Low Level Descriptors for Automatic Violin Transcription

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Abstract

On top of previous work in automatic violin transcription we present a set of straight forward low level descriptors for assisting the transcription techniques and saving computational cost. Proposed descriptors have been tested against a database of 1500 violin notes and double stops.

Keywords: Violin, Automatic Transcription.

1. Introduction

Automatic transcription is a problem that has been addressed using many different approaches [1]. Most of these tackle the problem from an instrument-free perspective such as 'music transcription' or 'monophonic and polyphonic transcription'. And among the ones that specialize on specific sections (drums and percussion) or instruments (piano) very few focus on violin [2][3][4].

In this context, this paper aims a step forward in the implementation of a clear-cut violin transcription system first described in [5], originally thought to be used for distant education, self-learning and evaluation. We introduce a set of low level descriptors by which the system can improve its performance and adapt the complexity of the analysis algorithms that are being applied. The general block diagram of the system is represented in Figure 1.

Following sections introduce improvements in the pitch estimation; present first derivative zero crossing descriptor and modulation descriptor for upper octave polyphony detection; and inharmonic descriptor for any other duo-phony detection. So once the pitch analysis receive a note, stability descriptor decides which frames to use for the pitch estimation, and inharmonic descriptor decides whether pitch estimation algorithm deals with a single note or a double-stop region. For those cases in which monophonic pitch analysis has been applied, the upper octave descriptors, one of them using the already estimated pitch, decide whether the upper octave note has to be given as transcription output as well.
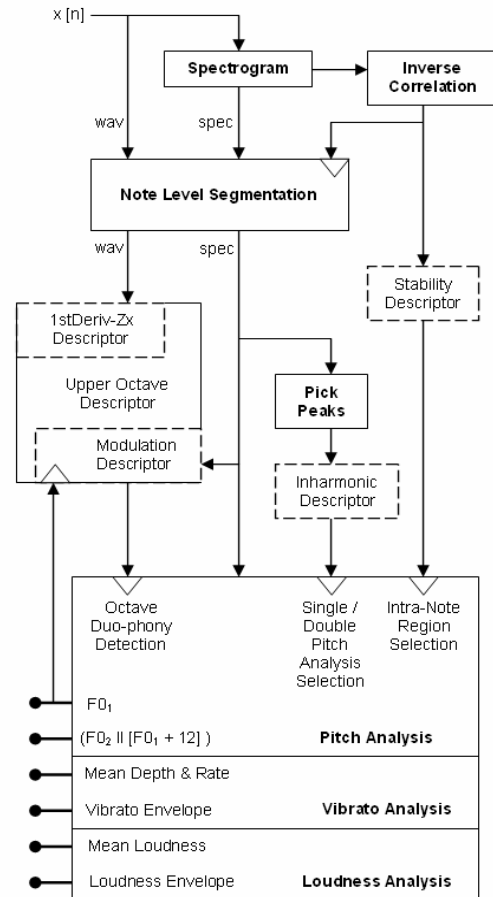
Figure 1. General block diagram of the automatic violin transcription system where dotted lines represent descriptors, triangles represent controls and rounded-end lines represent outputs

2. Note Level Segmentation

Note Level segmentation uses implementation from previous system [5] based on the autocorrelation of the Note Spectrogram. While this approach is efficient sorting out monophonic pitch changes, it sometimes lacks of resolution for detecting timbre modulations, amplitude modulations, and pitch modulations. This, far from being a drawback, allows the note level segmentation to work free from such kind of modulations, which enrich the sound but do not define the note itself. However, specific cases such

as note repetitions, fast performance, or deep modulations require additional processing.

3. Pitch Analysis

Previous system [5] already confronted the problem of octave errors by means of adding a compression term ruled by parameter α (set to 5 in [5]) in the summation of the Semitone Band Spectrum (SBS) $p(w)$ as formulated in equation:

$$A(w) = \sum_{k=1}^{5} \min(p(k \cdot w), \alpha \cdot p(w)) \qquad (1)$$

This compressed addition has been proven useful for getting rid of lower octave errors. When w is set to be $F_0/2$ (being F_0 the pitch), we add the real fundamental and harmonics up to a certain proportional value. If no peak is at $F_0/2$ no relevant energy will is added to $A(w)$. However, as we discuss in section 3.1.2, this technique does not get rid of upper octave errors

3.1 Improved Pitch Estimation

A couple of generic modifications (both for monophonic and polyphonic pitch estimation) are introduced: steady state detection for reducing computational cost and avoiding transients, and octave error pruning.

3.1.1 Stability Descriptor

For each of the note regions given by the note-level segmentation, a stability descriptor is computed so that the pitch estimation is performed using only the most stable sub-segment of the note. This selection is done by means of the inverse correlation descriptor [5].

3.1.2 Upper Octave Pitch Error

Pitch estimation of monophonic signals is a problem that can be considered solved. However, upper octave errors can occur when analyzing the monophonic note samples using the formulation presented in [5]. These errors take offset values of 12 or 19 semitones which correspond to the second and the third harmonic respectively.

In order to solve such errors, a new term is added in the summation of the harmonics in the SBS. This term punishes the energy in the sub-harmonics frequencies using the following expression:

$$A(w) = \sum_{k=1}^{5} \min(p(k \cdot w), \alpha \cdot p(w)) +$$
$$\beta \cdot \left(\sum_{k=1}^{4} p\left(k \cdot w - \frac{w}{2}\right) + \sum_{k=1}^{3} p\left(k \cdot w - \frac{w}{3} - \frac{2 \cdot w}{3}\right) \right) \qquad (2)$$

After running several experiments, β was set to 3. With such value we have achieved error-free pitch estimation for monophonic notes.
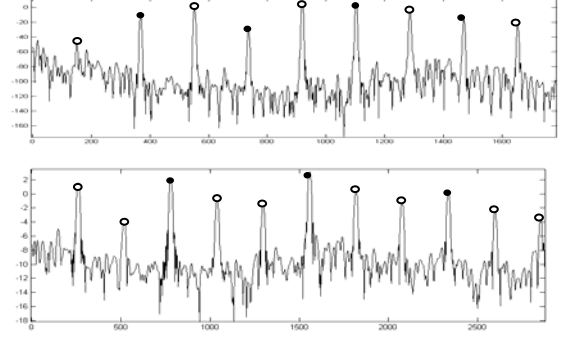
Figure 2. Local view of spectrums for typical pitch errors: B3 second harmonic confusion error (upper figure), and F4 third harmonic confusion error (lower figure). Black dots show mistaken fundamental and harmonics, empty dots show the rest of original harmonic peaks.

3.2 One Octave Duo-phony Detection

Our earlier system did not consider polyphonies in which one of the notes was an octave higher or lower from the other. The difficulty of pitch detection in such cases is that there is 100% overlap of harmonics, i.e., the harmonic spectra of the higher octave note hides under the lower octave note harmonics. In order to take such cases into consideration, we propose to include a detector in charge of resolving whether the note being considered was played together with its upper octave note or not.

Our octave duo-phony detector is based on the analysis of the magnitude spectrum modulation around the even harmonics ($2*k*F_0$ for $k=1, 2, 3,..$), and the zero-crossing factor of the first derivative of the low-pass filtered waveform.

3.2.1 Modulation Descriptor

Since the violin is not a perfect tuned instrument [1], the assumption is that whenever we have an octave distance duo-phony, even harmonics will suffer from amplitude and frequency modulations because of the frequency juxtaposition. The modulation descriptor is formulated as the mean value:

$$Md = \frac{\sum \overline{|\Delta_t FSpectrogram| \cdot AvSpectrogram}}{\sum AvSpectrogram} \qquad (3)$$

where *AvSpectogram* is the spectrogram averaged along time and *FSpectrogram* is the spectrogram of the input signal filtered by an adaptive FIR comb filter which has zeros placed over the fundamental frequency and odd harmonics, as shown in Figure 3.

$$y(n) = \frac{1}{2} \cdot \left(x(n) + x\left(n - \left[\frac{F_s}{2 \cdot F_0} \right] \right) \right) \qquad (4)$$

where F_s is the sampling frequency and F_0 is the estimated pitch.
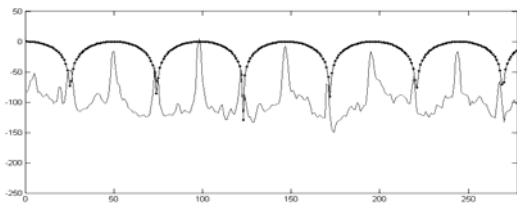
Figure 3. Local view (lower spectra) of the F_0 dependent comb filter (dotted line) and the resulting filtered violin average spectra (log magnitude versus frequency index)
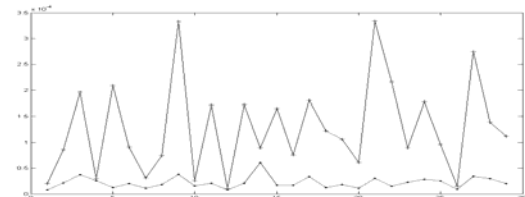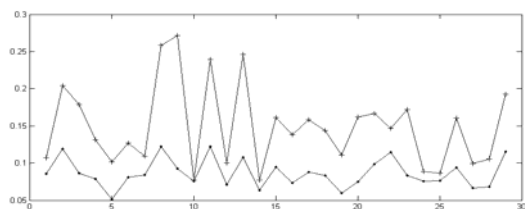

Figure 4. Amplitude/Frequency modulation along notes (A#3, A#4, A#5, A3, A4, A5, B3, B4, B5, C#4, C#5, C4, C5, D#4, D#5, D4, D5, E4, E5, F#4, F#5, F4, F5, G#4, G#5, G3, G3, G4, G5) for duo-phonic (+), and solo lower note (.)

Figure 4 shows the values of our modulation descriptor along our octave duo-phony recordings. In average terms the modulation descriptor obtained in the octave duo-phonic notes (~1.3e-4) are six times the values obtained for the solo notes (~2.2e-5). Note that the modulation parameter has a strong impact on performance. Indices 26 and 27 refer to the same note (G3) but performed in a completely different way; for index 26 the upper octave is extremely subtle and very well-tuned.

3.2.2 First Derivative Zero-Crossing Descriptor

The zero-crossing factor of the first derivative of the waveform counts the number of times a signal changes from decreasing to increasing and vice versa. After removing some high frequency components using a low-pass pre-filtering, the descriptor will be proportional to the higher pitch, assuming the signal is a summation of two components an octave apart.

Figure 5. Two sets of parameters obtained from 29 files (A#3, A#4, A#5, A3, A4, A5, B3, B4, B5, C#4, C#5, C4, C5, D#4, D#5, D4, D5, E4, E5, F#4, F#5, F4, F5, G#4, G#5, G3, G3, G4, G5) for duo-phonic (+), and solo notes(.)

Results shown in Figure 5 use a 10 point average filter. The mean descriptor value obtained in the octave duo-phonic notes (~0.15) is around twice the mean value obtained for the solo notes (~0.08). Lowest values such as

the one obtained for note 10 (C#4) most of the times are due to an extremely soft upper octave note, being this note only distinguishable at the release or transition.

3.3 Duo-phony Detection for Double Pitch Estimation

The harmonic descriptor is for guiding the pitch estimation process by telling whether the input note is monophonic or polyphonic. Based on this discrimination, simple or more demanding pitch estimation techniques are applied accordingly. With the harmonic descriptor, octave distance duo-phonies should be detected as monophonic.

The inharmonic descriptor is based on the spectrum peaks distribution along frequency axis. While most existing harmonic descriptors assume a prior knowledge of the pitch, our method is "blind". The descriptor picks first eight most prominent magnitude spectral peaks and measures the divisibility among frequency distances defined by all possible different pairs of them.

The spectral peak detection uses a modification of *PickPeaks* procedure from [6]. Only those peaks above a lower frequency boundary, which is set to the lowest possible violin pitch, are considered, and all peaks below an adaptive noise threshold are discarded. Being *PeakFreq* the vector containing sorted frequency positions of the peak, the descriptor can be formulated as:

$$InHd = \overline{\sum_{i=1}^{8}\sum_{j=i}^{8}\left|res\left(\frac{\Delta_f\big(PeakFreq\{i\}\big)}{\Delta_f\big(PeakFreq\{j\}\big)}\right)\right|} \quad (5)$$

where $res(x/y) = y \cdot [x/y] - x$.

Most non-duo-phony notes with high inharmonic score occur with the highest violin notes, where the bow noise becomes more significant and spectral peaks become more distant among them. Consequently, some parasite peaks are gathered mistakenly.
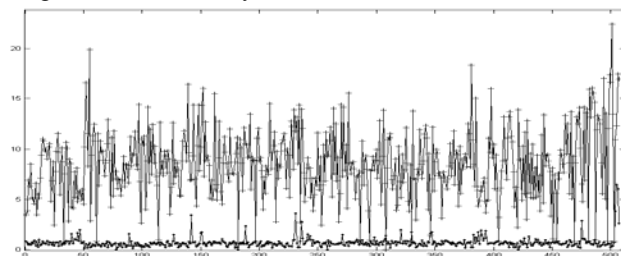
Figure 6. Inharmonic descriptor obtained from 478 files for duo-phonic (+), and monophonic (.) notes.

Pitch estimation technique presented in section 3.1 does not fit into duo-phonic pitch analysis well. Formulations such as (1) and specially (2) do not make sense anymore since $F_0/2$ and $F_0/3$ might confuse with harmonics of the second note. Better results can be achieved by trying to get two pitches at one step rather than two step analyses (analysis, subtraction, and analysis) similar to [7].

4. Vibrato Analysis

Violin vibrato is produced by a periodic rolling motion of a finger on the string, which results in a frequency modulation. Due to instrument body resonance, the frequency modulation (FM) generates also amplitude modulations (AM) in each partial [8]. FM and AM nearly always coexist in all musical instruments in a way that it is impossible to have frequency vibrato without amplitude vibrato but not vice versa [8]. In the case of violin vibrato, AM seems to be perceptually more relevant than FM [9]. One may then assume AM to be the natural feature for vibrato detection. However, experiments show there is strong correlation between fundamental's FM and partials' FM while no such correlation appears for AM.

Because of above considerations, the vibrato analysis proposed for our automatic transcription uses FM to determine vibrato presence while employing both FM and AM to characterize its manifestations. Our current vibrato analyzer is implemented based on [10], where the so-called Time-Varying Amplitude (TVA) and the Time-Varying Frequency (TVF) for the jth harmonic at the mth time frame is calculated by formulas:

$$TVA_n^m = \sqrt{\sum_j \left| S^m(f_j) \right|^2} \quad (6)$$

$$TVF_n^m = \sum_j f_j \cdot \left| S^m(f_j) \right|^2 \Big/ \sum_j \left| S^m(f_j) \right|^2 \quad (7)$$

where in our adaptation, j takes values between 0 and 4, $S^m(f)$ is the spectrum of frame m, and f_j (being the fundamental) covers, for every index j, a range of 100 cents centered around the jth harmonic frequency.
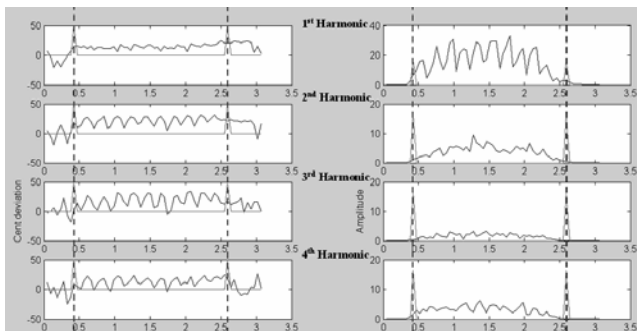
Figure 7. *TVF* (left column) and *TVA* (right column) for the first four harmonics of an A4, performed with vibrato. Dashed lines indicate bounds of vibrato regions.

5. Concluding Remark and Future Work

This paper has presented the current state of an ongoing research project. For our intended application, we have studied the problem of note-level segmentation, pitch estimation, and vibrato analysis. Experience tells us reliable note-level segmentation based solely on audio signal is a very challenging goal to achieve. Preliminary results show that it is possible to improve note-level segmentation with the help of visual cues from associated video clips. This approach is currently under progress. We also plan to include dynamics attribute extraction in future releases since its importance in the educational context, especially for advanced students. Regarding pitch estimation, although accuracy has been improved due to our modifications on previous system. We believe it should allow a non-fixed scale analysis, due to the fact that amateur students can perform significantly out of tune.

References

[1] Klapuri, A, "Automatic music transcription as we know it today," Journal of New Music Research, Vol. 33, No. 3, pp. 269-282, Sep. 2004.

[2] Yin, J., Wang, Y., and Hsu, D., "Digital Violin Tutor: An Integrated System for Beginning Violin Learners" ACM Multimedia, Hilton, Singapore, 2005.

[3] Wilson, R. S., "First Steps Towards Violin Performance Extraction using Genetic Programming", In John R. Koza editor, Genetic Algorithms and Genetic Programming at Stanford 2002, pages 253-262, Stanford, California, 2002.

[4] Krishnaswamy, A. and Smith, J. O., "Inferring control inputs to an acoustic violin from audio spectra", in Proceedings of the International Conference on Multimedia Engineering, New York,2003, IEEE Press.

[5] Boo, J. Wang, Y., Loscos, A., "A Violin Music Transcriber for Personalized Learning", in Proceedings of the ICME06 Conference, Toronto, Canada, 2006.

[6] Zölzer, U., et al. "DAFX - Digital Audio Effects', ISBN: 0-471-49078-4, John Wiley & Sons, 2002, Chapter 11. Available: http://www2.hsu-hh.de/ant/dafx2002/DAFX_Book_Page/matlab.html

[7] Fujishama, T., "Real-time chord recognition of musical sound: A system using Common Lisp Music", in Proceedings of the International Computer Music Conference, Beijing, 1999

[8] Rossing, T.D., Fletcher, N. H., "The Physics of Musical Instruments", Springer, 2nd edition, 1998

[9] Järveläinen, H., "Perception-based control of vibrato parameters in string instrument synthesis", in Proc. International Computer Music Conference, Sweden, 2002

[10] Liu, N., "Vibrato analysis and synthesis for violin: an approach by using energy density spectrum analysis", internal report, National University of Singapore, 2005