Comparison Performance of Spectrogram and Scalogram as Input of Acoustic Recognition Task

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***Abstract*—Acoustic recognition is a common task for deep learning in recent researches, with the employment of spectral feature extraction such as Short-time Fourier transform and Wavelet transform. However, not many researches have found that discuss the advantages and drawbacks, as well as performance comparison of them. In this consideration, this paper aims to comparing the attributes of these two transforms, called spectrogram and scalogram. A Convolutional Neural Networks for acoustic faults recognition is implemented, then the performance of them is recorded for comparison. A latest research on the same audio database is considered for benchmarking to see how good the designed spectrogram and scalogram is. The advantages and limitations of them are also analyzed. By doing so, the results of this paper provide indications for application scenarios of spectrogram and scalogram, as well as potential further research directions.**

Keywords—spectrogram and scalogram, acoustic faults recognition, Convolutional Neural Networks.

I. INTRODUCTION

In acoustic recognition task, features in audio signal are extracted using spectral and time analysis techniques, which are commonly applied as Short-time Fourier transform (STFT) and Wavelet transform (WT). STFT decomposes signal in linear frequency manner while WT decomposes the time-domain signal into variant scales of frequency. The output of these transforms are then produced as spectrogram and scalogram respectively, and being fed into a deep learning model to train and perform classification task. A number of researches have been done in recent years for this topic.

Adoption of spectrogram for speech emotion recognition, Badshah, Ahmad, Rahim and Baik [1] employ Convolutional Neural Networks (CNNs) to predict the emotions of audio speech. Before feeding into CNNs for training, the spectrograms are produced as images. The model includes only three convolutional layers and three fully connected layers, but it performs better than the famous pre-trained model AlexNet. Santos and Nilizadeh [2] propose a solution for acoustic event detection (AED) by application of spectrogram and CNNs. Audio of surveillance system is transformed to spectrogram as images, then being classified by a CNNs binary classifier if it is the sound of gun shot or siren. This model outperforms a benchmarking AED-capable system. Purohit et al. [3] develop abnormal machinery sound detection by mean of spectrogram and autoencoder. Two types of audio data including normal and abnormal sound collected in factory are then transformed to images of spectrogram. An autoencoder-base model is designed for this binary classification task to detect whether the machine is in normal condition or damaged.

Scalogram is another audio feature extractor which has been recently growing in application. Tran, Liu, and Tran [4] implement a deep CNNs to detect milling chatter using scalogram. The system is designed for real-time detection where the cutting force is measured to determine if it is in healthy operation or not. The combination between scalogram and CNNs has achieved an excellent performance in comparison to the benchmark methods, which employed some machine learning models. Copiaco, Ritz, Fasciani, and Abdulaziz [5] also apply the same approach for domestic audio classification task. Scalogram is produced by the output of continuous WT, then it is fed into pre-trained neural network and additional Support Vector Machine model to predict whether the sound is made by social activities, or vacuum machine. Chen et al. [6] make use of scalogram and CNNs for audio scene modeling. The research shows a better performance of trained model for scalogram than spectrogram. However, the model which uses spectrogram as input, is not a CNNs model. Therefore, the comparison does not make sense much for these two types of feature extractors.

As can be seen above, although a large number of researches have been done for audio recognition using spectrogram or scalogram incorporation with deep learning, not many researches do comparison the performance of these two types. If anything, the benchmarking is restrictedly done for different deep learning models, or at most, as in [6], the comparison is quite relative by purely comparing the performance, with different prediction models. Considering these aspects, this paper is aiming to a development of an approach for a fairly tight comparison of spectrogram and scalogram as two types of audio feature extractors. For this purpose, the design of experiment for spectrogram and scalogram is done identically, including original used audio data, format of input for deep learning model, complete configuration of CNNs model, training and evaluation method and metrics. The only distinction is the spectrogram and scalogram itself.

II. THEORETICAL FOUNDATION

A. Short-time Fourier transform

STFT [7] is a method to perform Fourier transform (FT) in sections of time. It means that the signal is firstly captured in each time frame, and then being calculated the FT for these framed signals. By this way, signal is not only decomposed in frequency domain to tell which frequencies are included in the signal, but also the variation of signal over time is captured to indicate those frequencies occurring in which point of time. STFT stretches the signal from one dimension (time) into two dimensions (time and frequency) as (1). STFT is a function of time shift τ and frequency ω. By windowing using function $\gamma^{*}(t-\tau)$, for each defined period, a part of the signal within the window is taken for FT, the remaining parts are suppressed to zero. Therefore, the spectrum of a small duration of time is computed. The window is then shifted along the time axis to capture all portions of signal then performed FT. By doing so, the whole signal is decomposed by STFT.

$$STFT\{x(t)\} = X(\tau, \omega) = \int_{-\infty}^{\infty} x(t)\, \gamma^*(t-\tau) e^{-j\omega t} dt \quad (1)$$

In practice, signals are processed in time-discrete format, and STFT is performed in discrete manner using window with length of N, called frame size. This frame can shift in a sample-wise manner. However, shifting by a single sample creates huge data volume, which is redundant as neighbor spectra are very similar. Instead, the shifting step contains a large number of samples, called hop size H, usually selected as a half of window length H = N/2. This selection is considered as a good compromise between time resolution and volume of generated data [7]. Each point of sample in data length M where STFT is calculated, called frame index m (m = M/H). In a frame, the FT of a discrete signal with length of N points in time results a vector of N points in frequency. Nonetheless, two halves of the spectrum are mirrored with each other via Nyquist frequency, so that only the first half of spectrum is consider in result of STFT to remove the redundancy. Consequently, frequency index k of STFT is considered up to value N/2 (k = 0…N/2). The Fourier coefficient for m^{th} time frame is represented by a complex number X(m, k). For a specific point in time m^{th}, FT is a spectral vector of size K+1, resulting STFT as a matrix size (m = M/H, k = 1 + N/2).

To visualize better STFT, one kind of heat map called spectrogram [8] is normally used. It is a two-dimensional representation of the squared magnitude of STFT as (2). Spectrogram is often visualized by image with time dimension in the x-axis and frequency dimension in the y-axis. The squared magnitude of STFT is represented by the color density of pixels on image. To show how high the values of each point, typically a range of colors is used. For instance, the color ranges from dark blue for lowest value to dark red for highest value as illustrated in the Fig. 1 (a). For better visualization, frequency axis and density of spectrogram is presented in logarithmic scale.

$$S(\tau, \omega) = |X(\tau, \omega)|^2 = \left| \int_{-\infty}^{\infty} x(t)\, \gamma^*(t-\tau) e^{-j\omega t} dt \right|^2 \quad (2)$$

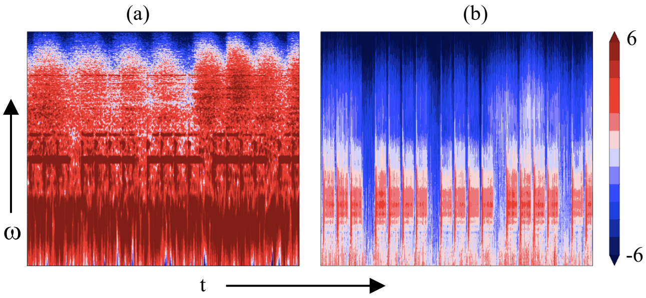

Fig. 1 Visualization of spectrogram (a) and scalogram (b)

B. Wavelet transform

WT is a technique converting a function or signal into a form that represents certain features of original signal better for further processing [9]. More specifically in audio signal processing, it is the way to decompose a signal in time domain (one dimension) into time and frequency domain (two dimensions) by using mother wavelet, being identified as (3). The WT is a function of time shift b and frequency scale a. The factor $1/\sqrt{a}$ help normalizing the energy of signal to ensure the same energy level at every scale. In the transformation process, the mother wavelet is contracted and dilated when the scale is varying. Each modified shape of the wavelet then slides along the time axis to convolute with the signal $x(t)$, resulting a matrix of so-called wavelet coefficients. Each coefficient in matrix represents for the magnitude of wavelet transform at time translation b and frequency scale a. The wavelet transform, therefore, could be considered as cross-correlation of the signal with various versions of scaled and translated wavelet [9].

$$WT\{x(t)\} = X(b, a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^*\left(\frac{t-b}{a}\right) dt \qquad (3)$$

Continuous WT (CWT) in discretized signal is computed by performing a naïve discretization of the transform, replacing the integral by a discrete summation of values within sampling interval. The translation parameter and scale parameter are also in discrete forms, with the translation is sample-wise. For each sample, and each scale, WT is a coefficient. Therefore, CWT will produce a matrix with size (data length = N, scale = a). Discrete WT (DWT), in other hand, is implemented by filter banks whose computational expense is much less than CWT. However, the result of the transformation is not a matrix, hence it is not suitable for generation of heat map. In addition, its time resolution and frequency resolution for feature extraction are not as good as CWT, so that it is not suitable for recognition task.

Squared magnitude of WT is one kind of heat map named scalogram, being calculated as (4). In case of CWT, result of transform is a matrix, so that, as spectrogram, scalogram is also used to visualize the distribution of signal energy across time and frequency dimension as an heat map having intensity being expressed by a range of colors. The frequency dimension (scale) and intensity of scalogram are also presented in logarithmic scale for better visualization as illustrated in Fig. 1 (b).

$$S(b, a) = |X(b, a)|^2 = \left| \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t) \psi^*\left(\frac{t-b}{a}\right) dt \right|^2 \qquad (4)$$

C. Time and frequency resolution of transforms

1) Uncertainty principle

To analyze the signal better, the time resolution and frequency resolution should be as high as possible. In other words, the variation of signal should be captured in a small shift of time and frequency. However, the uncertainty principle [8] imposes a constrain for the tradeoff between time and frequency as (5). If using narrow time window (small Δ_t) to capture signal, STFT/WT will be generated in a good time resolution, but poor frequency resolution (large Δ_ω). On the opposite, using a large time window (large Δ_t), in which the transforms is not able to distinguish the change of signal in short period of time, yields a poor time resolution, but better frequency resolution (small Δ_ω).

$$\Delta_t . \Delta_\omega \geq \frac{1}{2} \qquad (5)$$

2) Multiresolution

The Fig. 2 gives a visual illustration of WT by scalogram in comparison with STFT by spectrogram. As in the plot, the time signal x(t) has two periodic components and two Dirac impulses as Fig. 2 (a). The Fig. 2 (b) illustrates for spectrogram of x(t) with short window having high time resolution but low frequency resolution. Therefore, two distinctive impulses are clearly drawn in the center but two components in frequency axis are merged together. The Fig. 2 (c). illustrates spectrogram with long window having low time resolution but high frequency resolution. Hence, two red horizontal stripes indicating two frequency components are clearly separated, but two impulses are merged together in the center. Whereas scalogram represents both two distinctive impulses and two distinctive red horizontal stripes as the Fig. 2 (d). This capability of scalogram is enabled by the multiresolution feature, in which the WT produces high time resolution at high frequencies, and high frequency resolution at low frequencies.

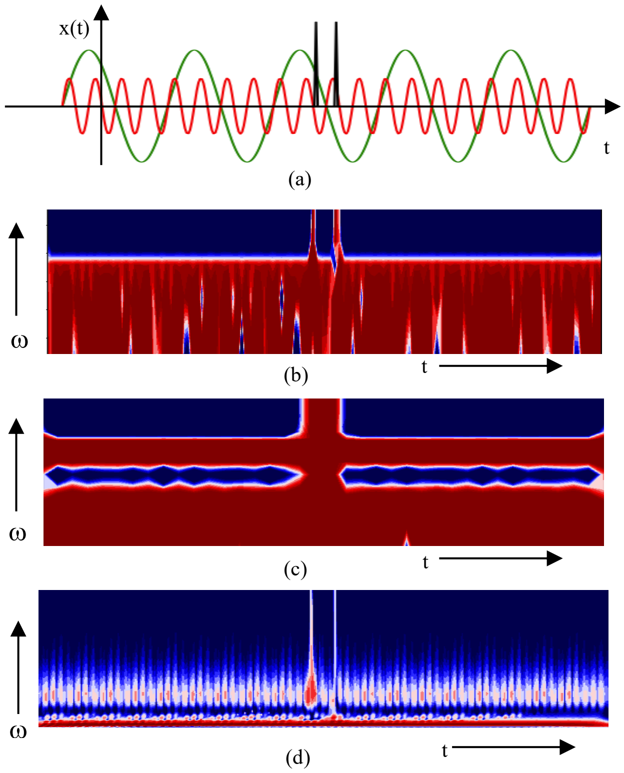

Fig. 2 Time and frequency resolution of spectrogram and scalogram

3) Comparison of time and frequency resolution

In addition to multiresolution section, a comparison for time-frequency resolution of the transformations is illustrated in Fig. 3. The top left diagram is the signal in time domain with zero information about frequency. This signal is then used to generate FT as in top right diagram with no information about time. Performing STFT of the signal results the diagram at bottom left with constant time-frequency resolution, representing by the same rectangles. WT with multiresolution capability, produces the transform as in bottom right figure with varying time-frequency resolutions representing by varying size rectangles.

III. METHODOGOLY

A. Programming libraries

In this paper, generation of STFT is done by Librosa library [10], a Python package for music and audio analysis. WT is created using Pywavelets library [11], a free Open Source software library. Tensorflow [12] is used for training and evaluation of CNNs model. Visualization images of spectrogram and scalogram is done by Matplotlib [13] library.

B. MIMII audio dataset

The MIMII dataset [3, 15] is the dataset made by Hitachi company in 2019. It provides a real-life sound data in factories for various machine types, including fan, pump, slider and valve. These machines produce both stationary and non-stationary sound, with different levels of difficulty for distinguishing between normal and abnormal condition. A number of damage scenarios of machine are captured such as contamination, leakage, rotating unbalance, and rail damage. The background noise in various factory scenarios is recorded, then mixed with the target machine sound, creating a sound data simulating real environment at 3 levels of signal to noise ratio: -6dB, 0dB, and 6dB. This dataset is used for machinery fault detection by acoustic recognition in this paper.

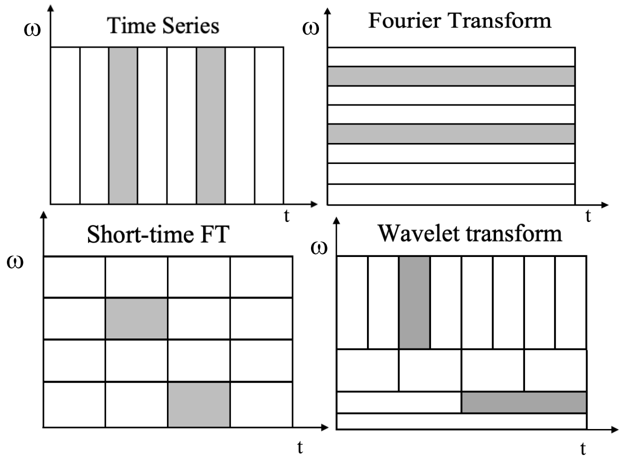

Fig. 3 Time and frequency resolution of transforms

C. Evaluation metrics

In machine learning, accuracy metric represents the general measure of how well the model performs prediction task on the whole dataset. However, it does not work well in case of imbalanced dataset, in which a class outnumbers the other classes. Therefore, the assessment for models based on accuracy seems to be helpless, since by simply predicting all elements as the highest weighted class, the model could achieve high accuracy. Due to this reason, another metric was introduced to provide a predictive performance of trained model independent of class distribution called Area Under Curve of Receiver Operating Characteristic (AUC-ROC) [15]. This metric is suitable for the Hitachi's dataset, and for benchmarking purpose.

IV. EXPERIMENT

A. Workflow

The whole workflow of the experiment is presented as the Fig. 4. The audio data is initially normalized to constrain the amplitude value within range [0, 1] before being transformed using STFT and WT respectively. This step is presented details in the next section. Following, the matrices produced at output after STFT and WT are used to create spectrogram and scalogram. They are then plotted as images, split into training set and validation set. The training set is fed into a CNNs to train the model, the validation set is used for evaluation of the trained model. The performance of trained CNNs model for two types of data is compared.

Since the target of this paper is to evaluate the performance of spectrogram and scalogram on CNNs model, all parts of the experiment, except for generation of spectrogram and scalogram, are kept same for both transform types, including normalization technique, configuration of plotted images, configuration of CNNs model. These settings are designed arbitrarily as long as the trained CNNs model achieves a relative good performance.

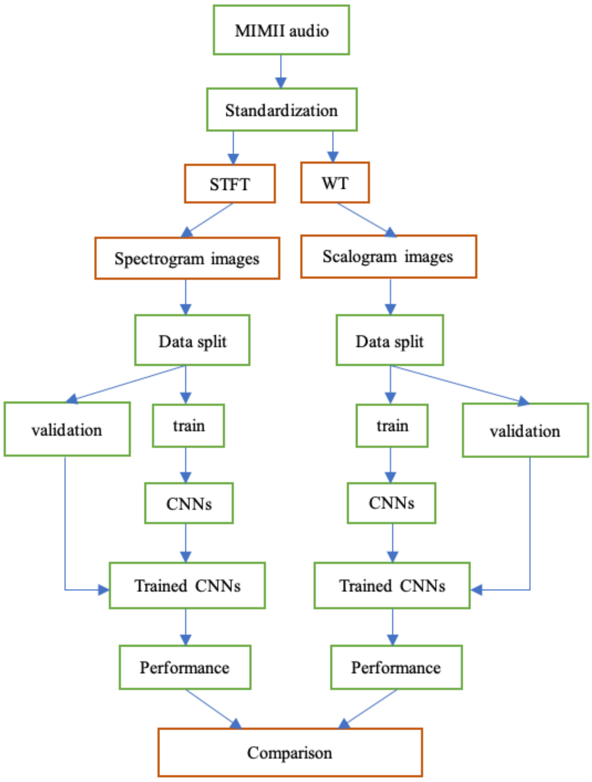

Fig. 4 Experiment workflow

B. *Audio normalization*

$$y_n = \frac{y_n}{|y_{max}|} \tag{6}$$

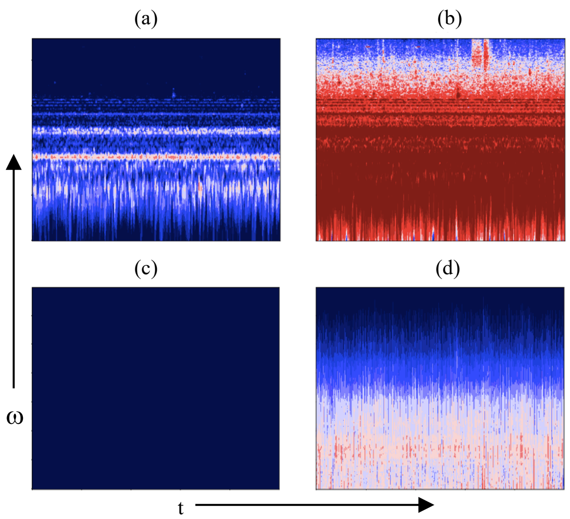

Fig. 5 Effect of normalization technique

In acoustical fault detection for machines in factories, the conditions of recording audio data are not always same in reality. Consequently, the amplitude of recorded audio varies from situation to situation for a same type of error, or even in the same situation, if the microphone is moved or vibrated. For example, the amplitude of recorded audio will be higher once the micro is placed nearer, or it is lower once the micro is placed further. To reduce the effect of this variation, in this paper, the audio signals are normalized to constrain the amplitude within the range [0, 1]. It means that the maximum amplitude of signal will be compressed to 1 if it is higher than 1, and will be expanded to 1 if it is lower than 1 as in (6). Maximum value of a signal is calculated as y_{max}, then other sample values are normalized by it. This would shape the structure of audio of same error type into more similar ones, and different error types into more distinctive ones. Indeed, the normalization step really enhanced the visibility of generated spectrogram and scalogram as illustrated in the Fig. 5. On the left as Fig. 5 (a) and (c) where there is no normalization, it is very hard for human eyes to see the heat map of spectrogram and scalogram, respectively. However, on the right side as Fig. 5 (b) and (d), the heat map is visualized much better by normalization technique.

C. *Input audio*

The input audio used for spectrogram and scalogram generation is remained as original audio dataset of Hitachi, which has 10 seconds length, 16 kHz sampling rate. Hence, each single discrete audio contains 160,000 samples.

D. *Implementation for Short-time Fourier transform*

STFT is performed in time-discrete manner. Initially the frame size N, hop size H are considered as hyper parameters for optimizing the performance of the trained model for first numbers of training, then a configuration of STFT with good prediction performance is selected as the table I. The output matrix after STFT has size (513, 313) for 160,000 samples per signal. This configurations is then applied on the whole audio dataset to generate STFT.

TABLE I. CONFIGURATION OF STFT

Frame size	Hop size	Output matrix size	
1024	512	513	313

E. *Implementation for Continuous Wavelet transform*

CWT is also performed in time-discrete manner. The scale would be a range of consecutive natural numbers. Since the scale controls the frequency resolution, a number of different scale would be examined on CNNs model training to find out a scale with good prediction performance as the table II. This scale is then used to generate CWT for the whole audio data.

TABLE II. CONFIGURATION OF CWT

Scale	Output matrix size	
[1, 128]	16,000	128

TABLE III. CONFIGURATION OF CNNS

Layer	Name
1	Rescaling (1/255)
2	Conv2D(16, 3, activation='relu', use_bias=True, bias_initializer='zeros')
3	MaxPooling2D
4	Conv2D(32, 3, activation='relu', use_bias=True, bias_initializer='zeros')
5	MaxPooling2D
6	Conv2D(64, 3, activation='relu', use_bias=True, bias_initializer='zeros')
7	MaxPooling2D
8	Flatten
9	Dense(128, activation='relu')
10	Dropout(0.25)
11	Dense(256, activation='relu')
12	Dropout(0.25)
13	Dense(units=2, activation='softmax')

F. *Implementation for Convolution neural networks*

Since the target of the paper is the comparison performance between spectrogram and scalogram, the CNNs model is designed arbitrarily as long as it gets a quite good performance. Few configurations of CNNs are examined, and a good configuration is selected as in the table III.

V. BENCHMARKING AND PERFORMANCE EVALUATION

A. *Benchmark research*

TABLE IV. COMPARISON WITH BENCHMARK METHOD

	Baseline	Spectrogram	Scalogram
Method	Supervised learning		
Metric	AUC ROC		
Normalization	Zero mean, unit standard deviation	$\frac{y_n}{\lvert y_{max} \rvert}$	
Spectral feature	MFCCs+SC+SB+ SR+ZCR+Chroma	Spectrogram	Scalogram
Input of model	output matrix	image	
Oversampling	yes	no	
Model	MLP	CNNs	

TABLE V. COMPARISON OF COMPUTATIONAL EXPENSE

	Single file		
	Spectrogram	**Scalogram**	**Deviation**
Time	0.58	22.38	21.8
	Whole dataset		
Time	10,451.02	392,814.2	392,814.2

The benchmark research [16] uses a number of spectral features for classification, including Chroma, Mel-frequency cepstral coefficients (MFCCs), Spectral Centroid (SC), Spectral Bandwidth (SB), Spectral roll-off (SR), Zero Crossing Rate (ZCR). However, the output of the transformation is not compressed as an image. Instead, the model uses directly the tuples containing spectral features. Before feeding into model for training, the abnormal sound is oversampled to get a balanced dataset. There are various algorithms used in this research, but only the Multilayer Perceptron (MLP) achieves the best performance, hence, its result is considered for benchmarking. The metric AUC is used as metric for performance evaluation. The tuples are normalized to zero mean and unit standard deviation before feeding into model for training and evaluation. MLP used in this research is a class of feedforward artificial neural network with three hidden layers. The detail comparison is presented as in the table IV.

TABLE VI. PERFORMANCE BENCHMARKING

	baseline	scalogram	spectrogram
-6 dB	0.893	0.9213	0.981
0 dB	0.9425	0.964	0.992
6 dB	0.9758	0.9885	0.997

TABLE VII. PERFORMANCE OMPARISON BETWEEN TWO TRANSFORMS

	scalogram	spectrogram
fan	0.9343	0.9883
pump	0.9623	0.9917
slider	0.9473	0.9957
valve	0.9877	0.9843

B. *Performance evaluation*

1) *Computational expense*

Since the calculation of STFT and WT are different, resulting output matrices are also different in size, a comparison for computational expense is necessarily considered. For the sake of simplicity, it is done by measuring the amount of time (in second) that is used for generation of spectrogram and scalogram by the hardware in this paper. As can be seen in the table V, scalogram has computational expense much more than spectrogram. The deviation for generation of a single file is 21.8 seconds, and for the whole dataset with 18019 audio files is 392,814.2 seconds. Generation of scalogram for whole dataset costs about 109 hours while just only about 2.9 hours for spectrogram. This huge deviation is obvious, since CWT computes for every single sample in 160,000 sample, whereas STFT computes only for every hop size samples.

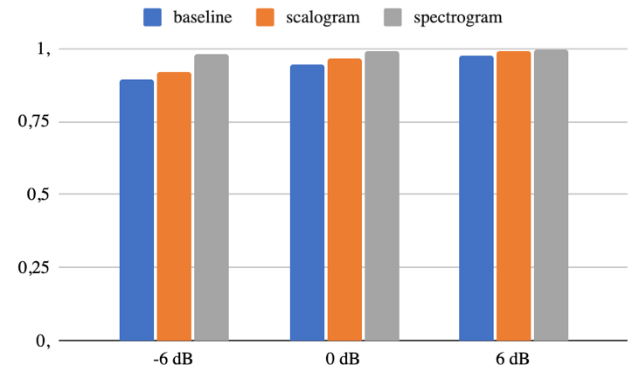

Fig. 6 Performance benchmarking

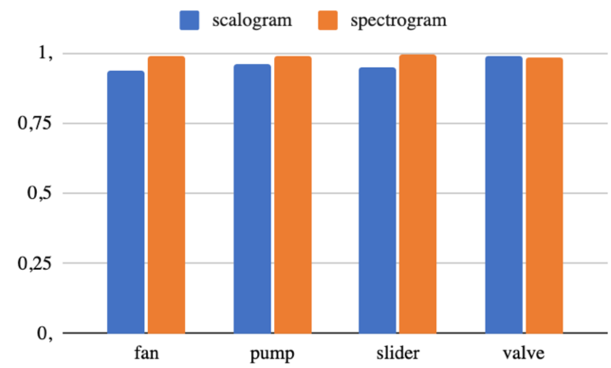

Fig. 7 Performance comparison between two transforms

2) *Model prediction performance*

The performance of CNNs model applying on spectrogram and scalogram is computed by averaging over 10 runs of training and evaluation. The results for benchmarking is shown in the table VI, and being illustrated by the chart in the Fig. 6. As being visualized, the averaged performance of model prediction increases consistently with the increase of SNR for both spectrogram and scalogram as well as the baseline. This covariation between SNR and performance is obvious, since improvement of SNR would make the sound of normal or abnormal machine clearer, meaning more distinguishing. Hence, the models can easily classify these two types of sound correctly. For benchmarking, the design of spectrogram and scalogram in this project always outperforms the benchmark research throughout 3 SNR levels. This shows that the design of spectrogram and scalogram have achieved a relative good performance.

For the comparison between spectrogram and scalogram in each machine type, the result showes in the table VII and being visualized in the Fig. 7. The spectrogram always performs better then the scalogram. There is just one case of valve where the CNNs predict audio base on scalogram better than audio base on spectrogram. This is caused by the fact that audio signal of valve is non-stationary [3], which is impulsive and sparse in time. And the WT producing scalogram with multiresolution feature could enhance the feature extraction for non-stationary signals [8]. In opposite direction while looking at performance on audio of fan, the spectrogram achieves much higher performance than scalogram. The possible reason is that the sound of fan is stationary [3] where constant time and frequency resolution of spectrogram could extract the feature much better than scalogram.

VI. Conclusion and future work

A. Conclusion

In this paper, comparison of two approaches for acoustic recognition are implemented by presenting knowledge of two types of audio extractor spectrogram and scalogram, as well as comparing their design. The classification task for normal and abnormal sound is done successfully by employing CNNs. With arbitrary design of CNNs, configuration of spectrogram and scalogram have shown a good performance when it always outperforms the benchmark method. The paper actually achieved the main purpose by providing a quite tight comparison between spectrogram and scalogram, in term of their attributes, configuration of each transform, and the model performance evaluation. In general, the design of STFT in this paper almost performs better than design of WT, except for audio of valve which is non-stationary. For stationary audio of fan, STFT perform much better than WT.

B. Future work

As being analyzed when designing configuration for STFT and WT, the output of matrices for these two transform are different in size. This is caused by the computation of CWT requiring for every single sample data, whereas computation of SFTT requires every each hop size samples. Consequently, the comparison may not be as tight enough. This limitation would be a potential topic in future when the translation parameter and the scale of WT are tuned in a way that can produces output matrix having same size as STFT. By doing so, the computational expense of them would be more similar, and the comparison is tighter. In addition, the current Pywavelets library is only able for tuning the scale, but not for the translation parameter. Hence, development of a library for CWT with a tunable translation parameter is a potential direction in reduction of computational expense, and making STFT and WT more comparable.

The experiment of this paper uses the normalization technique, which constrains the signal amplitude to 1, seems to be a beneficial step for applying on the audio signals before performing STFT and WT. In addition, other common normalization techniques, such as moving the mean to zero and deviation to one, have not been tested to check which normalization technique is better. Therefore, experiment different normalization techniques to compare their robustness, or application of each normalization technique for different datasets to see test its generality, would be a promising topic.

Finally, in the discussion part of the performance comparison, the scalogram performs better than spectrogram when audio signal is non-stationary thanks to its multiresolution, and in the other way round, the spectrogram has better prediction when the audio signal is stationary due to its linear resolution. Hence, future research about how the stationary level of signals impacts on the performance of spectrogram and scalogram would be interesting. The task may be a derivation of a function representing the dependence of CNNs model performance on the stationary degree of signal, as the SNR plays its role on the performance of CNNs model in this paper.

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