalogram, uses wavelet functions of various shapes (such as Morlet, Haar, or Daubechies wavelets), allowing adaptive analysis based on signal characteristics. Unlike STFT, which is constrained by the trade-off between time and frequency resolution, the wavelet approach provides a more detailed and flexible insight into the local characteristics of a signal.

Scalograms are widely used in biomedical signal analysis (e.g., EEG and ECG) (Bialasiewicz, 2015), (Kumar et al., 2004), seismic signal processing (Li et al., 2006), audio signal analysis (Peng et al., 2002), and pattern recognition (Sharan, 2020), (Salles and Ribeiro, 2023). Due to their ability to identify transients, sudden changes, and complex patterns in signals, scalograms have become an indispensable tool in modern signal processing and scientific research. A schematic representation of the frequency-time plane, which is important in the process of creating a scalogram, is shown in Fig. 1.

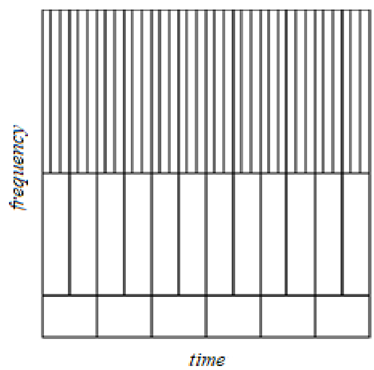

Figure 1. Frequency-time plane using wavelets.

RESULTS AND DISCUSSION

As it was mentioned before, for the purpose of this paper, MATLAB software is used. At the beginning, it is important to show examples of DC motor sounds in the time and frequency domains. Two representative examples are selected for further analysis. The differences between the two selected motors are that one operates without any faults, while the other has a fault in its operation. The time domain is shown in Fig. 2.

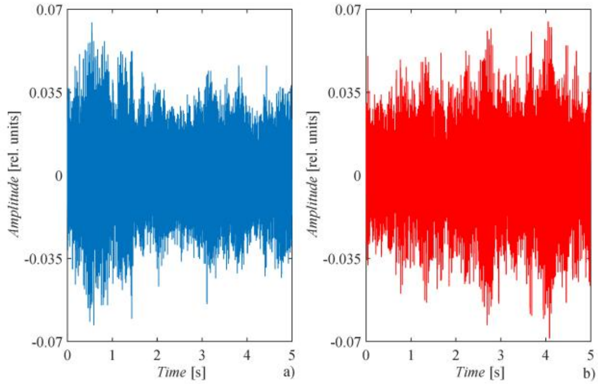

Figure 2. Time domain of two DC motor sounds: a) without fault, b) with fault in work.

Representative frequency domains of selected motors are presented in Fig. 3.

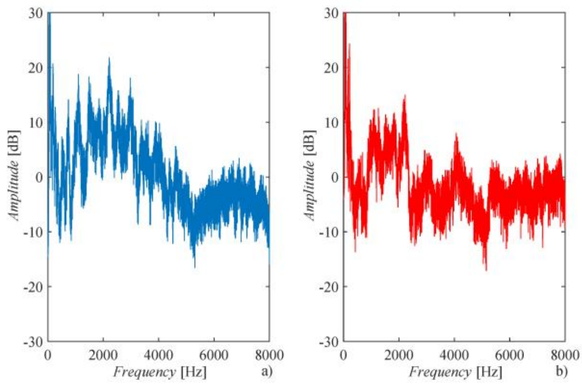

Figure 3. Frequency domain of two DC motor sounds: a) without fault b) with fault in work.

Analyzing representative audio signals in the time and frequency domains can be challenging without applying specific methods, as it was shown in Fig. 2 and 3. In the time domain, the signal is represented as a function of time, but this approach doesn't provide enough information about the signal's frequency components. Noise and interference can also obscure the signal's true characteristics. On the other hand, analyzing the signal in the frequency domain reveals its frequency distribution, but this method can still be difficult to interpret without advanced techniques. Even using the Fourier transform may result in the loss of important details in the time component.

To effectively analyze audio signals, advanced methods like wavelet transform, spectrogram, or scalogram analysis are needed, as they combine both domains and allow for a better understanding of the signal's features. In the next lines, scalograms of selected signals will be presented. Figure 4 presents a scalogram of the DC motor sound without fault, while Figure 5 presents a scalogram of the DC motor sound with fault. The analysis employs the Morlet wavelet to generate the scalogram. The Morlet wavelet uses a complex representation for improved localization and analysis of frequency components. It is characterized by the use of only positive frequency components and is particularly suitable for precise analysis of complex signals (Silik et al., 2021).

On the x-axis, the time interval of the signal is shown in seconds, while the y-axis represents the logarithmic frequency in Hz (from low to high frequency). On the right side, the scale of the intensity of energy (magnitude) at different moments in time is given. Brighter colors indicate a higher presence of a certain energy at a given moment. Brighter colors (yellow) represent higher energy at that frequency, while darker colors (blue) represent lower energy.

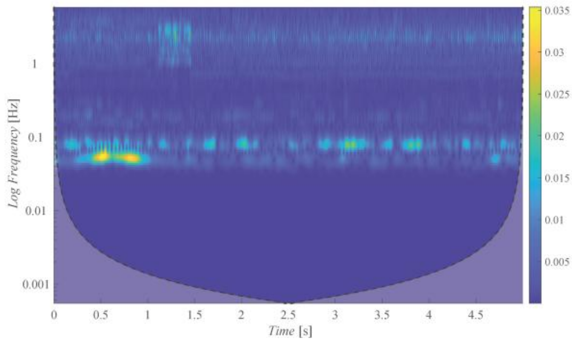

Figure 4. Scalogram of the DC motor sound without fault.

A comparison of the two scalograms shows that both signals exhibit dominant energy at approximately the same frequencies. However, over time, it is evident that the faulty motor signal exhibits more fluctuations. This results in the motor having certain deficiencies in its operation. Such conclusions could not be observed from the spectra shown in Fig. 3.

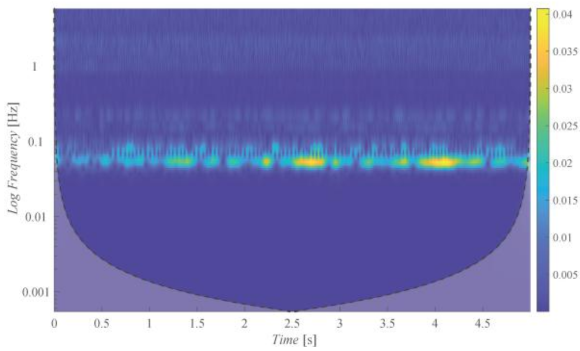

Figure 5. Scalogram of the DC motor sound with a fault.

The identification of dominant frequencies in a signal represents a key step in the analysis of time-frequency characteristics. Dominant frequencies are those components that have the highest energy contribution and the most pronounced intensity within certain time intervals. It is often useful to extract only those frequencies that exceed a certain energy threshold, ignoring weaker components that may result from noise or less significant signal features. This approach not only enables a better analysis of the dominant frequency components but also contributes to a clearer understanding of the signal's structure over time. The following figures show the scalograms of the previously analyzed signals, with a focus placed specifically on the dominant frequencies (Figure 6 for motors without faults, and Figure 7 for motors with faults).

Now that the dominant frequencies are more pronounced, the previous statement is confirmed: the energy of both signals is concentrated at approximately similar frequencies, but the faulty motor signal exhibits more distinct details in the scalogram. It is important to note that the y-axis differs in this type of scalogram, as a logarithmic scale is no longer used, making the frequencies clearly visible.

This method of analysis is excellent for further feature extraction from signals and the creation of a corresponding database. Such a database would be suitable for further processing, for example, as images, with the aim of classifying a large number of samples, distinguishing between motors without fault and those with fault.

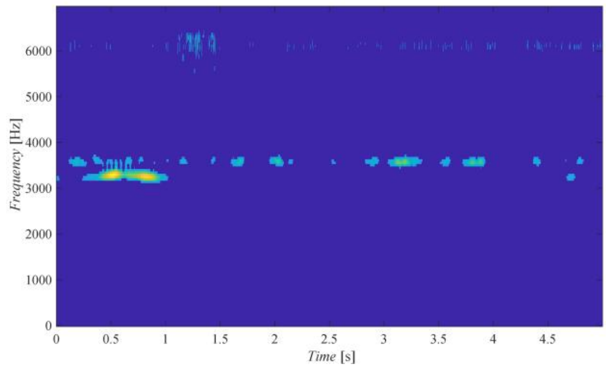

Figure 6. Scalogram with dominant frequencies of the DC motor sound without fault.

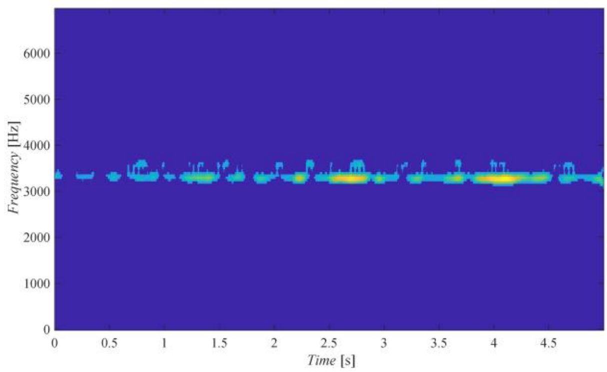

Figure 7. Scalogram with dominant frequencies of the DC motor sound with fault.

CONCLUSIONS

Converting an audio signal into a type of image can be a highly developed and interesting discipline within scientific research. If such images are treated as features of the audio signal, classification could later be performed. Wavelets represent one of the methods for processing audio signals and transforming them into scalograms, where certain frequency features can be observed.

This paper offers such a possibility and describes in detail the process of image formation, that is, the formation of a scalogram using wavelet transform. The entire procedure is demonstrated on sound recordings of DC motors, where one motor had a fault in its operation while the other operated correctly (without fault).

The Morlet wavelet was used, and in addition to the basic scalogram analysis, a detailed analysis was performed by further processing the obtained scalograms in order to highlight the dominant frequencies. In this procedure, the focus was on identifying frequencies that exceed a certain energy threshold. As a result, the scalograms became clearer, with dominant frequencies being more pronounced, thus facilitating further analysis.

Future work would be based on the classification of the obtained images, that is, scalograms of a large number of audio signals. It is always advisable to use a different type of wavelet as well, in order to compare the obtained results and select those with the greatest potential.

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DECLARATIONS OF INTEREST STATEMENT

The authors affirm that there are no conflicts of interest to declare in relation to the research presented in this paper.

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