A WEIGHTING FUNCTION FOR DYNAMIC PROGRMAMING BEAT TRACKER

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ABSTRACT

This study proposed a weighting function for a dynamic (DP) programming approach as the cost function to handle beat tracking. The function is utilized to adapt bandwidth of tempo deviation which reciprocal represents likelihood of relative beat position. The beat tracking surpass those scores of other algorithms for MAZ dataset, in which seven out of ten performance indexes outperforms in MIREX2013 audio beat tracking contest.

***Index Terms* –** Weighting Function, Cost for DP

1. INTRODUCTION

Rhythmic information is the essential element in music. The prominent features of rhythm are beat position and tempo which comprise the basic characteristic of music. Although the sense of beat sometimes is obvious for human being, the exact estimation is still challenging task when especially the music has time-varying tempo.

Conventional beat tracking schemes [1] handle certain music contents with stable tempo well. Under the related stable-tempo assumptions, most approaches of beat tracking are accomplished by two phases. In the first phase, the onset detection of music along time, called onset detection function, onset strength and *novelty curve*, is obtained to indicate the possible positions of note onsets. In the following phase, the quasi-periodic patterns in novelty curve are analyzed to discover the possible tempo value and the corresponding beat positions. Usually in the deduction process, tempo is assumed to be stable throughout the whole piece of music. However, the above-mentioned assumptions do not hold true universally, especially for music of classical and jazz. Music of these genres often has significant tempo variations, making it unreasonable to make the assumption of stable tempo. In our work, we break the assumption of stable tempo. Therefore, we generate the tempogram from the novelty curve, which the tempo information is embedded. Then we apply dynamic programming (DP) to the tempogram to derive the so-called *tempo curve*, which represents the most likely tempo at each time frame which is time-varying.

There are several important previous studies that attempted to deal with time-varying meters. Klapuri et al. [2] used the bandwise time-frequency method to obtain accentuation information, then used comb filter resonators and probabilistic models to estimate pulse width and phase of different music meters, including tatum, tactus, and measurement. Davies and Plumbley [3] proposed the use of complex spectral difference onset function to obtain middle level representation. Their algorithm employs two-state switching model, including general state and context-dependent state, to obtain final beat positions. Groshe and Muller [4] used the novelty curve to generate predominant local pulse (PLP) for estimating time-varying tempos. G. Peeters and H. Papadopoulos [5] propose a probabilistic framework for estimation of beat and downbeat simultaneously given information of tempo and meter. The probabilistic model is based on HMM (Hidden Markov Model) which has beat-times and their associated beat-position-inside-a-bar (BPIB) as the hidden states. The model is based on non-casual signal observations of the local bar which the beat is located in. This provides the work with an inherent local optimization of the probabilities (an adaptation to the local properties of the signal).

In this study, we follow the three-phase framework [6] of beat tracking and attempt to remove the stable-tempo restriction by developing a two-fold DP approach for robust beat tracking with time-varying tempos. In the second DP, the tempogram strength values adaptive to the weighting window with the relative position to previous beats are obtained by learning process. DP with a cost determines the current beat position candidates relative to the previous beat, in which they are searched in backward or forward direction. The following section describes the flowchart of the system and illustrates the detail of the weighting function.

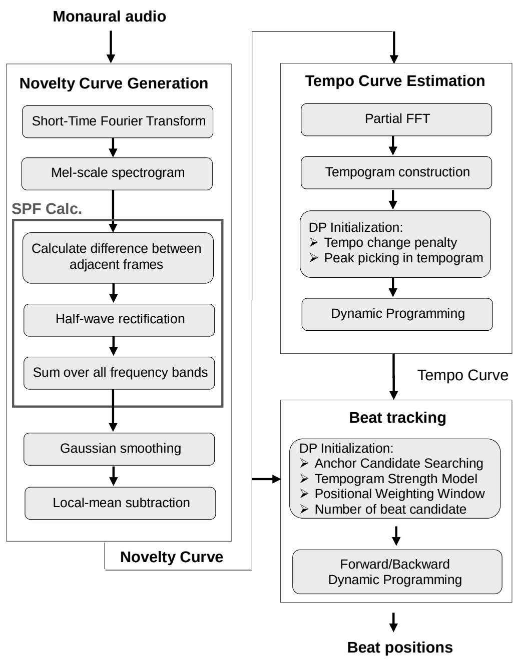

Figure 1 Flowchart of the beat tracking system

2. WEIGHTING FUNCTION

The proposed beat tracking system is shown in Figure 1. The first block computes the novelty curve, while the second block generates the tempogram and estimates the tempo curve from the novelty curve [7]. The third block of beat tracking setups a DP cost model to count the strength of novelty curve and relative position window weighting to previous beat position, which illustrated in the subsection.

2.1 Weighting Function for the cost of DP

This beat tracker utilizes both the tempo curve and the novelty curve to find a sequence of beat positions that fits the tempo curve, and the window weighted strength of onset detection function as much as possible. To achieve this task, we apply another DP-based method in a cost functional framework to perform forward and backward beat searching, starting from the anchor beat position (the position of the most prominent peak) of the novelty curve. We proposed the weighting window model, which is transformed to be transitional probability for every beat transition. The weighting function is given by the equation 1 and Figure 2 shows its curve for different positions.

$$\boldsymbol{w(range)} = \mathbf{e}^{-(\alpha * \log_2(range * t_p))^2} \tag{1}$$

where range is the range of beat position in times of the reciprocal of tempo $\boldsymbol{t_p}$ in tempo curve; $\boldsymbol{\alpha}$ is decay factor

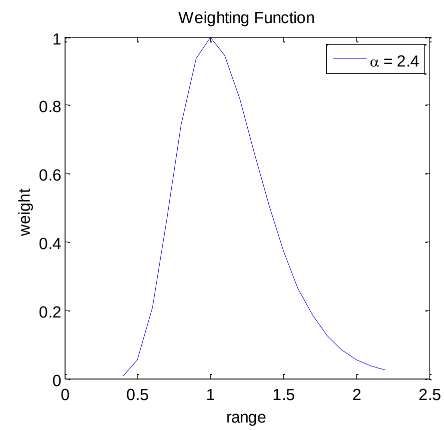

Figure 2 Curve of the weighting function

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