

# Time-scaling Phase Vocoder

Audio Signal Processing

Yoch Lacombe

MVA 21/22  
ENS Paris-Saclay

March 29, 2022

# Sommaire

---

## 1. Introduction

## 2. Main algorithms

- 2.1 The pipeline
- 2.2 PV-TSM based approaches
- 2.3 Extension - HPS

## 3. Observations

## 4. Conclusion

# Introduction

## Time-scale modification (TSM)

Time-scale algorithm aims at stretching the length of an audio signal while preserving its pitch and timbre. There are two main paradigms for TSM [Driedger, 2016].

- **Time-domain-based vocoders** modify the audio via the time domain. Mostly based on Overlapp-Add(OLA).
- **Frequency-domain-based vocoders** modify the audio via the phase of the short-time Fourier Transform (STFT). Mostly based on Phase-Vocoder (PV).

## Some notation

- $N$  denotes the length of the windowed signal of the STFT and  $F_s$  is the framerate of the input audio signal  $x$
- $R_a$  and  $R_s$  respectively denotes the analysis and the synthesis hop sizes.
- $h$  is a window of size  $N$ , here the hanning window.

# The basic pipeline

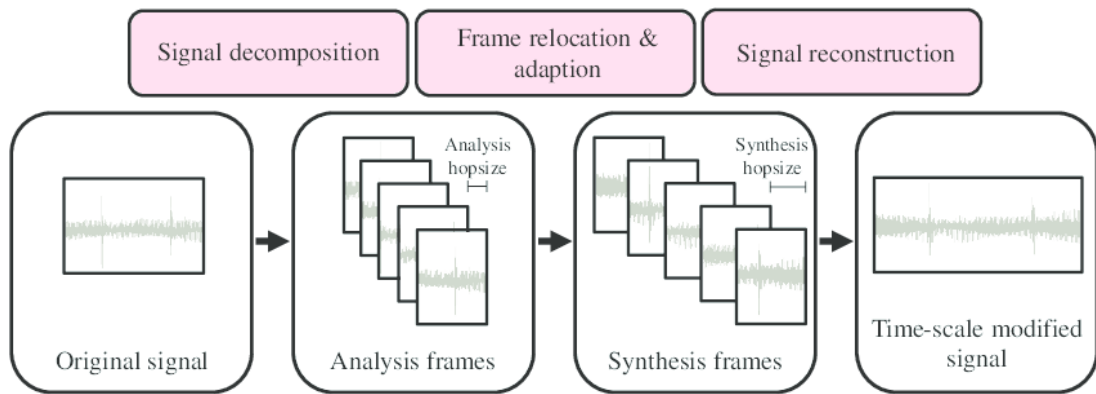


Figure: TSM process. Analysis, Modification, Synthesis. From [Driedger, 2016].

# Analysis

---

## Analysis stage

Basically, analysis applies STFT to the input signal  $x$ .

$$X(m, k) = \sum_{n=0}^{N-1} h(n)x(n + mR_a)e^{-2i\pi kn/N} \quad (1)$$

## On the bins

$(m, k)$  is a time-frequency bin associated to the time  $mR_a/F_s$  and frequency  $kF_s/N$ .

# Synthesis

---

The **synthesis** stage typically uses the inverse (in the least square sense) STFT. Short-time signals  $y_m(n)$  are obtained by computing the inverse FFT of  $Y$ . These signals are then weighted by a synthesis window  $h$  (typically the hanning window) and overlapp-add by a synthesis hop  $R_s$  to compute the output signal  $y$ .

$$y_m(n) = \frac{1}{N} \sum_{k=0}^{N-1} Y(m, k) e^{2i\pi kn/N}$$

$$y(n) = \sum_{m=-\infty}^{\infty} h(n - mR_s) y_m(n - mR_s)$$

# PV-TSM

## Recurrence

With  $\Phi_*$  denoting the phase, at time  $m$ ,

$$\Phi_Y[m, :] = \Phi_Y[m-1, :] + R_s IF(m) \quad (2)$$

where  $IF(m) = \Omega + \frac{1}{R_a}[\Phi_X[m, :] - \Phi_X[m-1, :] - R_a \Omega]_{2\pi}$  with  $\Omega = \{k \frac{2\pi}{N}\}_{k \in \mathbb{N}_N}$

## Initialisation

$$|Y| = |X| \quad (3)$$

$$\Phi_Y[0, :] = \beta \Phi_X[0, :] \quad (4)$$

Here,  $\beta$  is a parameter that is usually set to 1 which [Laroche, 1999] brings to solve the phasiness issue.

# Issues and proposed improvements

---

## Issues with PV-TSM

Main issues are:

- **Transient smearing** - loss of percussiveness
- **Phasiness** - the speaker seems to be away from the mic

Phasiness is identified to be caused by lack of vertical phase coherence.

## Some proposed improvements

To solve this vertical phase coherence issue, [Laroche, 1999] proposes phase-locking.

Other improvements could be:

- Resetting the output frames to the input frames every  $D$  processed frames.
- Dynamically change the phase either horizontally or vertically according to gradient.
- Automatically adapt the time-frequency resolution to analyse and resynthesize.



# Phase-locking

---

**Vertical phase coherence:** a sinusoidal component may affect multiple adjacent frequency bins of a single analysis frame.

## Assumption

A frame's magnitude is representative of a particular sinusoidal component and that the surrounding bins with lower magnitude are affected by this very same sinusoidal component

## A naive first approach - *loose phase-locking*

By simply computing a vertical rolling sum on the resulting STFT, the bins of higher amplitude dominate their neighbors.

$$Y_{new}[:, k] = Y[:, k - 1] + Y[:, k] + Y[:, k + 1]$$

# Identity Phase-locking

**Identity phase-locking** [Laroche, 1999] consists in the following steps, for each analysis frame.

1. Identify the peaks which are identified as bins where the magnitude is larger than the 4 nearest neighbors.
2. Compute the synthesis frame phase of each peak according to Equation [2].
3. Identify the closest channels to each peak.
4. For a channel  $k$  and its closest channel  $k_l$ , update the synthesis phase such that:

$$\Phi_Y[m, k] = \Phi_Y[m, k_l] + \Phi_X[m, k] - \Phi_X[m, k_l]$$

## Issues

While highly improving the quality of the TSM, it still suffers from transient smearing and to recurring interruptions (when harmonic signal happens at the same time as transient smearing).

# HPS-based TSM [Driedger, 2014]

With regards to the remaining issues of phase-locked PV-TSM, we remark that:

- PV-TSM is particularly adapted for the harmonic part of a sound
- OLA (overlap-add approach) is particularly adapted for the percussive part of a sound.

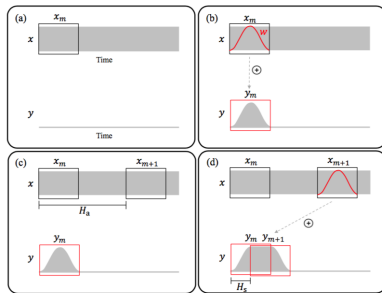


Figure 3. The principle of TSM based on overlap-add (OLA). (a) Input audio signal  $x$  with analysis frame  $x_m$ . The output signal  $y$  is constructed iteratively; (b) Application of Hann window function  $w$  to the analysis frame  $x_m$  resulting in the synthesis frame  $y_m$ ; (c) The next analysis frame  $x_{m+1}$  having a specified distance of  $H_a$  samples from  $x_m$ ; (d) Overlap-add using the specified synthesis hopsize  $H_s$ . 992

Figure: OLA principle explained (from [Driedger, 2016]).

# HP-based TSM - 2

1. Separate harmonic and percussive components by applying vertically and horizontally median-filters.
2. Apply OLA to the percussive component and PV-TSA to the harmonic component.
3. Add back the two resulting signals.

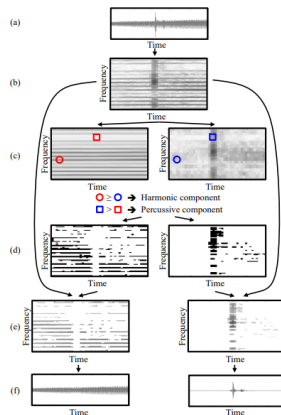


Figure: HPS approach's pipeline (from [Driedger, 2016]).

# Informal observation - 1

---

## Overall observation

- Despite the transient smearing and some unpleasant interruptions, the Identity Phase-Locked PV stays a really strong algorithm with satisfactory results. It efficiently solves the phasiness issue.
- HPS-TSM performs really well too. As expected it solves the transient smearing and most of the unpleasant interruptions are cleared.

## On hyperparameters

- **Lengths of the median filters:** Important parameters. The most robust values I found are 100 for time spectrogram and 25 for frequency spectrogram.
- **N:** As expected, crucial as it is a tradeoff between time and frequency resolutions. Set to correspond to 100 ms.  $N = 0.1F_s$ .

# Informal observation - 2

---

## On hyperparameters - Hop Sizes

- Most of the papers I have read recommend setting  $R_s = N/2$  and thus  $R_a = R_s/\alpha$ .
- However,  $R_s$  and  $R_a$  become too large. The analysis STFT loses information.
- Might explain some of the inconsistencies of [Laroche, 1999] such as the importance of  $\beta$  and the Scaled Phase-Locked results.
- With hop sizes set to reasonable values (ex.  $R_a = 128$  and  $R_s = \alpha R_a$ ), every algorithms sound better with every sound samples.

## On HPS

Even without applying TSM, the separation of harmonic and percussive components work particularly well. See the following slide for example.

# HPS example

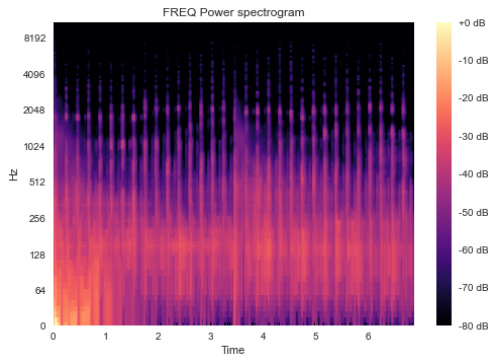


Figure: Frequency component after applying the percussive mask.

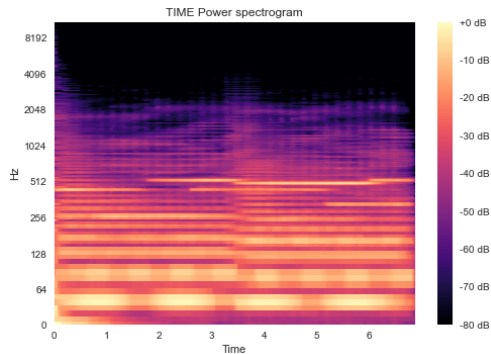


Figure: Time component after applying the harmonic mask).

# Conclusion

---

- Some hyperparameters are crucial to hear pleasant results. Moreover, the values recommended in the literature appeared are not suited for the time-stretching task.
- **Limitation:** Should have tested with more complex polyphonic sounds. I haven't test the algorithms with polychannel audio signals as well.
- To truly evaluate methods, we should conduct formal listening test. The consistency measure proposed in [Laroche, 1999] which compares  $Y$  to the STFT of  $y$  appears not to be used in other papers and is not based on any valid background.



# References

---



Jonathan Driedger and Meinard Muller.(2016)

A review of time- scale modification of music signals.

Applied Sciences, 6(2)



Laroche and M. Dolson (1999)

Improved phase vocoder time- scale modification of audio

7(3):323–332, 1999



Jonathan Driedger, Meinard Muller and Sebastian Ewert. (2014)

Improving time-scale modification of music signals using harmonic-percussive separation.

21:105–109, 2014

**The End**