ABSTRACT
In this paper, we propose a novel method to search for precise locations of paired note onset and offset in a singing voice signal. In comparison with the existing onset detection algorithms, our approach differs in two key respects. First, we employ Correntropy, a generalized correlation function inspired from Rényi's entropy, as a detection function to capture the instantaneous flux while preserving insensitiveness to outliers. Next, a novel peak picking algorithm is specially designed for this detection function. By calculating the fitness of a pre-defined inverse hyperbolic kernel to a detection function, it is possible to find an onset and its corresponding offset simultaneously. Experimental results show that the proposed method achieves performance significantly better than or comparable to other state-of-the-art techniques for onset detection in singing voice.

Index Terms—onset detection, offset detection, singing voice, entropy, pairwise peak picking

1. INTRODUCTION

Onset detection is a problem of finding the precise location of discrete musical events, and thus is an important preprocessing step in many music applications, including pitch estimation, beat tracking, and automatic music transcription, to name a few. In music signal processing, note onset detection still remains a challenging problem, particularly for singing voice, because of several reasons such as a large variance in articulation, singer-dependent timbral characteristics, and slowly-varying onset envelopes. The report from Music Information Retrieval Evaluation Exchange 2012 (MIREX 2012) for solo singing voice reflects these difficulties, where the best-performing algorithm yields the F-measure of merely 55.9% [12]. It is noteworthy that singing class gives much lower F-measure value than other classes like polyphonic pitched, solo brass, and wind instruments classes.

Numerous methods have been proposed so far to solve the onset detection problem [1]. Majority of existing methods are generalized by the two-stage procedures: detection function and peak picking [1–8]. Generating detection function refers to transforming audio signals into feature vectors more relevant to indicating onsets. Due to the fact that singing voice contains many soft onsets [1], a recent study focuses on finding the harmonic regularity instead of using the conventional, energy-based techniques [4]. If a properly designed detection function is provided, onset candidates will give a rise to certain local peaks. The peak-picking procedure then finds precise onset locations from the detection function.

This paper explores a new detection function and a peak-picking method for onset/offset detection in singing voice. The use of correntropy for detection function brings us two major advantages: first, it provides a compact front-end like a conventional correlation function; second, the property of correntropy preserves robustness to outliers – such as noise or subdominant changes in frequency, amplitude or phase – by projecting an input signal into a high dimensional Reproducing Kernel Hilbert Space (RKHS).

Figure 1 illustrates an overview of the proposed system. We describe a novel detection function based on correntropy in Section 2. An ad-hoc kernel optimizer continuously updates a localized parameter required for correntropy estimation. The detection function yields a regular shape with distinct local peaks, or (−)/(+1) peaks, which correspond to on-
set/offset, respectively. This regular shape motivates us to
design a pairwise peak-picking method in Section 3. The
experimental results are presented in Section 4, followed by
concluding remarks in Section 5. A relation to prior work is
addressed in Section 6.

2. DETECTION FUNCTION BASED ON CORRENTROPY

Our detection function first passes the time-domain input sig-
nal sampled at 11,025 Hz into an auditory filterbank [18]. We
map center frequencies of 64-channel gammatone filterbank
according to the Equivalent Rectangular Bandwidth (ERB)
scale between 80 Hz and 4,000 Hz. Hereafter, $x_c(t)$ refers
to the amplitude of the filtered parallel output, where $c$ and $t$
denote the channel and discrete time indices, respectively.

2.1. Correntropy-based Formulation

Correntropy function incorporates both distribution and tem-
poral structures of a time series in random processes [10].
There are various applications of correntropy to non-linear
and non-gaussian signal processing where correlation func-
tion is not sufficient. Let $\{x_t : t \in T\}$ be a random process
with $T$ denoting an index set. Correntropy function $V$ is
defined as

$$V(x_{t_1}, x_{t_2}) = \mathbb{E}[\kappa(x_{t_1}, x_{t_2})],$$

where $\kappa(*)$ is a Parzen kernel and $\mathbb{E}$ is an expectation oper-
ator. $V$ is advanced to measure the distance between the two
discrete vectors.

The properties reveal that correntropy has very similar
characteristics to a conventional correlation function. Liu et
al. showed that the sufficient condition to satisfy $V(t, t-\tau) =$

$$V(\tau) = \mathbb{E}[\kappa(t, t-\tau)]$$

is advanced to measure the distance between the two
regions. (b) bad case using global optimum for 45 s. (c) im-
proved result with “loosely” localized $\sigma$. (d), (e) zoomed-in
parts from (b) and (c). We observe more contrast in (e).

$V(\tau)$ is that the input random process must be time shift-
variant on the even moments. More specifically, this is
a stronger condition than a wide-sense stationarity involv-
ing only second-order moments. We estimate correntropy
$V$ given $t, \tau$ and lag $\tau$ by computing the sample mean of a size
$N$ window as follows:

$$V_{t,c}(\tau) = \frac{1}{N} \sum_{n=1}^{N} N_\sigma(x_c(t+n), x_c(t+n+\tau)), \quad (2)$$

where $N_\sigma(p, q) = \frac{1}{\sqrt{2\pi}\sigma} \exp\{-\frac{(p-q)^2}{2\sigma^2}\}$, and $\sigma$ is a Gaussian
bandwidth parameter. In practice, both the window size $N$ and
maximum $\tau$ are set to sampling rate/80, when the lowest
band-limit is 80 Hz. Then the correntropy coefficient for each
channel is “pooled” into a non-negative summary matrix $W$
as follows [9]:

$$W_t(\tau) = \sum_c V_{t,c}(\tau). \quad (3)$$

The detection function $\Delta W(t)$ is then calculated by the rect-
tified difference with a hop-size $h$ as follows:

$$\Delta W(t) = \sum_{\tau} W_{t+h}(\tau) - \sum_{\tau} W_t(\tau). \quad (4)$$

A monophonic singing example in Figure 2 illustrates on-
set/offset regions and their relation to the detection function.
We estimate onset/offset locations by finding the first time $t$ at
which $\Delta W(t) < 0$, and the first time after $t$ where $\Delta W(t) >
0$, respectively.

2.2. Ad hoc Kernel Optimization

A free parameter $\sigma$ in Equation (2) acts as a sensitivity con-
troller for detection function: the larger $\sigma$ becomes, the faster
the higher-order moments decay. To keep both nonlinearity
and discrimination ability, one way to select the optimal $\sigma$ is

Fig. 2. Singing voice example. From top to bottom: (a), (b) and (c) are input signal, $W_t(\tau)$ and detection function $\Delta W(t)$, respectively. Red dashed-lines are onset positions that correspond to (-) peaks in (c). Black solid-lines are (+) peaks near the offset.

Fig. 3. Examples of $W_t(\tau)$ in Section 2.2: (a) $\sigma = 0.017$ preserves good contrast between stationary and non-stationary regions. (b) bad case using global optimum for 45 s. (c) improved result with “loosely” localized $\sigma$. (d), (e) zoomed-in parts from (b) and (c). We observe more contrast in (e).
given by Silverman’s Rule of Thumb [16]. Assuming that \( \kappa \) is a Gaussian kernel, the optimal \( \sigma \) can be simplified to

\[
\sigma = b \cdot \hat{\psi} N^{-1/5},
\]

where \( b, \hat{\psi} \) and \( N \) denote the constant scale factor, sample standard deviation, and the number of samples, respectively.

The sensitivity of the detection function can be observed from the contrast in colors in \( W_i(\tau) \). Figure 3(a) is a good example where the boundaries would yield a relevant detection function using the global optimum \( \sigma \). However, Figure 3(b) reveals that the global optimum parameter does not always guarantee good contrast on the entire song. On the other hand, a strongly localized parameter would not guarantee temporal contrast. In this situation, a “loosely” localized optimal parameter is required for robust detection of real-world singing onsets. Figure 3(c) displays \( W_i(\tau) \) with improved contrast by an ad-hoc optimizer. It updates \( \sigma \) with an interval \( h \). In practice, we achieve good performances by computing the optimal \( \sigma \) using Equation (5) with an observation window size of 7 s and \( h = 5 \text{ ms} \). This improves the precision by over 10% in comparison with a global optimization method.

3. PAIRWISE SIMULTANEOUS PEAK PICKING

A pairwise peak-picking approach is motivated by the regular shape of the detection function observed in Figure 3(c): a basic idea is to capture a pair of falling and rising peaks by calculating a fitness to a pre-defined kernel. Figure 4 illustrates this concept.

We first generate a set of pre-defined inverse hyperbolic kernels, whose shape is similar to expansion or shrinkage of detection function. This kernel \( \Lambda \) is defined as

\[
\Lambda(z) = \frac{z}{1 + \alpha - |z|},
\]

such that \(-1 + 10^{-5} \leq z \leq 1 - 10^{-5} \), where \( \alpha \) is a sharpness factor. The range of \( z \) is set to avoid division by 0, and \( \alpha \approx 0.15 \) is empirically found. Given an observation window length \( \omega \) and sample index \( i = \{1, 2, \ldots, \omega\} \), we chop \( z \) into \( \omega \) samples by a linear scale. In our default settings, \( \omega_{\min} \) is set to 4 samples (=20 ms) and \( \omega_{\max} \) is set to 500 samples or larger (\( \geq 2.5\) s) for 5 ms-correntropy hopsize \( h \). Hence, any event less than 20 ms will be ignored. Figure 4(a) displays the generated kernel matrix for a set of observation length \( \omega \).

To find a pair of offset/onset, we calculate the fitness between the detection function and the pre-defined kernel as we expand the kernel size. The fitness is calculated by

\[
\text{Fit}(\Lambda'_{i\omega}, W_{i\omega}) = (\Lambda'_{i\omega} - W_{i\omega})^2 \cdot \omega^{-k},
\]

where \( \Lambda'_{i\omega} \) is the pre-defined kernel sampled at \( \omega \), and \( W_{i\omega} \) is the \( \omega \)-long rectangular windowed detection function. \( k \) is a weighting factor for close peaks and we set \( k = 1 \). For reference, Equation (7) is derived from lack-of-fit sum of squares which has been widely used in classical F-test statistics [17]. To find a pair of onset/offset, we start from the last onset position and perform the same calculation but use \(-\Lambda \).

The above procedures are summarized in Algorithm 1. This pairwise approach makes sense in monophonic sources: if an onset is found, then its corresponding offset must exist before the next onset.

4. EXPERIMENT

4.1. Dataset

The dataset is obtained from the authors of referenced paper [14]. It allows us to directly compare the performance of proposed algorithm to theirs. The total length of audio clips is about 13 minutes, which is much longer than singing data included in the MIREX audio onset detection task [11]. The dataset consists of 13 male and 2 female singers’ recordings of popular songs. Onset labels are cross-validated by three persons who have professional careers in music. In total, the dataset contains 1,567 onsets with annotations. Audio files are produced in mono with the sampling rate of 44,100 Hz.

4.2. Results and Discussion

We followed the evaluation procedure for onset detection described in MIREX [11]. The tolerance value is set to +/-
Input:  
\(\omega\) = window size, \(\Lambda\) = inverse hyperbolic kernel.  
\(W\) = detection function.

Output:
- \(*, \odot\) are onset and offset marking on time index, \(t\).

while \(t \rightarrow T\) do
  \% find onset, \(*\)
  for \(t' : (t + \omega_{\text{min}}) \rightarrow (t + \omega_{\text{max}})\) do
    \(F(t') = F^t(\Lambda', W')\)
  end
  \(* = t + \arg \max_{t'} (F(t'))\)
  \(t = *\)
  \% find offset, \(\odot\)
  for \(t' : (t + \omega_{\text{min}}) \rightarrow (t + \omega_{\text{max}})\) do
    \(F(t') = F^t(-\Lambda', W')\)
  end
  \(\odot = t + \arg \max_{t'} (F(t'))\)
  \(t = \odot\)
end

Algorithm 1: Pseudo code for pairwise peak picking described in Section 3.

| Class   | # of Onset | Precision | Recall  | F-measure |
|---------|------------|-----------|---------|-----------|
| male    | 1,533      | 80.9      | 80.1    | 80.3      |
| female  | 34         | 93.8      | 88.4    | 91.4      |
| Total   | 1,567      | 81.1      | 80.2    | 80.6      |

Table 1. Performance of the proposed algorithm

We proposed a pairwise approach to onset/offset detection for singing voice recordings. The proposed method differs from previous approaches in two main aspects. First, we employed higher-order statistics to capture onset/offset events in a time-domain signal. We also demonstrated that a compact adaptive kernel method improved the results. Secondly, a new peak picking algorithm was derived for this detection function. By searching a precise location where the fitness between a pre-defined kernel and the detection function is maximized, a set of onset and its corresponding offset was simultaneously found. We evaluated the proposed method with a recognized dataset. The average F-measure for onset detection by the proposed algorithm was 80.6%, which is highest among all methods in comparison.

5. CONCLUSION

So far, a solid idea in this paper was that the higher-order statistics using correntropy would provide more robustness to general onset detection problem. A previous application to monophonic pitch detection exists. The use of Rule of Thumb for kernel parameter optimization was recommended in Liu. We extended these concepts to a novel feature representation for a detection function.

For peak picking, adaptive threshold method has been widely used. Others have formulated such decision making into a machine learning problems. The proposed method is novel in that it jointly estimates onset/offset, and it can be generalized as dynamic programming.
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