Remote Heart Rate Measurement through Broadband Video via Stochastic Bayesian Estimation

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Abstract

A novel method for remote heart rate sensing via standard broadband video is proposed. Points are stochastically sampled from the cheek region and tracked throughout the video, producing a set of skin erythema time series. From these observations, a photoplethysmogram (PPG) is estimated via Bayesian minimization, with the required posterior probability estimated through an importance-weighted Monte Carlo approach. From the estimated PPG, an estimated heart rate is produced through frequency domain analysis. Results indicate improved accuracy over current state of the art methods.

1 Introduction

Remote heart rate measurement is useful in a variety of applications, including low-cost health monitoring, vehicle operator awareness systems, and human computer interaction. Current methods rely on the accurate construction of a photoplethysmogram (PPG), a remote measure of blood volume change. Since blood volume changes with each heart beat, it is possible to discern the heart rate from frequency domain analysis of the acquired PPG.

Poh *et al.* [1, 2] propose two methods for remote heart rate detection from broadband video. Both methods create time series from the average red, green, and blue channel values of the entire face region bounding box and apply independent component analysis (ICA) to separate underlying source signals. Three signals are returned by ICA, though the relevant signal is unknown. In the first method [1], the second source signal is always selected for processing. In the second method [2], the source signal containing the maximum magnitude in the frequency domain is selected. In addition, detrending techniques are applied prior to applying ICA, after which temporal filters are applied. Li *et al.* [3] aim to improve upon these works by confining the region of interest to skin regions and better compensating for motion and illumination.

Though these methods offer reasonably accurate estimates, the unpredictability of the returned source signal poses a problem with automation. In addition, the analyzed regions of interest in these methods encompass areas unlikely to provide a clean PPG signal, introducing additional noise. For this reason, a predictable and robust method for remote heart rate sensing is required.

2 Methods

The proposed method relies on an accurate estimation of a PPG signal. Because of skin erythema's high correspondence to hemoglobin concentration [4], its fluctuation provides a biologically motivated means to estimate heart rate. We first estimate a PPG, $\hat{\phi}(t)$, via a Bayesian minimization approach, using many skin erythema time signal observations measured from points stochastically sampled from the cheek region. The skin erythema transform, $\psi(t)$, for a single observation, x, can be expressed as

$$\psi(t) = \log_{10}\frac{1}{\bar{x}_g(t)} - \log_{10}\frac{1}{\bar{x}_r(t)}, \qquad (1)$$

where $\bar{x}_g(t)$ and $\bar{x}_r(t)$ are defined as the average green channel and red channel values within a window surrounding point x, respectively. We formulate and solve the Bayesian minimization as

$$\hat{\phi}(t) = \arg\min_{\hat{\phi}(t)}(E((\hat{\phi}(t)-\phi(t))^2|X)) = \int \phi(t)p(\phi(t)|X)d\phi(t), \qquad (2)$$

where $E(.)$ denotes the expectation and X represents a set of accepted observations. The likelihood that an observation is added to the set X is determined by the variance of frequency within an operating band. It can be seen that the posterior probability, $p(\phi(t)|X)$, is required to solve the minimization, however, this is difficult to obtain analytically. For this reason, an importance-weighted Monte Carlo sampling approach [5] is used. This is formulated as:

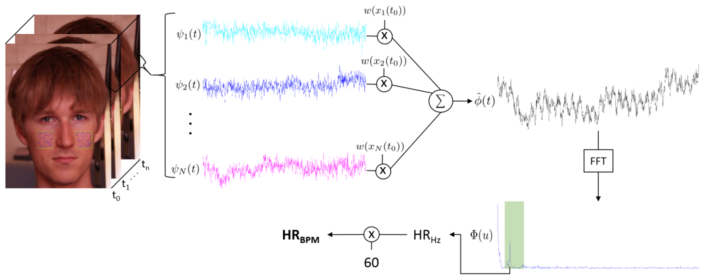

Fig. 1: Flow chart of the proposed algorithm. Bayesian minimization is used to estimate a PPG from many erythema time series ($\psi(t)$). From the estimated PPG, a heart rate can be inferred.

$$\hat{p}(\phi(t)|X) = \frac{\sum_{k=0}^{N} w(x_i(t_0))\delta(\phi(t)-\psi_i(t)))}{\sum_{i=0}^{N} w(x_i(t_0))} \qquad (3)$$

where $w(x_i(t_0))$ is the weight given to the i^{th} signal acquired from $x_i \in X$, determined based on the local spatial variance. After estimating $p(\phi(t)|X)$, the Bayesian minimization can be solved to yield an estimated PPG, $\hat{\phi}(t)$. By calculating the location of the maximum peak of $\hat{\phi}(t)$ within an operating band of ([$0.7-4$] Hz) in the Fourier domain, the heart rate frequency can be estimated. A general flow diagram can be seen in Fig 1.

3 Experiments

The proposed method was validated against a database consisting of seven videos, each containing the face of one of three different subjects. Each video is approximately 30 seconds in duration and was captured at 30 frames per second under ambient lighting conditions.

To provide comparison to state of the art methods, the two methods proposed by Poh *et al.* [1, 2] and the method proposed by Li *et al.* [3] were also implemented and tested against the database. The root mean squared error ($RMSE$) and the mean error (M_e) are tabulated in Table 1 with the best results indicated in bold face.

Table 1: Ground truth and estimated heart rate for the seven videos in our self-recorded data set.

	Our Method	Poh *et al.* [1]	Poh *et al.* [2]	Li *et al.* [3]
$RMSE$	**0.06**	12.44	25.91	5.45
M_e	**0.07**	5.54	15.01	-2.34

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