NON-UNIFORM TIME-SCALING OF CARNATIC MUSIC TRANSIENTS

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ABSTRACT

Gamakas are an integral aspect of Carnatic Music, a form of classical music prevalent in South India. They are used in rāgas, which may be seen as melodic scales and/or a set of characteristic melodic phrases. Gamakas exhibit continuous pitch variation often spanning several semitones.

In this paper, we study how gamakas scale with tempo and propose a novel approach to change the tempo of Carnatic music pieces. The music signal is viewed as consisting of constant-pitch segments and transients. The transients show continuous pitch variation and we consider their analyses from a theoretical stand-point. We next observe the non-uniform ratios of time-scaling of constant-pitch segments, transients and silence in excerpts from nine concert renditions of varnams in six rāgas.

The results indicate that the changing tempo of Carnatic music does not change the duration of transients significantly. We report listening tests on our algorithm to slow down Carnatic music that is consistent with this observation.

Index Terms— Carnatic Music, Pitch transients, Time-scaling.

1. INTRODUCTION

Gamakas form an integral part of Indian classical music. These are continuous pitch variations that traverse pitches between notes in typical musical scales. In Carnatic music, gamakas carry important information relating to the definition and identity of a rāga (a rāga is roughly comparable to scales in Western classical music). It is important that gamakas are rendered accurately to preserve the nuances of a raga.

Descriptions of gamakas in Carnatic musicology texts are believed to be the first, but names at least one earlier source) give a feel for what they are. For example, the kampita gamaka (regarded as the most representative one in Carnatic music) is described in [1] as “Keeping the fingers of the left hand on any svara sthāna [fret] in the vina [a fretted Carnatic instrument] with the mīṭṭu [pluck] and shaking the string is kampita.” The ‘shake’ can span over three semitones. However, these descriptions are not directly useful in a mathematical characterization, as was recognized in the CompMusic project [3].

Although Carnatic music is considered replete with gamakas, even seasoned practitioners agree that some rāgas are 'gamaka-heavy' while others are not. Thus, some interesting questions arise:

1. How much of Carnatic music consists of gamakas?
2. How do gamakas scale with tempo?
3. Do gamakas influence emotional responses to music?

We show in this paper that even for rāgas seen as gamaka-heavy, the time-scaling is not uniform. As a result, the first question cannot be answered without a tempo being assumed. The third question is related to the first and we come back to it in Section 6. Our analysis would conceptually be applicable to any genre of music with gamaka-equivalent features, notably Hindustani music.

An important compositional form of Carnatic music, the varnam, is usually sung in two speeds (at least roughly the first one-third is) and are thus ideal for our analysis to answer the second question above. The only notation from Carnatic music we will use in this paper is given in Table 1.

The rest of the paper is organized as follows. Section 2 describes relevant previous work, while windowing-based techniques to track gamakas are analyzed in Section 3. Additional results from analysis of concert recordings in Section 4 support an alternative approach to time-scaling in Carnatic music. The results of listening tests to evaluate this technique, presented in Section 5 are followed by a discussion in Section 6.

2. PREVIOUS WORK

If there is continuous pitch variation, as in gamakas, a natural approach is to track the curve(s) the variation follows. Piece-wise linear fitting was used in [5] for retrieval, while Bezier curves were used to characterize them for synthesis [6]. In [7], the variation was ‘quantized’ to eight cubic polynomial curves for retrieval. However, none of these characterizes gamakas satisfactorily.

There have also been many studies of Western classical music vibratos. An extensive survey of results relating to vibrato can be found in [8]. However, though similar in spirit to gamakas, vibratos are much faster and the range of pitch variation is much smaller and techniques developed for analysis of vibrato do not scale for gamaka analysis. A recent article [9] describes glissandos, but they are really counterparts to jārus, which is a particular type


Table 2: Typical variable values of lower Ni in bhairavi for a male voice. See Fig. 1 for the meanings of the variables.

| Variable | $f_0$ | $f_1$ | $t_{c1}$ | $t_{c2}$ | $t_T$ |
|----------|-------|-------|----------|----------|--------|
| Value    | 125 Hz| 150 Hz| $\geq$ 70 ms | $\geq$ 70 ms | 200 ms |

Figure 1: Pitch contour for a phrase DN in bhairavi. Three positions of the analysis window, of width $W = 40$ ms, are shown. The x-axis is time in seconds and the y-axis, frequency in Hz.

In the leftmost position of the window, it is safe to assume (because the pitch is not changing) that the time-windowed, digital signal can be viewed as:

$$s_1[n] = h[n] \times a_1 \cos[2\pi f_0 n T_s + \theta_1]$$ (1)

where $a_1$ is the constant amplitude of the signal, $\theta_1$ is a random phase parameter, and $T_s$ is the uniform sampling period.

We call such segments constant-pitch segments or CP-notes. A working definition is the longest sequence of pitch values whose minimum and maximum are within 0.3 semitones of the mean, while the magnitude of the slope of the best fit line through those values does not exceed 1 semitone per second. The short-term Fourier transform of $s_1[n]$ is:

$$S_1(e^{j\omega}) = a_1 H(e^{j(\omega - 2\pi f_0 T_s)}) e^{j\omega \theta_1} + H(e^{j(\omega + 2\pi f_0 T_s)}) e^{-j\omega \theta_1}$$ (2)

Similar equations would apply for the right-most position of the window, except $\theta_2 \neq \theta_1$ and $a_2 \neq a_1$ in general.

The form of (2) is amenable to reasonably accurate pitch-tracking, provided the main-lobe width of $H(e^{j\omega})$, $B_H$, satisfies $B_H \leq 2\pi f_0 T_s$. This last condition can be ensured by choosing a long-enough window size.

For the ‘middle’ position of the window, an equation such as (2) is much harder to formulate. However, we do know that the signal within the window has a variation in frequency, expressed as a ratio $\rho$, which must equal or exceed in parts that of the linear variation from $f_0$ to $f_1$ (in duration $t_T/2$). That is, $\rho \geq \rho_L$ where

$$\rho_L = 1 + \frac{f_1 - f_0}{f_0} \times \frac{W}{t_T/2} = 1 + \frac{1}{15} = 1.06$$ (3)

This ratio seems small at first sight, but it is greater than a semitone. In fact, the pitch in this window cannot be defined because its spectrum would have energies spread between $f_0$ and $f_0(1 + \rho)$. Further, it is impractical to progressively decrease the window size to reduce $\rho$ because the resolution of nearby frequencies (i.e. harmonics in case of real musical signals) worsens, which is due to widening of the main lobe in the window’s spectrum. Only the very slow gamakas (like a slow jāra, or ‘slide’) can be analyzed in this manner. It does not work for the typical range of transient durations (100 to 200 ms).

This analysis suggests that transients should not be analyzed by reducing the time-shift between windows ($w$) while leaving ($W$) large. Fortunately, in Carnatic music, there may not be the need to precisely find the curve of a gamaka, as we found in informal experiments, and is supported by the number of successful interpolation techniques for synthesis [15,6,11].

4. NON-UNIFORM SCALING OF TRANSIENTS AND CP-NOTES

The foregoing analysis leads to an interesting question: Do transients slow down with tempo? Surprisingly, it appears that they scale to only within a limited range as we show below.

4.1. A close look at time-scaling of transients

Consider the two speeds of rendering a single svara, Ri, in kēdāragoula rāga. The pitch contours (estimated from [13]) are shown in Fig. 2a. Transients are manually marked with red curves.

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1Unless we make assumptions about the curve, which we do not.
and CP-notes, with blue lines. It is fairly evident from the figure that
the transients and CP-notes do not scale the same way. To aid see-
ing this better, Fig. 2 has the pitch contours of the faster renditions
shifted so that the transients are aligned. The figure clearly shows
that CP-notes are scaled down much more than the transients. This
is analogous to speech, where the duration of consonants is pre-
served across different speeds, while the duration of vowels suffers
significantly. In order to identify words that are spoken, consonants
are necessary. The importance of vowels cannot be undermined,
though: the distinction between beet and bit is just the vowel.

4.2. Non-uniform scaling in longer examples

The examples discussed so far were analyzed manually. The scal-
ability of this approach is established by analyzing varnams in six
rāgas. The pitch contour of a given varnam is first estimated using
the MELODIA algorithm [16]. The pitch contour is further seg-
mented into CP-notes, silence (corresponds to regions where the
pitch estimate is zero) and transients (everything other than CP-
notes and silence). The varnams are a particular class of items,
where some lines (about a third of the composition) are usually
rendered in at least at two different speeds. The durations of CP-
segments, segments and silence segments in the first and second
speeds are obtained.

Next, the ratios of the durations in the first speed to the cor-
responding durations in the second speed were found. The overall
ratio is defined as the total duration in the first speed to that in the
second. Table 3 shows very clearly that there is a large difference
in the ratios of the CP-notes and transients (and silence).

4.3. Proposed Algorithm

Based on the observations presented, we propose Algorithm 1 to
slow down music by a factor $R \geq 1$. The actual slowing down
(statement 24) is similar to the TD-PSOLA algorithm [17, 18].
However, that is not the main contribution of the algorithm.
Recalling the analysis in Section 3 it is to be noted that when dealing
with transients, it is often not possible to define the pitch curve ex-
actly. This immediately implies that a pitch-synchronous method of
time-scaling transients would be ambiguous. Instead, as a first
approximation, we do not scale transients at all (statement 17). The
algorithm is given for the case of integer $R$, but it can be appropri-
cately extended to other cases. The tonic, $f_0$, was found manually.

Algorithm 1 was used after `snapping’ stationary points to the
nearest CP-notes, which cluster around scale notes (Table 1) with
very sharp peaks [19]. If the pitch values for 80 ms around a station-
ary point were within 0.3 semitones from any of the CP-note peaks,
they are counted as a CP-note (the slope condition in the definition
of a CP-note is not enforced). Second, based on the result in
[20], CP-notes shorter than 250 milliseconds are not extended bey-
ond this limit. This technique results in an effective slowing-down
factor being $R' < R$. In the experiments described in Section 5, $R'$
ranged from 1.79 to 1.81 for $R = 2$.

Clearly, Algorithm 1 is only one way of slowing down music,
but the result in Section 3 shows equally clearly that uniform scaling
of transients is not the way to do it. Non-uniform scaling of the
transients within the limits of Table 4 may help for a larger range of
$R$, but it is beyond the scope of this paper.

Algorithm 1: Non-uniform slowing down of Carnatic music

1. Segment the music samples into non-overlapping frames of
length $W = 32$ ms.
2. Find the, say $K$, silence segments [5], each lasting from $x_k$ to
$y_k$ frames, $1 \leq k \leq K$.
3. Track the pitch in each frame [5] (algorithm modified to use
phase-information of the spectrum) to obtain $f[l], 0 \leq l < L$.
4. In the regions of music (i.e. not silence), find the pitch in sem-
tones with respect to the tonic, $f_0$, as $n[l] = \lfloor f[l] / f_0 \rfloor$.
5. Identify, say $C$, CP-notes according to the definition in Section
3. Let the $j$th CP-note start at frame $c_j$ and end at frame $d_j$.
6. for $1 \leq j \leq C$ do
7. Mark the nominal start and end of the $j$th slowed-down CP-
   note as $\hat{c}_j \leftarrow Rc_j$ and $\hat{d}_j \leftarrow Rd_j$.
8. end for
9. Identify, say $I$, transients (other than silence and CP-notes). Let
each start at frame $s_i$ and end at frame $e_i$.
10. for $1 \leq i \leq I$ do
11. Set the beginning and end of the slowed-down transient as
   $\hat{s}_i \leftarrow Rs_i$, and $\hat{e}_i \leftarrow (R - 1)s_i + e_i$.
12. Find the nearest CP-note or silence segment on either side of
   the $i$th transient.
13. if an earlier CP-note (indexed by $j(i)$) or silence (indexed by
   $k(i)$) flanks the transient then
14. $\hat{d}_{j(i)} \leftarrow \hat{s}_i - 1$ or $\hat{y}_{j(i)} \leftarrow \hat{s}_i - 1$.
15. end if
16. if a later CP-note (indexed by $j(i)$) or silence (indexed by
   $k(i)$) flanks the transient then
17. $\hat{c}_{j(i)} \leftarrow \hat{e}_i - 1$ or $\hat{y}_{j(i)} \leftarrow \hat{e}_i - 1$.
18. end if
19. end for
20. for $1 \leq j \leq C$ do
21. Divide the signal by the interpolated amplitude of the CP-
   note (energy in frames $c_j$ to $d_j$).
22. Interpolate the original amplitude from frames $\hat{c}_j$ to $\hat{d}_j$.
23. Find the numbers of frames of attack and decay of the CP-
   note. Let these be $a_j(\geq 1)$ and $b_j(\geq 1)$ respectively.
24. Pitch-synchronously, extend the steady part of the CP-note
   in frames $c_j + a_j$ to $d_j - b_j$ to occupy frames $\hat{c}_j + a_j$ to
   $\hat{d}_j - b_j$.
25. Multiply the signal by the interpolated amplitude.
26. Copy the signal from frames $c_j$ to $c_j + a_j - 1$ to frames $\hat{c}_j$
to $\hat{c}_j + a_j - 1$ and similarly for frames $d_j - b_j + 1$ to $b_j$.
27. end for
28. for $1 \leq k \leq K$ do
29. Extend the signal in frames $x_k + 1$ to $y_k - 1$ by repetition
   (with any excess repetition deleted) to occupy frames $\hat{x}_k + 1$
to $\hat{y}_k - 1$.
30. Copy the signal from frames $x_k$ and $y_k$ to frames $\hat{x}_k$ and $\hat{y}_k$
    respectively.
31. end for

2The second speed is actually twice that of the first, but it is common
practice that lines of the varnam are repeated in the first speed and not in
the second. This explains why the overall ratio is well above 2 in Table 4.
Figure 2: Pitch contours of the rendering of the phrase RGRS in the rāga kēdāragoula, in three speeds. Transients have been manually marked with red curves, and CP-notes, with blue lines. The x-axis is time in mm:ss format and the y-axis, frequency in Hz.

Table 3: Durations and ratios of constant-pitch segments and transients in two speeds of the first parts of several varṇams in six rāgas.

| Rāga       | Number of varṇams | Duration in the 1st speed (seconds) | Ratio (1st speed to 2nd speed) |
|------------|-------------------|------------------------------------|-------------------------------|
|            |                   | CP-notes | Transients | Silence | Overall | CP-notes | Transients | Silence | Overall |
| Tōḍī       | 1                 | 37.7     | 69.7       | 10.5    | 117.9   | 8.66     | 2.61       | 3.79    | 3.49    |
| Bhairavi   | 1                 | 56.0     | 100.2      | 64.1    | 220.3   | 10.27    | 2.58       | 5.44    | 3.93    |
| Kāmbhōjī   | 1                 | 52.1     | 79.3       | 29.1    | 160.5   | 6.2      | 1.9        | 2.8     | 2.7     |
| Sankarābharaṇam | 1     | 43.6     | 87.1       | 11.7    | 142.4   | 12.3     | 3.48       | 2.33    | 4.23    |
| Sahānā     | 3                 | 144.4    | 237.2      | 78.9    | 460.5   | 9.5      | 2.8        | 3.8     | 3.8     |
| Kalyāṇi    | 2                 | 114.6    | 220.1      | 59.6    | 394.3   | 10.1     | 3.0        | 4.5     | 4.1     |

5. EXPERIMENTS AND RESULTS

The algorithm described in Section 4.3 (with the stated modifications) was implemented on 1.5 min-long, de-noised (using [13]) audio samples in three rāgas [21, 22, 23]. Each output was split into two 1-minute clips. Similarly, the outputs from an existing, uniform slowing-down algorithm in [13] were also split at the same locations. The slowing-down factor given to the existing algorithm was R' (not R), which could vary piece by piece.

The original clip was also made into two clips according to the split in the slowed-down pieces. The resulting 18 clips were played in a blind listening test where participants were asked to rank the slowed-down clips on a scale of 1 (worst) to 5 (best) relative to the original clip. The order of the slowed-down clips was random. Participants also rated their own familiarity with the rāgas.

The result is strongly in favor of non-uniform scaling. Eighteen users (12 experts) took the test and the proposed algorithm was preferred to the existing one in 84% of the cases (90% among experts). The average rating of the proposed algorithm was 3.6 (experts: 3.74) and that of the existing one was 2.45 (experts: 2.38). The small difference in preference suggests that the experts based their evaluations on rāga-identity more than others did.

6. DISCUSSION

We conclude with a discussion touching on the three questions mentioned in Section 1. It is clear that transients scale non-uniformly with tempo and that immediately implies that the fraction of music with gamakas (as against CP-notes) would vary. For any conclusion more specific than ‘the fraction of music containing transients increases with speed,’ future studies are needed.

In [11], which considered speed doubling, the synthesis step (from notation) was preceded by a manual analysis of gamakas. The first example we considered in Section 4 shows that it is useful to view a svara with a gamaka, as consisting of a CP-note and one or more transients. In the language of [11], we believe that focal pitches of CP-note segments of a gamaka must be treated differently from focal pitches in transients.

We proposed an algorithm that does not scale transients when slowing down Carnatic music. This was clearly preferred by listeners over uniform slowing down. For future work, we propose that tempo change algorithms should be parameterized with a priority choice between CP-notes (which we prioritized in our algorithm) and transients. This may depend on the rāga: e.g., bhairavī and mōthanam could prioritize transients and CP-notes respectively. Thus, it is not always a case of changing ‘detail’ as noted in [11].

Finally, previous work on musical emotion in Carnatic and Hindustani music [24, 25] has worked at the level of rāgas. Yet, for example, in tōḍī, long stretches of svaras that eschew S and P build up ‘tension’ and a transient-heavy gamaka can release it to give a calming effect. A future, underlying mechanism of musical emotion in Indian music (see [26] for its need in Western music) should thus account for the effects of CP-notes and transients.

7. ACKNOWLEDGMENTS

The authors thank the Raga Surabhi team (http://www.ragasurabhi.com/index.html) for their kind permission to use three recordings [21, 22, 23] for the experiments described in this paper, and all participants of the listening test. V Viraraghavan thanks Ms. Anju Leela Thomas for her help in setting up this test.
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