A FAST AND ACCURATE PITCH ESTIMATION ALGORITHM BASED ON THE PSEUDO WIGNER-VILLE DISTRIBUTION

Yisi Liu¹, Peter Wu³, Alan W Black², Gopala K. Anumanchipalli³

¹Department of Electronic and Information Engineering, University of Chinese Academy of Sciences
²Language Technologies Institute, Carnegie Mellon University
³Berkeley Artificial Intelligence Research Lab, University of California, Berkeley
liuyisi19@mails.ucas.ac.cn, peterw1@berkeley.edu, awb@cs.cmu.edu, gopala@berkeley.edu

ABSTRACT

Estimation of fundamental frequency (F0) in voiced segments of speech signals, also known as pitch tracking, plays a crucial role in pitch synchronous speech analysis, speech synthesis, and speech manipulation. In this paper, we capitalize on the high time and frequency resolution of the pseudo Wigner-Ville distribution (PWVD) and propose a new PWVD-based pitch estimation method. We devise an efficient algorithm to compute PWVD faster and use cepstrum-based pre-filtering to avoid cross-term interference. Evaluating our approach on databases with speech and electroglottograph (EGG) recordings yields a state-of-the-art mean absolute error (MAE) of around 4Hz. Our approach is also effective at voiced/unvoiced classification and handling sudden frequency changes.

Index Terms— Pitch tracking, pseudo Wigner-Ville distribution (PWVD)

In recent years, researchers have proposed data-driven algorithms for pitch estimation. Previously, machine learning methods were unable to outperform traditional approaches [13] due to a lack of annotated data [15]. CREPE [16] circumvented this constraint and achieved state-of-the-art results by training on a synthetically generated dataset for F0 tracking [17]. Later, SPICE [15] used self-supervised learning to obtain pitch estimation results comparable to CREPE, a fully supervised model.

So far, among traditional signal processing methods, those based on time-frequency representations have not gained much attention. One primary reason for this is that time and frequency resolutions are restricted by the Heisenberg uncertainty principle [18]. Specifically, one cannot increase time and frequency resolutions simultaneously without introducing artifacts. For traditional short-time Fourier transform (STFT) and wavelet transforms, more time support means worse time resolution and finer frequency resolution, and vice versa.

The Wigner-Ville distribution (WVD) has high resolution in both the time and the frequency domains, making it one of the most powerful and fundamental time-frequency representations [18, 19, 20]. Despite these remarkable properties, WVD has not been widely used, since: (1) WVD is computationally expensive; (2) the existence of interference (cross terms) among different components may introduce false information; and (3) WVD is highly non-local.

In this paper, we overcome the drawbacks of WVD and present a high-performance pitch tracker based on the pseudo WVD (PWVD). Inspired by [21], we utilize the Hilbert transform, downsampling, and segmentation as well as implement the WVD in terms of the fast Fourier transform (FFT) in order to compute the PWVD faster. Additionally, we use cepstrum-based pre-filtering to eliminate cross terms between F0 and its multiples. Finally, PWVD is used to make our pitch tracker more sensitive to frequency changes. We show that our algorithm outperforms the widely used SWIPE [22], REAPER and STRAIGHT methods, and is comparable to or better than state-of-the-art approaches like pYIN and CREPE, in terms of both mean absolute error (MAE) and F0 Frame Error (FFE).

1. INTRODUCTION

Fundamental frequency (F0), defined as the inverse of the vocal fold vibration period, is often estimated through the pitch tracking task. Reliable pitch tracking has a wide range of applications, including speech synthesis [1], speech prosody analysis [2], speech manipulation [3, 4], melody extraction [5], glottal source processing [6], and intonation teaching [7].

Traditional methods for pitch estimation can generally be split into three categories. First is the cepstrum-based method [8, 9], where large peaks in the cepstrum correspond to pitch periods in the frequency domain. Second is the correlation-based method, which can be viewed in terms of three sub-categories: (a) auto-correlation-based [10], where the auto-correlation of the output of a spectrum flattener is utilized; (b) normalized-cross-correlation-based, which is also the key algorithm for REAPER[11]; and (c) YIN-based [4, 12, 13], where the cumulative mean normalized difference function is used in addition to auto-correlation function. The third category of traditional methods leverage time-frequency representations, among which wavelets [14] are the most popular.
2. METHOD

This section describes our proposed PWVD-based pitch tracker step by step to show what makes it efficient and effective. First, we present the basic theory of WVD. Then, we introduce a five-stage pipeline, which includes downsampling, voiced/unvoiced (V/UV) classification, segmentation, cepstrum-based pre-filtering, and PWVD, in order to show the implementation of our method.

2.1. Basics of WVD

The Wigner-Ville distribution of signal $x(t)$ is given by

$$W_x(t, \omega) = \int_{-\infty}^{\infty} x(t + \frac{\tau}{2})x^*(t - \frac{\tau}{2})e^{-j\omega \tau} d\tau. \quad (1)$$

Defining the instantaneous auto-correlation function $R(t, \tau)$ as

$$R(t, \tau) = x(t + \frac{\tau}{2})x^*(t - \frac{\tau}{2}), \quad (2)$$

we note that $W_x(t, \omega)$ can be viewed as the Fourier Transform of $R(t, \tau)$ along the $\tau$ axis, i.e.,

$$W_x(t, \omega) = \int_{-\infty}^{+\infty} R(t, \tau)e^{-j\omega \tau} d\tau. \quad (3)$$

We utilize this property in our FFT step in Section 2.6. One standard way of defining the discrete version of WVD is

$$W_x[n, k] = \sum_{m=N-1}^{m=N-1} x[n + \frac{m}{2}]x^*[n - \frac{m}{2}]e^{-j2\pi km}. \quad (4)$$

This definition involves half-integer indices, which are computed in the MATLAB built-in function wvd using interpolations. In Section 2.6, we introduce a more efficient algorithm for computing $W_x[n, k]$ that avoids interpolations. When there are multiple components in a signal $s(t)$, e.g.,

$$s(t) = s_1(t) + s_2(t), \quad (5)$$

the WVD of $s(t)$, i.e., $W_x(t, \omega)$ in (1), will contain cross terms $I(s_1, s_2)$ given by

$$I(s_1, s_2) = \int_{-\infty}^{+\infty} s_1(t + \frac{\tau}{2})s^*_2(t - \frac{\tau}{2})e^{-j\omega \tau} d\tau$$

$$+ \int_{-\infty}^{+\infty} s_2(t + \frac{\tau}{2})s^*_1(t - \frac{\tau}{2})e^{-j\omega \tau} d\tau. \quad (6)$$

The existence of cross terms does not mean that the original signal has energy distributed in the cross term’s time-frequency neighborhood. In this sense, $I(s_1, s_2)$ can be considered as artifacts that need to be removed [23]. An example of cross terms and WVD’s high time-frequency resolution can be found in Figure 1, where we compare the WVD and STFT of the following sum of two chirp signals:

$$s(t) = \cos(\pi kt^2 + 2\pi f_0 t) + \cos(\pi kt^2). \quad (7)$$

Fig. 1. The STFT and WVD of (7), where sampling frequency $f_s = 50$Hz, $k = 5$Hz/s, $f_0 = 3$Hz, and $s(t)$ resides in 0 to 4s.

2.2. Stage 1: Downsampling

Normally, for human speakers, pitch approximately stays between 60Hz and 400Hz. Based on this assumption, we filter out frequency components outside of this range. We then downsample the band-passed signal to decrease the sampling frequency to $f_d = 800$Hz and refer to the resulting signal as $x_d$. This downsampling operation noticeably reduces the amount of computation for PWVD.

2.3. Stage 2: V/UV Classification

Voiced sounds are quasi-periodic, while unvoiced sounds are more similar to noise and contain much higher frequency components. Based on the approach in [24], we use energy thresholding for voiced/unvoiced (V/UV) classification. Essentially, the voiced areas of $x_d$ generally have much higher energy than the unvoiced areas. We check the average energy of $x_d$ frame by frame and split higher-energy frames into subframes for more precise results. Here, we choose a frame size of 25ms, and a threshold of 0.2E, where $E$ is the average energy of $x_d$.

2.4. Stage 3: Segmentation

In this stage, we further divide each of the voiced areas into segments of around 150ms, i.e., 120 points at $f_d = 800$Hz. We base this segmentation operation on the assumption that shorter periods of time will make drastic frequency changes less likely to occur. This helps to reduce the appearance of cross terms and prepares the signal for the subsequent pre-filtering stage.
2.5. Stage 4: Cepstrum-based Pre-filtering

The purpose of pre-filtering is to filter out harmonic structures so that approximately only the fundamental frequency component remains, reducing most cross terms for the upcoming PWVD. In order to do this, the average F0 \( f_a \) of each voiced segments is required. Here, we combine cepstrum with spectrum to extract \( f_a \). First, we pass the pre-downsampling voiced segments (here sampled at \( f_s = 16kHz \)) into a low-pass filter (LPF) with stopband edge frequency 1kHz. Second, we do cepstrum maximum detection on the filtered segments to calculate \( f_{raw} \):

\[
f_{raw} = \frac{f_s}{\gamma},
\]

where \( \gamma \) is the quefrency index where the cepstrum reaches its maximum within the frequency range of 80Hz to 320Hz. Third, we generate \( f_a \) candidates as multiples and factors of \( f_{raw} \), also within the frequency range of 80Hz to 320Hz. Finally, we output the smallest candidate that has a prominent spectrum peak in its frequency neighborhood.

After extracting the average F0 values, we concatenate the respective neighboring points to each of the voiced segments in the time domain in order to mitigate the tendency of WVD to fade at the edges of a signal. Figure 1 contains an example of such unwanted edge behavior. Following this concatenation step, we apply pre-filtering on each voiced segment to just keep 0.7\( f_a \) to 1.4\( f_a \) frequency components.

2.6. Stage 5: PWVD

The pre-filtered voiced segments are passed into this stage. Recall (1), where interpolation is involved to compute WVD. Similar to the idea in [21], where the Hilbert transform is utilized to avoid spectrum aliasing, we can modify (1) into

\[
W_x[n, k] = \sum_{m=-N+1}^{m=N-1} \tilde{x}[n + m] \tilde{x}^*[n - m] e^{-j \frac{2\pi}{N} km} = \sum_{m=-N+1}^{m=N-1} \hat{R}[n, m] e^{-j \frac{2\pi}{N} km} \sim FFT(\hat{R}) + FFT^*(\hat{R}) - |\tilde{x}[n]|^2. \tag{9}
\]

Here \( \tilde{x} \) is the analytic signal of \( x \) and * means complex conjugate. \( 4\pi \) instead of \( 2\pi \) in the exponent just represents frequency stretching, i.e., the 3rd line is calculated first, and then all frequencies are divided by 2. We note that interpolation is avoided, and WVD is converted into an FFT computation.

After computing WVD, we estimate F0 by looking for the first prominent peak of WVD at each time index \( n \). Figure 2 shows an example of pitch tracking using WVD, which, although functional, fails to track the ground truth closely enough. This is due to the non-local nature of the WVD calculation, which assigns equal weights to the past, present, and future time points. If we apply a window function \( w[m] \) to \( \hat{R}[n, m] \) to emphasize the “present”, this non-local effect can be alleviated. This operation is called the Pseudo-WVD [23]:

\[
PW_x[n, k] = \sum_{m=-N+1}^{m=N-1} \hat{R}[n, m] w[m] e^{-j \frac{2\pi}{N} km}. \tag{10}
\]

Figure 2 compares pitch tracking using PWVD with the WVD method. Here we choose \( w[m] \) to be a hann window. Clearly, PWVD is more sensitive to frequency changes as a result of emphasizing the “present”.

3. RESULTS

3.1. Datasets

We conduct our experiments with the CMU ARCTIC databases [25] and PTDB-TUG database [26]. For CMU ARCTIC, each single-speaker speech database contains nearly 1150 phonetically balanced English sentences. We choose the speakers bdl (US male), jnk (Canadian male) and slt (US female) for evaluating pitch tracking, since they have EGG signals recorded simultaneously with clean speech signals under studio conditions. For PTDB-TUG, it contains 4720 recordings from 10 male and 10 female speakers, along with simultaneously recorded EGG signals. The F0 and V/UV ground truths are extracted from differentiated EGG signals.

3.2. Error Metrics

Two error metrics were chosen for comparison: mean absolute error (MAE) and F0 frame error (FFE) [27]. MAE describes
3.3. Time Efficiency

The built-in wvd of MATLAB takes around 60s to process 0.5s of a signal sampled at $f_s = 16$kHz. Moreover, once the duration of the input signal exceeds 1s at $f_s = 16$kHz, memory shortage will stop the execution. In comparison, with the proposed algorithm mentioned in Section 2, a runtime evaluation over the three databases (over 3000 utterances) yielded a result of 0.665RT. I.e., it takes about 0.665s to process 1s of a signal on average, which is much more time efficient.

3.4. Evaluation

We compare our proposed PWVD method with 5 popular pitch trackers: REAPER [11], STRAIGHT [4], SWIPE [22], pYIN [13] and CREPE [16]. Since CREPE does not support V/UV classification, we perform experiments with CREPE using our V/UV method. Figure 4, 5 summarize the results. We group PTDB-TUG speakers in Figure 4 by gender for readability, and the x axis in Figure 5 represents the average F0 of different speakers. In general, our proposed PWVD-based method has the top 2 lowest FFE and MAE for all datasets. For MAE, PWVD performs the best in the datasets bdl and jmk, with the lowest MAE and a p value less than $10^{-10}$, indicating a fairly accurate tracking performance. For FFE, PWVD has the lowest FFE in datasets jmk, PTDB MALE and PTDB FEMALE, which is significantly lower than REAPER, STRAIGHT, SWIPE and pYIN with a p value less than $10^{-10}$, obtaining a state-of-the-art overall performance. Figure 5 indicates that all algorithms tend to have higher MAE as the speaker’s pitch increases, with our method generally having the lowest MAE in the analyzed frequency range. Figure 3 contains an example of CREPE’s and pYIN’s performance. Compared to PWVD (Figure 2), CREPE and pYIN fail to track sudden frequency changes closely enough. Moreover, pYIN tends to classify more voiced areas as unvoiced, which causes its high FFE.

4. DISCUSSIONS AND CONCLUSION

We present a pitch tracker based on the pseudo Wigner-Ville distribution (PWVD) that utilizes the high time-frequency resolution of PWVD. Additionally, we devise an algorithm that calculates WVD much faster than the previous implementation and use cepstrum-based pre-filtering to eliminate most cross terms. We also utilize PWVD in order to make WVD more sensitive to sudden frequency changes. An evaluation of five pitch trackers on three selected datasets yielded low MAE and FFE for the proposed pitch tracker, obtaining state-of-the-art performance with multiple dataset-metric combinations. Since PWVD is calculated in the voiced areas only, a more precise V/UV classifier can potentially improve the performance of $f_a$ extraction system mentioned in 2.5, and therefore reduce halving error and doubling error. Moreover, considering the estimated F0 of adjacent points when proposing $f_a$ candidates for the present point may enforce temporal smoothness, reducing abrupt frequency changes in the output.

5. ACKNOWLEDGEMENTS

This research is supported by the following grants to PI Anumanchipalli — NSF award 2106928, Google Research Scholar Award, Rose Hills Foundation and Noyce Foundation.
6. REFERENCES

[1] Y. Stylianou, “Applying the harmonic plus noise model in concatenative speech synthesis,” IEEE Transactions on Speech and Audio Processing, 2001.

[2] Maria Luisa Zubizarreta, Prosody, focus, and word order, MIT Press, 1998.

[3] Éric Moulines and Francis Charpentier, “Pitch-synchronous waveform processing techniques for text-to-speech synthesis using diphones,” Speech Commun., 1990.

[4] Hideki Kawahara, Alain de Cheveigné, Hideki Banno, Toru Takahashi, and Toshio Irino, “Nearly defect-free f0 trajectory extraction for expressive speech modifications based on straight,” in INTERSPEECH, 2005.

[5] Juan J. Bosch and Emilia Gómez, “Melody extraction in symphonic classical music: a comparative study of mutual agreement between humans and algorithms,” in CIM14, 2014.

[6] D. Wong, J. Markel, and A. Gray, “Least squares glottal inverse filtering from the acoustic speech waveform,” IEEE Transactions on Acoustics, Speech, and Signal Processing, 1979.

[7] Paul C. Bagshaw, Steven M. Hiller, and Mervyn A. Jack, “Enhanced pitch tracking and the processing of f0 contours for computer aided intonation teaching,” Eurospeech 1993, 1993.

[8] A. Michael Noll, “Short-time spectrum and “cepstrum” techniques for vocal-pitch detection,” The journal of the acoustical society of America, 1964.

[9] S. Ahmadi and A.S. Spanias, “Cepstrum-based pitch detection using a new statistical vuv classification algorithm,” IEEE Transactions on Speech and Audio Processing, 1999.

[10] M. Sondhi, “New methods of pitch extraction,” IEEE Transactions on Audio and Electroacoustics, 1968.

[11] David Talkin, “A robust algorithm for pitch tracking (rapt),” Speech Coding and Synthesis, 1995.

[12] Alain de Cheveigné and Hideki Kawahara, “Yin, a fundamental frequency estimator for speech and music,” The Journal of the Acoustical Society of America, 2002.

[13] Matthias Mauch and Simon Dixon, “Pyin: A fundamental frequency estimator using probabilistic threshold distributions,” in 2014 ICASSP, 2014.

[14] S. Kadambe and G.F. Boudreaux-Bartels, “Application of the wavelet transform for pitch detection of speech signals,” IEEE Transactions on Information Theory, 1992.

[15] Beat Gfeller, Christian Frank, Dominik Roblek, Matt Sharifi, Marco Tagliasacchi, and Mihajlo Velimirovic, “SPICE: Self-supervised pitch estimation,” IEEE/ACM Transactions on Audio, Speech, and Language Processing, 2020.

[16] Jong Wook Kim, Justin Salamon, Peter Li, and Juan Pablo Bello, “Crecpe: A convolutional representation for pitch estimation,” in 2018 ICASSP, 2018.

[17] Justin Salamon, Rachel M. Bittner, Jordi Bonada, Juan J. Bosch, Emilia Gómez, and Juan Pablo Bello, “An analysis/synthesis framework for automatic f0 annotation of multitrack datasets,” in ISMIR, 2017.

[18] Stphane Mallat, A Wavelet Tour of Signal Processing, Third Edition: The Sparse Way, Academic Press, Inc., USA, 3rd edition, 2008.

[19] B. Bouachache and P. Flandrin, “Wigner-ville analysis of time-varying signals,” in ICASSP ’82., 1982.

[20] B. Bouachache and F. Rodríguez, “Recognition of time-varying signals in the time-frequency domain by means of the wigner distribution,” in ICASSP ’84., 1984.

[21] B. Boashash and P. Black, “An efficient real-time implementation of the wigner-ville distribution,” IEEE Transactions on Acoustics, Speech, and Signal Processing, 1987.

[22] John G. Harris and Arturo Camacho, “Swipe: a saw-tooth waveform inspired pitch estimator for speech and music,” Journal of the Acoustical Society of America, 2007.

[23] Leon Cohen, Time-Frequency Analysis, Pearson College Div, 1st edition, 1995.

[24] Adapa B. Bachu R.G., Kopparthi S. and Barkana B.D., “Voiced/unvoiced decision for speech signals based on zero-crossing rate and energy,” in Advanced Techniques in Computing Sciences and Software Engineering, Khaled Elleithy, Ed. 2010, Springer Netherlands.

[25] John Komeinek and Alan W Black, CMU ARCTIC databases for speech synthesis, CMU-LTI-03-177, 0.95 edition, 2003.

[26] Gregor Pirker, Michael Wohlmayr, Stefan Petrik, and Franz Pernkopf, “A pitch tracking corpus with evaluation on multipitch tracking scenario,” in Interspeech, 2011.

[27] Onur Babacan, Thomas Drugman, Nicolas d’Alessandro, Nathalie Henrich, and Thierry Dutoit, “A comparative study of pitch extraction algorithms on a large variety of singing sounds,” in 2013 IEEE ICASSP, 2013.