Fast Algorithm for In situ transcription of musical signals : Case of lute music

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Abstract

In this paper, we propose a fast and accurate transcription method of a musical signal. It consists of extracting the musical information from the temporal evolution of the generated signal by the instrument. Each note (primary) will mainly be represented by a finite set of basic attributes (pitch, partial, energy, duration,). To do so, we begin by extracting each note by selecting the beginning of its appearance (onset detection), then proceeding by segmenting the signal, in order to delimit each note, which is to be identified later by determining its remaining features.

The proposed method is an extension of the well known spectral based method. It is specially designed for oriental music which is characterized by its richness in tone that can be extended to ¼ tone. It aims to detect and isolate notes from a real audio signal recorded from an Oriental lute in an ordinary environment, then exploits the constraints of the lute's sound to improve the performance of the proposed transcriber. This method also includes, preprocessing and post processing based mainly on the surrounding noise, and echo. Subsequently, we present an interpretation of the results and rigorous assessment of the method through modeling the lute string motion.

Keywords: *musical note, oriental music; onset, pitch, lute, tone, RAST, string motion*

1. Introduction

Music is a field where individual sounds are combined to compose melodies, rhythms and songs. It is an art in which information is transmitted and distributed by audio signals; it can be represented either by a symbolic level or a signal one.

In the Symbolic level case, the musical content is described in terms of structures according to the music theory (partition). While the signal Level representation corresponds to a time evolution of an analog signal from which the information can be extracted by signal processing tools.

Automatic transcription refers to the analysis and the automatic extraction of settings from a musical signal in an efficient manner to describe it.

Despite attempts dating back to 1970 [1] [2] and recent processes [3] [4] [5], Oriental music represents a large area of signals rich in term of information that requiring a deep exploration. This prompted us to focus our study on the signal of a string instrument as a lute. The choice of this instrument is made because its special physical structure allows us to split the octave by a fine quarter tone units. Unlike the most of standard musics that are played on semitone units.

In this sense, the proposed transcript procedure consists, initially, on the detection of the starting point of the note (onset) in the signal as in [6] and subsequently, the identification of the selected note using the pitch estimation procedure [7] [8].

This paper is organized as follows: in Section 2, we present a brief overview of an oriental music back ground. Theoretical modeling of the motion of a string lute is studied in section 3. Section 4 is devoted to the proposed transcriber and its various stages for signal analysis and its implementation, as well as the obtained results, and their discussions. A conclusion of this work, remarks and future perspectives are presented in the last section.

2. Oriental music back ground

Oriental music differs from occidental one by the existence of the quarter tone range that results in a rich melody. The intervals used in this music are closely represented by a ratio of successive integer numbers (n+1)/n as in [9] as follow: the tone (9/8), the diatonic semitone (20/19), the quarter-tone (37/36) and the complementary to the quarter-tone called the three quarters of tone (12/11).

The main range of that music which has the tonic note C is called the RAST range, and its symbolic representation is illustrated in Figure 1; it is the analogue of C major for the range of occidental music.

As mentioned above, we present the symbolic level of a music basing on the genetic code. Thus the genetic code of RAST range is: $1\frac{3}{4}\frac{3}{4}11\frac{3}{4}\frac{3}{4}$ so, the range RAST is:

C-D-E𝄳-F-G-A-B𝄳-C, which can be combined with its genetic

code and becomes: C 1 D ¾ E ¾ F 1 G 1 A ¾ B ¾ C.
For some partitions of the oriental music, the notes are called as in [9]: Rast(C); Doukah(D); Bousselik(E); Djahaka(F); Naoua(G); Housseini(A); Mahour(B).

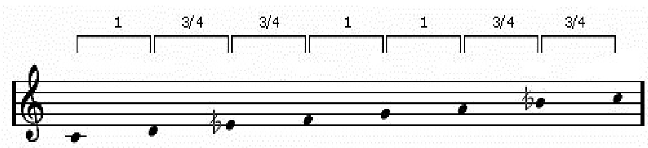


Figure 1: RAST range and its genetic code
ƀ: half-flat:

The signal level of the same RAST range is illustrated by the fundamental frequency of each note. Thus in the first octave, the notes and their frequencies are summarized as in table 1 below.

Table 1: Frequency notes of RAST range, in the first octave

Note	C	D	Eƀ	F	G	A	Bƀ	C
Freq (Hz)	65	73	79	87	98	110	120	131

Code	1	3/4	3/4	1	1	3/4	3/4
Gap (Hz)	8	6	8	11	12	10	11

According to the table 1, the developed transcription system must be able to extract the notes whose frequency difference can be about 6 Hz. In the octave 0, the transcriber resolution must be 3Hz.

3. String lute modeling

In this section, we represent a theoretical model of the string motion of lute when the string is excited at any time t. we assume also that the string length at rest is L, and it is attached at both ends (0, 0) and (0, L). We represent the vibrations of the string motion by a curve y= f (t, x) in a plane (x0y). The string in query is considered uniform and vibrates transversely,

Assumptions

1. Vibrations are only transverse, so the algebraic moving f(t, x), is lateral. (Figure 2)
2. Disturbances are small,: $|f(t,x)| \ll L$; and $\left|\frac{\partial f(t,x)}{\partial x}\right| \ll 1$
3. The gravity efforts are negligible
4. Once the string is excited, it is leaved free, and without damping within a fixed slot time.

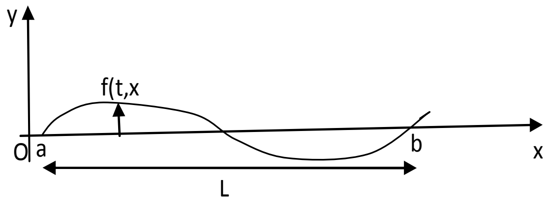


Figure 2: Modeling of string motion

Physical properties of the string:

- A linear density μ.
-A tension T, which is adjusted when tuning the lute by the artist,
- A length L: For the Arabic lute, Turkish lute and Iranian one, the total length is between 58cm and 65cm. Practically L is the distance between the bridge and the finger position on the handle of the lute.

Taking into account the different hypotheses, the string motion is governed by the following fundamental equation of dynamics:

$$\frac{\partial^2 f(t,x)}{\partial t^2} - C^2 \frac{\partial^2 f(t,x)}{\partial x^2} = 0 \qquad (1)$$

Where $C = \sqrt{\frac{T}{\mu}}$: Wave velocity propagated by the vibrating string.

Initial and boundary conditions:

- f(0,t)=f(L,t)=0 ; ∀ t ≥ 0
- $f(x,0)=f_0(x)$;and $\frac{\partial f}{\partial t}(x,0)=f_1(x)$; for $0 \le x \le L$
- $f_0(x)$ and $f_1(x)$ are the functions satisfying the following conditions: $f_0(0)=f_0(L)=0$, and $f_1(0)= f_1(L)=0$

Solving this equation leads to the expression 2 as in [10]

$$f(x,t) = \sum_{n=1}^{\infty} \frac{2\alpha L^2}{(n\pi)^2 c} . sin(k_n x) . sin(2\pi f_n t) \qquad (2)$$

Where: $k_n = \frac{n\pi}{L}$; and $f_n = \frac{nc}{2L}$:
f_n: is the n^{th} harmonic frequency.

The sound of the lute can be expressed by the effect exerted by the string on the bridge. The latter is connected to the harmonics table from which the acoustic signal representing the note is emitted. The sound s(t) emitted by the lute, over the time, is defined by:

$$s(t) = \left.\frac{\partial f(t,x)}{\partial x}\right|_{x=L} = \sum_{n=1}^{\infty} d_n . sin(2\pi f_n t) \qquad (3)$$

The resulted note has theoretically an infinite number of harmonics whose amplitude decreases as n increases. However in the practical domain, we restrict our study to a harmonic number P (partial) and we can write:

$$s(t) = \sum_{n=1}^{p} d_n . sin\,(2\pi f_n t) \quad (4)$$

Where d_n represents the n^{th} partial amplitude.

The fundamental frequency expression of the musical note is then:

$$f_0 = \frac{K}{2L} \quad (5)$$

Once the parameter **K** is adjusted by the artiste through the tension T, f_0 is inversely proportional to the length L. In practical case, the first string of the lute is generally assigned for the note C. thereafter the other musical notes can be determined according to the following table.

Table 2: Position of notes on the handle of a lute

Notes		Position (length from the bridge)
Octave 0	* (C)	L
Octave 1	C	L/2
	D	8L/9=0,88L
	E	64L/81=0,79L
	F	3L/4=0,75L
	G	2L/3=0,66L
	A	16L/27=0,59L
	B	128L/243= 0,52L
	Dƀ (≈C#)	2048L/2187=0,93L
	F#[≈Gƀ]	6144L/8748=0,7L
	Eƀ	2368L/2916=0,81L
	F#	108L/148=0,72L

* *Base note of the octave 0: It is freely adjusted through the string tension*

4. Transcription system

The proposed music lute transcriber has three main building blocks, designed Onset detection, Signal segmentation and Attributes extraction. It is indicated by the flow sheet in Figure 3.

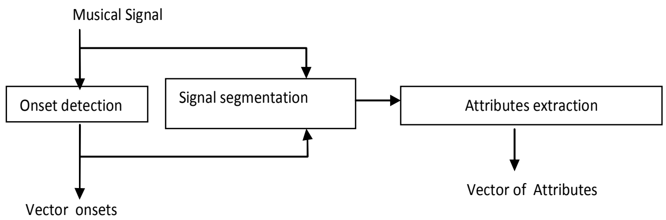


Figure 3: Transcriber scheme

The different stages of our proposed system are described as follow:

4.1. Onset detection and segmentation

4.1.1. Approach principle

Any musical note has a temporal allure showing some principal features:

- a start (onset: start time of the note)
- a transitional state: during which the spectral content is rapidly variable
- a steady state

The amplitude variation of the note is enclosed in a shape called the ADSR shape (an acronym of the words Attack, Decay, Sustain, Release), and has a behavioral pattern as in figure 4

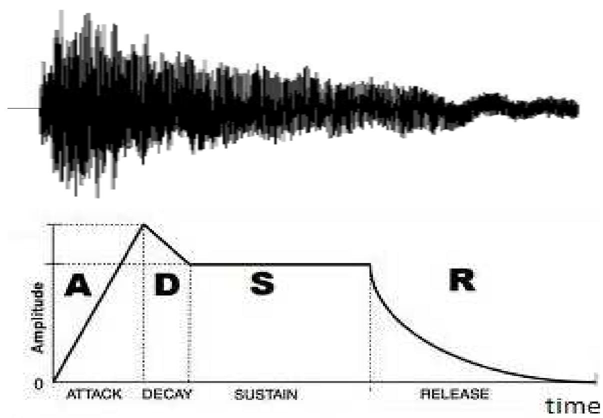


Figure 4: Allure of a note and its ADSR envelope

The four phases of this shape are:

- Attack: time during which the energy increases and the amplitude rapidly reaches its highest value.

- Decay: after the attack, a part of the initial energy is lost and the amplitude decreases.
- Sustain: amplitude maintains an almost constant level during this slot time.
- Release: the amplitude progressively decreases until it becomes negligible. .

Generally in the sustain phase, the amplitude of each high frequency decreases rapidly while low frequencies stay for long time.

In most cases, the detection of onset is based on the well known algorithm as in Figure 5a.

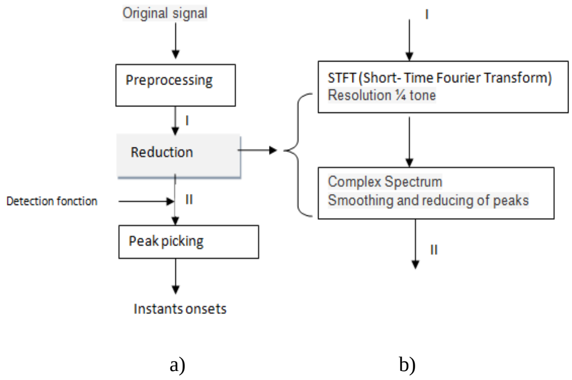


Figure 5: Diagram of the onset detection algorithm

The proposed onset detection algorithm is composed of the following steps:
-The Preprocessing stage: It consists: first, removing the present silences at the beginning and at the end of the signal. Secondly, split the signal into slices of width 4s each to facilitate and standardize the processing, because, this time is large and sufficient to extract the different features. Finally eliminate the DC component as Eq 6 and Eq 7, and normalize the signal as Eq 8.

$$s(n) = s(n) - \overline{s(n)} \tag{6}$$

Where

$$\overline{s(n)} = \frac{1}{L}\sum_{n=0}^{L-1} s(n) \tag{7}$$

And:
$$s(n) = \frac{s(n)}{max_n|s(n)|} \tag{8}$$

-The detection function: The ideal detection function is the one corresponding to a Dirac pulse train whose abscissas coincide with the moments of onsets. In reality, this function exhibits the peaks at each onset. In the literature, Bello et al **[6]** studied a set of detection functions based on: the temporal characteristics, energy, frequency and probabilistic behavior of the signal. The detection function can also be established on the basis of a non-negative factorization of the amplitude spectrum **[11]**. Also the onset detection can be achieved by a sequential algorithm based on computing a statistical distance measure between two autoregressive models **[12].** However the performance of each method is closely related to the signal (depending on the instrument) in query. Our method exploits both the temporal characteristics (string instrument) and frequency one (range of oriental music) of a lute music signal by calculating the Short-term Fourier transform (STFT) for any time n, and a frequency k of a signal x by:

$$X_k(n) = \sum_{m=-N/2}^{\frac{N}{2}-1} x(nh+m)w(m)e^{-2j\pi mk/N} \tag{9}$$

h: is the hope size : space between two slice analysis centers.

w(m) : is the weighting window of length N. That length is directly related to the resolution of the Short Term Fourier Transform.

According to Table No. 1, this resolution must be 6Hz for the first octave. In order to take into account of the non-stationarity of the musical signal and the distribution of frequencies in a quarter tone, the best manner is to choose a Hann window of variable size [13]. The variation of this size depends on the Constant Q Transform (CQT) approach, applied to the Rast range of oriental music **[13].** Its expression is:

$$N_k = 37.\frac{F_s}{k} \tag{10}$$

Where: F_s is the sample rate.

The amplitude spectrum of $\mathbf{X_k(n)}$ is considered it as an N-dimensional vector, so the approach based on changes in this spectrum is to formulate the detection function as a "distance" between two successive vectors as in Eq 11 below.

$$SD(n) = \sum_{k=-N/2}^{\frac{N}{2}-1} \{H(|X_k(n)| - |X_k(n-1)|)\}^2 \tag{11}$$

Where: $H(x) = \frac{x+|x|}{2}$ to take into account just the increasing state of the energy.
The phase spectrum $\varphi_k(n)$ is evaluated from the instantaneous frequency of the spectrum $X_k(n)$ by:

$$f_k(n) = (\varphi_k(n) - \varphi_k(n-1))/2\pi h.$$

And

$$f_k(n-1) = (\varphi_k(n-1) - \varphi_k(n-2))/2\pi h \tag{12}$$

So for a stationary sinusoid: $f_k(n) = f_k(n-1)$. Therefore

$$\varphi_k(n) - \varphi_k(n-1) = \varphi_k(n-1) - \varphi_k(n-2) \tag{13}$$

We define the phase deviation, characterizing the breakdown of stationarity of a signal for the frequency bin k, by the following equation:

$$\Delta\varphi_k(n) = \varphi_k(n) - 2\varphi_k(n-1) + \varphi_k(n-2) \qquad (14).$$

The aggregate measure of stationarity is then defined by a mean of the absolutes deviations as Eq 15.

$$\eta_p(n) = \frac{1}{N}\sum_{k=1}^{N} |\Delta\varphi_k(n)| \qquad (15)$$

In our case, we combined information about the deviation of the phase and the amplitude difference spectrum using the complex spectrum.

In fact: at time n, the estimated spectrum $\widehat{X}_k(n)$ from $X_k(n-1)$ (in the case of Stationarity) is:

$$\hat{X}_k(n) = |X_k(n-1)| e^{j\Delta\varphi_k(n)} \qquad (16)$$

The Stationarity of the signal is measured by calculating the Euclidean distance between the estimated spectrum and the observed one. This distance is given by the following equation:

$$\Gamma_k(n) = \left\{\left|\hat{X}_k(n)\right|^2 + |X_k(n)|^2 - 2\left|\hat{X}_k(n)\right||X_k(n)|\cos\left(\Delta\varphi_k(n)\right)\right|\right\}^{\frac{1}{2}} \qquad (17)$$

These distances are then summed across the frequency-domain to generate the onset detection function

$$\eta(n) = \sum_{k=1}^{N} \Gamma_k(n) \qquad (18)$$

The obtained result is shown in figure 6 below

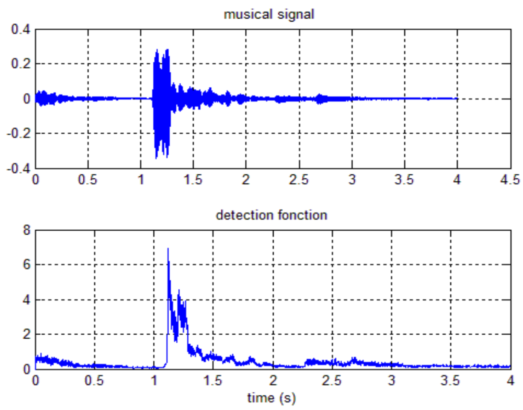


Figure 6: musical Signal and detection function

4.1.2. Smoothing and peaks selection

The physical structure of an oriental lute is particular by the fact that it can generate onsets with peaks of the detection function having low and high levels. Some peaks of high level do not necessarily mean that they are an instant of onset. Therefore, the detection function has significant peaks and insignificant ones that must be discarded. To do so, we proceed by:

• Smoothing the detection function using a median filter to reduce noise at the edges

$$d(n) = median\big(d(n-1) : d(n+1)\big) \qquad (19)$$

• Reduction and selection of peaks.

Despite of the smoothing stage, the number of peaks in the detection function is often greater than the number of real onsets of the signal. In order to eliminate the faulty peaks, three operations are executed:

- Keep the peaks that are greater than adaptive threshold which depends on the instantaneous energy of the signal, the threshold is calculated as [6] as follows:
  $$\tilde{\delta} = \delta + \lambda\, \mathrm{median}\{|d(n-M)|, \ldots, |d(n+M)|\} \qquad (20)$$
  In our case, δ: static threshold set at 0.22, λ is set at 2.
  M: Number of samples of the detection function of a window size of 50ms. The size 50ms is considered as the optimal width where the signal features do not have significant changes. This size allow us to have a good handle on the number of detected peaks
- Among the peaks that are greater than the adaptive threshold, we calculate the variation between two successive peaks: Δ (i) = peak (i)-peak (i-1) and we consider a peak(i) as significant and therefore retained, if Δ(i) is greater than 25 % of peak(i-1).

The result of our onset detection technique, applied to a real signal of a lute, is represented by the following figure

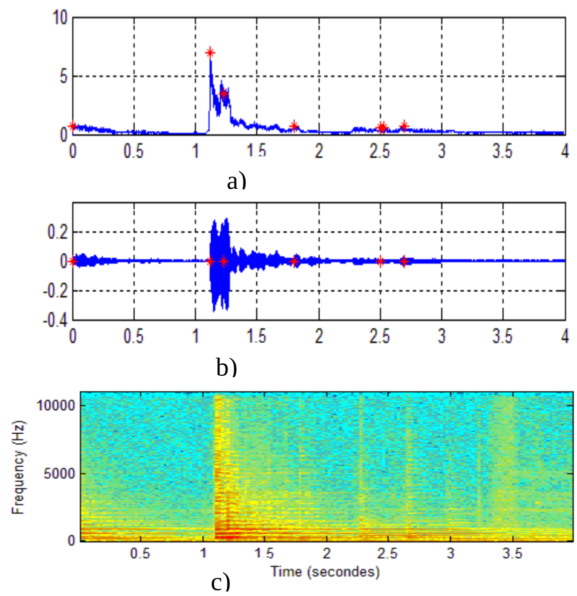


Figure 7: Results of onsets detection for a real signal lute
a) Detection function and significant peaks
b) Source signal and times of onsets
c) The music signal spectrogram

4.1.3. Segmentation

The task of the segmentation operation is to extract and isolate the musical notes from the signal in order to process them. The result of the segmentation procedure, according to the determined onset times, is shown in Figure 8 below

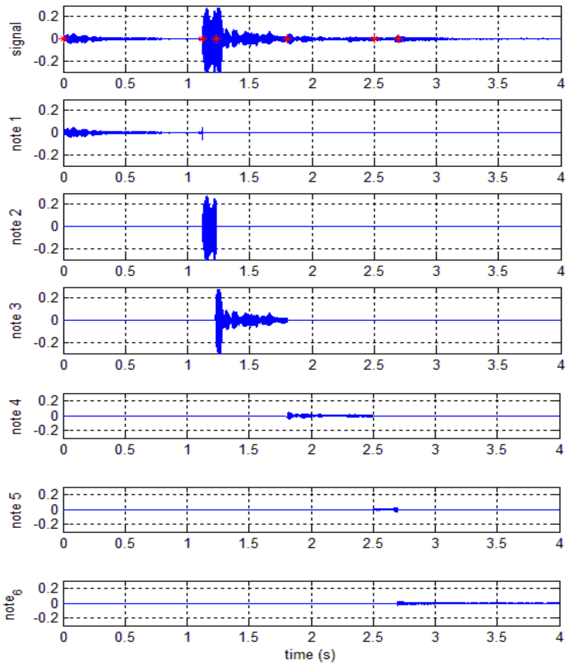


Figure 8: Switching signal according to onset

4.2. Attributes extractor

Musical notes are considered as carry meaning musical entities. Our task is to extract information allowing the passage of raw data to a more compact representation. Thus, each isolated note must be purified of noise (especially the echo) before starting the transcription process

4.2.1. Echo removing

The problem of echo can be described by a simple model of the form:

$$y(n) = x(n) + a.x(n - \Delta) \qquad (21).$$

Where:

- x(n): the original (echo free) signal;
- y(n): signal with echo.
- **a** and Δ are the amplitude and delay of the echo respectively.

The first task of this part is to estimate the parameters **a** and Δ for each note, using the autocorrelation technique:

$$C_{yy}(\tau) = E[y(n)y(n-\tau)]$$

$$= (1{+}a^2)C_{xx}(\tau) + a.C_{xx}(\Delta - \tau) + a.C_{xx}(\Delta + \tau) \qquad (22)$$

The autocorrelation function $C_{xx}(u)$ is maximum for u = 0, so $C_{yy}(\tau)$ exhibits peaks at the instants 0, Δ and −Δ, then

$$\Delta = Arg(max\,(C_{yy}(\tau))\,; with\ \Delta \neq 0. \qquad (23)$$

For the parameter a: we consider the ratio **r** defined by:

$$\boldsymbol{r} = \frac{C_{yy}(0)}{C_{yy}(\Delta)} = \frac{1+a^2}{a} \qquad (24)$$

Therefore **a** is the real solution of the following equation:

$$\boldsymbol{a^2} - a.r + 1 = 0 \qquad (25)$$

Having the parameters a and Δ, the echo phenomenon eliminator can be modeled by a filter transmittance,

$$\boldsymbol{H(z)} = \frac{Y(z)}{X(z)} = \frac{1}{1+a.z^{-\Delta}} \qquad (26)$$

So to remove the echo from y(n) and extract x(n) , we use a FIR filter transmittance F(z) with:

$$\boldsymbol{F(z)} = \frac{Xs(z)}{Y(z)} = \boldsymbol{1 + a.z^{-\Delta}} \qquad (27)$$

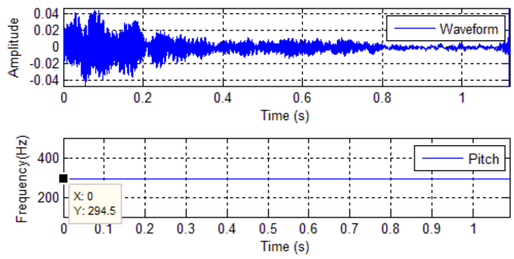
Xs(z) denote the original signal without echo

4.2.2. Pitch estimation

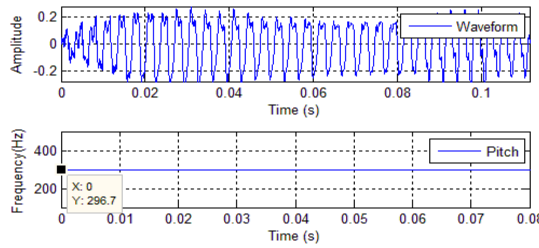
The pitch is the basic perceptual attribute used to characterize sound events and it is closely related to the fundamental frequency. The estimation of pitch is usually based on spectrum, autocorrelation, or cepstrum, or a mixture of these strategies **[7] [8]**. The main method presented in this paper to determine the pitch is the autocorrelation process .This is a most robust method that is based on the periodic characteristic of the music signal, and independent on its amplitude. The procedure for estimating the pitch of a note using the autocorrelation method is as follows:

1. Divide the signal expressing the note into frames of 5ms
2. Determinate the pitch of each frame.
3. Determinate the average pitch

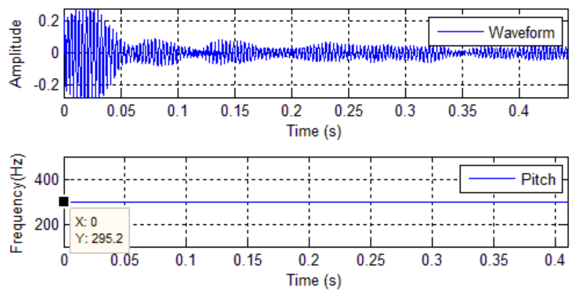
The results of the signal segmentation according to the instants onset, followed by the determination of pitch for each note are illustrated in figure 9 bellow:



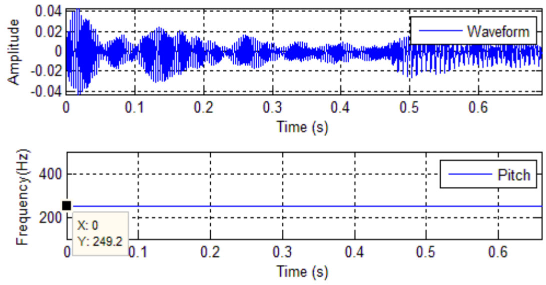
a) Note 1



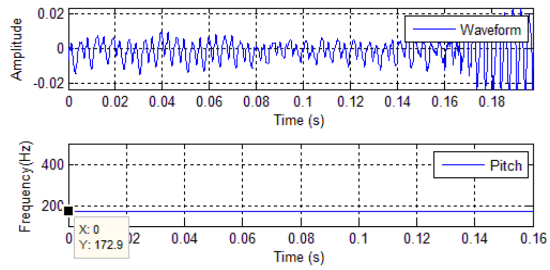
b) Note 2



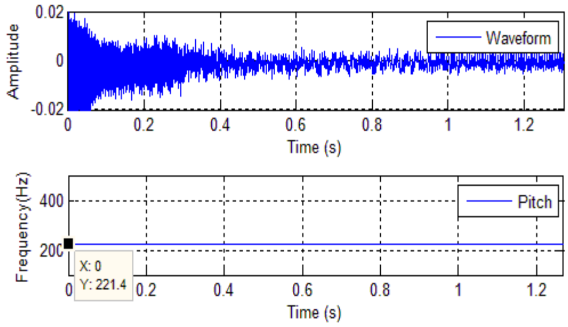
c) Note 3



d) Note 4



e) Note 5



f) Note 6

Figure 9: Alluring single notes and their pitches

The following table summarizes the results related to the transcript of each isolated note:

Table 3: Transcription results

Index note	Duration (s)	Measured Frequency Hz)	Normalized Frequency (Hz)	Absolute frequency error (Hz)	note Identificatio n	Energy
1	1,1	294,5	294	0,5	D4	1.877
2	0,1	296,7	294	2,7	D4	62.291
3	0,45	295,2	294	1,2	D4	37.786
4	0,7	249,2	247	2,2	B3	1.380
5	0,16	172,9	174	1,1	F3	0.247
6	1,3	221,4	220	1,4	A3	0.625

4.3. Obtained result analysis

The studied signal is recorded in normal conditions. Some retrieved fundamental frequencies do not correspond exactly to the normalized values. The error calculated as follow: see table 3.

$$\varepsilon = abs\,(F_{mesured} - F_{normalized})$$

That error is maximum for the musical note 2 (ε =2,7Hz), and it corresponds to the shortest musical note present in the signal. Generally, the errors are due to the fact that the position of the musician's finger may not exactly match the theoretical location. For an Arabic lute, the notes locations on the handle require a good selectivity to properly play the desired notes as mentioned above in Table 2.

To assess our procedure, we synthesized the musical signal, with the same notes, the same durations and the same energy but fundamental frequencies are normalized as mentioned in table 3. This signal is then analyzed by our transcriber. The obtained results are summarized in the following table 4:

Table 4. Measured Frequency of synthesized signal

Note index	Normalized Frequency (Hz)	Duration (s)	Measured Frequency (Hz)
1	294	1,1	293,8
2	294	0,1	292,5
3	294	0,45	294,8
4	247	0,7	248
5	174	0,16	173
6	220	1,3	220,3

Comparing the results of table 3 and table 4, we can see that the detection Pitch error increases as well as the note duration decreases.

According to the obtained result in figure 9, we can say that onsets moments depend on the previous note. For example, note 4 in figure 9.d is detected after a delay time of 0,25 sec, while the note 5 in figure 9.e is detected after 0,03 sec. However, the notified delays do not have significant impact on the result of transcription

5. Conclusion and future works

The proposed method is designed to detect and isolate notes from a recorded audio signal issued from an Oriental lute. The amplitudes of some tested notes were very low, and the beginning of a given note does not necessarily correspond to the end of the previous one. Our identification system is then more reliable, and more accurate for the long duration notes. In order to have accurate results, it is recommended to make pitch detection on the Sustain phase of the note, where the amplitude of the musical note stays unchanged. In fact, in this phase, the note is steady and indicates its periodicity. In the real context, this periodicity is used by the human ear to correctly distinguish the pitch of the note.

As the perspectives of this work, we propose to take into account the overlapping between successive notes (real context), and extend the method to more robust descriptors.

Applying these descriptors to several samples of real music, we will try to address a new process of extraction of the fingerprint and signature of musician.

For our mathematical modeling, this approach reflects just the steady state of the string motion when the oscillations are forced. In order to take into account the transitional regime and benefit from the signal and physical modeling techniques, a model that is based on the state space representation is required. This is another modeling problem that requires a deep analysis and this make our future work.

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