Heart Rate Detection Using an Event Camera

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***Abstract*—Event cameras, also known as neuromorphic cameras, are an emerging technology that offer advantages over traditional shutter and frame-based cameras, including high temporal resolution, low power consumption, and selective data acquisition. In this study we harnesses the capabilities of event-based cameras to capture subtle changes in the surface of the skin caused by the pulsatile flow of blood in the wrist region. We show how an event camera can be used for continuous non-invasive monitoring of heart rate (HR). Event camera video data from 25 participants with varying age groups and skin colours, was collected and analysed. Ground-truth HR measurements were used to evaluate of the accuracy of automatic detection of HR from event camera data. Our results demonstrate the feasibility of using event cameras for HR detection.**

***Index Terms*—Event camera, neuromorphic camera, heart rate, pulsation, periodicity**

I. Introduction

In recent years event cameras have emerged as a novel imaging paradigm and an alternative to conventional shutter- or frame-based cameras. The potential for event camera applications span a wide array from robotics to wearable electronics, where fast latency, reduced power consumption, and unpredictable lighting conditions are crucial [4].

Conventional frame-based cameras sample light intensity synchronously from an array of up to millions of photosites, typically at 25 Hz. Event cameras are an imaging sensor that record pixel-level brightness asynchronously and independently in response to alterations in scene luminance rather than adhering to predetermined frame intervals. Data recorded in an event camera is made up of a stream of information packets, each with the x and y coordinates or pixel locations, a timestamp for the recording, and an indication of the brightness change which caused the information packet or event to be generated. The temporal resolution of an event camera is such that events are recorded with accuracy down to the microsecond, achieving equivalent frame rates surpassing 10,000 frames per second [6].

The attributes of event cameras, encompassing remarkable temporal precision, minimal time lag, and extensive dynamic range, hold significant promise for enabling accurate, real-time, and non-contact monitoring of a driver's heart rate (HR) which is explored here.

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II. Background

A. Periodicity in Data

Periodicity is a property of time series data whereby a pattern recurs within a data stream at regular or periodic intervals. This refers to the regularity of things that occur repeatedly in nature as typical behaviour and deviations from regular or periodicity data are referred to as outliers. Periodicity is used to discover insights within data patterns which can lead to deeper understanding of the data and the underlying natural phenomenon [11] and the distribution of frequencies in a data stream is called a periodogram.

One example of periodicity in natural systems is heart rate (HR) or the number of beats of a heart in a given period, typically 1 minute. The human heart beats with a regular frequency which changes only slowly. When we are at rest, sitting for example, it may beat at 70 bpm and when we get up to walk somewhere it may rise to perhaps 100 bpm but this will happen gradually, not instantly.

B. Measuring Heart Rate

There are several non-contact pulse rate measurement systems based on the technique of photoplethysmography which measure both HR and heart rate variability (HRV) using an optical camera and which compensate for subject movement e.g. [1], [7]. This is based on using flashing LED lights and when paired with light-sensitive photodiodes they detect the flow of blood through the wrist on a continuous basis and has an acceptable mean absolute error and root mean square error (MAE/RMSE) of 2.11/2.93, 2.43/3.44, and 2.26/3.45 beats per minute (bpm) for biking, stepping, and treadmill exercises, respectively [2].

The human heart rate may also be determined manually by sensing the motion at parts of the body where an artery is close to the skin, such as the radial artery in the wrist the carotid artery in the neck or the superficial temporal artery near the temple on the head. It can also be measured in any place that allows an artery to be compressed near the surface of the body, such as at the neck, groin, behind the knee, and near the ankle joint. For some of these areas, notably the wrist and the neck, the pulsation from the artery can sometimes be observed on the surface of the skin as a throbbing motion, whose periodicity is the heart rate of the subject. Mostly however, this throbbing movement is so minor that it is not visible to the naked eye.

C. Event Cameras in Biomedical Applications

The application of event cameras in biomedical contexts remains largely unexplored, offering a realm of untapped possibilities. Event cameras with high dynamic range (HDR) and remarkable temporal resolution, are a compelling imaging technology well-suited to scenarios necessitating the capture of rapid motion. Their sensitivity to light enhances their utility in low-light environments, positioning them as a preferable choice for applications like driver monitoring. Notably, event cameras can achieve an extraordinary dynamic range of up to 140 dB, a considerable advancement over conventional frame-based cameras that typically offer around 60 dB [5].

In this work we use the concept of periodicity for determining the HR of an individual from observations of the movement on the inner surface of their wrist caused by the radial artery, similar to work reported in [10]. That work used very low power, non-ionizing radio frequency signals whereas we set out out to determine if an event camera can be used to detect pulse rate in humans from the sometimes invisible tiny movements on the surface of the skin caused by artery pulsation. We gather and detect event camera events from the wrist areas of a set of subjects and use periodicity detection [11] on these events to identify a recurring pattern with the same periodicity as the subject's HR.

III. Methodology and Data Gathering

Figure 1 provides an overview of our experimental pipeline. Pulse rates are measured in two setups: subjects at rest and subjects after completing some light exercise. Event camera recordings and smartwatch-based ground truth heart rates are collected in both setups. The accuracy of predicted heart rates from the event camera is evaluated against observed heart rates from the smartwatches.

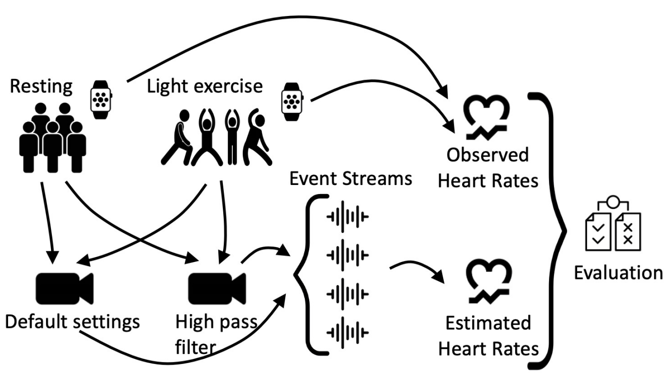

Fig. 1. Methodology for our experiments.

A. Camera Configuration and Bias Settings

A Prophesee EVK4 event camera[1] was used to gather event stream recordings for the experiments. Below are key bias settings for the camera along with their functionalities [9]:

[1]Prophesee, Paris, France https://www.prophesee.ai/event-camera-evk4/

1) bias_diff_on adjusts the contrast threshold for ON events. This determines the ON contrast threshold, the factor by which a pixel must get brighter before an ON event occurs for that pixel.
2) bias_diff_off adjusts the contrast threshold for OFF events. This determines the factor by which a pixel must get darker before an OFF event occurs for that pixel.
3) bias_fo adjusts the low-pass filter which changes how rapidly fluctuating light is filtered out.
4) bias_hpf adjusts the high-pass filter which determines how slow changes in illumination are filtered out.
5) bias_refr adjusts the refractory period which determines the duration for which a pixel is blind after each event has been recorded.

We conducted a thorough evaluation of bias settings to obtain the optimal settings for our environment. Drawing insights from prior research in camera optimisation [3], we identified the bias_hpf (high-pass filter) setting which we set to 25 in the Metavision software which controls the camera.

B. Event Detection

A dot about the size of a 1 cent coin was drawn on the skin of the inside of the wrist directly over or near to where the radial artery pulsates using a marker creating a high-contrast region compared to the surrounding skin. The variations in brightness caused by the slight pulsation movements not visible to the human eye produce events that stand out from the background and give the event camera a distinct signal to recognise. The designated dot shows up as a succession or burst of events in the output stream. Some sample dots drawn on the wrists of some of our subjects are shown in Figure 2.

Fig. 2. Sample dots drawn on the wrists of some of our subjects

We recruited University students and employees along with athletes attending a University gym as subjects. Their ages ranged from 20 to 50+ years, all were over 18 years of age and included a variety of skin tones with an almost 50-50 male/female ratio. Ethical approval was granted by the School of Computing Research Ethics committee.

C. Setup and Data Acquisition

After the subject had relaxed and was acclimatised to the laboratory environment, they were asked to place their arm close to a window with natural daylight. The subject remained still for 12 to 15 seconds while a recording with the event camera was made with the default bias settings and a second recording was made with bias_hpf (high-pass filter) value set to 25. Actual heart rates were recorded from a Apple Watch which the subjects wore.

The subject was then asked to perform some indoor exercise of their choice to elevate their HR. The same procedure to capture two more camera recordings was repeated for the elevated HR. The subject was then given a tissue and an alcohol-based sanitiser to remove the marked dot from their wrist.

D. Data Overview

We gathered data from 25 subjects as summarised in Table I. For each subject up to 4 event streams are recorded, 2 at resting HR with default and with alternative bias setting, and 2 during elevated HR also with different bias settings. Four subjects declined to do exercises to have an elevated heart rate reading giving 46 event stream recordings in total.

Each event stream file consists of a set of timestamps, x-y coordinates of pixels within the video frame and their polarity values (-1 or 1) depending on the change in brightness. The number of events for each of these files ranges from 850,000 to close to 3 million depending on the duration of the recording and the amount of movement during the recording.

E. Deriving Heart Rate

To calculate HR from the event stream camera data we calculated a heatmap for 1280×720 pixel frame to identify the 100×100 region where the sum of all pixel activations is highest, which is our area of interest (AoI). We then divided this into smaller, non-overlapping tiles of size 5×5 pixels in which we determine the dominant frequency from a periodogram as described earlier in Section II-A and that frequency is the estimated pulse rate for the recording.

During data capture and processing we encountered a number of challenges such as that subjects need to maintain a steady hand position which was not always the case because of natural tremor [8]. We also had to ensure that lighting conditions were constant by recording near to a window with natural light but that meant that lighting intensity varied across recordings depending on the level of sunlight at recording time.

IV. Experimental Results

Results from running our pulse detection algorithm are presented in Table I and show that we were able to detect pulse rates for 40 of the 46 recordings. For the other 6 recordings there had been an excess of the naturally-occurring sub-conscious movements or tremors in the hand for 3 of the recordings and for 3 others we have not been able to pinpoint the root cause for non-detection.

For detected HRs the largest difference between actual and detected was 5 beats per minute (bpm) occurring just twice, and in 24 of the 40 cases, HR was detected precisely or within 1 bpm. The mean absolute error (MAE) and root mean squared error (RMSE) values for our estimates of resting and elevated HR from 23 and from 17 subjects respectively are less than 2 bpm for MAE and just over 2 bpm for RMSE. This compares favourably with the MAE/RMSE figures of 2.11/2.93, 2.43/3.44, and 2.26/3.45 bpm for biking, stepping, and treadmill exercises respectively, as reported in [2] which is based on non-contact photoplethysmography. The best-performing camera bias settings was the customised high pass filter giving the best or joint-best performance on 29 of 40 recordings. Figure 3 shows a graph of actual vs. estimated HRs for resting and elevated settings for each subject with subjects sorted by the value of decreasing elevated HR. The differences between the actual vs. estimated HRs reflects the accuracy of our estimations.

V. Conclusions and Further Work

Our investigation into the potential for using event cameras for HR detection has demonstrated it is possible to achieve with an acceptable level of accuracy. Several avenues of further research can be explored to enhance the robustness and applicability of this approach.

Developing a real-time algorithm for pulse detection using event cameras is crucial for their practical use in applications like remote patient monitoring, driver awareness monitoring or fitness tracking. Optimising the computational efficiency of the algorithms while maintaining accuracy would be a significant focus for further research as would operating in variable and uncontrolled lighting conditions and catering for subject movement during monitoring. Finally, as with any remote monitoring technology, privacy and ethical concerns also need to be addressed. Conducting field studies to assess the practical usability and user experience of HR detection based on event cameras in real-world scenarios is also important. Understanding user acceptance, comfort, and satisfaction would be crucial for widespread adoption and use of the technology.

All data used in these experiments is publicly available at https://doi.org/10.6084/m9.figshare.24039501.v1.

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TABLE I
25 SUBJECTS, ACTUAL RESTING AND ELEVATED HRS AND HRS AS DETERMINED BY EVENT CAMERA. "ND" CORRESPONDS TO NOT DETECTED AND "-" CORRESPONDS TO A SUBJECT DECLINING TO PROVIDE DATA FOR AN ELEVATED HR. "BIASES USED" INDICATES WHICH CAMERA SETTING, EITHER DEFAULT (D) OR CUSTOMISED HIGH-PASS FILTER (C) GAVE THE BEST RESULT OR (B) IF BOTH SHOWED A SIMILAR RESULT.

Age	Gender	Skin Tone	Resting/Active Actual HR	Resting/Active Detected HR	Differences	Biases Used
20-30	M	Brown	66 / 93	65 / 91	-1 / -2	C / D
20-30	F	Brown	66 / 111	65 / 114	-1 / +3	C / B
50-60	F	White	78 / -	79 / -	+1 / -	C / -
20-30	M	White	80 / 116	80 / 116	0 / 0	D / B
20-30	M	Black	63 / 118	63 / ND	0 / ND	B / -
20-30	F	White	69 / -	69 / -	0 / -	B / -
30-40	M	Black	64 / 128	65 / 129	+1 /+1	D / B
20-30	F	White	81 / 105	79 / 105	-2 / 0	C / B
20-30	F	White	72 / -	71 / -	-1 / -	D / -
30-40	M	Brown	58 / 95	58 / 96	0 / +1	B / D
20-30	M	White	93 / 98	94 / 98	+1 / 0	B / B
20-30	M	White	57 / 86	58 / 83	+1 / -3	B / D
20-30	F	Black	76 / 102	ND / 105	ND / +3	- / C
20-30	F	White	79 / 113	76 / 113	-3 / 0	C / D
20-30	F	Brown	80 / 104	81 / 103	+1 /-1	B / C
20-30	F	White	84 / -	86 / -	+2 / -	D / -
30-40	F	Black	67 / 129	64 / 126	-3 / -3	D / C
20-30	M	White	71 / 105	71 / 101	0 / -4	C / B
20-30	F	White	96 / 154	ND / ND	ND / ND	- / -
20-30	M	Brown	107 / 115	102 / 114	-5 / -1	D / C
20-30	M	White	73 / 102	75 / 103	+2 / +1	D / C
20-30	M	Black	79 / 132	78 / ND	-1 / ND	C / -
20-30	F	Brown	109 / 130	109 / 129	0 / -1	C / C
20-30	F	White	67 / 161	63 / 156	-4 / -5	C / C
20-30	M	Brown	70 / 101	66 / ND	-4 / ND	C / -

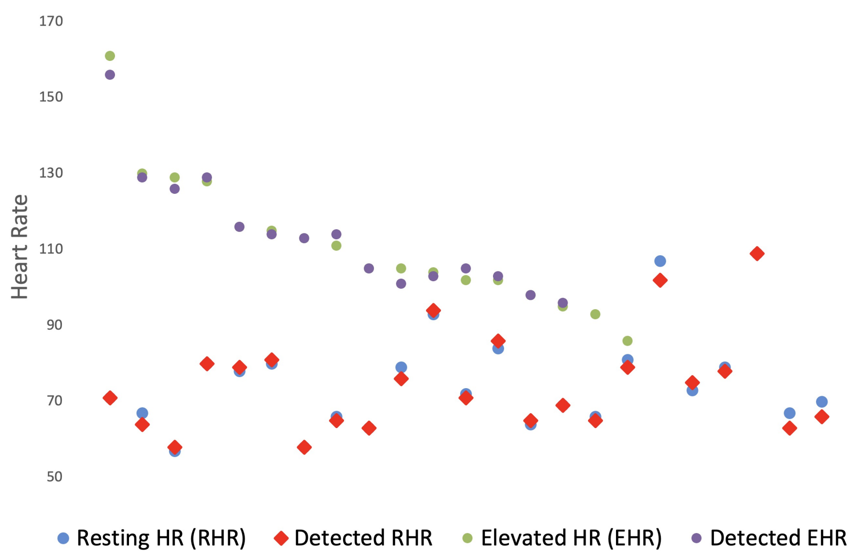

Fig. 3. Actual v estimated HRs for elevated & resting HRs. Where actual & estimated are the same or very close, one graph marker occludes the other.

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