INDIRECT ACQUISITION OF FINGERINGS OF HARMONIC NOTES ON THE FLUTE

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ABSTRACT

In this paper we present an approach for the realtime indirect acquisition of specific fingerings that produce harmonic notes on the flute. We analyse both temporal and spectral characteristics of the attack of harmonic notes which are being produced by specific control gestures involving fingering and potentially overblowing. We then show that it is possible to acquire this effect through signal analysis using a principal component analysis on the subharmonics of harmonic notes. An 8-fold cross-validation showed this approach to be successful for a single performer playing isolated notes.

1. INTRODUCTION

In order to create interactive music systems, it is necessary to acquire control information from a performer's actions such as fingering for the flute. One possibility is the use of *augmented instruments* constructed by attaching sensors to traditional instruments. For the flute, four examples can be found in the literature: the Hyper-Flute [1], McGill air jet sensor [2], the LMA Flute [3] and the MIDI Flute [4]. Table 1, adapted from [5], compares these systems in terms of the variables they extract and, as is the concern of this paper, their ability to detect specific harmonic notes. This particular technique allows a flutist to play the same note using different fingerings by changing the properties of the air jet [6]. For instance, a D6 [1] can be obtained using D6 fingering as well as D5 and D4 fingerings by overblowing. The score notation for these three configurations is given in Figure 1.

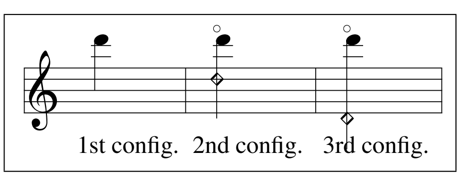

Figure 1. Score for three fingering configurations for D6. A diamond denotes the required fingering and a note with a circle above denotes the required pitch.

[1] We choose the convention where A4 corresponds to 440 Hz.

Device	Variables	Fing.	Air jet	Ob.
MIDI flute [4]	all key pos. (on/ off)	all	—	—
LMA flute [3]	all key pos. (cont.), sound amplitude	all	—	—
Hyper-flute [1]	2 key pos. (cont.), inclination, flute rotation, distance to computer	2	—	—
McGill Air-Jet Sensor [2]	total air pressure around mouthpiece, flute weight around thumb	—	pressure	—

Table 1. Comparison of various augmented flutes according to their purpose, the variables they extract, the possibility to detect fingerings, air jet and overblowing.

None of the systems in Table 1 can detect this performance parameter even though it is of common use for flutists playing contemporary music, jazz and other improvised music. One could imagine combining McGill's air jet pressure sensor [2] with the LMA Flute [3] to detect both fingering and overblowing. A possible drawback of this solution, however, would be the intrusive nature of the pressure sensor.

Viewpoint	Condition 1	Condition 2	Condition 3
Fingering	D6	D5	D4
Score [2]	D6	1st harmonic	3rd harmonic
Control	normal	overblow	overblow
F0	f_{D6}	$2\,f_{\mathrm{D5}} \approx f_{\mathrm{D6}}$	$4\,f_{\mathrm{D4}} \approx f_{\mathrm{D6}}$

Table 2. Naming convention for the fingering configurations in Figure 1.

Herein lies the interest of an approach relying mainly on an analysis of the sound. This type of approach, known as *indirect acquisition* [7], has many benefits, the main one being that no alterations to the instrument are required, apart from the need of a microphone. On the other hand, this method requires complex algorithms which can be computationally intensive. We will now outline our methodology and results in the preliminary study of indirect ac-

[2] Convention used by musicians.

quisition of fingerings of harmonic notes.

2. METHODOLOGY

We first present the data set we collected for indirect acquisition of fingerings of harmonic notes on the flute, and then discuss the choice of appropriate sound descriptors for future realtime analysis.

2.1. Data collection

We recorded 20 samples of each fingering (normal plus one or more harmonic notes) listed in Table 3. Depending on the point of view, the three configurations illustrated in Figure 1 can be expressed with a different lexicon (*cf.* Table 2). In this paper, we refer to configurations 1, 2 and 3 as D6 with normal fingering, D6 with D5 fingering (harmonic series of the second harmonic of D5 plus some subharmonics) and D6 with D4 fingering (harmonic series of the fourth harmonic of D4 plus some sub-harmonics). All of our recordings come from a single performer and were made using an EarthWorks SR 77 microphone (positioned approximately 10 cm above the flute mouthpiece) and an Apogee Rosetta 800 sound card (16-bit, 44.1kHz) on a Mac G5.

Grp	Note	Fingerings	Grp	Note	Fing.
1	D#5	D#5, D#4	5	F6	F6, F5
2	D6	D6, D5, D4	6	F#6	F#6, F#5
3	D#6	D#6, D#5, D#4	7	G6	G6, G5
4	E6	E6, E5	8	G#6	G#6, G#5

Table 3. Experimental data set: note and fingerings used to play this note for each of the 8 groups.

2.2. Strategy for analysing fingerings of harmonic notes

When a flutist plays a harmonic note using a given fingering and overblowing, several changes appear in the sound. For example, the fundamental frequency is not exactly the same as with the normal fingering (*cf.* Table 2). Also, differences arise in the spectral envelope of both the harmonic and residual components of the sound, as well as in the temporal and spectral structure of the attack. We did not use the slight difference in fundamental frequency since experienced flutists can correct it [3] by adjusting the air flow and tilting the flute. Additionally, detecting changes in the spectral envelope of the harmonics and residual noise requires non-realtime analysis, so we avoided this approach. Hence, only the temporal and spectral structures of the attack seem to allow for reliable realtime detection of fingerings of harmonic notes. We now present the analysis of the attack we consider in these two domains.

[3] "[T]he player must be sensitive to the subtleties of each fingering and must compensate appropriately for any inherent defects in intonation, dynamics, or tone quality", [8] p. 143.

3. TEMPORAL ANALYSIS OF THE ATTACK

3.1. Observations

We chose to examine the evolution of the short-time energy of the signal during the attack via the RMS profile. To obtain the best results, we assumed that we knew the pitch of the sound to perform a pitch-synchronous analysis. In figure 2, we display the average and standard deviation of the RMS profiles computed for the three fingering configurations of D6 presented in figure 1.

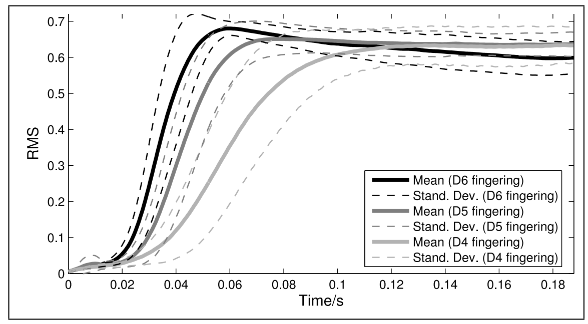

Figure 2. Mean and standard deviation of the RMS profile for three different fingerings of D6.

We noticed that the RMS profile increased faster for normal fingerings than for alternate fingerings. Also, we found a faster rise of the RMS for condition 2 (2nd harmonic note) than for condition 3 (4th harmonic note).

3.2. Results

In order to quantify the previous observations, we collected the inflexion point of the attack profiles for all the sounds in our data set. Figure 3 represents the inflexion points corresponding to three different fingerings for D6, together with the mean and standard deviation of the inflexion point for each fingering. The x-axis represents the time at which the inflexion is reached with respect to the onset. The y-axis represents the value of the slope at the inflexion point, the maximum slope of the RMS profile. It appears that, on average, the RMS profiles of the different fingerings tend to cluster in different regions of this 2-dimensional representation. Nevertheless, the distinction between those regions is not always very clear. In Fig. 4, for instance, we observe some overlap between the different types of fingerings for F6. Therefore it appears that although the RMS profile may not be perfectly suited for the identification of overblowing, it provides information about the attack. This information can be used in combination with spectral analysis for other applications such as attack type detection.

4. SPECTRAL ANALYSIS OF THE ATTACK

Since harmonic notes are produced on the flute by overblowing a given fingering of a lower note, we carried out a spectral analysis on the attack portion of our recordings

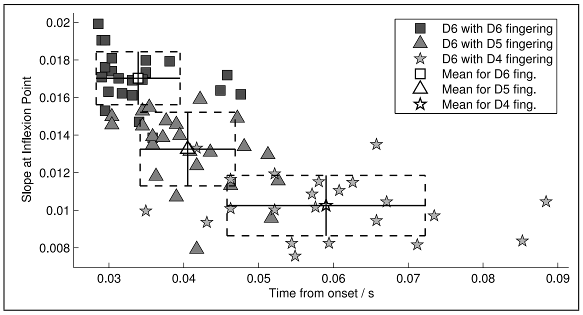

Figure 3. Slope vs. time of the inflexion point for D6.

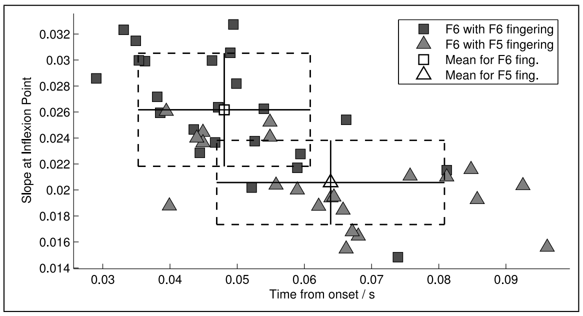

Figure 4. Slope vs. time at the inflexion point for F6.

(using IRCAM's Audiosculpt [9]). Figure 5 shows three sonograms of the note D6 played with alternate fingerings. It is quite obvious that, as the fingering changes from D6 to D5 to D4, energy still emerges at sub-harmonics of the D6 fundamental. The presence of sub-harmonics is especially pronounced during the attack of each note, and indicates that a portion of the air column is still oscillating at a lower frequency when harmonic notes are played.

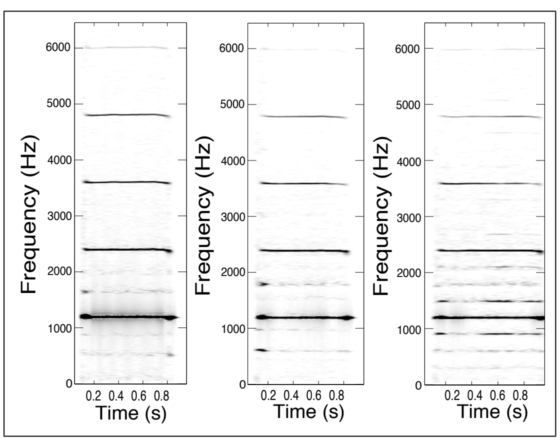

Figure 5. From left to right: sonograms for D6, 2nd harmonic of D5, 4th harmonic of D4.

We decided to extract the power in these sub-harmonics in order to determine their suitability for classification of overblowing on the flute. To simplify the feature extraction we assumed *a priori* knowledge of the pitch and onset time of each note. For a monophonic instrument like the flute, these parameters are relatively easy to extract. We performed an FFT on each flute recording using a 2048-point Hanning window and 1024-point hop size. For each of the first six sub-harmonics, the spectrum power was averaged on frequency intervals centered around the sub-harmonic frequency, for further analysis. Figure 6 shows a block diagram of the processing chain.

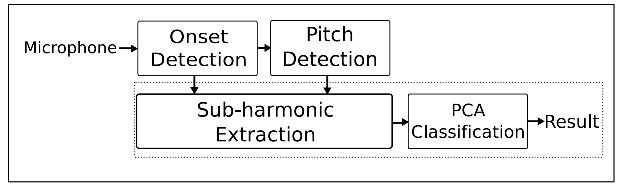

Figure 6. Block diagram for overblowing detection.

4.1. Principle Component Analysis

It is clear that the spectrum changes for each of the different fingerings, however, the mechanism for this change is not straightforward. For example, it is difficult to identify how the spectral envelope of sub-harmonics changes from one fingering to another. For this reason, we decided to experiment with principle component analysis to isolate the elements in our feature vector responsible for the greatest variance.

The principle component analysis (PCA) technique decomposes a data set onto the eigenvectors [4] of its covariance matrix [10]. A reduction in dimensionality can often be achieved using PCA since the first few eigenvectors (*principle components*) usually account for a high percentage of variance in the analysed data (in which case non-principle components may be discarded with minimal information loss). PCA can aid in the interpretation of data because it concentrates information previously spread across several interrelated variables; it can also be used as a classifier since separating the dimensions of a data set according to variance will often cause clustering in the eigenspace. In this paper we use PCA to classify harmonic notes fingerings on the transverse flute, similarly to how Egozy examined embouchure pressure and attack types on the clarinet [11].

4.2. PCA Results

We performed a separate PCA on each configuration in our data set (Table 3) and, to verify our results, we performed an 8-fold cross-validation. Cross-validation is the most widely used method for obtaining unbiased estimates of model performance in machine learning applications [12]. To perform the cross-validation we partitioned our data set into 8 subsets, each with 14 training recordings and 2 test recordings.

Figures 7 and 8 show typical results of the PCA. In each figure the gray shapes represent training data and the black shapes represent testing data. The first two principle components were found to account for over 90% of the

[4] These eigenvectors define a linear transformation between the original feature space and an *eigenspace*.

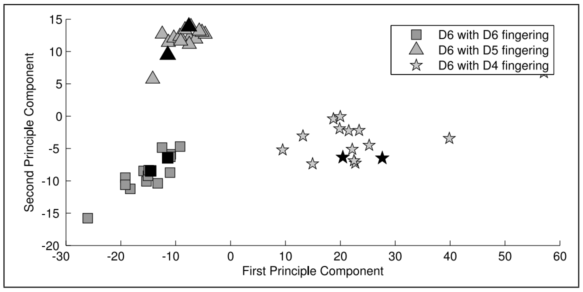

Figure 7. First two principle components for 3 configs of D6 (gray: training data; black: test data).

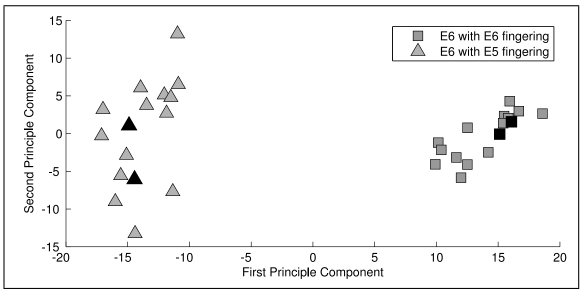

Figure 8. First two principle components for 2 configs of E6 (gray: training data; black: test data).

variance in each group. Referring back to the figures, notice that each configuration forms a distinct cluster in the eigenspace. We used a least-squares distance measure in order to classify the fingerings/overblowing used on each test recording. In other words, the squared distance between each test sample and the center of gravity of each training cluster was measured, and used to classify the test recordings. We found that all of the test recordings of this single performer were correctly classified using this metric. Realtime application of this classification scheme is possible, the training (PCA modeling) can be done offline.

5. CONCLUSION AND FUTURE WORK

This work has examined techniques for realtime indirect acquisition of fingerings of harmonic notes on the flute. Although the RMS profile was not sufficient for classification, we believe this feature could be very useful for other analyses such as attack type classification. On the other hand, we have demonstrated that it is possible to identify different flute fingerings/overblowing by applying PCA to the energy of the sub-harmonics. The results for a single performer were very robust, giving 100% correct classification on eight different notes, using an 8-fold cross-validation. A natural next step would be to extend this study using multiple performers and different flutes. It remains to be seen whether a performer invariant system would be possible, or whether a PCA calibration would be required on a performer by performer basis. We would also like to test the success of this technique in more realistic musical conditions, for example, on a series of articulated notes.

6. ACKNOWLEDGEMENTS

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