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EXTREME AUDIO TIME STRETCHING USING NEURAL SYNTHESIS

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ABSTRACT

A deep neural network solution for time-scale modification (TSM) focused on large stretching factors is proposed, targeting environmental sounds. Traditional TSM artifacts such as transient smearing, loss of presence, and phasiness are heavily accentuated and cause poor audio quality when the TSM factor is four or larger. The weakness of established TSM methods, often based on a phase vocoder structure, lies in the poor description and scaling of the transient and noise components, or nuances, of a sound. Our novel solution combines a sines-transients-noise decomposition with an independent WaveNet synthesizer to provide a better description of the noise component and an improve sound quality for large stretching factors. Results of a subjective listening test against four other TSM algorithms are reported, showing the proposed method to be often superior. The proposed method is stereo compatible and has a wide range of applications related to the slow motion of media content.

Index Terms—Audio systems, deep learning, neural networks, spectral shape, timbre.

1. INTRODUCTION

Time-scale modification (TSM) refers to a change in the duration or the playback speed of a sound that does not affect its spectral characteristics, such as pitch, timbre, and brightness [1][2][4]. If an audio signal is simply played at a different sample rate, the frequency content is deemed to be changed as the formants of the sound are moved. TSM methods are applied to avoid this phenomenon, aiming to preserve or retrieve the original spectral characteristics of the sound.

TSM has been long used in speech, e.g. in audio books and language–learning services [4][5][6], music and remixing [7], broadcasting services [2], and streaming platforms [8]. The ratio between the modified and the original time support is controlled by the TSM factor \( \alpha \), defining time stretching for \( \alpha > 1 \) and time compression for \( \alpha < 1 \). All of the speech TSM applications typically involve small TSM factors (0.25 \( \leq \alpha \leq 4 \)), and do not allow for more extreme time-scaling operations, as state-of-the-art TSM algorithms present poor audio quality at large stretch factors [9][10]. In such cases, the sounds typically present strong phasiness and heavily smeared transients, both known artifacts in phase-vocoder-based TSM implementations [11][9]. There is however an interest for extreme audio time-stretching in applications such as slow motion [12] and ambient sound generation [13][14].

Recent work by Fierro and Väliläinki [15] showed that the quality of a TSM algorithm can be improved by providing a better description of its sines, transient, and noise (STN) components, which can be separated and individually processed according to their classification. The three-way decomposition was originally introduced by Verma and Meng [16], who showed the benefit of extending spectral modeling synthesis [17] with transient sources in the context of audio analysis and synthesis, and adopted by Daudet and Torrésani [18] for audiophonic signal encoding. Fierro and Väliläinki [15] also hinted that the potential weakness of the fuzzy phase vocoder [9], which received the highest overall score both on average and for the largest tested \( \alpha \) in a recent comparison of audio TSM methods [10], lies in the poor description and scaling of the “noisy” component of percussive events, whose smearing is not countered by the phase randomization and that would not benefit from a full preservation as the time support of the time-stretched event would be incorrect.

The introduction of WaveNet, a deep generative model capable of synthesizing raw audio waveforms [19], opened new possibilities for applications related to audio synthesis. The WaveNet synthesizer can be used for TSM by adjusting the number of audio samples generated per frame of the local conditioning signal, similarly to how the hop size between consecutive frames is adjusted from analysis to synthesis in traditional DSP methods. This idea was first proposed by Huang et al. [20], although the TSM performance of such a model was not evaluated as time-stretching was out of its scope.

In this work, we propose a deep learning based method for TSM capable of producing state-of-the-art results for real-world environmental sounds when large TSM factors are used. The proposed solution combines established DSP algorithms and deep learning to produce a hybrid TSM method, whose novelty lies in the neural resynthesis of the noise component, which is separated from sines and transients using the STN decomposition.

The rest of this paper is structured as follows. Sec. 2 summarizes the STN decomposition technique. Sec. 3 describes the proposed WaveNet architecture, used to synthesize the stretched noise component. Sec. 4 details the TSM pipeline. Sec. 5 evaluates the proposed method against four previous techniques, and Sec. 6 concludes.

2. STN DECOMPOSITION

The STN separation method proposed by Fierro and Väliläinki [15] decomposes a sound into three abstract classes: sines (tonal content), transients (impulsive events), and noise (sound nuances). The decomposition is achieved through soft spectral masks that are derived from the signal spectrogram and allow for perfect reconstruction.

To derive the class masks for an audio signal \( x(n) \), median filtering is first applied to its magnitude spectrogram \( |X(m, k)| \) to highlight vertical and horizontal structures [21]:

\[
X_s(m, k) = \text{med} \left[ |X(m, k - \frac{L_v}{2} + 1)|, \ldots, |X(m, k + \frac{L_v}{2})| \right] \quad (1)
\]

\[
X_t(m, k) = |X(m, k)| - X_s(m, k)
\]

\[
X_n(m, k) = |X(m, k)| - X_s(m, k) - X_t(m, k)
\]

further processed with the following median filters:

\[
\text{med} \left[ X_t(m, k - \frac{L_v}{2} + 1), \ldots, X_t(m, k + \frac{L_v}{2}) \right]
\]

\[
\text{med} \left[ X_n(m, k - \frac{L_v}{2} + 1), \ldots, X_n(m, k + \frac{L_v}{2}) \right]
\]
and

\[ X_h(m, k) = \text{med}\left[ |X(m - \frac{L_h}{2} + 1, k)|, \ldots, |X(m + \frac{L_h}{2}, k)| \right], \quad (2) \]

where \( \text{med}[\cdot] \) is the median function, and \( X_c \) and \( X_h \) are the resulting vertically- and horizontally-enhanced magnitude spectrograms, respectively. Parameters \( L_h \) and \( L_c \) are the median filter lengths (in samples) in the time and frequency directions, respectively.

Matrices \( X_h \) and \( X_c \) are then used to extract the tonalness \( R_s \) and transientness \( R_t \) matrices with the following elements [21):

\[ \begin{align*}
R_s(m, k) &= \frac{X_h(m, k)}{X_h(m, k) + X_c(m, k)} \quad (3) \\
R_t(m, k) &= 1 - R_s(m, k) = \frac{X_c(m, k)}{X_h(m, k) + X_c(m, k)}. \quad (4)
\end{align*} \]

respectively. Finally, the soft masks are obtained as follows:

\[ \begin{align*}
S(m, k) &= f \left( R_s(m, k) \right), \quad (5) \\
T(m, k) &= f \left( R_t(m, k) \right), \quad (6) \\
N(m, k) &= 1 - S(m, k) - T(m, k), \quad (7)
\end{align*} \]

where

\[ f(\alpha) = \begin{cases} 
1, & \text{if } \alpha \geq \beta_u \\
\sin^2 \left( \frac{\pi}{2} \frac{\alpha - \beta_l}{\beta_u - \beta_l} \right), & \text{if } \beta_l \leq \alpha < \beta_u \\
0, & \text{otherwise},
\end{cases} \quad (8)\]

which are consequently imposed onto \( X(m, k) \) via element-wise multiplication to obtain the separated components. A group of functions to determine soft STN masks for \( \beta_u = 0.8 \) and \( \beta_l = 0.7 \) is visualized in Fig. 1.

This decomposition process is repeated for two consecutive stages [15]. The first implements a large analysis window for better frequency resolution, separating the sines from the transient and noise residual mixture; the second uses a short analysis window for better temporal resolution, extracting the transients from the residual. An example of two-stage STN decomposition for a violin and castanet sound mixture is shown in Fig. 2.

The STN decomposition enables the application of different TSM algorithms for each component. While traditional signal processing techniques have been optimized to deal with either the sines or the transients, the noise component remains relatively unexplored and hence is suitable for a deep learning approach.

### 3. NOISE TIME STRETCHING VIA WAVENET

This section introduces a WaveNet architecture to synthesize the time-stretched noise component.

#### 3.1. WaveNet synthesizer

WaveNet is an autoregressive generative model capable of synthesizing raw audio waveforms [19]. It was initially proposed for speech synthesis, and the model and variants thereof are still commonly used as part of audio synthesis pipelines. It consists of a stack of dilated 1D-convolutional layers, with the dilation factor increasing exponentially at each layer. The input to the network is also a raw audio waveform, with the model being trained to predict the subsequent sample in the sequence, given the prior audio samples.

Additionally, it is possible for the WaveNet model to incorporate a conditioning signal, allowing control over the audio generated by the model. There are broadly two types of conditioning information: global and local. The first describes features that influence the entirety of the generated audio, e.g., the speaker identity in a speech synthesizer. The latter is used to represent time-variant features of the desired audio waveform, such as spectrograms and other time-frequency representations. In this work, we only consider local conditioning signals.

#### 3.2. WaveNet-based TSM

Time stretching via WaveNet is achieved by adjusting the number of audio samples generated per frame of the local conditioning signal, according to \( \alpha \). For example, if the conditioning signal is the spectrogram extracted from a target audio signal with a hop size of 256 samples, then the re-synthesis for \( \alpha = 2 \) will generate 512 audio samples for each frame of conditioning signal. This is equivalent to applying nearest neighbour interpolation to the conditioning signal.

In the proposed approach, the WaveNet synthesizer is used to re-synthesize the noise component of the target signal, extracted using the two-stage STN decomposition, according to the desired TSM factor \( \alpha \). Three different time-frequency representations were tested.

![Fig. 1: Functions for determining soft spectral masks for STN separation, as described in [15].](image1)

![Fig. 2: STN decomposition of a castanet and violin mixture.](image2)
as local conditioning signals for the network: spectrogram, mel-spectrogram, and Constant-Q Transform (CQT) spectrogram. Different models were trained using each of these representations, and it was found that using the CQT-spectrogram produced the highest quality results. Note that the choice of time-frequency representation is fixed and is part of the model architecture, so it cannot be changed during or after training.

The use of the CQT spectrogram as a conditioning signal for a WaveNet synthesizer was first proposed in [20]. The CQT transform [22] is a time-frequency analysis method in which the frequency bins are logarithmically spaced. Previous work has shown that the CQT is a good choice for synthesis of musical sounds [20], environmental sound classification [23] and general audio inverse problems [24]. In this work, to extract the CQT we use the same parameters as in [20], a 5.8 ms hop size (256 samples at the 44.1-kHz sample rate), a minimum frequency of 32.7 Hz, a maximum frequency of Nyquist (22.05 kHz), and 48 CQT bins per octave. This results in a total of 451 frequency bins.

The network was trained at a sample rate of 44.1 kHz, and a 10-component Mixture-of-Logistic distributions sampling method was used to generate raw 16-bit audio [25]. Training was run for a total of 1,900,000 iterations, and took approximately 200 hours on a GPU. At inference time, the beam-search algorithm described in [20] was used to remove spurious impulse events generated by the probabilistic sampling method. The beam-search algorithm works by generating multiple candidate segments of audio from the same conditioning signal, in parallel. The CQT of each candidate waveform is calculated and compared to the conditioning signal. The generated waveform that is closest to the CQT conditioning signal in terms of L2 distance is kept, whilst all others are discarded. This process is applied iteratively in 2048 sample blocks until the full signal is generated.

### 3.3. Dataset

To include a diverse range of sounds, a dataset was constructed from three source datasets. The datasets used were the ESC-50 dataset [26], a labeled collection of environmental audio recordings, the Freesound Loops dataset [27], a collection of short musical clips including electronic and acoustics instrument sounds, as well as speech sounds from the LJ-speech dataset [28]. Samples were randomly removed from the LJ-speech and Freesound loops datasets, so the different classes of sounds were evenly represented in the combined dataset. In total, the dataset used for training contained approximately 4 hours of audio.

#### 4. HYBRID TSM METHOD

The proposed model combines the use of traditional digital signal processing techniques and the Wavenet synthesizer to improve the time-scale modification performance for extreme time-stretching factor, and it is designed and trained to provide high quality stretching for environmental sounds. The TSM pipeline of the proposed method described in this section is visualized in Fig. 3.

### 4.1. Processing the individual STN components

The input audio signal is decomposed as described in Sec. 2. Transition regions for the STN masks are defined by $\beta_0 = [0.8 \ 0.85]$ and $\beta_1 = [0.7 \ 0.75]$, where the two elements refer to the different transition region in each stage of the decomposition [15]. The chosen median filters lengths are 500 Hz in the frequency direction and 200 ms in the time direction [15].

The sines are processed via phase vocoder with identity phase locking (IPL) [29], as used in [9]. The transient signal is segmented and each segment is appropriately repositioned on the new time axis [30]. The noise component is neurally-synthesized at the desired TSM factor, as described in Sec. 4.

### 4.2. Post-processing

Before mixing the three components, the temporal envelope of the original signal is computed using a leaky integrator and then applied to the time-stretched sines+noise mixture (see Fig. 3), to compensate for the pre-echo effect that is typical of spectrogram-based TSM methods [3]. Finally, the three components are added and the time-stretched output is obtained, as also illustrated in Fig. 3.

A time-stretching output example is shown in Fig. 4 for the Soda sound detailed in Table 1 and a TSM factor $\alpha = 4$. The ‘hiss’ of the can opening is correctly resynthesized by the network, together with the noisy part of the later clicks which are imposed over the preserved transients. The STN decomposition is particularly helpful in this situation, as the merging of unaltered transients and the neurally-synthesized noise helps generate realistic sounds that retain the punch of percussive events while avoiding common artifacts, such as loss of presence, metallic tones, and phasiness.

### 4.3. Stereo compatibility

The process described so far can be individually applied to the two channels of a stereo sound, as STN decomposition is transparent with respect to the stereo field. When a sound is decomposed into its individual components and then recomposed, the stereo balance between the left and the right channel, computed according to [31], is preserved: this allows independent processing for each channel.
The proposed method is validated and compared with previous TSM methods in a listening test, which is reported in this section.

### 5. Evaluation

#### 5.1. Listening Test Design

A formal blind listening test was conducted on a selection of 14 experienced listeners, all of which reported previous experience in test design and no hearing impairment or other relevant medical condition. The test software, a customized version of WebMushra [32], was run on a desktop machine running MacOS 10.14.6, using a single pair of Sennheiser HD 650 headphones, inside a sound-proof listening booth at the Aalto Acoustics Lab, Espoo, Finland. A set of six audio samples, listed in Table 1, were selected. As the test involves extreme stretching factors, of up to 8 times, a very short duration for each sample (approximately 2 s) was necessary to ensure that even the longest time-stretched sounds remained below 18 s long.

The proposed method (PROP) was evaluated against the fuzzy phase vocoder (FPV) [9], harmonic-percussive TSM (HP) [33], the two-step phase vocoder with IPL [29], and WSOLA [4], which was provided as the low-quality anchor (ANC). All the processed sounds were loudness normalized according to ITU-BS.1770 recommendation [35] to prevent loudness differences from affecting the grades. In each trial of the test, subjects were presented with one of the audio excerpts, referred to as reference, and were asked to blindly rate the quality of the time-scaling operation. The original reference was not included among the samples to be rated. Subjects were instructed to rate each sample on a scale from 0 to 100, with no obligation of using the full scale, as the concept of perfect TSM is undefined and it was anticipated that none of the samples would be perceived to be an ideal processing.

The test was divided in two parts of twelve trials (six trials repeated twice for consistency) each, the first presenting a TSM factor of 4 and the second a TSM factor of 8, for a total of 24 trials and 72 audio samples under investigation. Listeners were allowed a short training session before starting the actual test to get acquainted with the interface, the keyboard shortcuts, and the task itself. The results of the training session were not included in the statistical analysis. Prior to the test, familiarity of the subjects with the concepts of time-scale modification and transient smearing was assessed.

#### 5.2. Results

Mean Opinion Scores (MOS) were computed from the ratings given by the subjects to estimate the quality of the time-scaling for the methods under test. Barplots displaying the mean and 95% confidence intervals of the data are shown in Fig. 5. The proposed method clearly outperforms the other algorithms under test under both time-stretching conditions for all samples but Rooster. The majority of the test participants commented on this audio excerpt that the noisy nature and the lack of sharp transients of the reference made it a hard task to generate an expectation for a time-stretched version.

### 6. Conclusion

In this paper, we present a novel algorithm for extreme TSM, which takes advantage of the decomposition of sound into sines, transients, and noise to individually resynthesize the noise component using a deep neural network. Sines and transients are processed using established techniques which also benefit from the decomposition. The results of a subjective listening test suggest that the proposed algorithm performs significantly better than previous TSM methods for real-world environmental recordings, when a large time-stretching factor is used. Future work involves redesigning the neural synthesis for standard time-stretching factors, involving a larger dataset of more relevant sounds.

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**Table 1**: Audio samples used in the listening test.

| Name  | Description                                |
|-------|--------------------------------------------|
| Fireworks | Two fireworks exploding in the air           |
| Soda  | Hiss and click sound from a can opening    |
| PingPong | A clip from an amateur ping pong game      |
| Saw   | Handsaw sawing through wood               |
| Sneeze | A person sneezing two times               |
| Rooster | A rooster crowing in the morning          |

**Fig. 5**: Barplots relative to the results of the subjective listening test, showing the average mean opinion scores and 95% confidence intervals of the data for TSM factors (a) $\alpha = 4$ and (b) $\alpha = 8$. The proposed method outperforms the opposing algorithms in both cases for most of the samples under test.
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