Wavelet Analysis for Onset Detection

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Abstract

The first stage of many higher level analysis, detection and synchronisation tasks is the identification of note onsets. We present a method that involves no prior knowledge of the input signal, and may be applied to non–musical sounds. The technique highlights note onsets for various timbres in the presence of overlapping notes, and will also attempt to specify which harmonics have begun at the onset. A semitone–based wavelet analysis is used to generate a time–frequency plane of modulus values, that is then transformed according to metrics derived from the study of auditory perception. The plane is then viewed as a series of vectors, and calculation of the distance between groups of vectors adjacent in time shows peaks in the distance function at onset locations. The final stage of interpretation involves detecting peaks in this function, and classifying the peaks as onsets, or otherwise.

We show a selection of examples, and describe the results of an experiment conducted to investigate the effects of loudness envelope and harmonic complexity.

1. Background

Onset detection has mostly been attempted in the context of automatic transcription ([Foster et al 82], for example). Because of this, and since amplitude information alone is insufficient in all but the most simple examples, early attempts often relied on pitch detection. However, pitch detection is potentially a more complex problem, and there are many situations in which detecting the onset of unpitched sounds would be useful.

An alternative approach utilises knowledge of the particular instruments involved, however this makes generalisation difficult ([Goto and Muraoka 95] describes a technique tailored to detecting bass and snare drums, for example).

All methods share some time–frequency decomposition as a first stage, and [Smith 95] describes how a decomposition based on the human auditory system might be used in conjunction with a neural network to locate onsets in individual frequency bands. Whilst this does not rely on pitch detection, it appears difficult to automate the interpretation of the onset data (an analagous situation is described herein).

Before explaining the decomposition we have adopted, it should be noted that, to date, almost all onset detection attempts have been based on the assumption of monophonic input. This means that only a single melodic line is present, and notes do not overlap. Whilst this is also the case here, the method we will describe is capable of locating onsets in the presence both of interfering notes, and the environmental reverberation present on most recordings.

2.Wavelet Analysis

Traditionally, time–frequency decomposition of audio signals has been achieved via Fourier analysis. However, its linear division of the frequency scale does not correspond well with our perception of pitch (which is logarithmically related to frequency). In addition, the basis sinusoids are not localised in time – audio is usually split into short time segments, and an average spectrum is calculated for each on the (invalid) assumption of its periodicity.

These problems have prompted the investigation of wavelet analysis. The basis functions are well localised in both frequency and time, and there is an inherent logarithmic division of the frequency scale. A time series of complex coefficients is generated for each frequency band (or scale level), with time resolution dictated by width and centre frequency of the band. From these, planes of modulus or phase values can be calculated (an introduction in the context of signal processing is given in [Rioul & Vetterli 91]). Wavelet analyses have, however, mainly been based on octave frequency bands, which are too wide in a musical context.

Early investigations showed that discontinuities in the input signal produced convergent lines of constant phase [Kronland-Martinet et al 87]. Work on an onset detection method based on this observation (which also uses semitone division of the frequency range) is described in [Solbach et al 95]. It is unclear, though, how this method would cope with a range of examples, including those with reverberation (which can disrupt the phase plane).

Our analysis is based solely on the modulus plane, and uses the harmonic wavelet analysis of [Newland 95]. This is efficient, and allows a semitone division of the frequency scale, making it ideally suited to musical input (our main area of concern). We will show that the unavoidable decrease in time resolution is not, in practice, a handicap.

Figures 2.1 and 2.2 show the examples we will use throughout this paper. The computed modulus values are mapped to dot densities and plotted against time (upper and lower scale levels containing negligible energy have been omitted).

Fig 2.1 – modulus values from clarinet solo [Mozart 74].

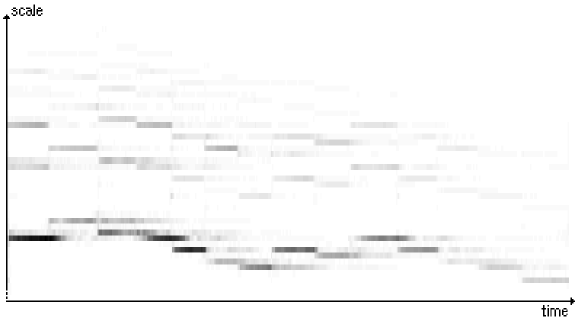
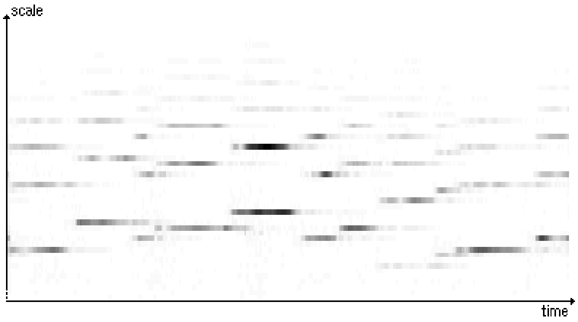


Fig 2.2 – modulus values from french horn solo [Schubert 91].



3.Transforming the Modulus Plane

Whilst we do not aim to create an auditory model, observations of the auditory system have informed further transformations of the raw modulus plane. For example, perception of loudness is related to amplitude on a logarithmic scale, so that there is some justification for mapping the modulus values to a logarithmic scale. In fact, this procedure does enhance significant features, as well as improving the results of further analyses.

Also, the auditory system is not equally sensitive to all frequencies. This implies that a weighting could be applied to each level of scale, based on its centre frequency, to emphasise features that occur in frequency ranges where auditory sensitivity is highest. Many researchers have attempted to derive such a measure experimentally. [Stevens 72] presents a frequency weighting function derived by combining the results of a large number of such studies, and an approximation of this (extrapolated to the low and high frequency regions not covered in the studies) has been applied to the output of the wavelet transform.

The last transformation we have implemented is adaptive normalisation of the modulus values. This is necessary, because the quieter notes in a passage tend to be dwarfed by the louder notes. We overcome this by first finding the maximum modulus values in adjacent time windows, and then interpolating. A normalisation and thresholding factor is thus found which adapts to the current loudness. This is not directly related to the auditory system, but overcomes the problems presented by dynamic variation in the input (as may be observed in figure 2.1, which becomes quieter towards the end).

In summary, the raw modulus plane is first adaptively normalised, and then mapped to a logarithmic scale. The transformed versions of the modulus planes in figures 2.1 and 2.2 can be seen in figures 5.1 and 5.3.

4.Highlighting Onsets

In order to investigate time varying behaviour, the plane of modulus values is divided into vectors, each constituting a slice through the plane at the highest time resolution. Vectors are compared by treating them as points in *N* dimensional space (if *N* semitone bands are being analysed), and considering the distance between them as given by the Euclidean norm:

$$d_{ij} = \sqrt{\sum_{k=0}^{N-1} (M_{ik} - M_{jk})^2}$$

where M_{ik} is the modulus value for semitone k in the vector at time i, and semitone levels 0 to N-1 at times i and j are being considered. A vector distance will thus exist if a change in frequency and/or amplitude takes place between the two points in time under consideration.

The method we have adopted is to calculate the distance between the average of the vectors in two adjacent sliding windows (whose size is dictated by a minimum note length). The averages are representative of the state of the modulus plane over a short interval, and peaks in the calculated function are evident even when only gradual change occurs between notes. Of course, the output of this method is somewhat smoothed, and the peaks are broadened — but this makes automatic detection of the peaks much easier, and is acceptable as long as short notes are not obscured. In fact, to further aid peak detection, the output is smoothed by replacing each calculated distance by an average of itself and a few others on either side.

The results of applying this technique to the transformed versions of figures 2.1 and 2.2 are shown in figures 4.1 and 4.2.

Fig 4.1 – distances from transformed figure 1.1.

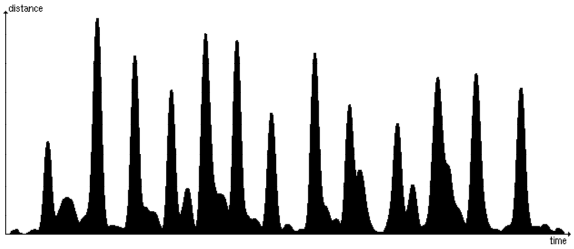
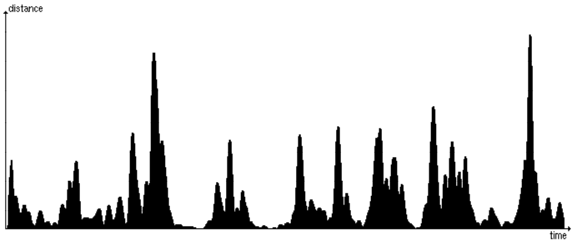


Fig 4.2 – distances from transformed figure 1.2.



Both of these examples are from orchestral recordings, with considerable reverberation, and are in legato style (with onsets not heavily punctuated). However, peaks are produced at all onset locations.

The peaks are detected by simply locating points at which a series of successive increases is followed by a series of successive decreases. A small threshold is also introduced, and peaks must be separated by at least the minimum note length.

Many peaks will correspond to onsets, however others will correspond to offsets and some will be spurious. Therefore, we must attempt to classify each peak based on the behaviour of the modulus plane around its location in time.

Currently, this is achieved by traversing scale levels at the location of the onset, and locating the point in the analysis window at which the difference between the averages on either side is maximised. A level is marked as a partial onset if its average is increasing and its later average is both above a threshold, and significant when compared with the change between the two averages. Partial onsets are counted and a peak is classified as an onset if several are detected.

Figures 5.1 to 5.4 show the results of applying this procedure (with identical parameters) to the examples already illustrated.

Fig 5.1 – detected onsets marked on modulus plane of clarinet piece.

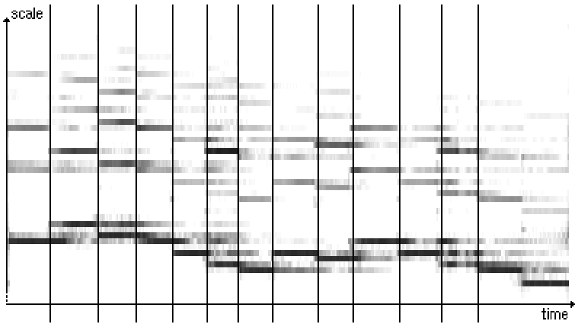
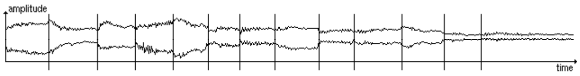


Fig 5.2 – detected onsets marked on amplitude envelope of clarinet piece.



Every onset except the last is located in the first example, and the second shows all onsets marked (with a single spurious detection, third from last).

Fig 5.3 – detected onsets marked on modulus plane of french horn piece.

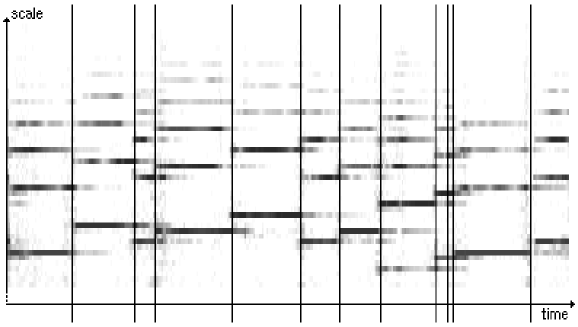
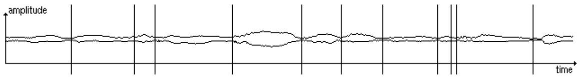


Fig 5.4 – detected onsets marked on amplitude envelope of french horn piece.



6.Conclusions and Further Work

The harmonic wavelet transform provides a useful tool for analysis of all kinds of sound, but more work is required in its practical application (one of the authors has described a vector-based similarity measure for detecting repetition in [Tait 95]). We feel that the onset detection method described herein performs well on a variety of cases (in that onsets generally produce peaks in the distance function), however the classification of peaks could be improved.

Also, a persistent problem in the course of this research has been the lack of a set of established test cases. In [Tait & Findlay 95], we presented an experiment to investigate the effects of loudness envelope and harmonic complexity. This showed that, even in the presence of overlapping notes, onsets involving slow attacks produced peaks in the vector distance function. However, there are many more variables and a set of recordings providing some degree of coverage is required.

We have begun to design an experiment which would be based around a single piece of music (including various phrasings and dynamics). This piece would then be played on a range of instruments which would be intended to cover different types of attack characteristics and timbres. In addition, results obtained in the presence of glissando, degrees of vibrato and tremolo, degrees of reverberation and interference, and some representative non–musical sounds would have to be examined separately.

Finally, we illustrate the benefit of not relying on pitch perception, which widens the scope of possible applications considerably. Figures 6.1 to 6.3 show the results of analysing the sound of 11 footsteps, with background music increasing in loudness (the regular rhythm is interrupted by a scraping foot between steps eight and ten).

In examples with greater polyphony, or background sounds, adaptive normalisation is not so appropriate and only logarithmic scaling has been applied in figure 6.1 (the distances in figure 6.3 were calculated exactly as before, however the classification parameters were changed slightly in order to highlight all of the steps).

Fig 6.1 – modulus plane of footsteps with background music, logarithmic scaling applied [JTQ 88].

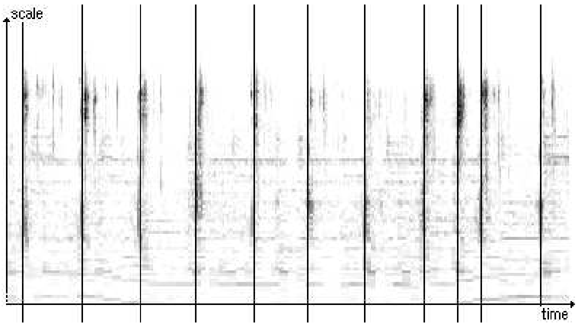


Fig 6.2 – footsteps marked in the amplitude envelope.

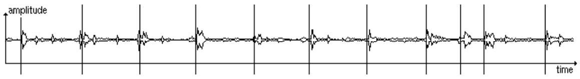
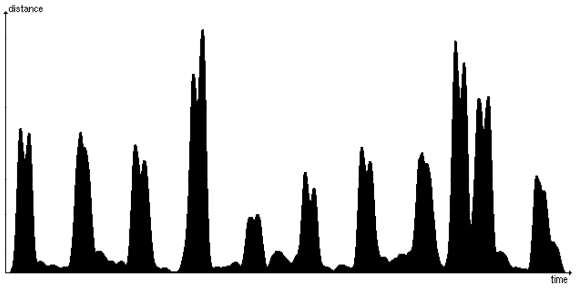


Fig 6.3 – distances from figure 6.1.



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