DISCRETE CANDIDATE ANALYSIS FOR HEART RATE MONITORING USING WRIST-TYPE PHOTOPLETHYSMOGRAPHIC SIGNALS DURING INTENSIVE EXERCISE

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ABSTRACT

Wrist-type photoplethysmographic (PPG) signals are an increasingly popular way to monitor heart rate during intensive exercise. However these signals are highly influenced by motion artefacts. This paper proposes a novel system for heart rate extraction termed Discrete Candidate Analysis (DCA). The DCA extracts a discrete set of possible heart rates from PPG signal, from which the sequence of most likely candidates is chosen based on accelerometric data, harmonic and temporal analysis. On a dataset of 23 PPG recordings, the proposed system obtained an average error of 3.02 beats per minute.

***Index Terms*—** Photoplethysmograph (PPG), Heart Rate Monitoring, Discrete Candidate Analysis, Temporal Path Finding

1. INTRODUCTION

Photoplethysmographic (PPG) signals from wrist-type pulse oximeters are an increasingly popular mean to monitor heart rate during intensive exercise. The PPG signals are quasi-periodic with the heart rate, but are are very sensitive to any relative motion between the oximeter and skin. This makes their usage challenging during periods of exercise due to strong *motion artefacts* (MA) caused by such motions.

To combat the effects of MA, simultaneously recorded accelerometer data can be used to capture motion, allowing for subsequent MA removal from PPG signals using adaptive filtering [1, 2], producing promising results.

In this paper, we present a novel system termed *Discrete Candidate Analysis* (DCA) for heart rate monitoring using wrist-type PPG signals. It focuses on the analysis of a set of possible heart rate outputs termed PPG candidates. It uses accelerometer and temporal information to compute a comprehensive suite of confidence coefficients for each candidate in order to distinguish the most likely candidate for output.

2. RELATION TO PRIOR WORK

Similar to previous work of [3], the proposed system uses the periodogram to find the dominant spectral peaks of PPG signals. However, instead of picking the strongest peak, the proposed system finds a number of peaks and consider them candidates for the true heart rate. From here, accelerometer data is used to filter out *motion artefact* (MA). However, unlike the time domain adaptive filtering techniques of [2], Wiener filtering techniques of [4] and signal decomposition approach of [5], the proposed system works in the frequency domain, looking at the difference in frequency between the candidate and any accelerometer spectral peak. This allows for more flexibility in MA removal, such as allowing easy suppression of heart rate candidates near all harmonics of accelerometer spectral peaks even if those harmonics are not present in the accelerometer spectrum.

The work by Lopez et al. [6] considers a similar approach as the proposed system. However, it uses a smaller suite of confidence coefficients with lower distinguishing power to pick the best output candidate.

The proposed DCA system was developed for the University of New South Wales entry to the IEEE Signal Processing Cup 2015 [5]. It was ranked 6th based on the *Average Absolute Error* (AAE) in *beats per minute* (BPM) [5]. On a competition test set of 10 PPG recordings, the proposed DCA system achieved AAE of 3.70 BPM, while the top 3 teams achieved 3.44, 2.27, 3.26 BPM respectively [7]. According to [7], these top 3 systems all include time signal based MA removal techniques such adaptive and Wiener filtering, which is different to the proposed candidate based MA removal.

3. DATABASE

The proposed DCA system was developed using 23 datasets supplied by Zhang et al. [5]. Each dataset contains simultaneously recorded dual-channel PPG signal, three-axis accelerometer signal, and a ground-truth ECG signal - all sampled at 125 Hz. The PPG signal was recorded using a pulse oximeter which was embedded in a wristband together with accelerometer and worn by subjects during intensive exercise. The ECG signal was recorded from the chest using wet ECG sensors. During data recording, subjects did one of three activities: walk/run on a treadmill, rehabilitation arm exercises, or intensive arm movements (boxing), as summarised in [4].

4. DISCRETE CANDIDATE ANALYSIS SYSTEM DESCRIPTION

The key characteristic of the proposed DCA system is the focus on analysis of candidates. A candidate is a dominant frequency in a frame of a signal estimated as a local maxima in the power spectrum. For every frame, the DCA estimates a set of heart rate candidates (termed PPG candidates) and assesses them against a number of criteria in order to choose the most likely candidate as output.

The system can be broken down into four main components (Figure 1): (i) Compute set of possible output frequencies, termed PPG candidates, from the dual-channel PPG signal frames (Section 4.1); (ii) Compute a set of motion artefact candidates from the 3-axis accelerometer signal frames (Section 4.2); (iii) Compute a suite of confidence coefficients for each PPG candidate using artefact candidates and temporal, harmonic analysis (Section 4.3); (iv) Decide the best PPG candidate for heart rate output based on the coefficients from (iii) (Section 4.4). Note, the DCA is a frame based system, where a sliding window of T seconds is used with an incremental step size of M seconds. In our set-up, $T = 8$, $M = 2$.

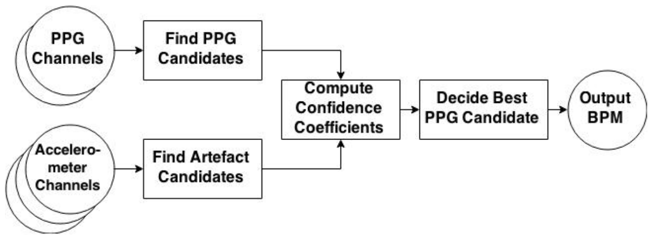

Fig. 1. DCA Overall system: sets of heart rate and artefact candidates are chosen from PPG and accelerometer signals respectively. They are analysed and one heart rate candidate is chosen for output

4.1. Compute set of PPG candidates

The aim of this component is to compute a discrete set of candidates from a frame of dual-channel PPG signal (Figure 2). The PPG signals are initially band-pass filtered to remove out-of-band noise. The power spectrum estimates are then computed via DFT based periodogram and the local maxima are extracted as the candidates. This forms the base set of candidates for output heart rate (Figure 4).

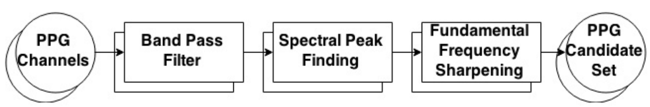

Fig. 2. Compute PPG Candidates: 2 set of heart rate candidates are extracted from dual-channel PPG signals by finding the dominant frequencies in the power spectrum

4.1.1. Band Pass Filtering

A 10th order Butterworth filter is used, with lower and higher cut-off frequencies of 1 Hz (60 BPM) and 6 Hz (360 BPM) respectively.

4.1.2. Spectral Peak Finding (SPF) Algorithm

A DFT-based periodogram estimated from a Hanning windowed frame of PPG signal is used for power spectrum estimation, from which a set of local maxima are extracted. The number of points in DFT calculations was empirically chosen as $N_{DFT} = 50,000$, giving accurate local maxima with reasonable computational load.

The biggest local maxima are then chosen as candidates subject to two condition parameters: (i) the maximum number of local maxima chosen is N_{peak} in order to limit the computational load on subsequent stages of the proposed algorithm. (ii) All local maxima below the noise floor threshold K_{peak} are ignored. We empirically set $N_{peak} = 4$ and $K_{peak} = 200$.

It should be noted that the two sets of PPG candidates are computed independently for the two channels of PPG signals.

4.1.3. Fundamental Frequency Sharpening

Once PPG candidates are found, the power value p' of each PPG candidate is sharpened according to eqn (1). This reduces the relative power value of noise candidates.

$$p' = S_i + \beta \times S_{2i} \tag{1}$$

where i is frequency of candidate, S_i and S_{2i} are power estimates of corresponding PPG channel at frequencies i and $2i$ respectively. β is a constant empirically set to 0.5.

4.2. Compute set of Artefact candidates

The aim of this component is to compute a discrete set of artefact candidates from a frame of the 3-axis accelerometer signal (Figure 3). These artefact candidates are estimates of the frequencies of motion by wearer (Figure 4), and will be subsequently used (Section 4.3.2) to assess whether each PPG candidate is a *motion artefact* (MA).

One set of artefact candidates is computed from each channel of the given accelerometer signal block, using the SPF algorithm (Section 4.1.2). The three sets are then concatenated and passed to the Artefact Candidate Processing algorithm for further processing (Section 4.2.1). The parameters for the SPF algorithm when applied to accelerometer signals are $\hat{N}_{peak} = 4$, $\hat{K}_{peak} = 0.5$. In addition to these, an extra constraint, $\hat{L}_{peak}$, is introduced where only candidates with frequency above $\hat{L}_{peak}$ are chosen in order to eliminate slowly varying noise components. Here $\hat{L}_{peak}$ was empirically set as 10 BPM.

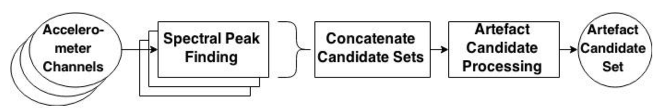

Fig. 3. Compute Artefact Candidates: 3 sets of artefact candidates are extracted from 3-axis accelerometer signals by finding the dominant frequencies in their power spectrum. The sets are concatenated and then processed to form one set

4.2.1. Artefact Candidate Processing

Given a set of artefact candidates, the aim here is to filter out irrelevant candidates then add in extra "missing" harmonic candidates. This was inspired by two observations: (i) motion artefacts usually have strong 2nd and/or 3rd harmonics in the accelerometer signal; (ii) in cases where one of the 2nd or 3rd harmonics is not present in the accelerometer signals, the missing harmonic may still cause a strong motion artefact in the PPG signal at that harmonic frequency.

For a set of artefact candidates, the algorithm finds candidates that have a 2nd or 3rd harmonic relationship with at least one other candidate. Every candidate found with a harmonic relationship have their 2nd or 3rd harmonic added to the candidate set if it is not present. Of the resultant set, candidates within 1 BPM of another candidate are deemed duplicates and removed. Candidates without this harmonic relationship are deemed to be noise and are removed unless their power value is greater than a threshold $\hat{K}'_{peak}$ (set to 10 empirically).

4.3. Compute Confidence Coefficients

For each PPG candidate, a suite of confidence coefficients are computed to determine its' likelihood of being the heart rate. They are described in Table 1. These coefficients are crucial to the decision process (Section 4.4) in order to output the most likely sequence of heart rates.

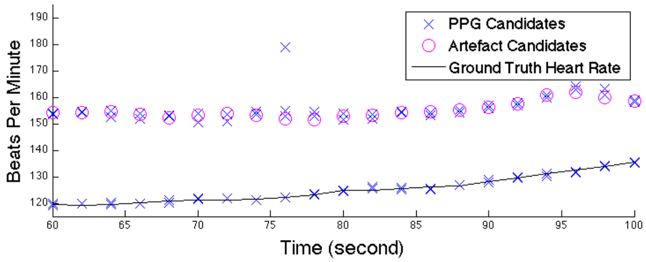

Fig. 4. Example sets of PPG candidates and artefact candidates from multiple frames, plotted against ground truth heart rates. PPG candidates are the set of possible choices for output heart rate, and should include the ground truth heart rate. Artefact candidates indicate the frequencies of motion artefacts, and are subsequently used in choosing the correct PPG candidate

Table 1. Confidence coefficients and their meanings

C_p	Power of candidate
C_a	Assess: Is candidate a motion artefact
C_h	Assess: Is candidate harmonic of another candidate
C_t	Assess: Is candidate part of a temporal path
C_{ta}	Mean C_a of candidates on temporal path
C_{th}	Mean C_h of candidates on temporal path
C_m	Frequency difference between candidate, last output

4.3.1. *Power Coefficient C_p*

The maximum sharpened power value (Section 4.1.3) in current set of PPG candidates is found as p'_{max}. C_p [6] is then given by:

$$C_p = \frac{p'}{p'_{max}}. \tag{2}$$

where p' is sharpened power value of candidate.

Note, there are two sets of PPG candidates, one from each channel, and the C_p coefficients of each set are computed independently. The two sets of PPG candidates are then concatenated to form one set.

4.3.2. *Motion Artefact Coefficient C_a*

This coefficient assesses PPG candidates for their proximity in frequency to any artefact candidate in current frame. C_a is given by:

$$C_a = \left\langle \frac{\min_{j \in A} |(i-j)|}{D_a} \right\rangle \tag{3}$$

where i and j are frequencies in BPM of PPG candidate and artefact candidate respectively, A is set of artefact candidate frequencies in current frame, and D_a is a constant empirically set to 10 BPM. $\langle \cdot \rangle$ denotes saturation to $[0, 1]$.

4.3.3. *Harmonic Coefficient C_h*

This coefficient assesses whether the PPG candidates are 2nd/3rd/4th harmonics of another candidate in the set. C_h of PPG candidate with frequency j is given by:

$$C_h = \left\langle \frac{\min_{\forall i,j} \delta_{i,j}}{D_h} - 1 \right\rangle, \quad i \in P, j \in P, i \leq j \tag{4}$$

where P is set of PPG candidate frequencies in current frame, $\langle \cdot \rangle$ denotes saturation to $[0, 1]$, D_h is a constant empirically set to 0.05, and $\delta_{i,j}$ is given by:

$$\delta_{i,j} = \min_{n=2,3,4} \left| n - \frac{j}{i} \right| \tag{5}$$

4.3.4. *Temporal Coefficients C_t, C_{ta}, C_{th}*

The temporal coefficient C_t assesses whether PPG candidates are part of a smooth temporal sequence. This is motivated by the observation that heart rate should always follow a smooth trajectory in time [8]. The coefficients C_{ta} and C_{th} assesses whether a temporal sequence is contaminated with MA and harmonics respectively.

The objective is to find an optimal temporal path of length $\hat{N}$ candidates, terminating on a candidate in the current frame with frequency j. $\hat{N}$ is empirically set to 10. Let $P_{\hat{N},j}$ denote the score of such a path, given by:

$$P_{\hat{N},j} = \max_{\forall h,i} \prod_{n=2}^{\hat{N}} E_{h,i}, \quad h \in F_{n-1}, i \in \begin{cases} F_n & n < \hat{N} \\ \{j\} & n = \hat{N} \end{cases} \tag{6}$$

where F_n is the set of PPG candidate frequencies at frame offset n. Note $n = \hat{N}$ corresponds to the current frame. Edge score $E_{i,j}$ is given by:

$$E_{i,j} = \langle M \times |i-j| + B \rangle \tag{7}$$

where i and j are candidate frequencies, M and B are constants empirically chosen such that the straight line $y = Mx + B$ has x-intercept of 10 BPM, and y=1 at 3 BPM. $\langle \cdot \rangle$ denotes saturation to $[0, 1]$.

This optimal path problem is solved via dynamic programming where eqn (6) is computed recursively as:

$$P_{n,j} = \max_{\forall i \in F_{n-1}} (P_{n-1,i} \times E_{i,j}) \tag{8}$$

In our experiment, we also allow a maximum of 1 break in an otherwise continuous path. The modified path score is given by:

$$P'_{n,j} = \left[\max_{\forall i \in F_{n-1}} (P'_{n-1,i} \times E_{i,j}), \max_{\forall i \in F_{n-2}} (P_{n-2,i} \times E_{i,j}) \right] \tag{9}$$

where $[\cdot]$ denotes the maximum of multiple input values.

C_t of candidate in current frame with frequency j is given by:

$$C_t = P'_{\hat{N},j} \tag{10}$$

To compute C_{ta} and C_{th} for each candidate, the algorithm retraces the path from the candidate back to the head of path. C_{ta} and C_{th} are computed as the arithmetic mean C_a and C_h of all candidates in the path. C_a and C_h of candidates beyond the head of a broken path (where $E = 0$) are treated as 0.

4.3.5. *Memory Coefficient C_m*

This coefficient assesses PPG candidates' proximity in frequency to the previous output heart rate. The memory coefficient of candidate with frequency i is given by:

$$C_m = \left\langle 1 - \frac{1}{D_m} \frac{|i' - i|}{i} \right\rangle \tag{11}$$

where i' is the last chosen output heart rate frequency, D_m is constant set to 0.3. $\langle \cdot \rangle$ denotes saturation to $[0, 1]$.

Unlike the memory coefficient of [6], the DCA's memory coefficient does not use a decay mechanism but instead prevents the incorrect tracking of strong MA via a robust decision method described in Section 4.4.

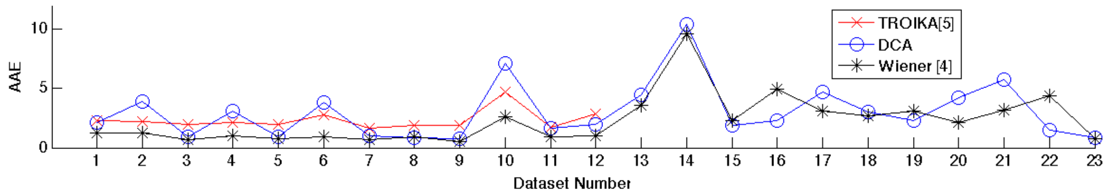

Fig. 5. Comparison of Average Absolute Error (AAE) between TROIKA [5], system of [4] and proposed DCA system over 23 datasets

4.4. Robust PPG Candidate Selection

Given one set of PPG candidates and the suite of confidence coefficients (Section 4.3), this component decides on one candidate as the output heart rate (Figure 6).

There are four parts to deciding the output candidate, outlined below.

(i) Compute $\bar{C}$: Confidence coefficients of candidates are merged into one value as a weighted average $\bar{C}$, given by:

$$\bar{C} = C_p + C_a + C_h + C_t + 2C_m \tag{12}$$

The C_m weight was set higher to encourage a smooth path in heart rate outputs.

(ii) Repeat Threshold: If the highest $\bar{C}$ score of the set is lower than a threshold K_D (set to 0.6 in our experiment), repeat the last chosen candidate and finish. This prevents a single impulsive bad candidate from corrupting the memory coefficient calculation. Consecutive repeats are not allowed.

(iii) Search Range: Candidates with frequencies differing from the last chosen output candidate by more than ± 20 BPM are invalidated [5]. The remaining candidate with highest $\bar{C}$ score is chosen as output candidate. In the case where all candidates are invalidated, choose candidate with highest $\bar{C}$.

(iv) *Motion Artefact* (MA) Verification: Given the chosen candidate Ω from (iii), a final verification is carried out to prevent tracking of a strong MA path. The algorithm searches for a PPG candidate in current set with C_t, C_{ta} and C_{th} greater than thresholds K_t, K_{ta} and K_{th}, and its $C_{ta} > \alpha \times C'_{ta}$ where C'_{ta} is coefficient of Ω. If this condition is met, it means that a significantly better path is available uncorrupted by MA and Ω is overwritten. In our experiment, $K_t = 0.7, K_{ta} = 0.9, K_{th} = 0.9, \alpha = 4$.

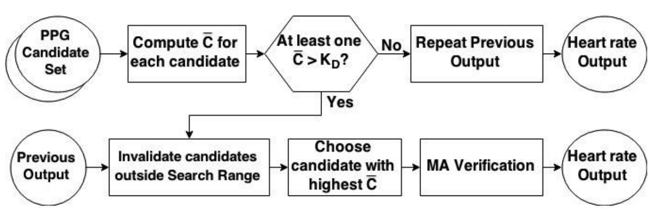

Fig. 6. Decision Logic to choose the most likely PPG candidate for heart rate output

5. EXPERIMENTAL RESULT

The *average absolute error* (AAE) is a metric proposed by [5] to evaluate PPG heart rate extraction systems. The AAE of the proposed DCA system is presented in Table 2. It is also plotted in Figure 5 together with those reported by TROIKA [5] and system of [4].

The AAE of DCA over all 23 datasets is 3.02 BPM which is slightly higher than the 2.27 BPM achieved by the Wiener filter based system of [4]. Over the 12 datasets common to TROIKA [5], DCA and TROIKA produced similar AAE of 2.35 and 2.34 BPM respectively.

Of the 12 datasets common to all three systems, there are 8 datasets where DCA performed better than TROIKA and similar to system of [4]. However, for datasets 2, 4 and 6, the DCA performed worse because it temporarily tracked a strong *motion artefact* (MA) path. This is due to a MA path crossing and hence severing the heart rate path. Despite this, the difference is only minor due to DCA's ability to recover via MA Verification (Section 4.4). For dataset 10, the DCA performed worse due to a strong MA path being very close to heart rate path for large portion of the dataset. The DFT-based periodogram was unable to identify many spectral peaks that are due to heart rate because of spectral smearing of periodogram.

Of the 10 datasets common to DCA and system of [4], the two performed similarly with AAE of 3.70 and 3.61 BMP respectively.

Table 2. Absolute Average Error (AAE) of the proposed DCA system over 23 datasets (D) provided by [5]

D	AAE	D	AAE	D	AAE	D	AAE
1	2.1100	7	1.0107	13	4.4256	19	2.2685
2	3.9333	8	0.8291	14	10.4639	20	4.2164
3	0.9145	9	0.7582	15	1.884	21	5.7338
4	3.0694	10	7.1123	16	2.3113	22	1.4717
5	0.9040	11	1.6588	17	4.7328	23	0.87898
6	3.8529	12	1.9874	18	3.0175		

6. CONCLUSION

In this paper, we described the proposed Discrete Candidate Analysis system for heart rate monitoring during intensive exercise. The DCA extracts a discrete set of possible heart rate candidates from PPG signal, from which the mostly likely candidate, representing our heart rate estimate, is chosen based on a suite of confidence coefficients. This suite is comprehensive as it includes accelerometric-data, harmonic and temporal analysis, thus allowing accurate removal of motion artefacts and robust tracking of underlying heart rate. Compared to techniques that focus in the time domain such as [5], the DCA has low computation complexity because all confidence coefficients can be computed in the candidate domain in polynomial time, where the number of candidates per frame is significantly less than the number of signal samples per frame. Future work will include refining the DCA through trialling high-resolution power spectrum estimation techniques, as well as Wiener/adaptive filtering MA removal techniques as a preprocessing step. Experimental results indicate that the DCA is an accurate and robust method of heart rate monitoring during intensive exercise.

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