MINISTRY OF EDUCATION AND SCIENTIFIC RESEARCH

TECHNICAL UNIVERSITY
OF CLUJ-NAPOCA

FACULTY OF AUTOMATION AND COMPUTER SCIENCE
COMPUTER SCIENCE DEPARTMENT

# LICENSE THESIS TITLE

## LICENSE THESIS

**Graduate: Firstname LASTNAME**
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**2015**

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# Contents

# Chapter 1

# Introduction - Project Context

The title of each chapter is formatted using Heading 1 style, numbering with one digit (Chapter x. Chapter Name ), font Times New Roman, size 14 points, Bold.

This chapter will present:

- Project context
- Specify the precise domain
- Use about 5% of the paper

## 1.1 Project context

The font used for the text in this document is Times New Roman, size 12 points, as defined in the Normal style, Line spacing equal to 1.0 (Paragraph, Line spacing) and Justify.

The first line for each paragraph must be indented (implicit in Normal Style), and no additional space is inserted between successive paragraphs[1].

### 1.1.1 Subsection

Each table used in this document is labeled as Table x.y, where x represents the chapter number, and y shows the table number within the current chapter. Leave a blank line between and after each table, relative to the adjacent paragraphs (table 1.1).

Each figure used in the document must be cited within the text (ex: in figure x.y the system components are presented... ) and labeled. The labeling must be as Figure x.y where x represents the chapter number, and y shows the number of the figure within the current chapter. E.g.: figure **??**.

[1]Sorry for the Word's users. In Latex these are automatically solved.

Table 1.1: Nonlinear Model Results

| Case | Method#1 | Method#2 | Method#3 |
|---|---|---|---|
| 1 | 50 | 837 | 970 |
| 2 | 47 | 877 | 230 |
| 3 | 31 | 25 | 415 |

@bookwedel2011stereo, title=Stereo scene flow for 3D motion analysis, author=Wedel, Andreas and Cremers, Daniel, year=2011, publisher=Springer Science & Business Media

Each chapter must start on a new page.

# Chapter 2

# Project Objectives and Specifications

Describe the proper theme (as a research/design proposal, clearly formulated, with clear objectives, and some explanatory figures).

Stretches over about 10% of the paper.

## 2.1 Title

## 2.2 Other title

# Chapter 3

# Bibliographic research

must be about 9 pages

Optical Flow problem is an old subject in computer vision. The fundamental method for robust optical flow, referenced in over 10000 articles up to the newest, was published in 1980, by Horn and Schunch [1]. They define the optical flow as

"the distribution of apparent velocities of movement in an image."

and state the problem as a minimization of a squared penalty function from the brightness constraint and the smoothness constraint.

Based on this approach, many other algorithms were published. All this formulations, spatially-discrete, derived from Horn-Scunk are referred in literature as "clasics" [2, 3]. They all combine a data term and a spatial term, and apply an optimization procedure to minimize the function.

Another heavily cited article was published in the same year by Lucas and Kanade [4]. This approach solves the problem as a sum of squared differences, and proposes a coarse-to-fine solution for large displacements. As stated in chapter 3 from [5] the main weakness of this algorithm compared to Horn Schunk 's is the lack of regularization.

## 3.1 Differential methods

Differential techniques compute the optical flow trough spatio-temporal derivatives. Most algorithms start from the brightness constraint and from a Taylor expansion, obtaining the gradient constraint. Details of the numerical scheme of this chapter will be furthered discussed in 4.1.1

Then, for a complete formulation of the problem, a regularization term is needed. In the first chapter of [6], the algorithms are classified in two categories, depending on the regularization term, variational and feature-based, meaning it does or does not depend on neighbouring pixels' flow computations.

### 3.1.1 Horn Schunk

The first important formulation of te global optical flow was stated by Horn and Schunk in [1]. They started from the brightness constraint, a moving point does not change its brightness in time. From this constraint results the temporal derivative of the brightness of a sequence is 0. Then, using multi-dimensional Euler-Lagrange equations, from the expansion of the derivative, optical flow can be formulated in one equation as the data term. But the optical flow has two components, the horizontal flow, and the vertical flow. To solve this problem, another constraint is introduced, the spatial smoothness constrained.

Smoothness constraint is a variational method, that means it takes into account flow solutions of neighbourhood pixels. By assuming a continuous flow, the neighbouring pixels should have similar velocities[1]. Further, by applying the Laplacian operator on the flow, the result should be 0. By minimizing the Laplacian, the flow propagates on texureless objects.

By combining the two constraints, the results a convex energy function:

$$\iint ((\nabla I + I_t)^2 + \lambda(\|(\nabla u)\|_2^2 + \|(\nabla v)\|_2^2))dxdy \tag{3.1}$$

where $\lambda$ is the smoothness term coefficient. Although, $\lambda$ is set to 100 in the by Horn and Schunk, in the original version, some later analysis of the algorithm claim that if the coefficient ot set to values down to 0.5 [7], the algorithm yields better results. This proves that there is no optimal general value for $\lambda$, it should be approximated for each different set of images.

To solve the optical flow, the sum energy function 3.1 must be minimized. In order to obtain this minimization, variational calculus is applied. A set of two equations is obtained for the field. Further, each vector is estimated with Gauss-Seidel iterations. This means that each point is computed from the anterior estimation. Gauss-Seidel iterations will be further discussed in 4.4.1

### 3.1.2 Lucas Kanade

Published in th same year with Horn and Schunk, the Lucas Kanade method, offers a local approach for solving the optical flow problem.

## 3.2 Coarse-to-fine

Differential methods work well when the motion is small, about 1-2 pixels, because the differential techniques applied. The coarse to fine method, as described by Lucas and Kanade in [4] allows computation of greater displacements. for each image is computed a Gaussian Pyramid. Usually [2], the standard deviation used for the Gauss anti-aliasing

filter is

$$\frac{1}{\sqrt{2d}} \tag{3.2}$$

where $d$ is the downsamplig factor.

The flow is estimated between each level, from the bottom, then warped to the next, finer level. At each finer scale, the residual motion is computed between the first image and the second image warped to the first.

**Pyramid Height** About the height of the pyramid, it can vary from case to case. A general solution is to downsample until the top level has about 20-30 pixels in height or width [2].

**Downsamplig** Also, they say the downsamplig factor should be 0.5. most of the solutions take this value, but are some implementations that set the downsamplig factor at 0.8. There should not be any difference in the result as the minimization function is convex. A good practice is considered to set it at 0.5 [2].

**Warping** In [2], various methods are tested for wrapping. Their results state that good number for the warping times is 3. The difference in accuracy between 3 warps an 10 is insignificant.

**Interpolation technoques** Further, they compare the interpolation technique used before warping. The diference between them is not significantly high, but they found that spline-based bicubic interpolation yields slightly better results.

**Drawbacks** In chapter 15 of [8] the pyramid method is discussed. The author draws attention over the drawbacks of the coarse to fine methods. Each level's flow depends on its predecessor. If at some point in the computation of the velocities is erroneous, for example if aliasing or occlusions occur, it will be propagated up to the finest level.

### 3.2.1 Solving the minimization problem

Most of the formulation of the optical flow are stated as a minimization problem. If the penalty function is squared the solution can be achieved trough variational calculus. This is the case of the differential methods. For the L1 the classic methods do not apply any more.

**Gauss Seidel Iterations**

## 3.3 $L^1$ techniques

### 3.3.1 Proximal Point

### 3.3.2 LMN

## 3.4 Improvements

### 3.4.1 Low Pass Filter

As stated above, most of the algorithms use a coarse to fine estimation, and, for each level, an iterative approximation is performed. One of the downside of this approach is that if any outliers are present in the for at a lower level, this error will be propagated to all finer levels up to the final result, damaging the overall outcome of the algorithm.

In the papers comparing some of the existing algorithms, the implementations take a median filter somewhere in the algorithm.

In [8], the problem of aliasing is considered for bigger displacements, in th sampling procedure. The authors solve this problem by applying a blurring filer over the images, before computing the gradients of the images. From this they apply estimate the velocities for each level.

Also, in [2], by analysing the best practices in solving the optical flow problem, it is proven that, if a median filter applied after each warp, th robustness and the accuracy of the algorithms is increased. The robustness is a weak point of the differential methods. Outliers can completely throw off the energy function, especially in $L^2$ methods. Their results compare different sizes of the median filter, and no filer of different algorithms. The best results are obtained with a $5 \times 5$ kernel. Also the accuracy of the results when no filter was applied is significantly lower.

### 3.4.2 Cross Correlation

The cross correlation function measures the similarity between 2 signals. The normalized cross correlation takes values in $[0, 1]$, where 1 is a total match between the signals and 0 is a total mismatch between them.

In [9], the classical sum of squared difference, the data term is expressed as a zero normal cross correlation, this being more discriminative.

$$C(i) = \frac{I(s) - \mu(i)}{\sigma(i)} \tag{3.3}$$

As shown above, each point of the image, if passed trough a cross correlation transom, from which results a matrix of the same size as the neighbourhood considered. to find the minimum, the data term is further expanded with classic differential methods it is added the smoothness term.

### 3.4.3 Bilateral Filter

The bilateral filter is a smoothing filter, but the accuracy along edges is kept. As proposed in [10], the filter has two elements. The geometric distance, from the classical lowpass filter, let's take Gaussian for example. Each neighbour pixel will influence the output proportionally with its distance to the current pixel. On the other hand, the chromatic component measures the photochromacy between the neighbours and the central pixel. This can be expressed as the difference between the intensity of the neighbour pixel and the centre.

In the Gaussian case, one could get the normalization term, which is

$$e^{-\left(\frac{\Delta_c(i,s)}{2\sigma_c^2}+\frac{\Delta_d(i,s)}{2\sigma_d^2}\right)} \tag{3.4}$$

This normalization term can measure the likelihood of being on the edge of a pixel.

In [9], this formulation of the bilateral filter is used as a component of smoothness term. The smoothness constraint says that, the velocity of the neighbour pixels is the same. This applies, of course only if the neighbour pixels belong to the same object. The classic methods based on the smoothness constraint have large errors along the edges. By considering the bilateral filter term 3.4, one can easily reduce the smoothness penalty for velocities that do not belong to the same object, by simply applying the dot product between th bilateral filter term and the first norm of the difference.

# Chapter 4

# Analysis and Theoretical Foundation

There are different approaches in computing the optical flow. From the fundamental methods, the field of study advanced tremendously in terms of speed and accuracy of solving the problem. Although highly improved results, the newer approaches are based on the same assumptions and start from the same point as the original formulation of Horn and Schunch, and Lucas and Kanade.

Although this algorithms are quite different, one being global formulation and the other a local one, modern approaches apply principles from both. The brightness consistency assumption is a good start point for many approaches, but it might be formulated in different form. Some algorithms use the Lukas Kanade approach style for a region based detection or feature tracking algorithms.

## 4.1 Differential Methods

The Horn and Schunk's solution is the basis of modern differential approaches. The optical flow is formulated as a equation that must be minimized.

To avoid the aperture problem, the equation is formulated from two constraints. Originally, the brightness constraint and the smoothness constraint. In most algorithms from this category the brightness constraint is kept and the second constraint is modified.

### 4.1.1 The Brightness Constraint

The brightness constraint requires a Lambertian surface (ideally mate), is valid only under constant lightening, the main illumination source should be at such a distance that it will not change the brightness of the objects. Also secondary illumination should not exist, so no inter-object reflection can appear.

Also, a small motion is assumed from one frame to the next.

Although all its requirements which are almost never respected, at least not entirely, in real world, the brightness assumption has proven it's efficiency in may algorithms, being considerd a good start point.

The brightness constraint assumes that the moving pixels of an image do not change their intensity in an image in time.

$$\frac{\partial I}{\partial t} = 0 \tag{4.1}$$

From this, using multi-dimensional Euler-Lagrange equations (see appendix B for full demonstration), we obtain

$$\frac{\partial I}{\partial x}\frac{dx}{dt} + \frac{\partial I}{\partial y}\frac{dy}{dt} + \frac{\partial I}{\partial t} = 0 \tag{4.2}$$

The optical flow is given by the $x$ and $y$ derivative in time. Considering this, let

$$u = \frac{dx}{dt} \quad , \quad v = \frac{dy}{dt} \quad and \quad \nabla I = \begin{bmatrix} I_x I_y \end{bmatrix}^T \tag{4.3}$$

be the optical flow, $\boldsymbol{v}$ components. Denoting the temporal derivative with $I_t$, we obtain the gradient constraint.

$$\nabla I \cdot \boldsymbol{v} + I_t = 0 \tag{4.4}$$

### 4.1.2 The Aperture Problem

Im motion perception, each neuron captures only a small part of the visual field. This can be associated with seeing motion trough a small window. Because of the lack of context, uncertainty in speed, direction might appear. This uncertainty is called the aperture problem.

In the optical flow detection, it arises from the uncertainty of the motion. The problem usually appears in object with smooth texture.

As shown in figure 4.1.2, let the rectangle be the aperture, and the motion be given by the line moving from left to right. Let us consider the bolted point. the viewer can only say with certainty that the bolted dot will move from left to righr, having no information about the movement on vertical, not th speed of the dot. The line can move either pure horizontally, slightly up, or slightly down. It is only when the viewer takes in account the end points of the line, he can state that the line is moving slightly up.

By combining information from neighbour neurons, our brain solves this problem and can see the hole image as a unit.

In optical flow, the simplest solution is the brightness assumption, that neighbouring pixels have the same movement.

### 4.1.3 Lucas-Kanade

Lucas-Kanade method solves the flow as a feature tracking algorithm. This differential method takes in account only the neighbourhood, solving for each pixel with last square estimation. From the brightness assumption, for a neighbourhood $\Omega$, the flow vector

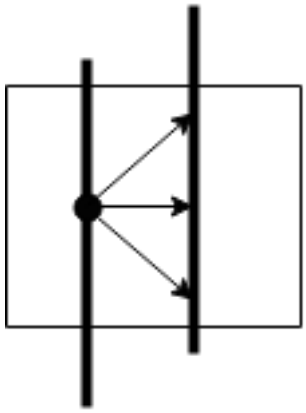

Figure 4.1: Example of aperture problem by the movement of a line.

$[u_i, v_i]$ must satisfy:

$$\begin{aligned} &I_x(x_1) + I_y(x_1) = -I_t \\ &I_x(x_2) + I_y(x_2) = -I_t \\ &\vdots \\ &I_x(x_n) + I_y(x_n) = -I_t \end{aligned} \tag{4.5}$$

where $x_1$, $x_1$, ..., $x_n$ are in the neighbourhood of pixel $i$.

Using the least square method, for each pixel in the image the enrgy function can be stated as:

$$E(x) = \sum_{x \in \Omega} W^2(x)[\nabla I(x) \cdot \boldsymbol{v} + I_t(x)]^2 \tag{4.6}$$

where $W$ is a window function, gaussian like, giving more weight to the canter pixel, rather than the neighbours.

To minimize $E(x)$, variational calculus is applied, and the derivatives of the equation 4.6 with respect to $u$ an $v$, respectively will be 0.

$$\begin{aligned} \frac{\partial E}{\partial u} &= \sum_{x \in \Omega} W^2(x)[I_x^2 u + I_x I_y v + I_x I_t] = 0 \\ \frac{\partial E}{\partial v} &= \sum_{x \in \Omega} W^2(x)[I_x I_y u + I_y^2 v + I_y I_t] = 0 \end{aligned} \tag{4.7}$$

If we demote

$$\begin{aligned} A &= \left[\nabla I(x_1),\ \ldots,\ \nabla I(x_n)\right]^T \\ W &= diag\left[W(x_1),\ \ldots,\ W(x_n)\right] \\ b &= \left[-I_t(x_1),\ \ldots,\ -I_t(x_n)\right] \end{aligned} \tag{4.8}$$

for each $n$ points $x_i \in \Omega$. Then, to minimize equation 4.6, we differentiate and the solution will be given by,

$$A^T W^2 A\boldsymbol{v} = A^T W^2 b \tag{4.9}$$

We multiplied the equation with $A^T$ on the left hand side, make the matrix nonsingular and be able to compute it's inverse. The Flow vector will be equal with:

$$\boldsymbol{v} = [A^T W^2 A]^{-1} A^T W^2 b \tag{4.10}$$

where,

$$A^T W^2 A = \begin{bmatrix} \sum W^2(x) I_x^2(x) & \sum W^2(x) I_x(x) I_y(x) \\ \sum W^2(x) I_x(x) I_y(x) & \sum W^2(x) I_y^2(x) \end{bmatrix} \tag{4.11}$$

and

$$A^T W^2 b = \begin{bmatrix} -\sum W^2(x) I_x(x) I_t(x) \\ -\sum W^2(x) I_y(x) I_t(x) \end{bmatrix} \tag{4.12}$$

by simple calculations we obtain

$$\begin{aligned} u &= \frac{-\sum W^2 I_y^2 \ \sum W^2 I_x I_t + \sum W^2 I_x I_y \sum W^2 I_y I_t}{\sum W^2 I_x^2 \sum W^2 I_y^2 - (\sum W^2 I_x I_y)^2} \\ u &= \frac{\sum W^2 I_x I_t \ \sum W^2 I_x I_y - \sum W^2 I_x^2 \sum W^2 I_y I_t}{\sum W^2 I_x^2 \sum W^2 I_y^2 - (\sum W^2 I_x I_y)^2} \end{aligned} \tag{4.13}$$

## 4.2 Coarse-to-fine

Differential methods cannot approximate large displacements. This is due to the small motion assumption. This problem can be solved with coarse-to-fine method.

Firstly, Gaussian Pyramids are built by successively blurring and unsampling into images of smaller and smaller resolutions. The unsampeling is done until the smallest resolution is about 30 pixels width or height. Then, the flow is iteratively computed between each level of the pyramid, from the corest to the finest.

### 4.2.1 Gaussian Pyramids

The pyramid of an image is a multi-scale representation of it. In order to obtain the pyramids, successive smoothing and subsampling techniques are applied. Each level is

computed from the previous, recursively.

**Building The pyramid** Let us consider an image $I$ of size $m \times n$. The first level of the pyramid, the base is the image, $I_0$ is the image $I$, itself. The next level, $I_1$, is computed from $I_0$. The image $I_0$ is convoluted with a Gauss kernel, than the filtered image is sampled. $I_1$ is obtained with the dimensions $(m_0/samplingfactor \times n_0/sampligfactor)$.

Similarly, the next levels are obtained, the $I_2$ is computed from $I_1$, $I_3$ from $I_2$, and so on.

Usually a sampling factor of 0.5 is considered. If we consider $L$ the current level of the image, than we can obtain the $I_{L+1}$ image as fallows

$$\begin{aligned} I_{L+1}(x,y) =& \frac{1}{4} I_L(2x,2y) + \\ & \frac{1}{8}(I_L(2x-1,2y) + I_L(2x+1,2y) + I_L(2x,2y-1) + I_L(2x,2y+1)) + \\ & \frac{1}{16}(I_L(2x-1,2y-1) + I_L(2x+1,2y+1) + I_L(2x-1,2y+1) + I_L(2x+1,2y-1) \end{aligned} \tag{4.14}$$

**Choosing the pyramid height** As stated in the chapter before 3.2, the height of the pyramids is usually chosen to have around 20-30 pixels on the height of the image, or width, respectively. The height is given by

$$pyramid_{height} = \frac{\log\left(\frac{p}{\min(ht,wt)}\right)}{\log(d)} \tag{4.15}$$

where p is the number of pixels on th top level on the minimum between width $wt$ or the height $ht$.

### 4.2.2 Warping the flow on the image

At new level of the pyramid, the second image is warped to the first. The new computed flow is considered. If we consider the current level $l$, and the computed flow $\boldsymbol{v}_l$. On the next level $l+1$, the second image is warped with the $\boldsymbol{v}_l$ velocities from the previous level. At a certain level $l+1$ the warped image is

$$I_w = interpolation(I_l, w_l + dw) \tag{4.16}$$

where $w_l$ is the flow computed until the level $l$ and $dw$ the residual flow computed at level $l$. Some algorithms, like proximal point approximation, do not compute the residual flow, but update directly the new flow.

## 4.3 $L^1$ approaches

When the penalty function, $E(x)$ is of type $L^2$, like $\sigma(x)^2$, the minimization problem is simple. One can reach the solution trough variational calculus, by differentiating the whole energy function with respect to $u$ and $v$, equalising with 0, and solving the system. For a faster convergence, some of the current algorithms use a $L^1$ penalty function, like modulus, others use a combination of both $L^2$ and $L^1$ penalty functions, for example, one for the data energy and one for the smoothness energy.

## 4.4 other

### 4.4.1 Gauss-Seidel

For this kind of formulations, the minimization can not be done any more trough differential techniques, and other approaches are used.

# Chapter 5

# Detailed Design and Implementation

Together with the previous chapter takes about 60% of the paper.

The purpose of this chapter is to document the developed application such a way that it can be maintained and developed later. A reader should be able (from what you have written here) to identify the main functions of the application.

The chapter should contain (but not limited to):

- a general application sketch/scheme,
- a description of every component implemented, at module level,
- class diagrams, important classes and methods from key classes.
- about color code.
- about filters
- about downsampling

# Chapter 6

# Testing and Validation

About 5% of the paper

## 6.1 Title

## 6.2 Other title

# Chapter 7

# User's manual

In the installation description section your should detail the hardware and software resources needed for installing and running the application, and a step by step description of how your application can be deployed/installed. An administrator should be able to perform the installation/deployment based on your instructions.

In the user manual section you describe how to use the application from the point of view of a user with no inside technical information; this should be done with screen shots and a stepwize explanation of the interaction. Based on user's manual, a person should be able to use your product.

## 7.1 Title

## 7.2 Other title

# Chapter 8

# Conclusions

About. 5% of the whole
Here your write:

- a summary of your contributions/achievements,
- a critical analysis of the achieved results,
- a description of the possibilities of improving/further development.

## 8.1 Title

## 8.2 Other title

# Bibliography


[1] B. K. Horn and B. Schunck, "Determining optical flow," in *1981 Technical Symposium East*. International Society for Optics and Photonics, 1981, pp. 319–331.

[2] D. Sun, S. Roth, and M. J. Black, "Secrets of optical flow estimation and their principles," in *Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on*. IEEE, 2010, pp. 2432–2439.

[3] D. Sun, S. Roth, and M. Black, "A quantitative analysis of current practices in optical flow estimation and the principles behind them," *International Journal of Computer Vision*, vol. 106, no. 2, pp. 115–137, 2014.

[4] B. D. Lucas, T. Kanade *et al.*, "An iterative image registration technique with an application to stereo vision." in *IJCAI*, vol. 81, 1981, pp. 674–679.

[5] A. Mitiche and J. K. Aggarwal, *Computer Vision Analysis of Image Motion by Variational Methods*. Springer, 2014.

[6] A. Wedel and D. Cremers, *Stereo scene flow for 3D motion analysis*. Springer Science & Business Media, 2011.

[7] J. L. Barron, D. J. Fleet, and S. S. Beauchemin, "Performance of optical flow techniques," *International journal of computer vision*, vol. 12, no. 1, pp. 43–77, 1994.

[8] D. Fleet and Y. Weiss, "Optical flow estimation," in *Handbook of Mathematical Models in Computer Vision*. Springer, 2006, pp. 237–257.

[9] M. Drulea and S. Nedevschi, "Motion estimation using the correlation transform," *Image Processing, IEEE Transactions on*, vol. 22, no. 8, pp. 3260–3270, 2013.

[10] C. Tomasi and R. Manduchi, "Bilateral filtering for gray and color images," in *Computer Vision, 1998. Sixth International Conference on*. IEEE, 1998, pp. 839–846.

# Appendix A

# Relevant code

```
 /** Maps are easy to use in Scala. */
object Maps {
  val colors = Map("red" -> 0xFF0000,
                   "turquoise" -> 0x00FFFF,
                   "black" -> 0x000000,
                   "orange" -> 0xFF8040,
                   "brown" -> 0x804000)
  def main(args: Array[String]) {
    for (name <- args) println(
      colors.get(name) match {
        case Some(code) =>
          name + " has code: " + code
        case None =>
          "Unknown color: " + name
      }
    )
  }
}
```

# Appendix B

# Other relevant information (demonstrations, etc.)

# Appendix C

# Published papers