Audiogmenter: a MATLAB Toolbox for Audio Data Augmentation

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Abstract

Audio data augmentation is a key step in training deep neural networks for solving audio classification tasks. In this paper, we introduce Audiogmenter, a novel audio data augmentation library in MATLAB. We provide 15 different augmentation algorithms for raw audio data and 8 for spectrograms. We efficiently implemented several augmentation techniques whose usefulness has been extensively proved in the literature. To the best of our knowledge, this is the largest MATLAB audio data augmentation library freely available. We validate the efficiency of our algorithms evaluating them on the ESC-50 dataset. The toolbox and its documentation can be downloaded at https://github.com/LorisNanni/Audiogmenter.

Keywords

Audio augmentation; Data augmentation; Audio classification; Spectrogram; Convolutional neural network.

1. Introduction

Deep neural networks achieved state of the art performances in many artificial intelligence fields, like image classification [1], object detection [2] and audio classification [3]. However, they usually need a very large amount of labelled data to obtain good results and these data might not be available due to high labelling costs or due to the scarcity of the samples. Data augmentation is a powerful tool to improve the performance of neural networks. It consists in modifying the original samples to create new ones, without changing their labels [4]. This leads to a much larger training set and, hence, to better results. Since data augmentation is a standard technique that is used in most papers, a user-friendly library containing efficient implementations of these algorithms would be very helpful to researchers.

In this paper we introduce Audiogmenter, a MATLAB toolbox for audio data augmentation. In the field of audio classification and speech recognition, to the best of our knowledge, this is the first library specifically designed for audio data augmentation. Audio data augmentation techniques fall into two different categories, depending on whether they are directly applied to the audio signal [5] or to a spectrogram generated from the audio signal [6]. We propose 15 algorithms to augment raw audio data and 8 methods to augment spectrogram data. We also provide the functions to map raw audios into spectrograms. The augmentation techniques range from very standard techniques, like pitch shift or time delay, to more recent and very effective tools like frequency masking. The library is available at https://github.com/LorisNanni/Audiogmenter. The main contribution of this

paper is to share a set of powerful data augmentation tools for researchers in the field of audiorelated artificial intelligence tasks.

The rest of the paper is organized as follows: Section 2 describes the specific problem background and our strategy for audio data augmentation; Section 3 details the implementation of the toolbox; Section 4 provides one illustrative example; Section 5 contains experimental results; in Section 6 conclusions are drawn.

2. Related Work

To the best of our knowledge, Audiogmenter is the first MATLAB library specifically designed for audio data augmentation. Such libraries exist in other languages like Python. A well-known Python audio library is Librosa [7]. The aim of Librosa was to create a set of tools to mine audio databases, but the result was a large library useful in all audio fields. Another Python library is Musical Data Augmentation (MUDA) [8], which is specifically designed for audio data augmentation.

Many audio toolboxes are also available in MATLAB. A famous library is the TSM toolbox. It contains the MATLAB implementations of many time-scale modification (TSM) algorithms [9,10]. We use four of those toolboxes as building blocks of ours. These are the Large Time Frequencies Analysis Toolbox (LTFAT) [11],the Phase Vocoder toolbox (www.ee.columbia.edu/~dpwe/resources/matlab/pvoc/), the Auditory Toolbox [12] and the Audio Degradation Toolbox [13]. These libraries do not perform any data augmentation except for the Audio Degradation Toolbox. This library was initially designed to test the robustness of audio models against perturbations of the original audio signal. Its functions created new samples as if they were recorded with different devices or in different places. However, many of these functions can also be used as data augmentation algorithms.

Recently, the 2019b version of MATLAB included a built-in audio data augmenter for training neural networks. It contains very basic functions which have the advantage of being computed on every mini-batch during training, hence they do not use a large quantity of memory.

3. Background and strategy

On first approximation, an audio sample can be represented as an *M* by *N* matrix, where *M* is the number of samples acquired at a specific frame rate (e.g. 44100 Hz), and *N* is the number of channels (e.g. one for mono and more for stereo samples). Classical methods for audio classification consisted in extracting acoustic features, e.g. Linear Prediction Cepstral Coefficient or Mel-Frequency Cepstral Coefficients, to build feature vectors used for training Support Vector Machines or Hidden Markov Models [14]. Nevertheless, with the diffusion of deep learning and the growing availability of powerful Graphic Processing Units (GPUs) the attention moved towards the visual representations of audio signals. They can be mapped into spectrograms, i.e. graphical representations of sounds as functions of time and frequency, and then classified using Convolutional Neural Networks (CNN) [15]. Unfortunately, several audio datasets (especially in the field of animal sound classification) are limited, e.g. CAT sound dataset (2965 samples in 10 classes) [16], BIRD sound dataset (2762 samples in 11 classes) [17], marine animal sound dataset

(1700 samples in 32 classes) [18], etc. Neural networks are prone to overfitting, hence data augmentation can strongly improve their performance.

Among the techniques used in the literature to augment raw audio signals, pitch shift, noise addition, volume gain, time stretch, time shift and dynamic range compression are the most common. Moreover, the Audio Degradation Toolbox provides further techniques such as clipping, harmonic distortion, pass filters, MP3 compression and wow resampling [13]. Furthermore, Sprengel et al. [5] showed the efficacy of augmentation by summing two different audio signals from the same class into a new signal. For example, if two samples contain tweets from the same bird species, their sum will generate a third signal still belonging to the same tweet class. Not only the raw audio signals, but also their spectrograms can be augmented using standard techniques [6], e.g. time shift, pitch shift, noise addition, Vocal Track Length Normalization (VTLN) [19], Equalized Mixture Data Augmentation (EMDA) [20], Frequency Masking [21] and Thin-Plane-Spline Warping (TPSW) [22].

Given an audio dataset X with M classes and variable number of samples per class $X = \{x_{1,1}, ... x_{n_1,1}, x_{1,2}, ... x_{n_2,2}, ..., x_{1,M}, ... x_{n_M,M}\}$, where $x_{i,j}$ represents a generic audio sample i from the class j, we propose to augment $x_{i,j}$ with techniques working on raw audio signals and to augment the spectrogram $S(x_{i,j})$ produced by the same raw audio signals.

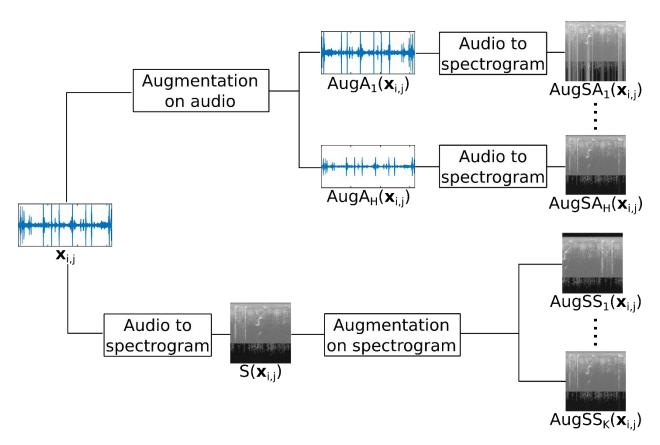


Figure 1. Augmentation strategy implemented in Audiogmenter. The upper branch shows how, from the original i-th audio sample $x_{i,j}$ from the class j, we obtain H augmented audio samples $AugA_h(x_{i,j})$ to be converted into the augmented "Spectrograms from Audio" $AugSA_h(x_{i,j})$.

The lower branch shows how K augmented "Spectrograms from Spectrogram" $AugSS_k(x_{i,j})$ can be obtained from the spectrogram of the original audio sample $S(x_{i,j})$.

In our tool we used the function sgram included in the Large Time-Frequency Analysis Toolbox (LTFAT) [11], to convert raw audios into spectrograms.

Figure 1 depicts our strategy; from the original audio sample $x_{i,j}$ we obtain H intermediate augmented audio samples $AugA_h(x_{i,j})$ that are then converted into the "Spectrograms from Audio" $AugSA_h(x_{i,j})$; from the original spectrogram $S(x_{i,j})$ we obtain K augmented "Spectrograms from Spectrogram" $AugSS_k(x_{i,j})$. The H+K augmented spectrograms can then be used to train a CNN. In case of limited memory availability, one CNN can be trained with the H AugSA spectrograms, another with the K AugSS spectrograms and finally the scores can be combined by a fusion rule.

4. Toolbox structure and software Implementation

Audiogmenter is implemented as a MATLAB toolbox, using MATLAB 2019b. We also provide an online help as documentation (in the ./docs/ folder) that can be integrated into the MATLAB Help Browser just by adding the toolbox main folder to the MATLAB path.

The functions for the augmentation techniques working on raw audio samples are included in the folder ./tools/audio/. In addition to our implementations of methods such as applyDynamicRangeCompressor.m and applyPitchShift.m, we also included four toolboxes, namely the Audio Degradation Toolbox by Mauch et al. [13], LTFAT [11], the Phase Vocoder from www.ee.columbia.edu/~dpwe/resources/matlab/pvoc/ and the Auditory Toolbox [12].

The functions for the augmentation methods working on spectrograms are grouped in the folder ./tools/images/. In addition to our implementations of methods such as noiseS.m, spectrogramShift.m, spectrogramEMDA.m, etc., we included and exploited also a modified version of the code of TPSW [22].

Every augmentation method is contained in a different function. In ./tools/, we also included the wrappers CreateDataAUGFromAudio.m and CreateDataAUGFromImage.m, using our augmentation techniques, respectively, from raw audio and spectrograms with standard parameters.

The functions for raw audio augmentation are the following:

1. *applyWowResampling* [13] is similar to pitch shift but the intensity changes along time. The signal *x* is mapped into:

$$F(x) = x + a_m \frac{\sin(2\pi f_m x)}{2\pi f_m}$$

where x is the input signal, and a_m , f_m are parameters.

- 2. addNoise adds white noise to the input signal.
- 3. applyClipping normalizes the audio signal leaving a percentage X of the signal outside the interval [-1, 1]. Those parts of the signal are then mapped to sign(x).
- 4. applySpeedUp modifie the speed of the signal by a given percentage.
- 5. *HarmonicDistortion* [13] applies the sine function to the signal multiple times.
- 6. applyGain increases the gain of the input signal.

- 7. applyRandTimeShift randomly takes a signal x(t) as input, where $0 \le t \le T$. Then a random time t^* is sampled and the new signal is $y(t) = x(mod(t + t^*, T))$. In words, the first and the second part of the file are randomly switched.
- 8. *applySoundMix* [23] sums two audio signals from the same class.
- 9. *applyDynamicRangeCompressor* applies, as its name says, Dynamic Range Compression [24]. This algorithm modifies the frequencies of the input signal. We refer to the original paper for a detailed description.
- 10. *appltPitchShift* increase or decrease the frequencies of an audio file. This is one of the most common augmentation techniques.
- 11. *applyAliasing* resamples the audio signal with a different frequency. It violates on purpose the Nyquist-Shannon sampling theorem [25] to degradate the audio signal.
- 12. applyDelay adds a sequence of zeros at the beginning of the signal.
- 13. applyLowpassFilter attenuates the frequencies above a given threshold f_1 and blocks all the frequencies above a given threshold f_2 .
- 14. applyHighpassFilter attenuates the frequencies below a given threshold f_1 and blocks all the frequencies below a given threshold f_2 .
- 15. *applyInpulseResponse* [13] modifies the audio signal as if it was produced by a particular source. For example, it simulates the distortion given by the sound system of a smartphone or it simulates the echo and the background noise of a great hall.

The functions for spectrogram augmentation are:

- 1. applySpectrogramRandomShifts applies pitch ad time shift.
- 2. applySpectrogramSameClassSum [23] sums the spectrograms of two images with the same label.
- 3. *applyVTLN* creates a new image by applying Vocal Tract Length Normalization (VTLN) [19]. For a more detailed description of the algorithm we refer to the original paper.
- 4. spectrogramEMDAaugmenter applies Equalized Mixture Data Augmentation (EMDA) [20]. This function computes the weighted average of two randomly selected spectrograms belonging to the same class. It also applies a random time delay to one spectrogram and a perturbation to both spectrograms, according to the formula

$$s_{aug}(t) = \alpha \Phi(s_1(t), \psi_1) + (1-\alpha) \Phi(s_2(t-\beta T), \psi_2)$$

where α , β are two random numbers in [0,1], T is the maximum time shift and Φ is an equalizer function. We refer to the original paper for a more detailed description.

- 5. *applySpecRandTimeShift* does the same as *applyRandTimeShift*, but it works for spectrograms.
- 6. randomImageWarp applies Thin-Spline Image Warping [22] (TPS-Warp) to the spectrogram, on the horizontal axis. TPS-Warp consists in the linear interpolation of the points of the original image. In practice, it is a speed up where the change in speed is not constant and has average 1. This function is much slower than the others.
- 7. *applyFrequencyMasking* sets to a constant parameter the value of a some rows and some columns of the spectrogram. The effect is that it masks the real value of the input for randomly chosen times and frequencies. It was proposed in [3].

8. *applyNoiseS* adds noise to the spectrograms by multiplying the value of a given percentage of the pixels by a random number whose average is one and whose variance is a parameter.

5. Illustrative Examples

In the folder ./examples/ we included testAugmentation.m that exploits the two wrappers detailed in the previous Section to augment six audio samples and their spectrograms, and plotTestAugmentation.m that shows the results from the previous function. The augmented spectrograms can be seen in Figures 2 and 3.

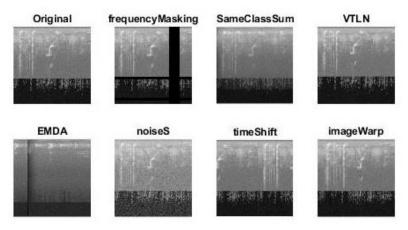


Figure 2. Spectrogram Augmentation. The top left corner shows the spectrogram from the original audio sample. Seven techniques were used to augment the original spectrogram.

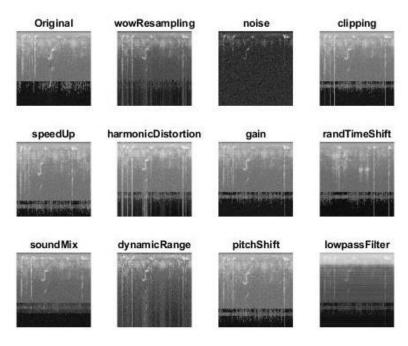


Figure 3. Audio Augmentation. The top left corner shows the spectrogram of the original audio sample. We used 11 audio augmentation methods and extracted the spectrograms.

In addition, we provide six audio samples from www.xeno-canto.org (original samples ./examples/OriginalAudioFiles/ listed table and as MATLAB in in ./examples/SmallInputDatasets/inputAugmentationFromAudio.mat) and six spectrograms samples generated sgram.m from the aforementioned audio (in ./examples/SmallInputDatasets/inputAugmentationFromSpectrograms.mat). The precomputed results for all the six audio samples and spectrograms are provided in folder ./examples/AugmentedImages/.

6. Experimental Results

The ESC-50 dataset [26] contain 2000 audio samples evenly divided in 50 classes. These classes are, for example, animal sounds, crying babies and chainsaws. The evaluation protocol proposed by their creators is a five fold cross-validation and the human classification accuracy on this dataset is 81.3%.

We ran three different experiments:

- 1. The first pipeline is our baseline. We transformed every audio signal into an image representing a Gabor spectrogram. After that we fine-tuned a pre-trained version of AlexNet [27] on the training set of every fold and we evaluated it on their corresponding test set. We trained it with a mini batch of size 64 for 60 epochs. The learning rate was 0.0001, while the learning of last layer was 0.001. The classification accuracy of this protocol is 62.7%.
- 2. The second pipeline is the augmentation of the raw audio files. It works in the same way as the baseline protocol, with the difference that every training set is 10 times larger due to data augmentation. We included in the new training set the original samples and 9 modified versions of the same samples obtained by applying (i) gain, (ii) pitch shift, (iii) time shift and (iv) speed up. Each one of these functions have random parameters, hence every sample is different. Due to a larger training set, we only used 14 epochs for the training. The classification accuracy of this protocol is 67.7%.
- 3. The third protocol consists in transforming the raw audios in spectrograms and then augmenting the training set. The functions used in this augmentation pipeline are (i) pitch shift, (ii) time shift, (iii) frequency masking and (iv) noise addition. We again created 9 new samples for each original one and used 14 epochs for the training. This protocol yields a 64.05% classification accuracy.

These results show the efficiency of our algorithms, especially when compared to other similar approaches [28,29] that use CNNs with speed up augmentation to classify spectrograms. [28] is a baseline CNN proposed by the creators of the dataset, while in [29] the authors train AlexNet as we do. In both cases, only speed up is used as data augmentation. We outperform both approaches, since they respectively reach 64.5% and 63.2% accuracy. Other networks specifically designed for these problems reach a 86.5%, although using also unlabeled data for training [19]. However, the purpose of these experiments was to prove the validity of the algorithms and the consistency with previous similar approaches. It was not reaching the state of the art performance on ESC-50. The code to replicate our experiments can be found in the folder ./demos/.

7. Conclusions

In this paper we proposed Audiogmenter, a novel MATLAB audio data augmentation library. We provide 23 different augmentation methods that work on raw audio signal and their spectrograms. To the best of our knowledge, this is the largest audio data augmentation library in MATLAB. We described the structure of the toolbox and provided examples of its application. We proved the validity of our algorithm by training a convolutional network on a competitive audio dataset using our data augmentation algorithms and obtained results which are consistent with similar approaches in the literature. The library and its documentation are freely available at https://github.com/LorisNanni/Audiogmenter.

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B1 Current code version

Ancillary data of the codebase is provided in Table 1.

Table 1 – Code metadata

Nr	Code metadata description	
C1	Current Code version	vI
C2	Permanent link to code / repository used of this code version	https://github.com/LorisNanni/Audiogmenter
C3	Legal Code License	List one of the approved licenses
C4	Code Versioning system used	none
C5	Software Code Language used	Matlab
C6	Compilation requirements, Operating environments & dependencies	at least Matlab2019b
C7	If available Link to developer documentation / manual	documentation is included in the tool. To integrate it in the Matlab Help Brower, add the tool folder to the Matlab path.
C8	Support email for questions	loris.nanni@unipd.it