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Android-based implementation of Eulerian Video Magnification for vital signs monitoring

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Abstract

Eulerian Video Magnification is a recently presented method capable of revealing temporal variations in videos that are impossible to see with the naked eye. Using this method, it is possible to visualize the flow of blood as it fills the face. From its result, a person's heart rate is possible to be extracted.

This research work is an internal project of *Fraunhofer Portugal* and its goal is to test the feasibility of the implementation of the Eulerian Video Magnification method on smartphones by developing an *Android* application for monitoring vital signs based on the Eulerian Video Magnification method.

There has been some successful effort on the assessment of vital signs, such as, heart rate, and breathing rate, in a contact-free way using a webcamera and even a smartphone. However, since the Eulerian Video Magnification method was recently proposed, its implementation has not been tested in smartphones yet.

The application will include features, such as, detection of a person's cardiac pulse, dealing with artifacts' motion, and real-time display of the magnified blood flow. Then, the application performance will be evaluated through tests with several individuals and the assessed heart rate compared to the one detected by the *Philips* application, and to the measurement of an heart rate monitor or a pulse oximeter.

Contents

List of Figures

LIST OF FIGURES

List of Tables

LIST OF TABLES

Abbreviations

EVM	Eulerian Video Magnification
ICA	Independent Component Analysis
PPG	Photo-plethysmography
FFT	Fast Fourier transform
FPS	Frames per second

Chapter 1

Introduction

This chapter introduces this work, by first presenting its context, motivation, and project's objectives, on sections 1.1, 1.2, and 1.3, respectively.

Finally, section 1.4 describes the document outline.

1.1 Context

Eulerian Video Magnification is a method, recently presented at *SIGGRAPH*[1] 2012, capable of revealing temporal variations in videos that are impossible to see with the naked eye. Using this method, it is possible to visualize the flow of blood as it fills the face [WRS+12]. Which provides enough information to assess the heart rate in a contact-free way using a camera [WRS+12, PMP10, PMP11].

The main field of this research work is *image processing and computer vision*, whose main purpose is to translate dimensional data from the real world in the form of images into numerical or symbolical information.

Other fields include *medical applications*, *software development for mobile devices*, *digital signal processing*.

This research work is an internal project of *Fraunhofer Portugal*[2] supervised by Luís Rosado. Fraunhofer Portugal a is non-profit private association founded by Fraunhofer-Gesellschaft[3] [Por13] and

> "aims on the creation of scientific knowledge capable of generating added value to its clients and partners, exploring technology innovations oriented towards economic growth, the social well-being and the improvement of the quality of life of its end-users." [Por13]

[1] http://www.siggraph.org/
[2] http://www.fraunhofer.pt/
[3] http://www.fraunhofer.de/en/about-fraunhofer/

1.2 Motivation

Due to being recently proposed, the Eulerian Video Magnification method implementation has not been tested in smartphones yet.

There has been some successful effort on the assessment of vital signs, such as, heart rate, and breathing rate, in a contact-free way using a webcamera [WRS+12, PMP10, PMP11], and even a smartphone [Tec13, Phi13].

Other similar products, which require specialist hardware and are thus expensive, include *laser Doppler* [UT93], *microwave Doppler radar* [Gre97], and *thermal imaging* [GSMP07].

Since it is a cheaper method of assessing vital signs in a contact-free way than the above products, this research work has potential for advancing fields, such as, *telemedicine*, *personal health-care*, and *ambient assisting living*.

Despite the existence of very similar products by *Philips* [Phi13] and *ViTrox Technologies* [Tec13] to the one proposed on this research work, none of these implements the Eulerian Video Magnification method. Moreover, the application to be developed during this research work will have additional features described on the next section 1.3.

1.3 Objectives

This research work goal is to test the feasibility of the implementation of the Eulerian Video Magnification method on smartphones by developing an *Android* application for monitoring vital signs based on the Eulerian Video Magnification method.

This application should include the following features:

- heart rate detection and assessment based on the Eulerian Video Magnification method;
- display real-time changes, such as, the magnified blood flow, obtained from the Eulerian Video Magnification method;
- deal with artifacts' motion, due to, person and/or smartphone movement.

It should be noted that a straightforward implementation of the Eulerian Video Magnification method is not possible, due to various reasons. First, the Eulerian Video Magnification method provides motion magnification along with color magnification which will introduce several problems with artifacts' motion. Second, the requirement of implementing a real-time smartphone application will create performance issues which will have to be addressed and trade-offs will have to be considered.

The application performance should then be evaluated through tests with several individuals and the assessed heart rate compared to the ones detected by another application [Tec13, Phi13], and to the measurement of an electronic sphygmomanomete.

1.4 Outline

The rest of the document is structured as follows:

Chapter 2 introduces the concepts necessary to understand the presented problem. In addition, it presents the existing related work, and a description of the technologies to be used.

Chapter 3 ...

Chapter 4 presents the approach taken to solve the problem. Moreover, it introduces the testing and evaluation methodologies.

Chapter 5 ...

Chapter 6 ...

Chapter 7 ...

Chapter 2

State of the art

This chapter presents several studies regarding the heart rate estimation from a person's face captured through a simple webcam.

Section 2.1 describe the concept that explains how the cardiac pulse is detected from a person's face in a remote, contact-free way.

Post-processing methods, which may be applied to the retrieved signal, are detailed on section 2.2.

In order to estimate the heart rate, a couple of techniques are also detailed on section 2.3.

Finally, section 2.4 reviews the main technologies and tools used throughout this work.

2.1 Photo-plethysmography

Photo-plethysmography (PPG) is the concept of measuring volumetric changes of an organ optically. Its most established use is in pulse oximeters.

PPG is based on the principle that blood absorbs more light than surrounding tissue thus variations on blood volume affect light reflectance [VSN08].

The use of dedicated light sources and infra-red wavelengths, and contact probes has been the norm [UT93, Gre97, GSMP07]. However, recently, remote, non-contact PPG imaging has been explored.

The method used on the article [VSN08] captures the pixel values (red, green, and blue channels) of the facial area of a previously recorded video where volunteers were asked to minimize movements. The pixel values within a region of interest (ROI) was then averaged for each frame. This spatial averaging was found to significantly increase signal-to-noise ratio. The heart rate estimation was then calculated by applying Fast Fourier transforms and the power spectrum as explained on section 2.3.1.

The authors of [VSN08] demonstrate that the fact that the green channel features a stronger heart rate signal as compared to the red and blue channels, is a strong evidence that the signal is due to variations in blood volume because (oxy-) hemoglobin absorbs green light.

2.2 Signal post-processing

After obtaining the raw pixel values (red, green, and blue channels), a conjunction of the following methods may be used to extract and improve the reflected plethysmography signal. However, each method introduces complexity and expensive computation.

2.2.1 Independent Component Analysis

Independent Component Analysis is a special case of *blind source separation* and is a relatively new technique for uncovering independent signals from a set of observations that are composed of linear mixtures of the underlying sources [Com94].

In this case, the underlying source signal of interest is the cardiac pulse that propagates throughout the body, which modify the path length of the incident ambient light due to volumetric changes in the facial blood vessels during the cardiac cycle, such that subsequent changes in amount of reflected light indicate the timing of cardiovascular events.

By recording a video of the facial region, the red, green, and blue (RGB) color sensors pick up a mixture of the reflected plethysmographic signal along with other sources of fluctuations in light due to artifacts. Each color sensor records a mixture of the original source signals with slightly different weights. These observed signals from the red, green and blue color sensors are denoted by $x_1(t)$, $x_2(t)$ and $x_3(t)$ respectively, which are amplitudes of the recorded signals at time point t. In conventional Independent Component Analysis model the number of recoverable sources cannot exceed the number of observations, thus three underlying source signals were assumed, represented by $s_1(t)$, $s_2(t)$ and $s_3(t)$. The Independent Component Analysis model assumes that the observed signals are linear mixtures of the sources, i.e. $x_i(t) = \sum_{j=1}^{3} a_{ij} s_j(t)$ for each $i = 1,2,3$. This can be represented compactly by the mixing equation

$$x(t) = As(t) \tag{2.1}$$

where the column vectors $x(t) = [x_1(t), x_2(t), x_3(t)]^T$, $s(t) = [s_1(t), s_2(t), s_3(t)]^T$ and the square 3×3 matrix A contains the mixture coefficients a_{ij}. The aim of Independent Component Analysis model is to find a separating or demixing matrix W that is an approximation of the inverse of the original mixing matrix A whose output

$$\hat{s}(t) = Wx(t) \tag{2.2}$$

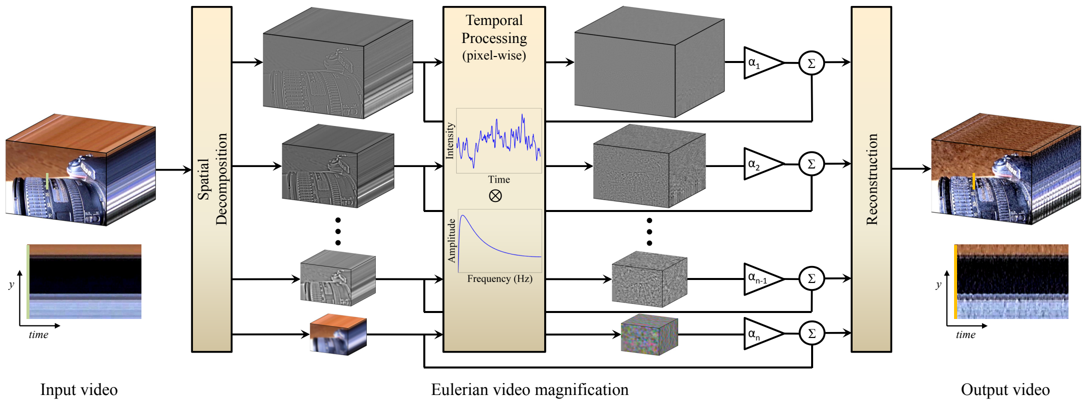


Figure 2.1: Overview of the Eulerian Video Magnification method.

is an estimate of the vector $s(t)$ containing the underlying source signals. To uncover the independent sources, W must maximize the non-Gaussianity of each source. In practice, iterative methods are used to maximize or minimize a given cost function that measures non-Gaussianity [PMP10, PMP11].

2.2.2 Eulerian Video Magnification

In contrast to the Independent Component Analysis model that focus on extracting a single number, the Eulerian Video Magnification uses localized spatial pooling and temporal filtering to extract and reveal visually the signal corresponding to the cardiac pulse. This allows for amplification and visualization of the heart rate signal at each location on the face. This creates potential for monitoring and diagnostic applications to medicine, i.e. the asymmetry in facial blood flow can be a symptom of arterial problems.

Besides color amplification, the Eulerian Video Magnification method is also able to reveal low-amplitude motion which may be hard or impossible for humans to see. Previous attempts to unveil imperceptible motions in videos have been made, such as, [LTF+05] which follows a *Lagrangian* perspective, as in fluid dynamics where the trajectory of particles is tracked over time. By relying on accurate motion estimation and additional techniques to produce good quality synthesis, such as, motion segmentation and image in-painting, the algorithm complexity and computation is expensive and difficult.

On the contrary, the Eulerian Video Magnification method is inspired by the *Eulerian* perspective, where properties of a voxel of fluid, such as pressure and velocity, evolve over time. The approach of this method to motion magnification is the exaggeration of motion by amplifying temporal color changes at fixed positions, instead of, explicitly estimation of motion.

This method approach, illustrated in figure 2.1, combines spatial and temporal processing to emphasize subtle temporal changes in a video. First, the video sequence is decomposed into different spatial frequency bands. Because they may exhibit different signal-to-noise ratios, they may be magnified differently. In the general case, the full Laplacian pyramid [BA83] may be

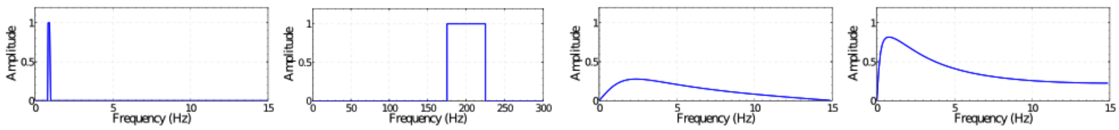


Figure 2.2: Examples of temporal filters.

computed. Then, temporal processing is performed on each spatial band. The temporal processing is uniform for all spatial bands, and for all pixels within each band. After that, the extracted bandpass signal is magnified by a factor of α, which can be specified by the user, and may be attenuated automatically. Finally, the magnified signal is added to the original and the spatial pyramid collapsed to obtain the final output.

2.2.2.1 Spatial filtering

As mention before, the work of [WRS+12] computes the full Laplacian pyramid [BA83] as a general case for spatial filtering. Each layer of the pyramid may be magnified differently because it may exhibit different signal-to-noise ratios, or contain spatial frequencies for which the linear approximation used in motion magnification does not hold [WRS+12, section 3].

Spatial filtering may also be used to significantly increases signal-to-noise ratio, as previously mention on section 2.1 and demonstrated on the work of [VSN08] and [WRS+12]. Subtle signals, such as, a person's heart rate from a video of its face, may be enhanced this way. For this purpose the work of [WRS+12] computes a layer of the Gaussian pyramid which may be obtained by successively scaling down the image by calculating the Gaussian average for each pixel.

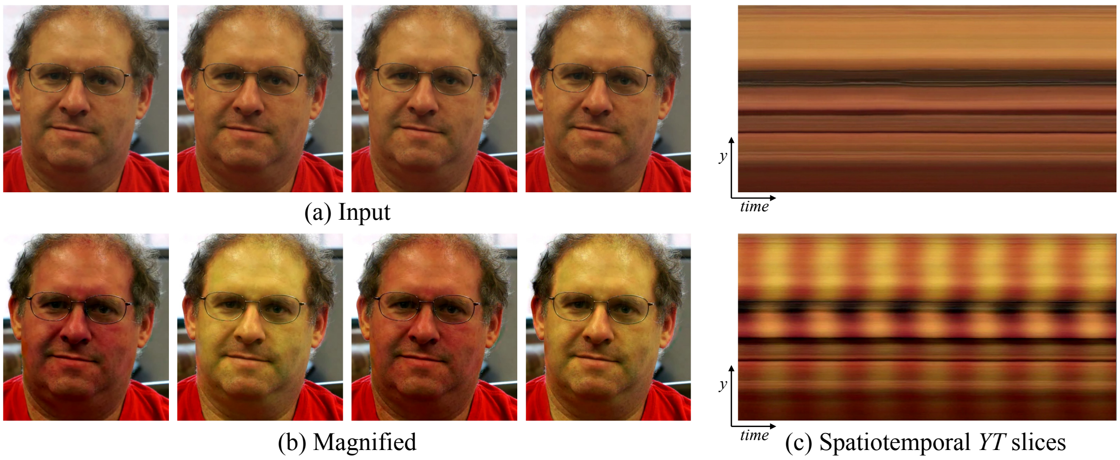
However, for the signal of interest to be revealed, the spatial filter applied must be large enough. Section 5 of [WRS+12] provides an equation to estimate the size for a spatial filter needed to reveal a signal at a certain noise power level:

$$S(\lambda) = S(r) = \sigma'^2 = k\frac{\sigma^2}{r^2} \tag{2.3}$$

where $S(\lambda)$ represents the signal over spatial frequencies, and since the wavelength, λ, cutoff of a spatial filter is proportional to its radius, r, the signal may be represented as $S(r)$. The noise power, σ^2, can be estimated using to the technique of [LFSK06]. Finally, because the filtered noise power level, σ'^2, is inversely proportional to r^2, it is possible to solve the equation for r, where k is a constant that depends on the shape of the low pass filter.

2.2.2.2 Temporal filtering

Temporal filtering is used to extract the motions or signals to be amplified. Thus, the filter choice is application dependent. For motion magnification, a broad bandpass filter, such as, the butterworth filter, is preferred. A narrow bandpass filter produces a more noise-free result for color



(a) Input (b) Magnified (c) Spatiotemporal *YT* slices

Figure 2.3: Emphasis of face color changes using the Eulerian Video Magnification method.

amplification of blood flow. An ideal bandpass filter is used on [WRS+12] due to its sharp cutoff frequencies. Alternatively, for a real-time implementation low-order IIR filters can be useful for both: color amplification and motion magnification. These filters are illustrated on 2.2.

2.2.2.3 Emphasize color variations for human pulse

The extraction of a person's cardiac pulse using the Eulerian Video Magnification method was demonstrated in [WRS+12]. It was also presented that using the right configuration can help extract the desired signal. There are four steps to take when processing a video using the Eulerian Video Magnification method:

1. select a temporal bandpass filter;
2. select an amplification factor, α;
3. select a spatial frequency cutoff (specified by spatial wavelength, λ_c) beyond which an attenuated version of α is used;
4. select the form of the attenuation for α —- either force α to zero for all $\lambda < \lambda_c$, or linearly scale α down to zero.

For human pulse color variation, two temporal filters may be used, first selecting frequencies within 0.4-4Hz, corresponding to 24-240 beats per minute (bpm), then a narrow band of 0.83-1Hz (50-60 bpm) may be used, if the extraction of the pulse rate was successful.

To emphasize the color change as much as possible, a large amplification factor, $\alpha \approx 100$, and spatial frequency cutoff, $\lambda_c \approx 1000$, is applied. With an attenuation of α to zero for spatial wavelengths below λ_c.

The resulting output can be seen in figure 2.3.

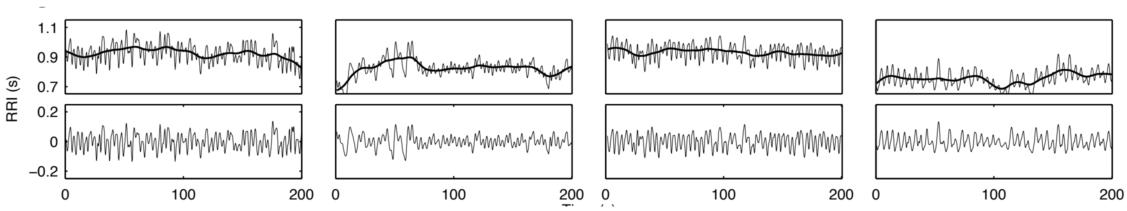


Figure 2.4: Original and detrended RR series.

2.2.3 Detrending

Detrending is a method of removing very large ultralow-frequency trends an input signal without any magnitude distortion, acting as an high-pass filter.

The main advantage of the method presented on the work of [TRaK02], compared to methods presented in [LOCS95] and [PB90], is its simplicity.

The method consists of separating the input signal, z, into two components, as $z = z_{stat} + z_{trend}$, where z_{stat} is the nearly stationary component, and z_{trend} is the low frequency aperiodic trend component.

An estimation of the nearly stationary component, $\hat{z}_{stat}$, can be obtained using the equation below. The detailed derivation of the equation can be found in [TRaK02].

$$\hat{z}_{stat} = (I - (I + \lambda^2 D_2^T D_2)^{-1})z \tag{2.4}$$

where I is the identity matrix, D_2 is the discrete approximation of the second order, and λ is the regularization parameter.

Figure 2.4 presents an example of what this method is able to achieve. The example, taken from the work of [TRaK02], uses real RR series and the effect of the method on time and frequency domain analysis of heart rate variability is demonstrated not to lose any useful information.

2.3 Heart rate estimation

In order to convert the extracted plethysmographic signal into the number of beats per minute (bpm), further processing must be done. Below are highlighted two methods capable of achieving this goal.

2.3.1 Power spectrum

Fourier transform is a mathematical transform capable of converting a function of time, $f(t)$, into a new function representing the frequency domain of the original function.

To calculate the power spectrum, the resulting function from the *Fourier transform* is then multiplied by itself.

Since the values are captured from a video, sequence of frames, the function of time is actually discrete, with a frequency rate equal to the video frame rate, FPS.

The *index*, i, corresponding to the maximum of the power spectrum can then be converted into a frequency value, F, using the equation:

$$F = \frac{i * FPS}{2N} \tag{2.5}$$

where N is the size of the signal extracted. F can then be multiplied by 60 to convert it to beats per minute, and have an estimation of the heart rate from the extracted signal.

2.3.2 Pulse wave detection

In [NI10], it is presented an automated algorithm for fast pulse wave detection. The algorithm is capable of obtaining an estimative of the heart rate from PPG signal, as an alternative to the power spectrum described above. Moreover, it also introduces validation to the waveform detection by verifying its shape and timing. Below is presented a simplified description of the algorithm. A more detailed description can be found in [NI10].

1. Identification of possible peaks and foots of individual pulses

   (a) Maximum (MAX)
   The signal is divided into consecutive $200ms$ time intervals and for every segment the absolute maximum is determined. Some of these maximums are rejected: if they fall below a predetermined amplitude threshold; or if the distance between two maximums is less than or equal to $200ms$, then the lower maximum is rejected.

   (b) Minimum (MIN)
   The absolute minimum is determined between every two adjacent maximums. A minimum is rejected, it is above a predetermined amplitude threshold. When a minimum is rejected, the lower-amplitude maximum of the two maximum adjacent to the rejected minimum is discarded too.

2. Examination and verification of the rising edges

   (a) Validation of a single rising edge
   If a rising edge is rejected, its maximum and minimum are rejected. A rising edge is rejected, if its amplitude ($AMPL = MAX - MIN$) is lower than amplitude threshold; or its duration is lower than a threshold that depends on the sampling rate; or its amplitude does not increase smoothly.

   (b) Estimation of the similarity of a rising edge to preceding and following rising edges accepted as valid
   Two rising edges are considered similar, if the amplitude of the lower-amplitude rising edge is greater than 50% of the amplitude of the higher-amplitude rising edge; and if the maximum of the lower-amplitude rising edge is between $\pm 60\%$ of the maximum of the higher-amplitude rising edge; and if the minimum of the lower-amplitude rising edge is between $\pm 60\%$ of the minimum of the higher-amplitude rising edge; and if the

duration of the shorter rising edge is greater then 33% of the duration of the longer rising edge. The valid rising edges are then categorized according to its characteristics for the following step. The categorization description is suppressed for brevity and can be found at [NI10].

(c) Verification of the current rising edge
The rising edges categorized on the previous step are considered valid edges of a pulse wave if they fulfill at least one of the decision rules presented on [NI10] and suppressed for brevity.

The validation process described here is important for discarding signals which are not representative of pulse waves. Providing a way of calculating the heart rate estimation only on valid pulse signals.

2.4 Technologies

Below are short descriptions of two of the main technologies that will be used during this research work.

2.4.1 Android SDK

Android SDK is the development kit for the *Android* platform. The *Android* platform is an open source, Linux-based operating system, primarily designed for touchscreen mobile devices, such as, smartphones.

Because of its open source code and permissive licensing, it allows the software to be freely modified and distributed. This have allowed *Android* to be the software of choice for technology companies who require a low-cost, customizable, and lightweight operating system for mobile devices and others.

Android has also become the world's most widely used smartphone platform with a worldwide smartphone market share of 75% during the third quarter of 2012 [IDC13].

Android consists of a kernel based on Linux kernel with middleware, libraries and APIs written in C. Applications, usually, run on an application framework which includes Java-compatible libraries based on *Apache Harmony*, an open source, free Java implementation. *Java bytecode* is then translated to run on the *Dalvik virtual machine*.

Porting existing Linux application or libraries to *Android* is difficult due to the lack of a native *X Window System* and lack of support for *GNU* libraries. Support for simple C and SDL application is possible, though, by the usage of *JNI*, a programming framework that allows Java code to call and be called by libraries written in C/C++.

2.4.2 OpenCV – Computer Vision Library

OpenCV is a library of programming functions mainly aimed at real-time image processing. To support these, it also includes a statistical machine learning library. Moreover, it is a cross-platform and open source library that is free to use and modify under the BSD license.

> "OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products." [Its13]

OpenCV is written in C/C++. There are binding for other languages, such as, Python, Java, and even Android. However, Java and Android implementation is recent and lacks features and stability.

2.5 Chapter summary

This chapter starts by describing the concept behind the extraction of cardiac pulse is possible from a person's face captured through a simple video or webcam.

It then presents several possible post-processing methods for to improve the extraction of the actual pulse signal. These methods include:

- *Independent Component Analysis*, a method capable of uncovering independent signals from a set of observations that are composed of linear mixtures of the underlying sources;
- *Eulerian Video Magnification*, a method inspired by the *Eulerian* perspective that exaggerates color variations by analyzing how each pixel value changes over time;
- *Detrend*, a method which removes small trends from an input signal without distorting its amplitude.

Then algorithms for obtaining the actual beats per minutes of the heart rate from the signal are described:

- *Power spectrum*, a set of equations capable of finding the frequency of a signal using the *Fourier transform*;
- *Pulse wave detection*, an algorithm for detecting and validating rising edges from a pulse signal.

Finally, important technologies for the work are described and explored:

- *Android*, a Linux-based operating system, primarily designed for touchscreen mobile devices;
- *OpenCV*, a *Computer Vision* library of programming functions mainly aimed at real-time image processing.

Chapter 3

Problem description

3.1 Eulerian Video Magnification

3.2 Chapter summary

Chapter 4

Solution architecture

4.1 Eulerian Video Magnification

4.2 Chapter summary

Solution architecture

Chapter 5

Implementation details

5.1 Eulerian Video Magnification

5.2 Android

5.3 Performance

5.4 Chapter summary

Implementation details

Chapter 6

Results

6.1 Heart rate comparison

6.2 Algorithm performance

6.3 Chapter summary

Chapter 7

Conclusions

7.1 Objective satisfaction

7.2 Future work

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