# Left and right-hand guitar playing techniques detection

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## ABSTRACT

In this paper we present a series of algorithms developed to detect the following guitar playing techniques : bend, hammer-on, pull-off, slide, palm muting and harmonic. Detection of playing techniques can be used to control external content (i.e audio loops and effects, videos, light events, etc.), as well as to write real-time score or to assist guitar novices in their learning process. The guitar used is a Godin Multiac with an under-saddle RMC hexaphonic piezo pickup (one pickup per string, i.e six mono signals).

## Keywords

Guitar audio analysis, playing techniques, hexaphonic pickup, controller, augmented guitar

## 1. INTRODUCTION

Guitar has maintained a close relationship with technological innovation throughout its history, from acoustic to electric and now to virtual [3]. The term "augmented instrument" is generally used to refer to a traditional (acoustic) instrument with added sonic possibilities. The augmentation can be physical like John Cage's sonic research on prepared pianos, but nowadays the term has acquired a more computational meaning: the use of digital audio to enhance the sonic possibilities of a given instrument as well as the use of sensors and/or signal analysis algorithms to give extra and expressive controls to the player. Guitar playing techniques detection are part of this last category and several of them have alreday been investigated. In [13] and [10] focus has been put on estimating the point where the string has been plucked, i.e the plucking point. In [5], left-hand fingering of a guitar player has been analyzed and characterized offline. In [6] algorithms to detect plucking and expression styles for bass guitar has been investigated. In [9] automatic note transcription from an hexaphonic pickup has been achieved. On the other hand, several studies focus more on the artistic side using added sensors and/or analysis algorithms to control synthetic sound parameters [7], [11], [12] or [4].

In this paper, we put our efforts on the audio signal analysis part, in order to detect guitar playing techniques. As they are closely linked to the guitarist it is a very natural way for the instrumentalist to control any type of media or effects and turn the guitar into a multi-media instrument / controller.

Our system could be compared to existing pitch-to-midi technologies like the [1]Axon AX 50 or the [2]Roland VG-99 systems but our approach is broader and more complete as we include all major guitar playing techniques.


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## 2. EXTRACTION OF PLAYING ARTICULATIONS

Articulations used to play the guitar can vary a lot from one guitarist to another as well as from one style to another. We worked on the most common guitar articulations (defined in [8]) listed as follows: hammer-on, pull-off, slide, bend, harmonic, palm muting.

Our algorithmic approach for articulation detection is described in Figure 1. The diagram emphasizes the discrimination between right-hand and left-hand attack as the first important element leading to the detection of all the articulations. We did not develop any pitch detector algorithm, as this question is a fairly well-known problem in signal processing. The following algorithms have been used: YIN (temporal), `sigmund~` Max MSP object (spectral) and MIR toolbox pitch detection algorithm (used with the autocorrelation method).

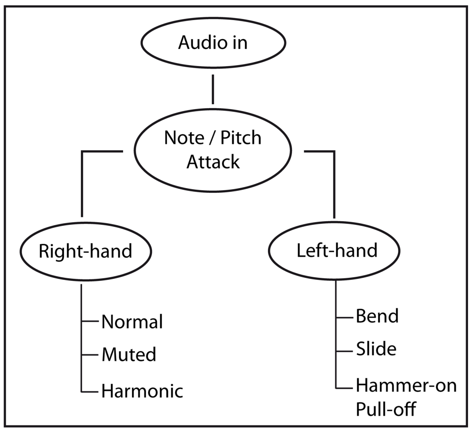


**Figure 1:** *Diagram of the articulations detection algorithm*

[1]http://www.axon-technologies.net/
[2]http://www.roland.com

# 3. BUILDING THE DATABASE

A Godin Multiac guitar with an under saddle hexaphonic RMC pickup and Alvarez Alliance HT classic nylon strings mounted on it has been used to build the database. Two styles of picking (finger and pick) have been recorded by two different guitarists, leading to the building of two databases for which: the range of the recorded notes is going from the open string to the $16^{th}$ fret; hammer-on, pull-off and slide notes range from a half-tone to one and a half tone of variation; slide notes have been recorded in both directions; bended notes couldn't hardly go above a half-tone of variation, as we were using nylon strings; the five first harmonics have been recorded for each string; normal notes have been played at three different positions: bridge, soundhole and fretboard; all recordings have been hand-segmented with [3]Sonic Visualizer software.

Each picking style database is made out of 1416 samples (normal notes: 288, palm muted: 96, hammer-on: 234, pull-off: 234, slide: 468, bend: 66, harmonic: 30).

The guitar database we recorded is available [4]online.

# 4. ONSET DETECTION

As a general scheme for describing onset detection approaches, one can say that they consist in three steps [2]. First, the audio signal is pre-processed in order to accentuate certain aspects important to the detection task, then, the amount of data from the processed signal is reduced in order to obtain a lower sample rate. Finally, thresholding and/or peak-picking can be applied to isolate the potential onsets.

## 4.1 Evaluation

Here, we have been comparing a range of onset detection algorithms which covers 18 variants of amplitude-based methods (including the energy, log-energy domains, and their time derivatives) and short-time Fourier transform based methods (including spectral flux in different domains, phase-based methods and their variants using amplitude weighting, and complex-based methods). Evaluation is performed using the approach proposed in [1]. A tolerance of plus or minus 50 ms on the timing of the detected onset has been used to still be considered as valid because of the lack of accuracy of the hand-annotated reference files. We have not been using methods requiring a pitch estimation. The monophonic recordings (sum of the 6 separate channels) of the guitar signals were used and we optimized the detection threshold for peak F-measure for each detection method individually. Table 1 presents the results for the four best performing methods, and provide the peak F-measure on the whole data set, as well as recall values for 4 categories of attacks: right-hand attack (i.e normal notes), harmonic, hammer-on, pull-off. Bends haven't been considered for this evaluation.

We observe that if the detection of right hand (including harmonics) attacks is generally not a problem, the detection of hammer-on and pull-off attacks is better achieved using STFTs-based methods. Indeed, a significant part of those left-hand attacks do not show any amplitude increase at all. Finally, the best performing approach has a F-measure above 96% with a recall close to 100% for right-hand attacks, 98% for hammer-ons, and a moderate 88% for pull-offs. Some further research would hence be necessary to understand how pull-offs can be better detected.

## 4.2 Discrimination between left and right hand attacks

When the string is plucked (by a finger or a pick), its vibratory regime is momentarily stopped, resulting in a trough just before the attack in the signal envelope. As opposed to a plucked note, legato attack doesn't stop the string's vibration leading to a shift in pitch without a significant change in amplitude. After several testing with different speeds of playing, it appears that the gap can vary from 20ms to 50ms. It has to be noticed that for faster playing, e.g tremolo, the gap disappears and a dedicated algorithm should be implemented to detect such audio event. Our left-hand / right-hand attack discrimination system is thus based on the observation of the very first milliseconds before the onset. A simple measure of the slope between the minimum energy point preceding the attack and the maximum point at the attack. Best results were obtained when computing the slope using two neighboring half-overlapping frames. This lead to a 94.0% correct classification rate when using a properly optimized threshold. We observed that classification errors are often due to string noise preceding right hand attacks, causing the energy slope to be smaller than it could be. We are hence looking into improving robustness to these playing artefacts.

# 5. LEFT-HAND ARTICULATIONS

Once the distinction between right-hand and left-hand attack is performed, it is thus possible to categorize the left-hand articulations by inspecting into the pitch profile of the note. The left hand works on the string tension and fretting, thus affecting the pitch. Our method of left-hand playing technique detection operates by measuring the pitch time derivative.

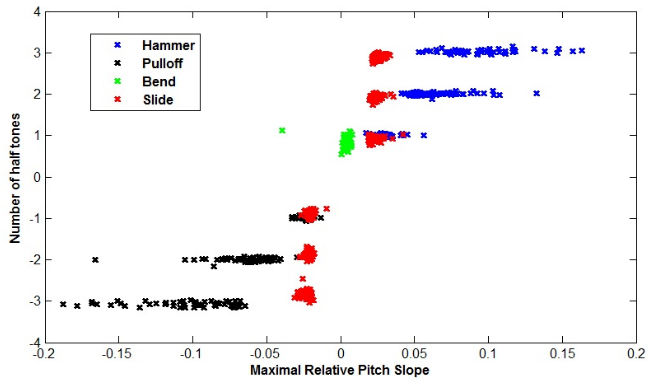


**Figure 2:** *Distribution of the number of transition half tones with the maximal relative slopes for notes with left-hand articulation: hammer-on (blue), pull-off (black), bend (green) and slide (red).*

Hammer-on (ascending legato) is characterized by an abrupt change in pitch, as well as its counterpart, the pull-off (descending legato). The bend shows a slower evolution in pitch. The slide has a pitch derivation similar to the hammer-on or pull-off, but with a "staircase" profile corresponding to the frets over which the sliding finger passes.

As a first step, two parameters are investigated: the number of half tones of the note transition, and the maximal relative pitch slope, defined as the maximal difference of pitch between two consecutive frames spaced by 10ms divided by the open string pitch value. Figure 2 shows how these two parameters are distributed for notes articulated with a hammer-on, a pull-off, a bend or a slide. It can be noted from this figure that the great majority of bended

[3]http://www.sonicvisualiser.org/
[4]http://www.numediart.org/GuitarDB/

| Method | F-measure | Normal Right-hand Recall | Harmonic Recall | Hammer-on Recall | Pull-off Recall |
|---|---|---|---|---|---|
| Spectral Flux | 96.2% | 99.6% | 100% | 97.9% | 88.0% |
| Weighted Phase Divergence | 95.8% | 98.9% | 100% | 97.4% | 87.6% |
| Amplitude | 92.4% | 99.6% | 100% | 92.3% | 75.2% |
| Delta Amplitude | 91.8% | 99.6% | 100% | 91.9% | 74.4% |

**Table 1: Results of the onset detection with four different techniques**

notes (green points) are easily identified as they present a very low pitch slope. Secondly, it can be observed that for transitions with more than one half tone, a perfect determination of slide versus hammer-on or pull-off is achieved. As a consequence, the only remaining ambiguity concerns the distinction of slide with hammer-on/pull-off for a transition of *a half tone*.

To address this latter issue, two parameters are extracted: the energy ratio and the spectral center of gravity ratio. Both of them are computed on two 40ms-long frames: one ends at the transition middle, while the other starts at that moment.

Based on the aforementioned approaches, a detection of left-hand articulated notes has been proposed simply by using thresholding. The results of the ensuing classification are presented in Table 2. It can be noticed that all bend effects are correctly identified. Slides are determined with an accuracy of 97.61%. Finally, hammers and pulloffs are detected in more than 93%. The main source of errors for these latter effects is the remaining ambiguity with slides of one half tone.

| | **Hammer** | **Pull-off** | **Bend** | **Slide** |
|---|---|---|---|---|
| **Hammer** | **93.27%** | 0.45% | 0% | 6.28% |
| **Pull-off** | 0% | **93.69%** | 0% | 6.31% |
| **Bend** | 0% | 0% | **100%** | 0% |
| **Slide** | 1.74% | 0.43% | 0.21% | **97.61%** |

**Table 2:** *Confusion matrix for detection of left-hand articulated notes*

# 6. RIGHT-HAND ARTICULATIONS

In this section, two right-hand articulations are studied: palm muting and harmonics notes.

## 6.1 Palm Muting

Palm muting is obtained by plucking the string with the palm of the right hand slightly touching the string. The produced sound is stifled, the sustain period of the palm muted note is shorter and decreases faster than the one of a normal note. Moreover high frequencies decrease faster than other part of the spectrum when the note is palm muted. As a consequence the spectrum was filtered out from 0 to 500Hz. Figure 3 shows the slopes (starting at the attack) of the spectral envelopes of four notes: three notes are played with a normal attack (at the bridge, soundhole and fretboard) and one is palm muted. For the three normal notes, one can see the longer sustain period as the curves stay rather flat compared to the palm muted note whose slope increase logarithmically.

Based on that behavior, our algorithmic approach calculates the value of the energy envelope slope at the attack and compares it to a defined threshold. The slope is computed as the energy ratio between two frames: one located at the energy peak following note onsets, and the one that follows. Table 3 shows the results of the algorithm which has been run on 48 normal notes for each strings (16 per position: bridge, soundhole, fretboard and 16 palm muted

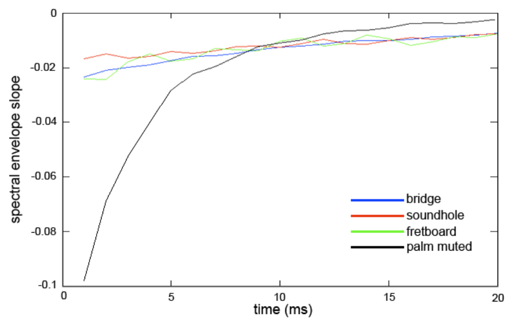


**Figure 3:** *Slope of the energy of four notes played at the bridge (blue), at the soundhole (red), at the fretboard(green) and palm muted (black)*

notes). The misclassified notes are mostly due to imperfect playing. 97.91% means that one note has been misclassified and 93.75% and 87.5% respectively leads to one and two misclassified notes.

| **String** | **Normal notes** | **Palm muted notes** |
|---|---|---|
| 1 (*thresh -0.06*) | 97.91% | 93.75% |
| 2 (*thresh -0.06*) | 100% | 100% |
| 3 (*thresh -0.06*) | 100% | 100% |
| 4 (*thresh -0.04*) | 100% | 100% |
| 5 (*thresh -0.05*) | 100% | 100% |
| 6 (*thresh -0.05*) | 97.91% | 87.5% |

**Table 3:** *Palm muting detection results for the six strings*

## 6.2 Harmonics

Harmonics are obtained by slightly fretting a note on a node of the string with the left hand. Two techniques are investigated to achieve this detection. One operates in the time domain, while the other one focuses on the spectral domain. Both approaches only consider the note attack, which allows for a real-time detection of harmonic notes. It has been attested that, after the attack, the differentiation between an harmonic and a normal note might become more difficult, especially for the $7^{th}$ and $12^{th}$ fret. The two methods are explained in the following.

- **Time-domain approach:** Figure 4 shows the waveform at the attack for a normal note and an harmonic. Two parameters are proposed: the attack duration is defined as the timespan during which the attack waveform remains positive; the relative discontinuity during the attack is defined as $Amin/Amax$ (right side of Figure 4).
- **Frequency-domain approach:** Figure 5 shows the magnitude spectrum of the attack for a normal note (left) and an harmonic note (right) using a 40ms Hanning window. On these spectra, we extracted a single parameter: the harmonic-to-subharmonic ratio is defined as the difference in dB between the amplitude of

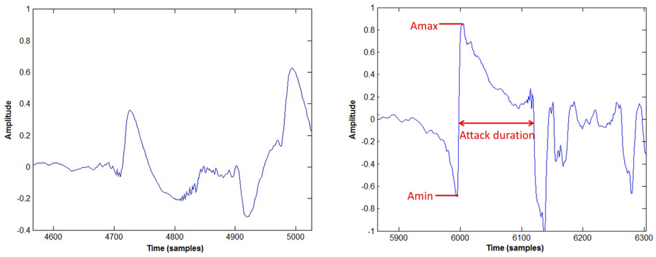


**Figure 4:** *Attack during the production of a normal note (left) and an harmonic note (right).*

the first harmonic (at $F0$) and the amplitude of the subharmonic at $1.5 \cdot F0$.

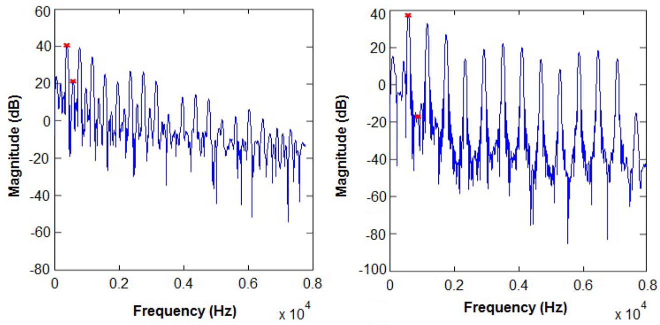


**Figure 5:** *Magnitude spectrum during the attack of a normal note (left) and an harmonic note (right).*

Based on the two previous approaches, a detection of harmonic notes has been proposed simply by using a threshold. The results of the ensuing classification are presented in Table 4. It can be noticed that all harmonic notes are correctly identified, while for normal notes, the best results are achieved for notes played on the fretboard (with only 0.52% of misclassification) and the worst ones are obtained for notes played at the bridge (with a bit less of 95% of correct detection).

| | Harmonic detection | Normal detection |
|---|---|---|
| **Harmonic** | 100% | 0% |
| **Fretboard** | 0.52% | 99.48% |
| **Soundhole** | 2.78% | 97.22% |
| **Bridge** | 5.38% | 94.62% |

**Table 4:** *Confusion matrix for harmonics detection.*

## 7. CONCLUSION AND PERSPECTIVES

This paper focused on features extraction from an hexaphonic guitar signal, in order to detect and recognize all the playing techniques commonly used on the guitar. The methodology was built on the successive detection and classification of 1) attacks/note onsets, 2) left-hand and right-hand discrimination, 3) articulation types: normal, mute, bend, slide, hammer-on, pull-off, harmonic and palm muting.

Playing techniques algorithm have been tested and implemented separately in Matlab and Max/MSP with positive feedback from informal live evaluations. However a global algorithm needs to be implemented to gather all playing techniques detection. This implementation should assessed the processing power issues encountered when using at least three detections in real-time. In addition, the defined algorithms have to be tested by different guitarists as well as with different types of guitar in order to build a relevant user-study. Finally, a machine-learning method should be considered to enhance the adaptation of the global algorithm to these different users.

## 8. ACKNOWLEDGMENTS

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