AMA: An Open-source Amplitude Modulation Analysis Toolkit for Signal Processing Applications

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***Abstract*—For their analysis with conventional signal processing tools, non-stationary signals are assumed to be stationary (or at least wide-sense stationary) in short intervals. While this approach allows them to be studied, it disregards the temporal evolution of their statistics. As such, to analyze this type of signals, it is desirable to use a representation that registers and characterizes the temporal changes in the frequency content of the signals, as these changes may occur in single or multiple periodic ways. Over the last few years, the amplitude modulation approach has shown useful for the analysis and synthesis of non-stationary signals across multiple applications, including telecommunications, speech and music perception, and biological signals (e.g., electrocardiogram, electroencephalogram and respiration). Despite their usefulness, no open-source toolkits exist that are application agnostic. In this work, we fill this gap. More specifically, we present AMA, the open-source Amplitude Modulation Analysis toolkit for MATLAB, Octave and Python. The toolkit provides functions to compute forward and inverse transformations between time, frequency, time-frequency and frequency-modulation-frequency domains for single- or multi-channel signals. Additionally, a graphical user interface is provided for real-time exploration of the signals and their representations across different domains. Lastly, example data and scripts are provided. With the development of this toolkit, we hope to facilitate the study of non-stationary signals in particular for the analysis of second-order periodicities. The toolkit is available at https://github.com/MuSAELab.**

***Index Terms*—Amplitude modulation, cyclostationarity, modulation spectrogram, spectrotemporal, wavelets.**

I. INTRODUCTION

Typically, signal processing techniques and methods assume (and require) the signals to be stationary. However, stationarity is a strict assumption rarely present in naturally occurring signals. As such, for practical purposes, signals are assumed stationary if they fulfill a softer stationarity definition named "wide-sense stationarity", which requires a constant mean and an autocorrelation function dependent only on the time difference. For a zero-mean signal, the equivalent of these conditions in the frequency domain is that of a time-invariant spectrum [1]. In practice, for the analysis of non-stationary signals with conventional signal processing tools, these signals are segmented into shorter time intervals where they are considered as stationary. For example, speech signals are assumed stationary in segments between 20-50 ms; spontaneous electroencephalography (EEG) signals, in turn, are considered stationary for segments as long as 20 s. Therefore, in order to analyze non-stationary signals, it is necessary to have a representation that is capable of registering the changes in frequency content over time, i.e., a spectrotemporal representation. An interesting property of many natural non-stationary signals is that the changes over time in their spectral content often occur in single or multiple periodic ways, resulting in cyclostationarity [2], [3]. In this sense, a non-stationary signal can be modeled as the result of the interaction of two independent signals, a low-frequency signal that changes (i.e., modulates) the properties (such as amplitude, phase and/or frequency) of a higher-frequency signal. This interaction is the well known non-linear process of modulation. Given the simplicity of its formulation, amplitude modulation (AM) modeling is often used and it has been shown to be an important tool for the analysis and synthesis of non-stationary processes in diverse fields such telecommunications [2], speech and music perception [4], as well in the study of biological signals, such as the electrocardiogram [5], [6], electroencephalogram [7] and respiration [3], [8].

Despite their usefulness, open-source AM toolkits are not readily available for research purposes. The modulation toolbox from the University of Washington, for example, has been developed and tailored for speech applications [9], thus limiting its usage in other domains. To overcome this limitation, we developed the Amplitude Modulation Analysis toolkit (AMA toolkit). The AMA toolkit is generic in the sense that it is not tailored to any specific application. It provides functions to compute and visualize the transformations of temporal, real-valued signals into frequency, time-frequency, and modulation domain representations. Moreover, the toolkit provides a graphical user interface (GUI) for the interactive exploration of the signals by allowing the user to change the parameters of the analysis in real-time, as well as the segment durations and number of channel under analysis. Additionally, examples on how to use the toolkit and data examples are provided. The source code and examples are provided under the MIT licence. The AMA toolkit is available at https://github.com/MuSAELab, where two implementations are provided: MATLAB/Octave and Python3.

The remainder of this paper is organized as follows. In Section II, a brief overview on the time-frequency domain representation of real-valued signals is presented, followed by the description of the amplitude modulation representation. In Section III, the functions and characteristics of the AMA toolkit are presented. Section IV presents examples and use cases. Finally, conclusions are drawn in Section V.

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II. METHODS

One of the most powerful tools for signal processing is the transformation between time and frequency domains, as the representations are complementary. Among the different methods of transforming signals from one domain to another, the most utilized is the Fourier transform (FT) and its inverse (IFT) counterpart [10]. The FT can also be regarded as a spectral analysis process that allows a time signal to be represented in terms of its frequency components, namely amplitude and phase. Under this approach, the IFT can be observed as a synthesis process where the frequency components are summed into a time signal. In the analysis of finite signals, the duration of the signal is inversely proportional to the minimum differentiable frequency value, or frequency resolution [11]. The FT and IFT are mathematically defined as:

$$X(f) = \mathcal{F}\{x(t)\} = \int_{-\infty}^{\infty} x(t)e^{-j2\pi ft}dt, \tag{1}$$

$$x(t) = \mathcal{F}^{-1}\{X(f)\} = \int_{-\infty}^{\infty} X(f)e^{j2\pi ft}df\ , \tag{2}$$

where $\mathcal{F}\{\cdot\}$ and $\mathcal{F}^{-1}\{\cdot\}$ are the FT and IFT operators, respectively, $x(t)$ is a signal in the time domain and $X(f)$ is a complex-valued function called spectrum or Fourier transform of $x(t)$.

For non-stationary signals, while the FT characterizes the spectral components of the signal, it does not provide information on their temporal changes. As such, a spectrotemporal representation is required. This spectrotemporal representation is usually obtained by splitting the non-stationary signal in short segments (where the signal can be consider stationary), and performing a time-to-frequency transformation for each segment. As the signal is now analyzed in shorter segments, the temporal resolution is better, i.e., it is possible to localize in time the changes in the spectral content; however, the frequency resolution worsens. This relationship between the time and frequency resolutions is known as the Gabor uncertainty principle [12]. Common non-parametric methods used to compute the spectrotemporal representation are the short-time Fourier transform (SFTF), continuous wavelet transform (CWT), and the use of filterbanks together with the Hilbert transform (HT). The spectrotemporal representation $X(t, f)$ obtained with these three methods can be regarded as the result of the convolution between the time signal $x(t)$ and a tapered complex oscillatory function $e^{j2\pi ft}$. As such they can be written in a general manner as:

$$X(t, f) = x(t) \star \lambda_f(t)e^{j2\pi ft}, \tag{3}$$

where $\lambda_f(t)$ is a real-valued time window function (low-pass filter), which can be different for different values of f. As a consequence, the product $\lambda_f(t)e^{j2\pi ft}$ can be seen as a filterbank. The main difference among the STFT, CWT and HT approaches lies in how the window $\lambda_f(t)$ is defined, and as a consequence, how the time and frequency uncertainties are handled. The detailed formulation and comparison of the SFTF, CWT and HT methods is presented in [11].

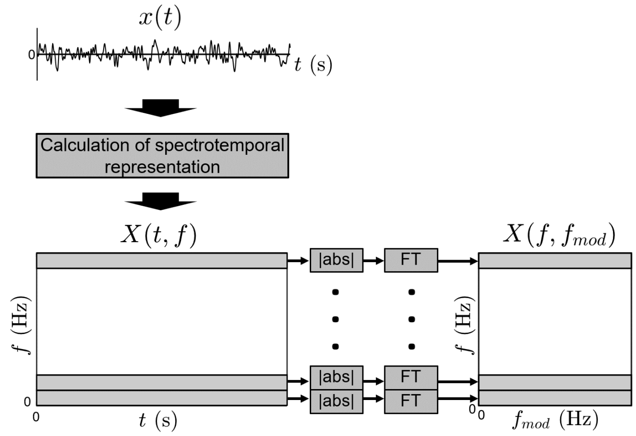

Fig. 1. Signal processing steps for the modulation spectrogram calculation.

The spectrogram $X(t, f)$ describes the temporal behaviour of the spectral components that conform the non-stationary signal, however it does not characterize their periodic behaviour. For any given frequency component f_0, its amplitude changes over time are given as $|X(t, f_0)|$. In this sense, it is possible to characterize the periodic changes in amplitude for each frequency component in $|X(t, f)|$ by calculating their spectra. The result of this process is the modulation spectrogram, which is a 2-dimensional representation of the conventional frequency components versus their modulation spectra, i.e.:

$$X(f, f_{mod}) = \mathcal{F}_t\{|X(t, f)|\}\,. \tag{4}$$

In summary, the modulation spectrogram or modulation-domain representation of a time signal is obtained by performing two transformations: (1) a time to time-frequency transformation is performed over $x(t)$ to obtain its spectrogram $X(t, f)$, and (2) a time to frequency transformation is performed over the amplitude time-series for all the frequency components of $|X(t, f)|$ [11], [13]. Figure 1 depicts the signal processing steps to compute the modulation spectrogram.

If the two transformations required to compute the modulation spectrogram are invertible, the time-domain signal $x(t)$ can be recovered (synthesized) from the spectrogram $X(t, f)$, and from its modulation spectrogram $X(f, f_{mod})$. This is particularly useful as it allows for filtering to be performed in the spectrotemporal and modulation domains where the signal and noise components can become separable [11], [13].

III. TOOLBOX DESCRIPTION

The AMA toolkit provides the functions to compute forward and inverse transformations between time, frequency, time-frequency, and frequency-modulation-frequency domains for single- or multi-channel real-valued signals. The time<–>frequency transformations are performed by the fast Fourier transform (FFT) and inverse FFT (iFFT) and windowing. Only the positive part of the spectrum is stored, as the negative frequency elements can be recovered as the complex

TABLE I
LIST OF FUNCTIONS INCLUDED IN THE AMA TOOLKIT AND THEIR DESCRIPTION.

Time <——> Frequency
rfft()
FFT of a real-valued signal
irfft()
Inverse FFT of real-valued signal
rfft_psd()
FFT-based PSD
irfft_psd()
Inverse of FFT-based PSD
Time <——> Time-frequency
strfft_ spectrogram()
STFFT-based spectrogram
wavelet_ spectrogram()
CWT-based spectrogram
istrfft_ spectrogram()
Inverse of STFFT-based spectrogram
iwavelet_ spectrogram()
Inverse of CWT-based spectrogram
Time <——> Modulation
strfft_modulation_spectrogram()
STFFT-based modulation spectrogram
wavelet_modulation_spectrogram()
CWT-based modulation spectrogram
istrfft_modulation_spectrogram()
Inverse of STFFT-based modulation spectrogram
iwavelet_modulation_spectrogram()
Inverse of CWT-based modulation spectrogram
GUI
explore_stfft_ama_gui()
GUI for the modulation spectrogram based on the STFFT method
explore_wavelet_ama_gui()
GUI for the modulation spectrogram based on the CWT method

conjugated of the components for positive frequencies, when the spectrum is computed for real-valued signals. The time to time-frequency transformation can be performed with two methods: (i) STFT based on the FFT, and (ii) CWT based on the complex Morlet wavelet [14]. The STFT and CWT are invertible, however, with the CWT approach, the quality of the recovered time signals depends on the used wavelet kernels. Finally, the modulation representation is obtained from the spectrotemporal representations by computing a time-to-frequency transform on the amplitude time series of each of the spectral components. As such, there are two versions for the modulation spectrogram, a STFT- and a CWT-based. The provided GUI is an interactive tool for the real-time exploration of signals and their representation in different domains. With this GUI, the user can change the duration and location of the signal under analysis, the parameters used for the computation of the STFT- or CWT-based representations, modify the channel under analysis, and the visualization parameters for the representations. A screenshot of the GUI is shown in the Figure 2. A list of the transformation functions included in the AMA toolkit and their respective description is presented in Table I.

IV. EXAMPLE USAGE OF THE TOOLKIT

Beside the functions and GUI provided, a set of examples is included with the AMA toolkit, alongside short samples of real data, including real and simulated electroencephalogram (EEG), electrocardiogram (ECG), and speech [15]. The provided examples aim to present the capabilities of the toolkit.

TABLE II
LIST OF EXAMPLES INCLUDED IN THE AMA TOOLKIT AND THEIR DESCRIPTION.

Examples
example_01
Shows the use of the GUI for the exploration of ECG and EEG signals
example_02
Shows the use of the transformation and plotting functions
example_03
Compares two different approaches to compute a series of modulation spectrograms for a long duration signals: 1) from segments of the full-signal spectrogram. 2) directly from each segment of the time signal
example_04
Presents the use of the AMA toolkit with audio signals
example_05
Shows the use of the back and forth transformations between different domains
example_msqi
Shows the use of the AMA toolkit to compute the modulation spectrum-based ECG quality index (MSQI)

Lastly, the so-called modulation spectrum-based quality index (MSQI), presented in [6], was implemented using the functions of the AMA toolkit. The MSQI is a blind estimator of ECG signal quality. The MSQI is based on the fact that the ECG signal presents periodic changes on its spectral components (due to the heart rate), while the artifacts do not present these periodic changes. As such, the ECG signal and artifacts are easily distinguishable in the modulation domain. This difference in the modulation domain can be seen in Figure 3, where a clean ECG signal is compared with its noisy version (contaminated with pink noise to have a 0 dB SNR) in time and modulation domains. Table II presents a list of the provided examples and their brief description.

V. CONCLUSION

In this work, we presented the open-source amplitude modulation analysis toolkit for MATLAB, Octave and Python. The toolkit provides the functions to perform forward and inverse transformations between time, frequency, time-frequency, and frequency-modulation-frequency domains for single- or multi-channel real-valued signals. In recent years, the amplitude modulation approach has shown to be a relevant technique for the analysis and synthesis of non-stationary signals, i.e., speech, ECG, EEG, where the conventional spectral analysis has limitations. The AMA toolkit has been developed to be an out-of-the-box solution for researchers to facilitate them the use of the amplitude modulation approach for the study, analysis, synthesis and understanding of signals across a wide range of domains.

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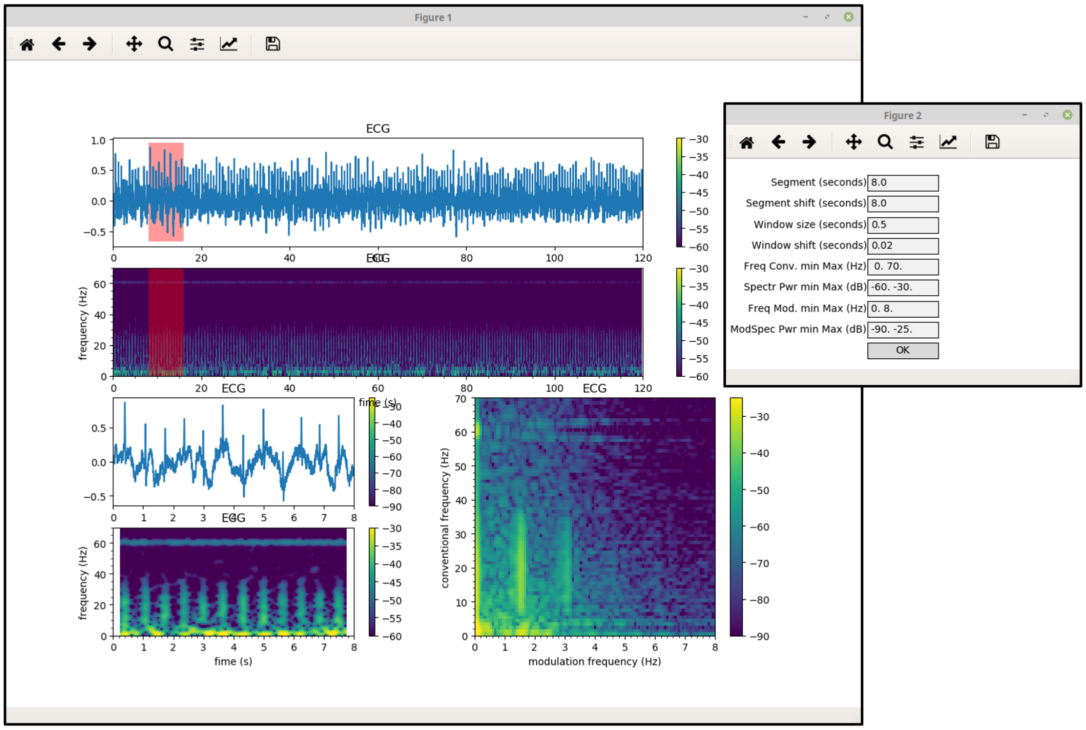

Fig. 2. GUI of the Amplitude Modulation Analysis toolkit.

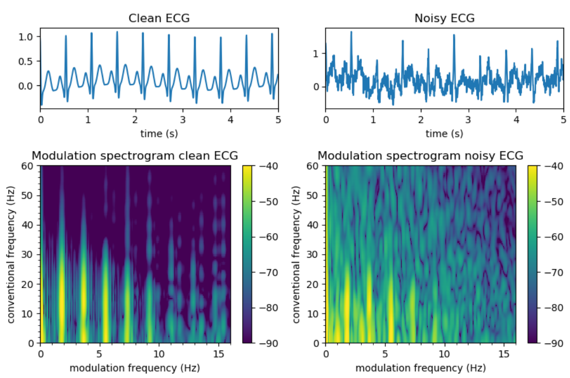

Fig. 3. Time and modulation domain representation of a clean ECG signal and its noisy version, contaminated with pink noise to have a 0 dB SNR. The MSQI values for both signals are 1.2 and 0.3, respectively.

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