

UNIVERSITÄT DES SAARLANDES

BACHELOR THESIS

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# Automated Data Selection for Nonlinear Diffusion Inpainting in Image Compression

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*Author:*  
Daniel Gusenburger

*Supervisor:*  
Prof. Joachim Weickert

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## Declaration of Authorship

I, Daniel Gusenburger, declare that this thesis titled, “Automated Data Selection for Nonlinear Diffusion Inpainting in Image Compression” and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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## *Abstract*

Faculty of Mathematics and Computer Science  
Department of Computer Science

Bachelor of Science

### **Automated Data Selection for Nonlinear Diffusion Inpainting in Image Compression**

by Daniel Gusenburger

A novel image compression technique developed over the last few years uses non-linear diffusion inpainting to reconstruct an image from a select set of datapoints. Until now, these points had to be selected manually in order to achieve acceptable results.

In this thesis, I will present an automated approach using a nearly parameter-less and fairly accurate corner and junction detection algorithm to find points of interest. Afterwards, I will compare it to the manual approach and we will see whether it results in a better reconstruction.



## *Acknowledgements*





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**AMSS** Affine **M**orphological **S**cale **S**pace





*dedicated to my cat*



## Chapter 1

# Selection of interest points

### 1.1 Available Methods for Corner detection

To find the points of interest we want to keep, I tried different corner detectors:

- Tomasi-Kanade
- Rohr
- Foerstner-Harris

All of the above methods have in common that they make use of the *structure tensor* defined as

$$J_\rho(\nabla u) := K_\rho(\nabla u \nabla u^T) = \begin{pmatrix} K_\rho * (u_x^2) & K_\rho * (u_x u_y) \\ K_\rho * (u_x u_y) & K_\rho * (u_y^2) \end{pmatrix}$$

where  $K_\rho$  is a gaussian convolution kernel with standard deviation  $\rho$  and  $u$  is a gaussian smoothed version of the original image  $f$ , i.e.

$$u = K_\sigma * f$$

While being fairly accurate (insert examples here), the above methods don't really succeed in finding the most relevant corners.

That's the reason I chose an algorithm proposed by Luis Alvarez (reference here) that is based on the so called Affine Morphological Scale Space (or short **AMSS**). He proposes a multiscale algorithm that tracks corners across the evolution of an image in this scale space.

The special property of this scale space is, that the shape of a corner evolves in such a way that the the actual tip of the corner moves linearly along the corner bisector. Using this property, one can extract the exact location of a corner.

#### 1.1.1 AMSS corner detection

##### The affine morphological scale space

The aforementioned AMSS is produced by the partial differential equation

$$u_t = t^{\frac{1}{3}} (u_{xx} u_y^2 + u_{yy} u_x^2 - 2u_x u_y u_{xy})^{\frac{1}{3}}$$