

Department of Physics and Astronomy

University of Heidelberg

Master thesis

in Computer Engineering

submitted by

Habib Gahbiche

born in Sousse

2018

(Title)
(of)
(Master thesis)

This Master thesis has been carried out by Habib Gahbiche

at the

Institute of Environmental Physics

under the supervision of

Prof. Dr. Bernd Jähne

and

Prof. Dr. Karl-Heinz Brenner

Institute of Computer Engineering

(Titel der Masterarbeit - deutsch):

(Abstract in Deutsch, max. 200 Worte. Beispiel: ?)

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquid ex ea commodo consequat. Quis aute iure reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint obcaecat cupiditat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Duis autem vel eum iriure dolor in hendrerit in vulputate velit esse molestie consequat, vel illum dolore eu feugiat nulla facilisis at vero eros et accumsan et iusto odio dignissim qui blandit praesent luptatum zzril delenit augue dui dolore te feugait nulla facilisi. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed diam nonummy nibh euismod tincidunt ut laoreet dolore magna aliquam erat volutpat.

Ut wisi enim ad minim veniam, quis nostrud exerci tation ullamcorper suscipit lobortis nisl ut aliquip ex ea commodo consequat. Duis autem vel eum iriure dolor in hendrerit in vulputate velit esse molestie consequat, vel illum dolore eu feugiat nulla facilisis at vero eros et accumsan et iusto odio dignissim qui blandit praesent luptatum zzril delenit augue dui dolore te feugait nulla facilisi.

(Title of Master thesis - english):

(abstract in english, at most 200 words. Example: ?)

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquid ex ea commodo consequat. Quis aute iure reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint obcaecat cupiditat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

Duis autem vel eum iriure dolor in hendrerit in vulputate velit esse molestie consequat, vel illum dolore eu feugiat nulla facilisis at vero eros et accumsan et iusto odio dignissim qui blandit praesent luptatum zzril delenit augue dui dolore te feugait nulla facilisi. Lorem ipsum dolor sit amet, consectetur adipiscing elit, sed diam nonummy nibh euismod tincidunt ut laoreet dolore magna aliquam erat volutpat.

Ut wisi enim ad minim veniam, quis nostrud exerci tation ullamcorper suscipit lobortis nisl ut aliquip ex ea commodo consequat. Duis autem vel eum iriure dolor in hendrerit in vulputate velit esse molestie consequat, vel illum dolore eu feugiat nulla facilisis at vero eros et accumsan et iusto odio dignissim qui blandit praesent luptatum zzril delenit augue dui dolore te feugait nulla facilisi.

Contents

1	Introduction	5
2	Theory	6
2.1	Bubble physics	6
2.2	Image processing	6
2.2.1	Fourier theory	6
2.2.2	Convolution	7
2.2.3	Smoothing	7
2.2.4	Edges and Derivation	8
2.2.5	Orientation and Structure Tensor	8
2.3	Machine Learning	8
2.4	The object detection problem	8
2.4.1	Evaluation Criteria	8
3	Related Work	11
4	Experimental Setup	12
4.1	Requirements	12
4.2	Aquarium	12
4.3	Aeolotron	12
5	The Algorithm	13
5.1	BubbleNet	13
5.2	Curvature based	13
5.3	Calibration	13
A	Lists	15
A.1	List of Figures	15
A.2	List of Tables	15

1 Introduction

This is my intro

2 Theory

In this chapter we explain the theoretical concepts relevant to this thesis. We start with explaining the physics behind our method in section 2.1, in particular how bubbles interact with light. Next, we discuss the mathematical basics necessary for image processing such as Fourier theory and convolution in section 2.2. Section 2.3 explains the principle behind machine learning that our method relies on for classification. Finally, section 2.4 formally introduces the object detection problem and our chosen criteria for evaluation.

2.1 Bubble physics

2.2 Image processing

In the following we represent an image as a two dimensional signal written as a matrix \mathbf{g} . Therefore, $g_{m,n}$ denotes the pixel (i.e. picture element) at the m -th row corresponding to the n -th column.

2.2.1 Fourier theory

The Fourier transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image. The *continuous* two-dimensional Fourier transform is defined as

$$\mathcal{F}\{g(\mathbf{x})\} = \hat{g}(\mathbf{k}) = \int_{-\infty}^{\infty} g(\mathbf{x}) \exp(-2\pi i \mathbf{k}^T \mathbf{x}) d\mathbf{x} \quad (2.1)$$

and the inverse Fourier transform

$$\mathcal{F}^{-1}\{\hat{g}(\mathbf{k})\} = g(\mathbf{x}) = \int_{-\infty}^{\infty} \hat{g}(\mathbf{k}) \exp(-2\pi i \mathbf{k}^T \mathbf{x}) d\mathbf{k} \quad (2.2)$$

Where \mathbf{x} and \mathbf{k} are the two dimensional space and frequency vectors respectively.

Images however are discrete two dimensional signals, we therefore need to apply the *Discrete* Fourier transform or DFT, defined as

$$\text{DFT}\{g_{m,n}\} = \hat{g}_{u,v} = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} g_{m,n} \exp\left(-\frac{2\pi i m u}{M}\right) \exp\left(-\frac{2\pi i n v}{N}\right) \quad (2.3)$$

Similarly, the inverse 2-D DFT is defined as

$$\text{IDFT}\{\hat{g}_{u,v}\} = g_{m,n} = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \hat{g}_{u,v} \exp\left(\frac{2\pi i m u}{M}\right) \exp\left(\frac{2\pi i n u}{N}\right) \quad (2.4)$$

2.2.2 Convolution

Convolution is one of the most important operations in signal processing. Convoluting two signals g and h produces a third signal that expresses how the shape of one is modified by the other. Formally, we define the continuous convolution as follows

$$(g \star h)(\mathbf{x}) = \int_{-\infty}^{\infty} h(\mathbf{x}') g(\mathbf{x} - \mathbf{x}') d\mathbf{x} \quad (2.5)$$

and the discrete two dimensional convolution as

$$g'_{m,n} = \sum_{m'=0}^{M-1} \sum_{n'=0}^{N-1} h_{m',n'} g_{m-m',n-n'} \quad (2.6)$$

One important property of convolution is that we can express it as a multiplication in the Fourier domain.

$$\mathcal{F}\{g \star h\} = NM \hat{h} \hat{g} \quad (2.7)$$

This property, together with the fast Fourier implementation of the Fourier transform allows a fast computation of convolutions.

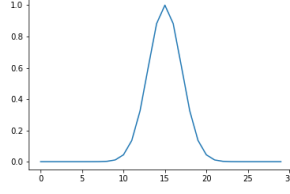
At the edge of the image, we typically extend the image with zero values (i.e. zero padding). This introduces an error when applying filters at the image border and we will mostly exclude the border when using filters (see chapter 5 for more details).

2.2.3 Smoothing

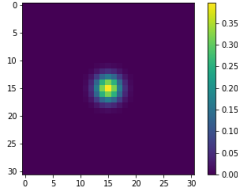
Smoothing an image means convolving an image with a smoothing filter. A smoothing or averaging filters must ideally fulfill following conditions

1. Zero-shift: $\Im(\hat{h}(\mathbf{k})) = 0$
2. Preservation of mean value: $\hat{h}(0) = 1$
3. Monotonous decrease: $\hat{h}(k_1) \leq \hat{h}(k_2)$ for $k_1 > k_2$
4. Isotropy: $\hat{h}(\mathbf{k}) = \hat{h}(|\mathbf{k}|)$ stimmt das ??

In this work, we will be using Gaussian filters for one and two dimensional smoothing. Although Gaussian filters are not ideal, e.g. isotropy is violated for small standard deviations, it is still a good approximation for an ideal low pass filter.



(a) 1D Gaussian signal
with $\mu = 15$ and $\sigma = 2$



(b) 2D Gaussian signal
with $\mu_x = \mu_y = 15$ and
 $\sigma_x = \sigma_y = 2$



(c) Original image



(d) After convolution with
2D Gaussian mask

Figure 2.1: Gaussian smoothing filter

Computing the Fourier transform (for convolution) is also faster for a Gaussian filter. The m -th component of a one dimensional Gaussian filter mask can be obtained from the Gaussian function

$$G_m = \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{(m - \mu)^2}{2\sigma^2}\right) \quad (2.8)$$

Where μ is the mean, i.e. Gaussian peak's position and σ is the standard deviation, i.e. peak's width.

Figure 2.1 show a Gaussian curve in one and two dimensions as well as the result of convolving an image with a Gaussian filter mask. Note how the image becomes blurry, i.e. large wave numbers have been suppressed.

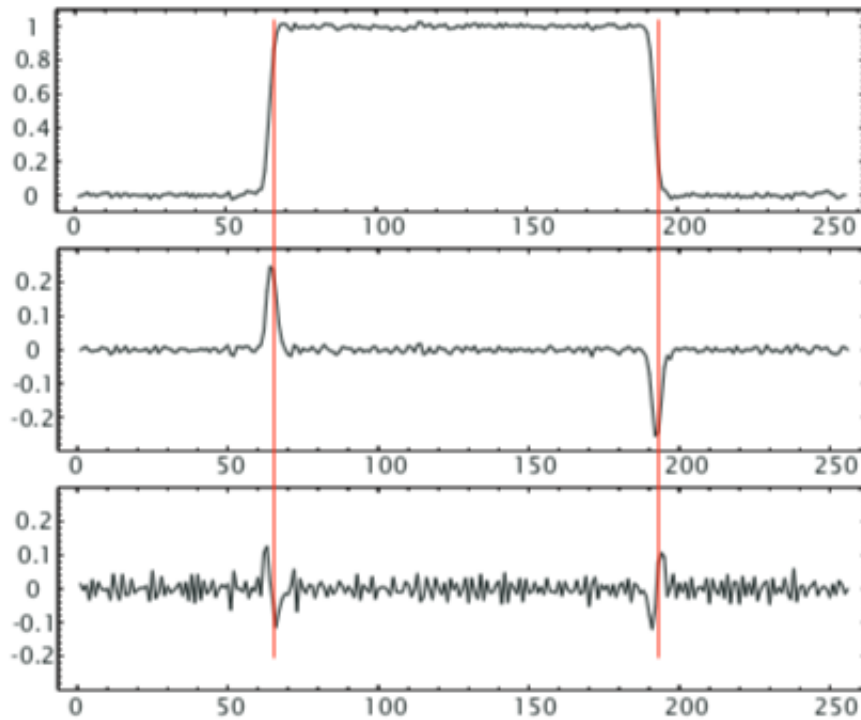


Figure 2.2: Original 1D signal. First derivative. Second derivative

2.2.4 Edges and Derivation

An edge can be defined as a set of continuous pixel positions where an abrupt change of intensity (i.e. gray value) occurs.

2.2.5 Orientation and Structure Tensor

2.3 Machine Learning

2.4 The object detection problem

2.4.1 Evaluation Criteria

3 Related Work

4 Experimental Setup

4.1 Requirements

4.2 Aquarium

4.3 Aeolotron

5 The Algorithm

5.1 BubbleNet

5.2 Curvature based

5.3 Calibration

Appendix

A Lists

A.1 List of Figures

2.1	Gaussian smoothing filter	9
2.2	Original 1D signal. First derivative. Second derivative	10

A.2 List of Tables

Erklärung:

Ich versichere, dass ich diese Arbeit selbstständig verfasst habe und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

Heidelberg, den (Datum)