VYSOKÉ UČENÍ TECHNICKÉ V BRNĚ
BRNO UNIVERSITY OF TECHNOLOGY

FAKULTA INFORMAČNÍCH TECHNOLOGIÍ
ÚSTAV INTELIGENTNÍCH SYSTÉMŮ

FACULTY OF INFORMATION TECHNOLOGY
DEPARTMENT OF INTELLIGENT SYSTEMS

# SUPERRESOLUTION

DIPLOMOVÁ PRÁCE
MASTER'S THESIS

AUTOR PRÁCE Bc. LUKÁŠ MEZERA
AUTHOR

BRNO 2010

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# ZLEPŠENÍ ROZLIŠENÍ PRO VÍCEČETNÉ SNÍMKY STEJNÉ SCÉNY

SUPERRESOLUTION

DIPLOMOVÁ PRÁCE
MASTER'S THESIS

AUTOR PRÁCE
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VEDOUCÍ PRÁCE
SUPERVISOR

Ing. FILIP ORSÁG, Ph.D.

BRNO 2010

**Brno University of Technology - Faculty of Information Technology**

Department of Intelligent Systems Academic year 2009/2010

# Master Thesis Specification

For: **Mezera Lukáš, Bc.**
Branch of study: Intelligent Systems
Title: **Superresolution**
Category: Image Processing

Instructions for project work:

1. Study the literature referring to a super-resolution of the images of the scene when multiple frames of the given scene are available.
2. Propose your own method of the super-resolution of the images of the scene when multiple frames of the same scene exist.
3. Implement the proposed super-resolution method.
4. Test its functionality, conduct the experiments and evaluate the results.

Basic references:

- Sonka, M., Hlavac, V., Boyle, R.: *Image Processing, Analysis, and Machine Vision.* Cengage-Engineering, 2007.
- Bradski, G., Kaehler, A.: *Learning OpenCV: Computer Vision with the OpenCV Library.* 1st edn. O'Reilly Media, Inc., 2008.
- Gonzalez, R. C. , Woods, R. E.: *Digital Image Processing.* 2nd Edition, Prentice Hall, 2002.

The Term Project discussion items:

- Items 1 and 2 of the task.

Detailed formal specifications can be found at http://www.fit.vutbr.cz/info/szz/

The Master Thesis must define its purpose, describe a current state of the art, introduce the theoretical and technical background relevant to the problems solved, and specify what parts have been used from earlier projects or have been taken over from other sources.

Each student will hand-in printed as well as electronic versions of the technical report, an electronic version of the complete program documentation, program source files, and a functional hardware prototype sample if desired. The information in electronic form will be stored on a standard non-rewritable medium (CD-R, DVD-R, etc.) in formats common at the FIT. In order to allow regular handling, the medium will be securely attached to the printed report.

Supervisor: **Orság Filip, Ing., Ph.D.**, DITS FIT BUT
Beginning of work: September 21, 2009
Date of delivery: May 26, 2010

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# Abstract

The goal of this thesis is to propose the super-resolution method for the image of the scene when multiple frames of the given scene are available. The theoretical part of this thesis brings the report about current multi-frame super-resolution methods. These methods are compared according to the optimal criteria. The own super-resolution method is proposed in the practical part of this thesis. However this method isn't rotation invariant and for this reason is proposed the improved super-resolution method. There are also suggested improvements of the improved super-resolution method in this thesis.



# Abstrakt

Úkolem této diplomové práce je navrhnout vlastní metodu pro zvýšení rozlišení v obraze scény, pokud je k dispozici více snímků dané scény. V teoretické části diplomové práce jsou jako nejlepší metody pro zvýšení rozlišení v obraze vybrány ty, které jsou založeny na principech zpracování signálu. Dále jsou popsány základní požadavky metod pro zvýšení rozlišení v obraze při přítomnosti více snímků stejné scény a jejich typická struktura. Následuje stručný přehled těchto metod a jejich vzájemné porovnání podle optimálních kritérií. Praktická část diplomové práce se zabývá samotným návrhem metody pro zvýšení rozlišení v obraze, pokud je k dispozici více snímků této scény. První navržená metoda je naimplementována a otestována. Při testování této metody je však zjištěna její špatná funkčnost pro snímky scény s nízkým rozlišením, které vznikly vzájemnou rotací. Z toho důvodu je navržena vylepšená metoda pro zvýšení rozlišení v obraze. Tato metoda využívá při svém výpočtu robustních technik. Díky tomu je již vylepšená metoda nezávislá na rotaci mezi snímky scény s nízkým rozlišením. I tato metoda je řádně otestována a její výsledky jsou porovnány s výsledky první navržené metody pro zvýšení rozlišení v obraze. V porovnání výpočetních časů je lepší první navrhovaná metoda, avšak její výsledky pro obrazy obsahující rotace nejsou kvalitní. Oproti tomu pro obrazy, které vznikly pouze posunem při snímání scény, jsou tyto výsledky velice dobré. Vylepšená metoda je tedy využitelná zejména pro obrazy obsahující rotace. V závěru této práce je ještě navrženo jedno vylepšení, které by mohlo zlepšit výsledky druhé navrhnuté metody pro zvýšení rozlišení v obraze scény.



# Keywords

superresolution, super-resolution, image processing, computer vision, OpenCV, image reconstruction, image interpolation, observation models, Lanczos resampling, Lucas-Kanade algorithm, homography, PSF, inverse filtration, SURF, RANSAC, OpenSURF

# Klíčová slova

zvýšení rozlišení obrazu, zpracování obrazu, počítačové vidění, OpenCV, rekonstrukce obrazu, interpolace obrazu, modely pozorování scény, Lanczos filtr, Lucas-Kanade algoritmus, homografie, PSF, inverzní filtrace, SURF, RANSAC, OpenSURF

# Citation

Lukáš Mezera: Superresolution, Master's Thesis, Brno, Faculty of Information Technology at Brno University of Technology, 2010

# Superresolution

## Prohlášení

Prohlašuji, že jsem tuto diplomovou práci vypracoval samostatně pod vedením pana Ing. Filipa Orsága, Ph.D., a uvedl jsem všechny literární prameny a publikace, ze kterých jsem čerpal.

........................
Lukáš Mezera
May 26, 2010

## Poděkování

Chtěl bych poděkovat panu Ondřeji Kotabovi ze společnosti Honeywell za podnětné návrhy týkajíci se vypracování práce a RNDr. Barbarě Zitové, Ph.D., z Ústavu teorie informace a automatizace Akademie věd České republiky za poskytnutí materiálů vztahujících se k tématu této práce.

# Contents

# Chapter 1

# Introduction

Super-resolution techniques as their name implies are designed in order to improve the resolution of the imaging system. The need of these techniques is apparent from the limiting property of a devices for capturing the image information. This feature is the ability to capture only a finite amount of information about the scene.

One example is the camera with poor quality optical system. If it is necessary to capture an object in the scene which is so far away that it is unable to focus it using the camera's optical system it is not possible to obtain a photo of the object in the scene with sufficient detail. How to obtain the required details in the picture if it is not able to capture the details of the scene using devices for capturing the scene? The answer is simple. It is possible to use the super-resolution techniques to improve the image resolution.

Super-resolution techniques can be divided into two main groups. The first group contains the methods that use only a single input image. This image is subjected to various analytical transformations. Overview of these methods can a reader find in the literature. For example the papers [9] and [6] deal with this issue. However, these methods are no longer mentioned in this work.

Representatives from the other group are techniques for working with large amount of input images. Their task is to obtain independent information from a variety of input images. The image with high resolution is created from these information.

Images of the scene with high resolution are such images which have large pixel density. Therefore these images are able to provide information including details in the captured scene. Creating an image with high resolution is possible if it is possible to capture the scene several times in a row or if it is available multiple sensors focusing on one scene. Then some of the methods for creating images with high resolution are applied on the sequence of images with low resolution which are obtained from the sensors.

High resolution images are useful for example in medical applications where high resolution of the image may help doctors to diagnose correctly. It is possible to obtain many of images with low resolution in magnetic resonance imaging or computed tomography. It directly offers using super-resolution methods for this type of data. Methods for super-resolution also find use in aviation or in the study of Earth from the space. Consider for example satellite imagery. Thanks to high resolution of the images it is easier to determine which object is on the picture and it is easier to work with the object. The work with the object can be realized either by using computer vision or by work of the man. In aviation the super-resolution may be used as a tool for collision detection of the aircrafts etc.

In chapter 2 are described possible approaches to increase the resolution of the image of the scene (super-resolution). As the best methods for increasing the resolution of the images are selected methods based on signal processing. Further in this chapter are compared the concepts like the image reconstruction, interpolation and super-resolution of images.

The goal of the chapter 3 is to familiarize a reader with the initial requirements of super-resolution methods, with observation models and with the typical structure of methods for super-resolution. Further in this chapter there are explained some important concepts for understanding the text that follows.

Chapter 4 contains the most common division of the methods into groups that can a reader find in literature. Each group of methods is briefly described and there are also outlined the advantages and disadvantages of different groups of methods for super-resolution of the images. In chapter 5 are these methods compared according to the optimal criteria.

The aim of this thesis is to propose the own super-resolution method. The design of super-resolution method and the implementation details are described in chapter 6.

After implementation it is necessary to make a number of tests in order to find any errors. Description of optimal test data and the testing itself can a reader find in chapter 7.

The testing of proposed super-resolution method revealed unsatisfactory results of this method for images that contain rotation. For this reason is proposed improved super-resolution method. In chapter 8 is described the design of improved super-resolution method.

The proposed super-resolution method is designed in order to deliver better results for input images with low resolution that contain rotation. Testing of improved super-resolution method for images that contain translation or rotation is described in chapter 9. In this chapter are compared results of proposed super-resolution method and improved super-resolution method.

In the chapter 10 of this thesis are summarized the results of both methods. There are also described other possible ways how to improve super-resolution methods described in this thesis.

Master's thesis is built on theoretical knowledge gained at work on the Term Project. These theoretical knowledge are also included in this thesis. These are chapters 2, 3, 4 and 5. Second part of the Term Project is dealing with design of super-resolution method. However this part of the Term Project is redesigned in the Master's Thesis.

# Chapter 2

# The motivation for using super-resolution methods

What are the general options of obtaining images with high resolution? What benefits do methods based on signal processing bring? What is the difference between image reconstruction and super-resolution of image? What is the difference between interpolation and super-resolution of image?

These are the questions which could a reader interested in before he started to read this thesis. Therefore, it would be good to answer these questions right from the start. The first question corresponds to section 2.1. There are described the basic techniques which make possible the super-resolution of image of the scene.

The second question corresponds to section 2.2. In this section can a reader find a number of reasons why the best option for super-resolution of images are just the methods based on signal processing.

The differences between the image reconstruction, interpolation and super-resolution of the image finds out a reader in sections 2.3 and 2.4.

This chapter is based on the knowledge obtained from the reference literature [12].

## 2.1 Possible approaches to increase the resolution in the image

Charge-Coupled Device (CCD) and Complementary Metal-Oxide-Semiconductor (CMOS) are widely used since 80th years of 20th century for capturing of digital images. These sensors are used not only in cameras or camcorders but also in astronomical telescopes. However the resolution of images captured by using these sensors will not be sufficient in the future.

There are three possible ways to improve the spatial resolution of these sensors:

1. **Reducing the size of a pixels in the sensor** - in other words the increasing of the number of pixels per unit area. This is probably the most direct solution of this problem. But this solution would require as changes in technological processes of production so the increasing of the required incident light on the sensor. Increasing of the incident light is important in order to avoid the creation of the noise on the sensor. Moreover, today's size of a pixel on the chip already reached such dimensions that further reduction is practically impossible.

2. **Increasing the size of the chip** has resulted in an increase of electrical capacity of the chip. Higher capacity leads to difficulties in speeding up the transmission of charges on the chip and therefore this method is considered as inefficient.

3. **Using some of the signal processing methods** is currently the best solution. These are exactly the methods which are serving to super-resolution of image. Their biggest advantage is the possibility to work with current sensors and these methods are deployed on output data from CCD or CMOS sensors. Methods of super-resolution are currently being investigated by many researchers.

## 2.2 Advantages of using methods based on signal processing

If a reader of this thesis isn't yet convinced of the advantages of signal processing methods for super-resolution compared to methods which dealing with the hardware adjustment of the sensors they are presented other possible factors which should lead a reader to the methods based on the signal processing.

If it is used of one of the commonly used sensors for capturing the scene (CCD, CMOS) the obtained digital image will always have plenty of errors. An ordinary user can't influence a creation of these errors. The process of acquisition of digital image is shown in Fig. 2.1.

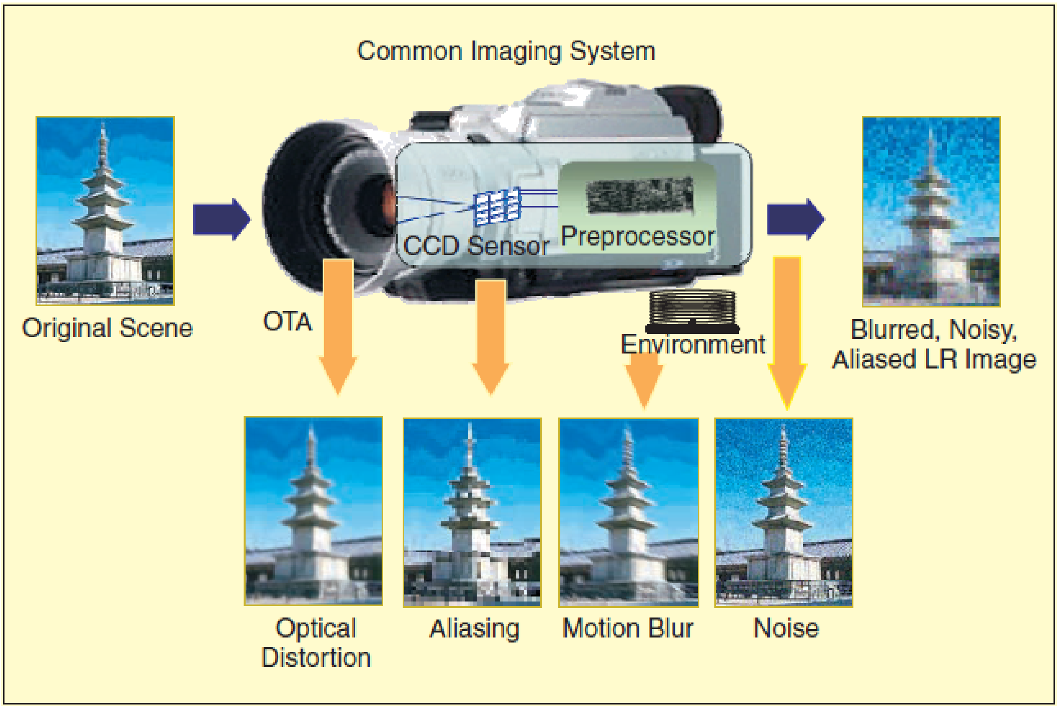



Figure 2.1: Errors generated during the process of obtaining of digital image data. Taken from [12].

Figure 2.1 shows the process of capturing the digital image data. During this process can arise a large number of errors which affecting resultant image. There is a natural loss of spatial resolution caused by the optical distortions in the common imaging system. In the sensor arises an aliasing. This is a phenomenon which may occur in sampling (the reduction of a continuous signal to a discrete signal). Also the motion blur may arise in the normal environment easily. If it moves the sensor or the scene the resultant image will be affected by the motion blur. This is due to limited shutter speed of the common imaging system. The transmission of the image can cause the occurrence of noise in the resultant image. When the signal passes through the sensor the noise is also generated.

The resultant image obtained by the common imaging system is thus affected by aliasing, motion blur and noise. But there are various techniques for image reconstruction which allows us to remove these negative effects of the common imaging systems.

So image reconstruction allows us to remove aliasing, motion blur and noise. But the resulting image has got one flaw still. This is the natural loss of spatial resolution caused by the optical distortions. This flaw can be removed using interpolation.

There is touched upon two unknown concepts in the previous text . These are the image reconstruction and the interpolation. In the next section is explained what these concepts mean and their relationship to super-resolution of image.

## 2.3 Image reconstruction vs. super-resolution

There is stated in the previous section that methods for image reconstruction can be used to remove errors caused by common imaging system. These errors are the aliasing, the motion blur and the noise generated in the sensor or in the transmission of the image. A reader might speculate why the super-resolution methods are therefore actually helpful. The answer is simple. It is possible to obtain essentially intact image of the original scene by using the methods of image reconstruction. However the methods for image reconstruction can't increase the resolution of the image. Therefore if there is interested only some detail in the image the methods for image reconstruction won't be able to satisfy us.

However it is important that the principles of the image reconstruction can be useful in the super-resolution methods. Either in the image preprocessing stage or in the stage of correction result of super-resolution methods.

## 2.4 Interpolation vs. super-resolution

Interpolation is used to enlarge a single input image. Because it isn't possible to obtain image's high-frequency information which are lost during the process of sampling for further improvements of the interpolation's properties it must be used more pictures of the same scene. The follow-up synthesis of information allows us to reconstruct scene with high resolution. For this reason it can't be talk about interpolation methods such as methods for super-resolution of images.

# Chapter 3

# Methods of super-resolution - requirements, structure and concepts

All super-resolution methods based on the principles of signal processing have got a common requirement for the sequence of input images. The initial requirement is described and justified in section 3.1.

Another requirement for super-resolution methods which use the signal processing methods is the observation model of the scene. It defines the relationship between the original image of the scene with high reolution and the surveyed images of this scene in low resolution. There are several observation models of the scene for static images. These models are described in section 3.2.

Methods for super-resolution of the image also have their typical structure. This structure is described in section 3.3.

The signal processing as a separate branch of science contains a large number of concepts. Less familiar concepts that are somehow linked to the methods for super-resolution will be explained in the last section of this chapter 3.4.

This chapter is based on the knowledge obtained from the reference literature [12] [10].

## 3.1 Basic requirements of methods for super-resolution

The fundamental assumption for spatial super-resolution is that there is available sufficient number of pictures in low resolution. These images represent the same scene from different viewpoints. The most important feature of these images is that they are subpixel shifted (the shift between pixels is not expressible by integer). If the images are mutually shifted by the pixel size then each image contains the same information about the objects in the scene. It follows that there is no new information which can be use to reconstruction of the image with high resolution from these images.

In order to obtain different perspectives on the same scene are used two approaches:

1. one sensor captures the scene at different time,

2. or multiple sensors capture the scene at the same time.

The satellite orbiting the Earth may be the example of the first of above mentioned approaches. The satellite captures images of the Earth surface. His position with respect to Earth will change by a certain length. And this change of his position takes a certain time. Images with low resolution captured by this method thus contain various data about the Earth's surface.

If it is known the motion in the scene with subpixel accuracy and if are combined these images with low resolution there is the possibility to reconstruct images with high resolution as it is shown in Fig. 3.1.

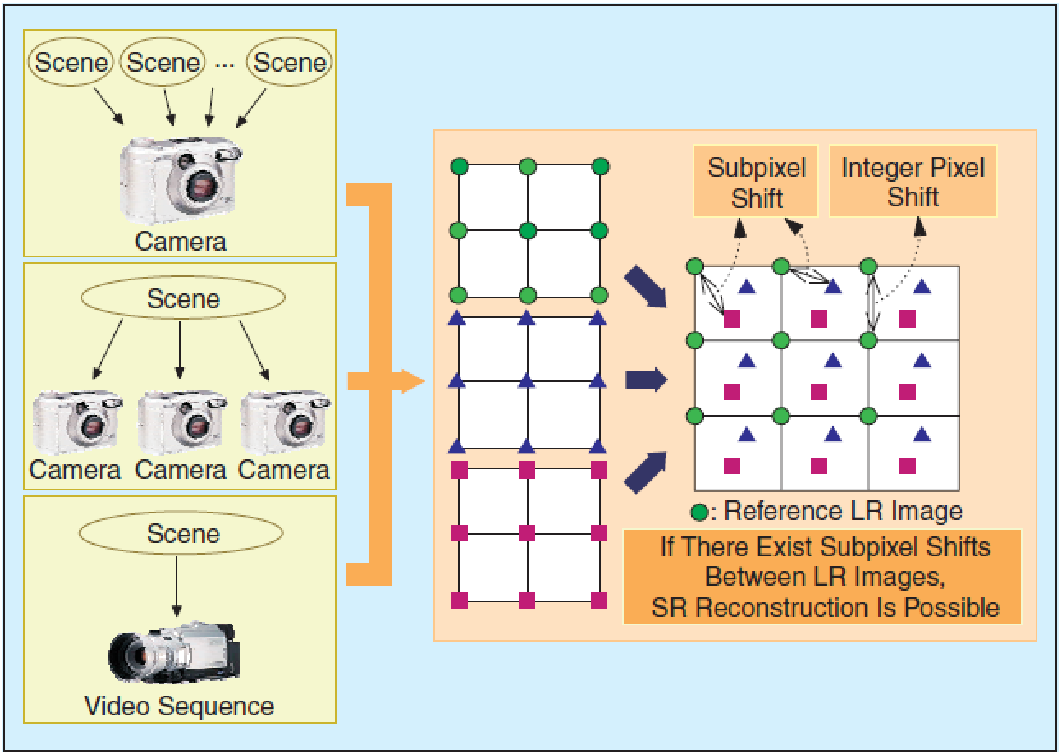



Figure 3.1: Possible approaches for obtaining images with low resolution and processing these images. Taken from [12].

## 3.2 Observation models for static images

As it is mentioned above the scene observation model defines the relationship between the original image of the scene and the surveyed images of this scene with low resolution. Observation model for static images is described by the equation:

$$y_k = DB_kM_kx + n_k \tag{3.1}$$

- $y_k$ denotes the individual images with low resolution ($1 \leq k \leq m$, where $m$ is a number of images with low resolution). The assumption is that each image with low resolution is corrupted by additive noise.

- $D$ is a subsampling matrix. This matrix is involved in the creation of an alias in the image. Super-resolution methods expect that the alias is always present.

- $B_k$ represents a blur matrix. Image blur can be caused by optical system, by relative motion between scene and the sensor or by point spread function (3.4.3) of the sensor.
- $M_k$ is a warp matrix.
- $x$ is the image with high resolution of the original scene which is constant during whole time of the capturing of images with low resolution. Exceptions permitted by the model are motion and degradation of the image.
- $n_k$ represents a lexicographically ordered noise vector.

The warp matrix $M_k$ thus represents a movement that occurs during acquisition of images with low resolution. Generally is represented the local or global translation, rotation, etc. in this matrix. Since this information is unknown generally we must estimate the motion of the scene for every captured image with low resolution in relation to a reference image with low resolution. This estimate is essentially a pixel pitch.

Slightly different model for images with low resolution can be derived by discretizing a continuous warped, blurred scene. This model can be expressed as follows:

$$y_k = W_k x + n_k. \tag{3.2}$$

- $k = 1, ..., m$, where $m$ is a number of images with low resolution.
- matrix $W_k$ represents through blurring, motion and subsampling the percentage of pixels of an image with high resolution in pixels of the image with low resolution.

Simply put, the goal is to estimate image with high resolution $x$ from a sequence of images with low resolution $y_k$.

## 3.3 Typical structure of super-resolution methods

Most of the methods for super-resolution described in the literature consist of three major steps. They are:

1. registration,
2. interpolation,
3. and restoration.

These steps are performed either separately or simultaneously depending on used method. A graphic representation of each step can be found in Fig. 3.2.

Image registration is essentially an estimate of motion between the images with low resolution. This estimate is calculated with subpixel accuracy. Accuracy of motion estimation between images with low resolution is critical for a super-resolution method.

Since the shifts between images with low resolution can be almost arbitrary the reconstructed image with high resolution is not always identical with uniformly distributed high resolutin grid of the original image. It is therefore necessary using the nonuniform interpolation to obtain uniformly distributed image with high resolution from the nonuniformly distributed images with low resolution.

Image restoration methods are applied to the resampled image with high resolution in order to remove blur and noise.

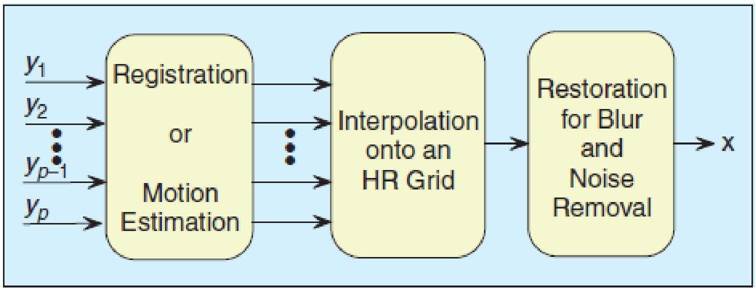



Figure 3.2: Typical structure of super-resolution methods. Taken from [12].

## 3.4 Important concepts

The goal of this section is to explain less familiar concepts in the field of signal processing related to super-resolution.

### 3.4.1 Well-posed Problem

French mathematician Jacques Hadamard defined **well-posed problem** [27] for mathematical problems. The **well-posed problem** means that mathematical models of physical phenomena should have the properties that:

1. a solution exists,
2. the solution is unique,
3. the solution depends continuously on the data, in some reasonable topology.

Problems that are not well-posed in the sense of Hadamard are termed **ill-posed**. Such problems often have to be discretized in order to obtain numerical solutions. Concerning the functional analysis, these problems suffer due to instability of the solutions.

Even if a problem is well-posed, it may still be **ill-conditioned**. This means that a small error in the initial data can cause much larger errors in the resulting data.

### 3.4.2 Bandlimited signal

A **bandlimited signal** [15] is a deterministic or stochastic signal whose Fourier transform or power spectral density is zero above a certain finite frequency.

An important feature of **bandlimited signal** is that the signal can be completely reconstructed from its samples.

### 3.4.3 Point Spread Function

The **point spread function (PSF)** [21] describes the response of an imaging system to a point source or point object. A more general term for the PSF is a system's impulse response. The degree of spreading (blurring) of the point object is a measure for the quality of an imaging system.

# Chapter 4

# Super-resolution methods

Most of super-resolution methods are based on image reconstruction. This means that the input images don't have any new information which are not included in input images with low resolution. There are also some methods which are benefiting from learning to gain new information about the image with low resolution. These methods are based on generative models.

This chapter briefly describes super-resolution methods which are based especially on image reconstruction. The mention of super-resolution methods based on learning is in section 4.5.

The first representative of the super-resolution methods working on the principle of image reconstruction are methods which are based on nonuniform interpolation. These methods are described in section 4.1. Main advantage of these methods is that they are most intuitive and they are the best in the illustration of typical structure of super-resolution methods.

The second representative of super-resolution methods based on image reconstruction are methods working in frequency domain 4.2. These methods use to calculate the image with high resolution the aliasing which is present in each image with low resolution.

More from this group of methods for super-resolution are methods based on regularization 4.3. There are described two approaches to obtain the image with high resolution in this section. They are regularized deterministic approach 4.3.1 and regularized stochastic approach 4.3.2.

The fourth group consists of methods based on the projection onto convex sets 4.4. These methods concatenate the step of interpolation with the step of restoration.

Another group of methods for super-resolution can be introduced through their typical applications. This application is super-resolution for human faces. These methods are based on optical flow and they benefit from the generalization of super-resolution methods to support the imaging of objects. These objects can be only non-planar, non-rigid, or objects which are subject to self-occlusion when rotated. These methods work well for small quantities of noise present in images with low resolution. However these methods are very sensitive to the accuracy of optical flow.

Other interesting techniques leading to super-resolution are described in the last one section of this chapter 4.6 .

This chapter aims to give readers an overview of existing methods leading to super-resolution. Therefore it is not treated in unnecessary details in this chapter. More detailed information may a reader find in reference literature [12] [10].

## 4.1 Super-resolution methods based on nonuniform interpolation

These methods are the most intuitive methods from all methods related to super-resolution. Typical structure of super-resolution methods is well-evident in these methods. There are gradually carried out all main steps described in section 3.3:

1. Image registration is performed in order to determine subpixel shift between images with low resolution.

2. Nonuniform interpolation is used for increase the image resolution.

3. Image reconstruction is performed in order to eliminate noise and blur in the resulting image.

Principle of the methods is shown in Fig. 4.1. After mapping a low resolution images onto a high resolution grid is created uneven distribution of samples in the grid of image with high resolution. Nonuniform interpolation has the task to modify this distribution of samples to the uniformly distributed grid of the original image. This is done either by direct or iterative way. Once is created a image with high resolution it is necessary to remove blurring of the image due to blur and the noise. One solution is to use any deconvolution which considers the presence of noise.

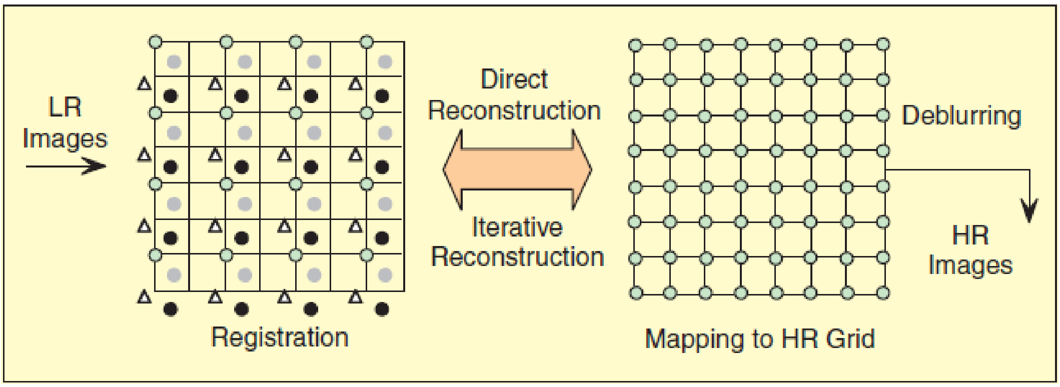



Figure 4.1: Principle of super-resolution methods based on image registration and interpolation. Taken from [12].

The advantage of methods based on nonuniform interpolation is the low computational complexity allowing the deployment in real-time applications.

The first disadvantage of these methods is that they require very accurate registration between images with low resolution. Another limitation is the degradation of the input images with low resolution which means that all images with low resolution must be equally affected by noise and blur (i.e. that the characteristics of blur and noise are identical for all images with low resolution). The step of image restoration isn't also optimal since it ignores the errors caused by interpolation.

## 4.2 Super-resolution methods working in the frequency domain

Super-resolution methods working in the frequency domain use aliasing to create an image with high resolution. Aliasing is present in all images with low resolution. Despite the absence of noise or blur in a sequence of images with low resolution is thus possible to reconstruct the image with high resolution. The calculation of image reconstruction by these methods runs recursively.

These methods are based on following three principles:

1. the shift property of the Fourier transform,
2. the aliasing relationship between the continuous Fourier transform (CFT) of an original image with high resolution and the discrete Fourier transform (DFT) of image with low resolution,
3. and the assumption that an original image with high resolution is bandlimited (3.4.2).

From the above mentioned three principles may be aliasing of the images with low resolution distributed into image free from aliasing with high resolution. The principle is outlined in Fig. 4.2.

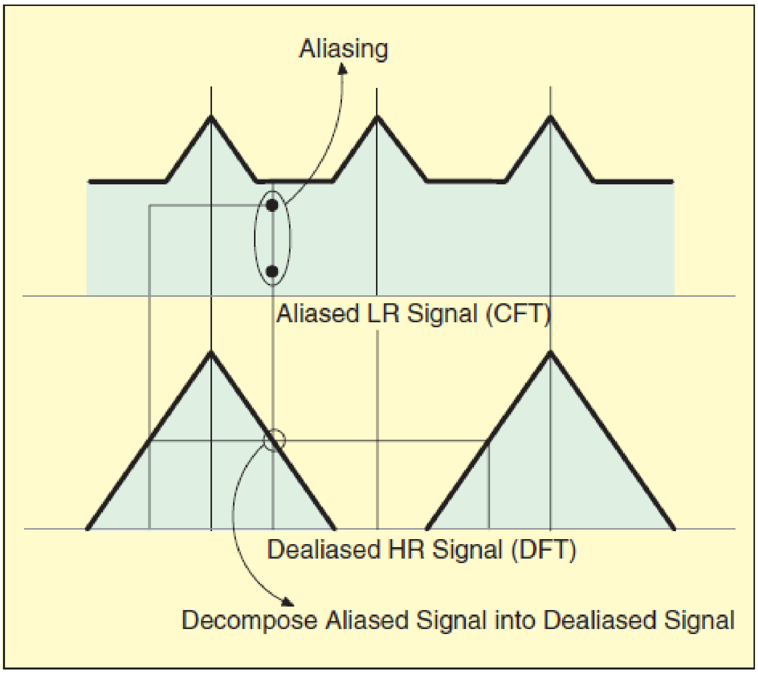



Figure 4.2: Aliasing relationship between image with low resolution and image with high resolution. Taken from [12].

The main advantage of this approach is that the relationship between the images with low resolution and the image with high resolution is clearly shown in the frequency domain. The methods are suitable for parallelization thus it offers deployment in hardware.

The biggest drawback is that the method is limited to the global translational motion.

## 4.3 Super-resolution methods based on regularization

Generally speaking the super-resolution of the image is an ill-posed problem (3.4.1) because on the input of methods is available insufficient amount of images with low resolution. The ill-conditioned problem of the blur operators is also evident. Procedures for stabilizing the ill-posed problem are called regularization. This section deals with deterministic and with stochastic approach to increase the image resolution.

### 4.3.1 Deterministic approach

The observation model 3.2 can be completely specified when are available the estimates of the registration parameters. The deterministic regularized super-resolution approach solves the inverse problem in 3.2 by using the prior information about the solution which can be used to make the problem well-posed (3.4.1). The whole process leads to the iterative calculation of the image with high resolution.

One example is constrained least square method to calculate the required $x$ (image with high resolution) such that:

$$\left[\sum_{k=1}^{m} ||y_k - W_k x||^2 + \alpha ||Cx||^2\right] \tag{4.1}$$

minimizes the functional cost.

A priori knowledge concerning a desirable solution is represented by a smoothness constraint suggesting that most images are naturally smooth with limited high-frequency activity and therefore it is appropriate to minimize the amount of high-pass energy in the restored image.

Parameter $\alpha$ which is known as the regularization parameter affects the trade-off between accuracy ($\sum_{k=1}^{m} ||y_k - W_k x||^2$) and smoothness ($||Cx||^2$) in the resulting image with high resolution. Higher values of parameter $alpha$ in general lead to smoother solutions. This is useful when is available a small number of input images with low resolution or when the accuracy of recording the images is small. This may be due to errors which were created during image registration process or could be caused by noise. On the other hand if it is available a large number of input images with low resolution and the content of noise in them is small the low value of the parameter $\alpha$ leads to good results of this method.

### 4.3.2 Stochastic approach

Stochastic approach to super-resolution methods based on regularization provides a flexible and convenient way to modelling the prior known knowledge regarding to the solutions. In this approach are mainly used Bayesian methods of estimation. But it is necessary to determine the probability density function of the image with low resolution.

Robustness and flexibility in modelling noise characteristics and the prior knowledge about the solutions are the main advantages of the stochastic approach.

## 4.4 Super-resolution methods based on the projection onto convex sets

These methods describe an iterative approach to the inclusion of prior knowledge about the solution into the reconstruction process (the process of super-resolution). These methods concatenate the step of interpolation with the step of restoration in the methods for super-resolution.

Incorporating a priori knowledge into the solution can be interpreted as restricting the solution to be a member of a closed convex set $C_i$. The set $C_i$ is defined as a set of vectors which satisfy a particular property. If the constraint sets have a nonempty intersection then a solution that belongs to the intersection set $C_s$ which is also a convex set can be found by alternating projections onto these convex sets. The $C_s$ convex set is created as the intersection of all sets $C_i$.

Methods based on the principle of projection onto convex sets can be used to find a vector that belongs to the intersection using recursion.

The advantage of such methods is their simplicity and this that they use the observation model in the spatial domain. This allows convenient inclusion of previously known information into the methods.

The disadvantages are the ambiguity solution, slow convergence and high computational complexity.

### 4.4.1 Hybrid method based on projection onto convex sets and on maximum likelihood estimation

This approach creates images with high resolution so that it minimizing the maximum likelihood cost function.

The advantage of a hybrid approach is that all a priori knowledge are effectively combined. This provides a single optimal solution unlike the methods 4.4.

## 4.5 Super-resolution methods based on learning

These methods are known as well as super-resolution methods based on generative models.

Super-resolution methods based on generative models use additional information which are not directly contained in the input sequence of images with low resolution to create an image with high resolution.

It is argued that these methods are significantly better than methods based purely on image reconstruction.

These methods are based on certain classes of prior knowledge about the image and these classes noticeably affect their functionality. Consider the method for recognizing faces in the image. If it is selected as the input image into this method a sequence of images with the panoramic landscape this method detects in panoramic landscape images anything that reminds a human face. The search result is thus something that looks like a human face even though it is not a human face. This is a restriction with which the users of these methods must be reconciled.

## 4.6 Other interesting techniques leading to super-resolution

Methods based on iterative back-projection approach 4.6.1 or methods based on adaptive filtering approach 4.6.2 can be included into this group.

### 4.6.1 Super-resolution based on iterative back-projection

The image with high resolution is estimated in the iterative back-projection methods using back projecting of the error between simulated images with low resolution. It is expected the use of imaging blur and the images with low resolution. This process is repeated iteratively to minimize the energy of the error.

The functionality of iterative back projection is shown in Fig. 4.3.

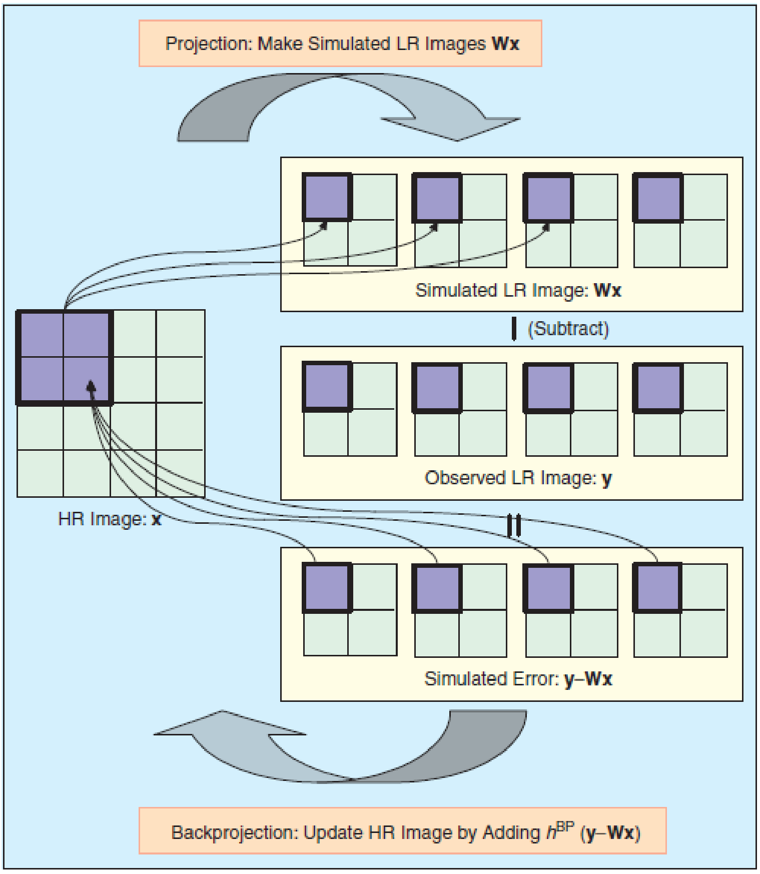



Figure 4.3: The functionality of iterative back projection. Taken from [12].

The value of variable $h^{BP}$ can be chosen arbitrarily. This variable can be used as additional constraints which represents the desired properties of the solution.

The advantage of iterative back projection is the intuitive understanding of this method.

The problems entails selecting the value of $h^{BP}$. Compared with the super-resolution methods based on the projection onto convex sets is a complicated application of advance known restriction.

### 4.6.2 Super-resolution methods based on adaptive filtering

In super-resolution methods based on adaptive filtering the steepest descent and normalized steepest descent are applied to estimate the image with high resolution at each time iteratively. The least mean square algorithm is derived from the steepest descent algorithm. As a result the image with high resolution at each time is calculated without computational complexity of a direct matrix inversion.

This approach has proven to be able to work with arbitrary output resolution, with linear time and spatially variable blur. This approach is also able to work with fluid motion. So it is possible to estimate a gradual sequence of images with high resolution.

In the reference papers were often discussed the analysis of convergence and computational complexity problems.

# Chapter 5

# Comparison of super-resolution methods

This chapter describes very briefly the comparison of super-resolution methods. A reader who is interested in comparison of super-resolution methods can find more in-depth information about this topic in source paper [10].

The most papers about super-resolution methods provide subjective results in comparison of the methods. It provides neither the clear way of comparing different methods nor the way to prove fitness of super-resolution method for the desired application. Comparison of super-resolution methods is built mainly on assumptions with which the super-resolution method has satisfactory results. In many cases are the test conditions biased in favor of the method proposed in the paper.

To achieve the objective comparison of super-resolution methods it is good to introduce objective criteria. These criteria may be for example:

1. **signal-to-noise ratio (SNR)** is defined as the ratio of signal power to the noise power corrupting the signal [25] (simply put the signal-to-noise-ratio expresses how much a signal has been corrupted by noise),

2. **peak signal-to-noise ratio (PSNR)** is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation [20],

3. **root mean square (RMS)** is a statistical measure of the magnitude of a varying quantity [23],

4. **mean absolute error (MAE)** is a quantity used in statistics to measure how close forecasts or predictions are to the eventual outcomes [18],

5. **mean squared error (MSE)** of an estimator is in statistics one of many ways to quantify the difference between an estimator and the true value of the quantity being estimated [19],

Description of the optimal criteria is taken from Wikipedia. For each of these criteria are listed pages which are cited.

However the front method for comparison of results of super-resolution methods remains less objective criterium - **visual quality of the result (VQ)**.

| Method | Criteria for comparison | | | | | |
|---|---|---|---|---|---|---|
| | SNR | PSNR | RMS | MAE | MSE | VQ |
| **Super-resolution methods based on nonuniform interpolation** | | | | | | |
| Komatsu | X | | | | | X |
| **Super-resolution methods working in the frequency domain** | | | | | | |
| Kim and Bose | | | | | | X |
| Kim and Su | X | | | | | X |
| Rhee and Kang | | X | | | | X |
| **Super-resolution methods based on regularization - Deterministic approach** | | | | | | |
| Bose and Koo | | X | | | | X |
| **Super-resolution methods based on regularization - Stochastic approach** | | | | | | |
| Tom and Katsaggelos | | | | | | X |
| Schultz and Stevenson | X | | | | | X |
| Hardie, Barnard, and Armstrong | | | | X | | |
| Cheeseman et al. | | | | | | X |
| **Super-resolution methods based on the projection onto convex sets** | | | | | | |
| Tekalp, Ozkan, and Sezan | | | | | | X |
| Patti, and Altunbasak | | | | | X | X |
| **Super-resolution methods based on optical flow** | | | | | | |
| Baker and Kanade | | | | | | X |
| Zhao and Sawhney | | | | | | X |
| **Other super-resolution methods** | | | | | | |
| Elad and Feuer | | | | | X | X |
| Irani and Peleg | | | | | | X |
| Baker and Kanade | | | X | | | |

Table 5.1: An overview of the results of different super-resolution methods. Partly taken from [10].

The table 5.1 provides an overview of the results of different super-resolution methods. There are selected only methods working with static images of the scene.

In this chapter were described optimal criteria for comparison of super-resolution methods. Further was noted that it is difficult to find optimal criteria for comparison of super-resolution methods. Another problem is to find which method is preferable for an application than others. It is mainly because each method is based on other assumptions.

# Chapter 6

# Design of the super-resolution method

This chapter contains the design of super-resolution method. The block structure of proposed super-resolution method is described in section 6.1. The method consists of five major steps. These are interpolation, registration and transformation, merging of images, PSF computation and deconvolution. The linking between major steps is described in first section of this chapter.

Functions of individual major steps are described in the next section of this chapter 6.2. A reader can learn more details about techniques used inside the blocks of the block structure and algorithms used for the desired function of these blocks in this section.

Section 6.3 describes implementation of techniques and algorithms mentioned in the previous section. Here can a reader find functions of the implemented program which are briefly described. More information can a reader find in source code of the program.

And finally the principle of computation of the proposed super-resolution method is shown in section 6.4. The artificial data are used for better understanding of the calculation process.

## 6.1 Block structure of proposed super-resolution method

The proposed super-resolution method consists of five main parts. Block structure of proposed super-resolution method is shown in Fig. 6.1.

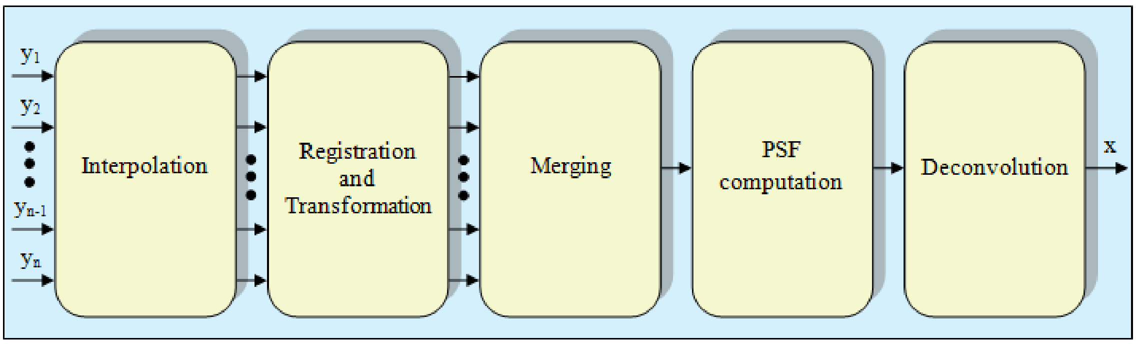



Figure 6.1: The block structure of proposed super-resolution method.

Input data into super-resolution method are images with low resolution (in the figure are labelled as $y_x$, where $x$ denotes the number of input images with low resolution). These images with low resolution must satisfy the basic requirements described in section 3.1. It means that the number of images with low resolution must be greater than one and the images must be subpixel shifted. More of the input images implies the better result of the super-resolution method. However the large number of input images implies bigger computational complexity of the super-resolution method.

After loading the images with low resolution is the next step of interpolation. The goal of interpolation is to increase the image resolution. The results of this step are thus images with high resolution. The interpolation is used because it has better visual results than ordinary zoom. It removes negative properties of ordinary zoom like for example the visibility of the raster of image. However this step can't be denoted as the step of super-resolution. The reason is described in section 2.4.

The step called registration and transformation has the task to map images with high resolution grid onto grid of the reference image with high resolution. As the reference image is taken the first input image. After mapping are the significant pixels of all images on the same coordinates which means that all images with high resolution are accurately aligned to the grid of the reference image with high resolution. The secondary result of this step are transformation matrixes between reference image with high resolution and all other images with high resolution.

The step of merging images with high resolution works on the principle of the arithmetic mean. The input images are aligned onto grid of the reference image with high resolution. This allows to determining the output image with high resolution using arithmetic mean of all pixels of images with high resolution on the same coordinates. But the resulting image with high resolution is still affected by the blur or noise.

The step of PSF computation is used in order to obtain the inverse filter kernel. The aim of this kernel is to represent negative properties which are caused by step of registration and transformation followed by the step of merging. The PSF computation step is critical for the visual quality of output's image of the proposed method.

Deconvolution is applied to the merged image with high resolution and the inverse filter kernel. Basically it is the inverse filtering. In the resulting image of this step are removed visual imperfections of the merged image with high resolution like the blur or noise. This resulting image with high resolution is also the resulting image of proposed super-resolution method.

## 6.2 Internal structure of blocks

The block structure of throughout the proposed method is described in previous section 6.1. This section deals with internal structure of each of the blocks.

### 6.2.1 Block of interpolation

The interpolation of each of the input image with low resolution is based on Lanczos resampling algorithm. Information about this algorithm are drawn from literature [16] and [1]. It were tested also other methods like Bicubic interpolation or Nearest-neighbor interpolation, but Lanczos resampling algorithm has the best results in proposed super-resolution method.

Lanczos resampling uses a convolution kernel to resample unknown data in a scaled image. There are pixels which have to be interpolated between original pixels of the input image with low resolution after resampling. The Lanczos resampling uses to interpolation of pixels a weighting influence on new pixel. The weights are relative to the position of the new pixel and are found by the Lanczos algorithm.

In one dimension is Lanczos resampling algorithm based on the following formula:

$$L(x) = \begin{cases} sinc(x)sinc(x/a) & -a < x < a, x \neq 0 \\ 1 & x = 0 \\ 0 & otherwise \end{cases} \tag{6.1}$$

In the implementation of this formula is useful to use the normalized sinc function. So the formula can be rewritten as:

$$L(x) = \begin{cases} \frac{a\sin(\pi x)\sin(\pi x/a)}{\pi^2 x^2} & -a < x < a, x \neq 0 \\ 1 & x = 0 \\ 0 & otherwise \end{cases} \tag{6.2}$$

- $x$ represents the distance to an original pixel from the actual pixel in the scaled image (if the distance is 0, then is processed original pixel and it is weighted fully),
- $a$ represents the size of the convolution kernel (typically 2 or 3).

### Implementation of algorithm

There is used the kernel size $a = 3$ and the size of image with low resolution is increased twice in the implementation. The own implementation of the algorithm consists of three major steps:

1. **Calculation of the Lanczos kernel** is critical for process of interpolation. The Lanczos kernel is shown in Fig. 6.2

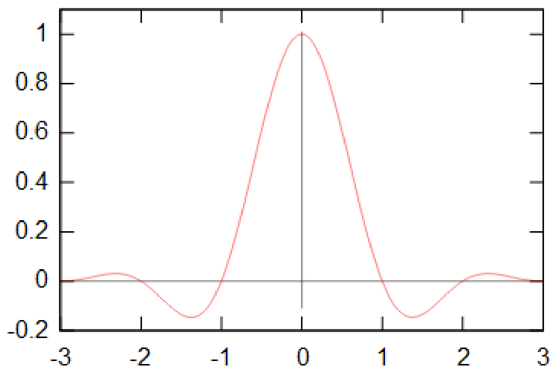



Figure 6.2: Lanczos kernel for $a = 3$. Taken from [16].

As shown in Fig. 6.2 the kernel's values for integers are zero. This means that these information are not applicable for the purpose of interpolation. Because the original image with low resolution was twice enlarged each empty new pixel in image with high resolution has the distance 0.5 from both original pixels. This is the reason why the Lanczos kernel consists of values $L(-2.5)$, $L(-1.5)$, $L(-0.5)$, $L(0.5)$, $L(1.5)$ and $L(2.5)$.

2. **Resampling of rows** is performed so that:

    - if the pixel of the image with high resolution corresponds to the original pixel of the image with low resolution this pixel is weighted fully. This means that the pixel's value of the image with low resolution is copied into pixel's value of the image with high resolution. This is shown in Fig. 6.3

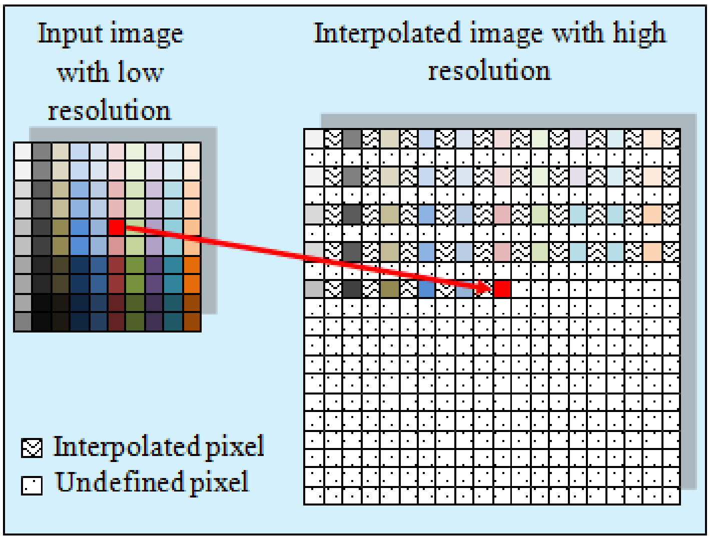



Figure 6.3: Copying of corresponding pixels.

    - if the pixel of the image with high resolution is the new pixel then his value is computed using Lanczos kernel and neighbouring pixels. Each from neighbouring pixels is multiplied by Lanczos coefficient which represents the weight with which a neighbouring pixel is counted. This value of the new pixel is then normalized. After normalization is this value used as the value of new pixel of the image with high resolution. This step is shown in Fig. 6.4.

3. **Resampling of cols** is very similar to resampling of rows. But there are two differences. The first one is that the coefficients are multiplied by the column of pixels instead of the row as in the previous step. The second difference is that the pixels to calculate the new pixel of image with high resolution are taken from the image with high resolution. There are used known values of pixels i.e. pixels on odd rows of the image with high resolution.

### 6.2.2 Block of registration and transformation

This section is closely based on the OpenCV library. Descriptions of used functions are partly taken from literature [2].

As it is mentioned in the overview of this section the task of this block is to map images with high resolution grid onto grid of the first image (the reference image) with high

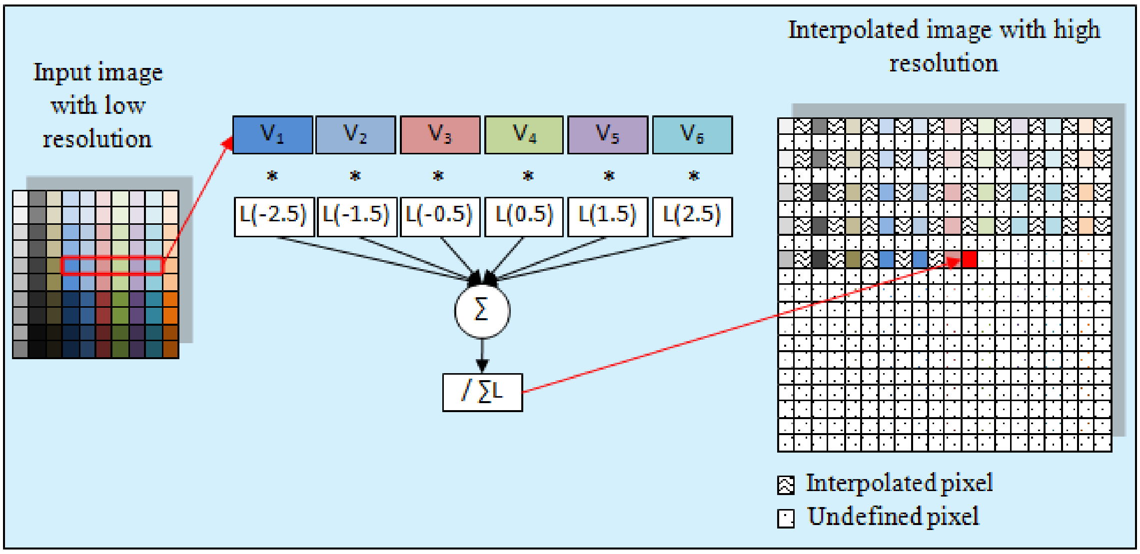



Figure 6.4: Calculation of the new pixel of the image with high resolution.

resolution. After mapping are the significant pixels of all images on the same coordinates which means that all images with high resolution are accurately aligned onto the grid of the reference image with high resolution. This is the primary goal of this block.

Secondary goal of this block is to determine transformation matrixes between reference image with high resolution and all other images with high resolution.

In this block are performed four steps in order to achieve the results. These are the steps of:

1. computation of good features to track,
2. computation of Lucas-Kanade optical flow between the reference image with high resolution and all other images with high resolution,
3. computation of the transformation matrixes between reference image with high resolution and all other images with high resolution,
4. and transformation of all other images with high resolution onto grid of the reference image with high resolution.

These steps are briefly described below.

### Good features to track

Good features to track are calculated using an OpenCV function `cvGoodFeaturesToTrack()`. This function computes the second derivatives (using the Sobel operators) that are needed and from those are computed the needed eigenvalues. It returns a list of the points that meet Shi and Tomasi definition of being good for tracking. These points are shown in Fig. 6.5.

The maximum number of feature points found in the reference image with high resolution is 400.

The result of `cvGoodFeaturesToTrack()` function is an array of pixels coordinates which will be searched in all other images with high resolution.

Figure 6.5: Good features to track. Found 400 points.

#### Lucas-Kanade optical flow

The text dealing with Lucas-Kanade optical flow is partly taken from [2] and [17].

The Lucas-Kanade optical flow algorithm is still one of the most popular versions of two-frame differential methods for motion estimation. This method can be applied in a sparse context because it relies only on local information that is derived from some small window surrounding each of the points of interest.

The Lucas-Kanade algorithm is based on three assumptions:

1. **brightness constancy** - the brightness of a pixel doesn't change from frame to frame,
2. **temporal persistence or small movements** - motions are small from frame to frame,
3. and **spatial coherence** - neighbouring points in a scene belonging to the same surface have similar motion.

The advantage of Lucas-Kanade method is the comparative robustness in presence of noise.

The disadvantage of using small local windows in Lucas-Kanade is that large motions can move points outside of the local window and thus become impossible for the algorithm to find. This problem led to development of the pyramidal Lucas-Kanade algorithm, which tracks starting from highest level of an image pyramid (lowest detail) and working down to lower levels (finer detail). Tracking over image pyramids allows large motions to be caught by local windows.

For that reason was used function `cvCalcOpticalFlowPyrLK()` from OpenCV library. The window size was chosen 10, the number of levels of the pyramid 5 and the calculation is terminated after 20 iterations or after reaching the accuracy of 0.03. In Fig. 6.6 are shown corresponding points of two input images.

The results of `cvCalcOpticalFlowPyrLK()` function are therefore coordinates of corresponding feature points between reference image with high resolution and all other images with high resolution.

#### Transformation matrixes

The computation of transformation matrixes between reference image with high resolution and all other images with high resolution is performed using planar homography. Planar

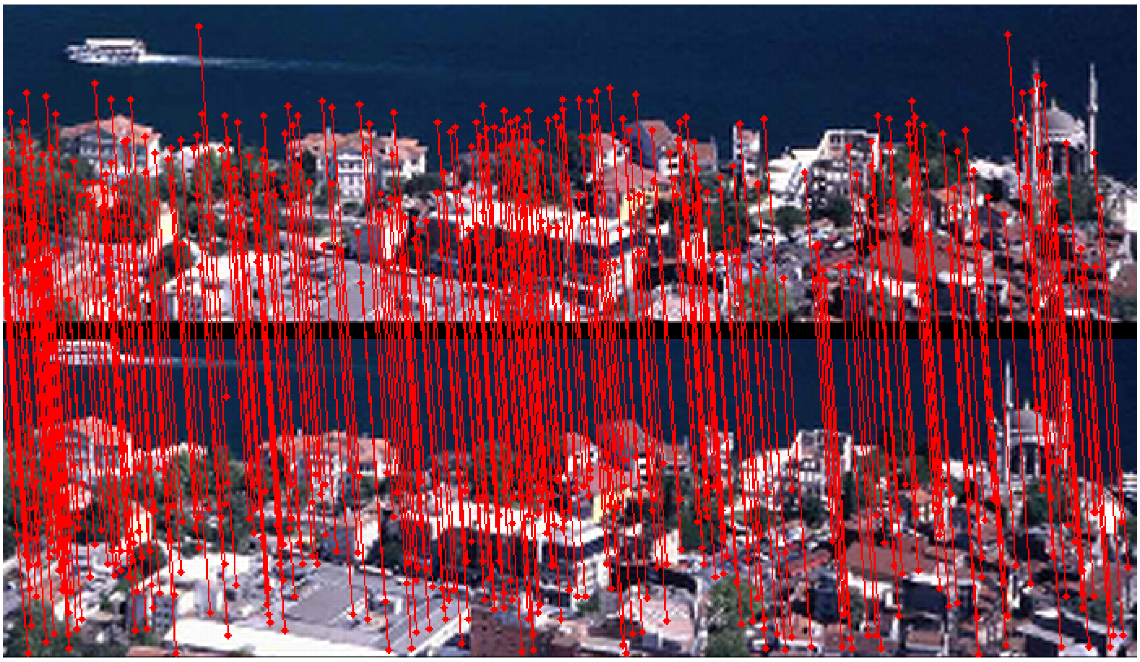


Figure 6.6: Corresponding points of two input images. Found 360 corresponding points.

homography can be defined as a projective mapping from one plane to another. It uses multiple images of the same object to compute both the individual translations and rotations for each view as well as the intrinsic.

The homography matrix $H$ relates the positions of the points on a source image plane to the points on the destination image plane. OpenCV library provides a handy function `cvFindHomography()` for the calculation of the homography matrix. This function takes a list of correspondences (the result of the previous step) and returns the homography matrix that best describes those correspondences.

The result of `cvFindHomography()` function is the homography matrix $H$ which describes the relationship between reference image with high resolution and all other images with high resolution.

#### Transformation of all other images onto grid of the reference image

The perspective transformation is a specific kind of homography. For this reason is applied `cvWarpPerspective()` function from the OpenCV library in order to map all other images with high resolution onto high resolution grid of the reference image with high resolution. This function performed the perspective transformation of a whole image.

Input into this function are thus two different views on the same scene and the homography matrix $H$. The output is the image with high resolution mapped onto high resolution grid of the reference image with high resolution.

As it is mentioned above the images with high resolution mapped onto high resolution grid of the reference image together with the homography matrixes are the results of this entire implementation block.

### 6.2.3 Block of merging images

The results of previous block are images with high resolution mapped onto uniform high resolution grid. Now it is possible to proceed the step of merging images.

Merging of images is based on the principle of the arithmetic mean. Into the output image with high resolution thus each of the images contributes by information about the scene which the image bears. The process of merging images is shown in Fig. 6.7.

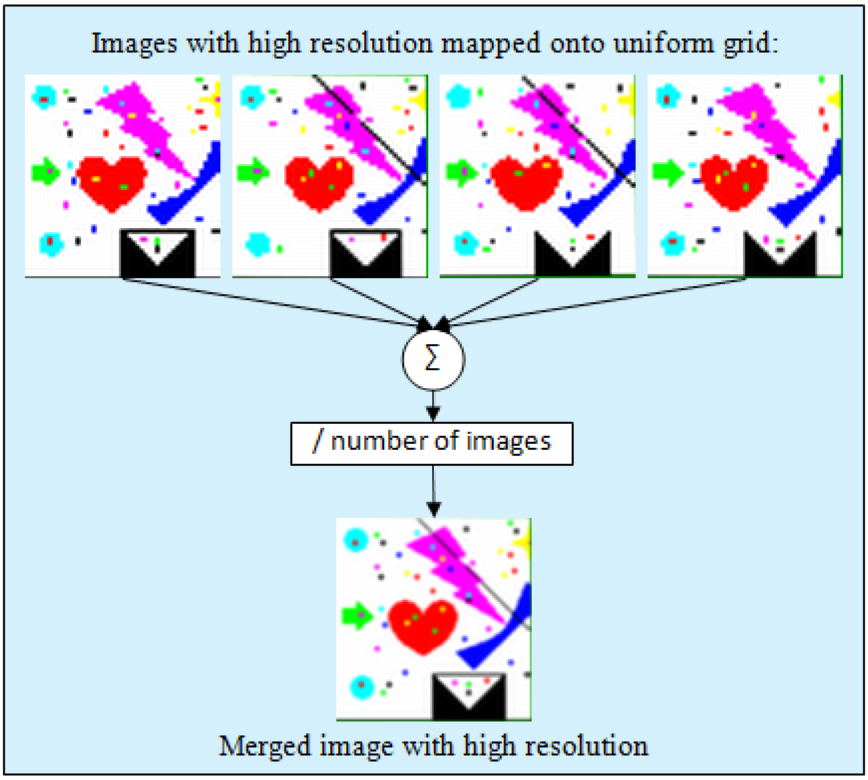



Figure 6.7: The process of merging images.

After a close examination of images which are mapped onto uniform high resolution grid a reader may notice the differences between images. For example the first and fourth image do not contain a black diagonal line in top right part of the image. In contrast the third and fourth image do not contain a black horizontal line in bottom right part of the image etc. From this perspective it appears the arithmetic mean as a good solution.

The resulting image of this block may still suffer from the negative visual features. These features are removed in the next two blocks of the proposed method.

### 6.2.4 Block of PSF computation

The step of PSF computation is used in order to obtain the inverse filter kernel. This kernel is used in the block of deconvolution in order to remove negative visual features of the merged image with high resolution. This means that the PSF computation block is critical for the visual quality of the output image of proposed method.

In the calculation of the PSF are used homography matrixes between reference image with high resolution and all other images with high resolution and the knowledge of feature points in all images with high resolution. These information are computed in the registration and transformation block. The calculation of PSF is simple and consists of the following steps:

1. finding of the feature point nearest to the center of the reference image with high resolution and the corresponding points in all other images with high resolution,
2. for all images with high resolution:
   - creation of the PSF filter with the size of image with high resolution,
   - setting all values of this filter to zero,
   - setting the PSF kernel on the coordinates of the feature point found in first step to value 1,
   - defocusing the PSF kernel by using convolution with Gauss filter in order to remove artifacts from the output image,
   - if currently processed image is not the reference image with high resolution then transform PSF kernel using `cvWarpPerspective()` function and corresponding homography matrix,
   - adding PSF kernel with the PSF kernel calculated in previous iteration,
3. normalization of the PSF kernel
4. reversal of the PSF kernel along both axes removes the camera motion during image acquisition process
5. cutting of the PSF kernel so that are eliminated insignificant zeros of the PSF filter

The PSF kernel that is calculated in this way represents negative properties of the image with high resolution that is affected by the processes of registration, transformation and merging.

### 6.2.5 Block of deconvolution

The deconvolution is last one block in the proposed super-resolution method. It uses results from the previous two blocks. The result of block of merging is an image with high resolution that may be affected by blur and by noise. The result of block of PSF computation is PSF kernel (inverse filter kernel) that represents negative visual properties of the merged image.

The deconvolution represents inverse filtering of the image in proposed super-resolution method. Information about inverse filtering are drawn from literature [13] and [5]. The main idea of inverse filtering is to recover an image from the corrupted image. The computation of inverse filtering for one channel image can be described by the following steps:

1. merged image and inverse filter kernel are converted to complex numbers,
2. DFT of merged image and inverse filter kernel are calculated,
3. division of merged image's spectrum and inverse filter kernel's spectrum is calculated,
4. IDFT of division of spectrums is calculated,
5. result of IDFT is converted into real numbers.

The conversion of one channel merged image and inverse filter kernel to complex numbers is realized by adding of the second channel into the merged image and into the inverse filter kernel. The values of the second channel are set to zero.

DFT calculation of one channel merged image and inverse filter kernel is performed by using OpenCV function `cvDFT()`. The usual procedure is to create a somewhat larger array for computing DFT. The optimal size for DFT computation is found using `cvGetOptimalDFTSize()` function from OpenCV library. This function takes the length of input array (one channel merged image or inverse filter kernel) and returns the first equal or larger appropriate size. The input array is then aligned with zeros.

The division of merged image's spectrum and inverse filter kernel's spectrum is essentially the division of complex numbers. The principle of division complex numbers is taken from [8]. The formula used for division of complex numbers is:

$$\frac{A}{B} = \frac{A\bar{B}}{B\bar{B}}. \tag{6.3}$$

If $A = a + bi$ and $B = c + di$ can be this formula rewritten to the form:

$$\frac{a+bi}{c+di} = \frac{(a+bi)(c-di)}{(c+di)(c-di)}. \tag{6.4}$$

In deconvolution is division of one channel merged image's spectrum and inverse filter kernel's spectrum computed using 6.4 formula.

The IDFT of resulting spectrum that was calculated in previous step is also performed using function `cvDFT()`. Only one difference is in used flags. It is necessary set the flags to `CV_DXT_INV_SCALE`.

Conversion of IDFT's result to real numbers is based on Pythagorean Theorem. The first channel of result represents the real component of complex number $re$ and the second channel represents the imaginary component $im$. The one channel resulting image in real numbers can be denoted as $image$. The resulting image of the whole super-resolution method is obtained by computation from formula:

$$image[x][y] = \sqrt{re[x][y]^2 + im[x][y]^2}, \tag{6.5}$$

for $\forall x : \{x \in \mathbb{Z} | 0 \leq x < imageWidth\}$ and $\forall y : \{y \in \mathbb{Z} | 0 \leq y < imageHeight)$.

## 6.3 Implementation of super-resolution method

For implementation is chosen C++ programming language. The advantage of this language is the availability of a large number of libraries. One of these is the OpenCV library [2]. OpenCV contains more than 500 functions for computer vision and image processing. For this reason is used in program implementation.

This section describes the implementation of individual blocks of the proposed super-resolution method. Algorithms and techniques of implementation are described above in section 6.2.

### 6.3.1 Description of program functions

#### Function load_images

```
void load_images(int argc, char* argv[], IplImage** loadImg)
```

Parameters:

- `argc` - number of input parameters of the program
- `argv` - vector of input parameters of the program
- `loadImg` - array of input images with low resolution

It reads the input images with low resolution into the array. Input images are the parameters of the program. The program is terminated if:

1. only one input image is given as the parameter,
2. the size of input images with low resolution is not the same,
3. the program is unable to load input images.

#### Function lanczos_coeficients

```
double lanczos_coeficients(double x, int a)
```
Parameters:

- `x` - distance to an original pixel from the actual pixel in the scaled image
- `a` - size of the convolution kernel (typically 2 or 3)
- `return value` - coeficient of Lanczos kernel.

It calculates the coefficient of Lanczos kernel. Calculation is based on formula 6.2.

#### Function lanczos_resample

```
IplImage* lanczos_resample(IplImage* sourceImg)
```
Parameter:

- `sourceImg` - input image with low resolution
- `return value` - interpolated image with high resolution

Interpolation of input image. The output image is twice bigger than input image. The whole process of interpolation is described in section 6.2.1.

#### Function transform_images

```
void transform_images(IplImage** srcImgs, IplImage** dstImgs, int imgCount,
                      CvMat** transform)
```
Parameters:

- `srcImgs` - array of images with high resolution
- `dstImgs` - array of images with high resolution transformed onto high resolution uniform grid of the reference image
- `imgCount` - number of images in the array
- `transform` - array transformation matrixes between reference image and all other images with high resolution

It maps images with high resolution grid onto grid of the reference image with high resolution. Mapping is done using the transformation matrixes between reference image with high resolution and all other images with high resolution. The whole algorithm is described in section 6.2.2.

### Function compute_PSF

```
CvMat* compute_PSF(CvPoint2D32f* featuresCurr, CvPoint2D32f** featuresPrev,
                   IpPairVec* matches, CvMat** transform, CvSize newSize,
                   int imgCount, bool robustMethod)
```

Parameters:

- `featuresCurr` - feature points in reference image with high resolution
- `featuresPrev` - array of feature points in all other images with high resolution
- `matches` - array of matching points between images (used for improved super-resolution method)
- `transform` - array of transformation matrixes between reference and all other images with high resolution
- `newSize` - size of images with high resolution
- `imgCount` - number of images
- `robustMethod` - improved super-resolution method
- `return value` - inverse filter kernel used in deconvolution

It computes inverse filter kernel. This is computed using feature points in images with high resolution (or matching points between images for improved super-resolution method) and transformation matrixes between these images. The whole technique is desctibed in section 6.2.4.

### Function deconv

```
void deconv(const IplImage* srcImg, IplImage* dstImg,
            const CvMat* kernelMat)
```

Parameters:

- `srcImg` - one channel image with high resolution
- `dstImg` - one channel image with high resolution after the step of inverse filtering
- `kernelMat` - filter kernel for inverse filtering

It performs the inverse filtering of merged image with high resolution in order to remove negative visual properties (blur and noise). The merged image must be divided into individual channels before this function is called. After computation must be merge individual channels of the resulting image with high resolution. The principle of deconvolution is described in section 6.2.5.

### Other functions of the program

The functions above are the basic building blocks of whole program. Therefore they pay more attention. The functions described below are especially the testing functions. A reader can obtain more information about these functions in the source code of the program.

The function `decimate_image()` serves to decimation of the image with high resolution to the image with low resolution. This function is based on arithmetic mean of four neighbouring pixels into the value of one pixel in the image with low resolution. This approach better represents behaviour of camera while shooting a scene than other types of decimation of images. The principle is evident from Fig. 6.8.

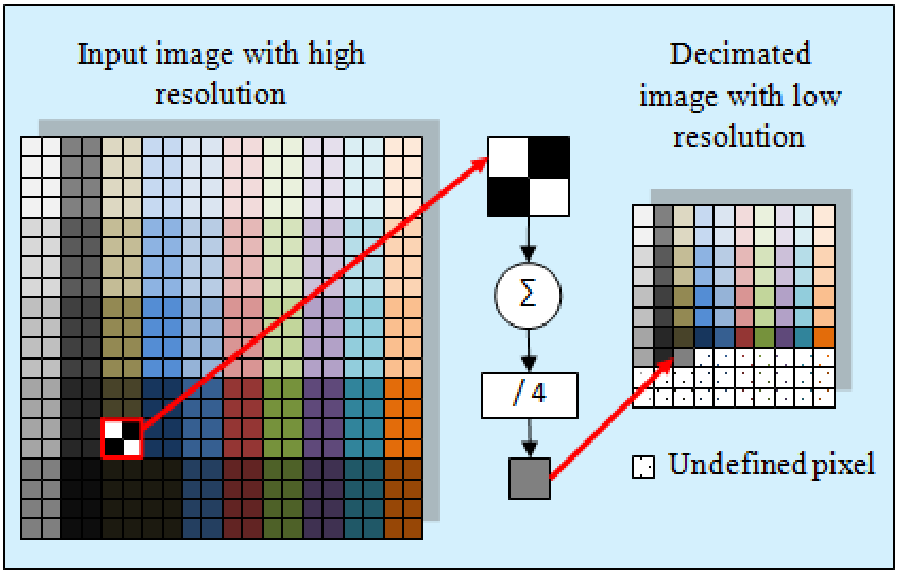



Figure 6.8: Principle of decimating image with high resolution.

Next function for testing purposes is a function called `interpolate_image()`. This function calls the functions for increasing the input image resolution. The method used for increasing resolution of image is specified at the beginning of the program source code. For increasing the image resolution can be used four techniques:

1. ordinary zoom of image followed by filtration using:
    - Lanczos kernel (this is computed using function `lanczos_kernel()`),
    - Gaussian kernel with values from the source [14] (computed using `gauss_kernel()` function),
    - internal representation of Gaussian filter (function `cvSmooth()` with parameter `CV_GAUSSIAN` from OpenCV library [2]),
2. Lanczos resampling (implemented in function `lanczos_resample()`).

The function `zoom_image()` has the task to zoom image twice. This is performed by copying of pixel's values from the image with low resolution to four corresponding pixels of the image with high resolution. The principle is evident from Fig. 6.9.

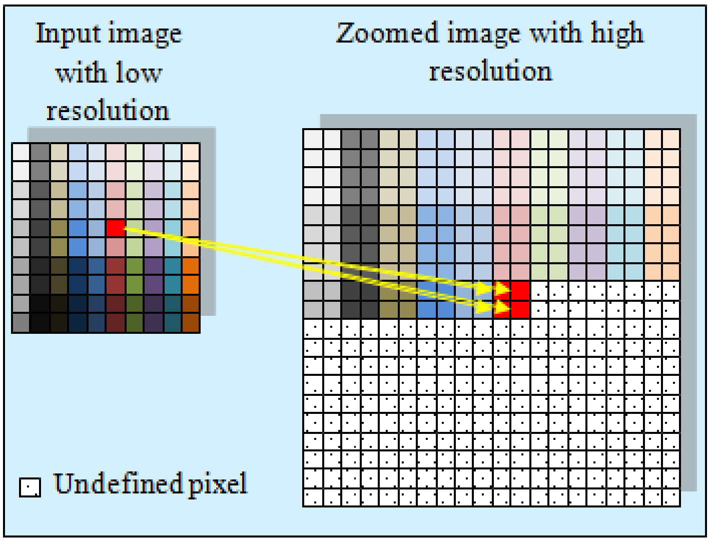



Figure 6.9: Principle of zooming image with low resolution.

Functions `print_filter()` and `print_filter_matlab()` print the content of filter's kernel. The first function prints filter's kernel as the matrix. The second one function prints content of the kernel in format for input to Matlab. The kernel is arbitrary matrix.

## 6.4 Computation of the super-resolution method

In this section is shown an example of computation which uses proposed super-resolution method. This example contains of artificially generated images. These images are images of the same scene and satisfy the condition of subpixel shift between images 3.1.

The images arose by the following way:

1. first image is the reference image of the scene,
2. second image is the reference image of the scene shifted by 5px to the left and by 2px up,
3. third image is the reference image of the scene shifted by 2px to the left and by 1px down,
4. fourth image is the reference image of the scene shifted by 3px to the left and 3px up.

After these shifts are performed these images are downsampled i.e. the size of images is reduced to half. It isn't used any kind of interpolation.

The whole process of computation is shown in Fig. 6.10.

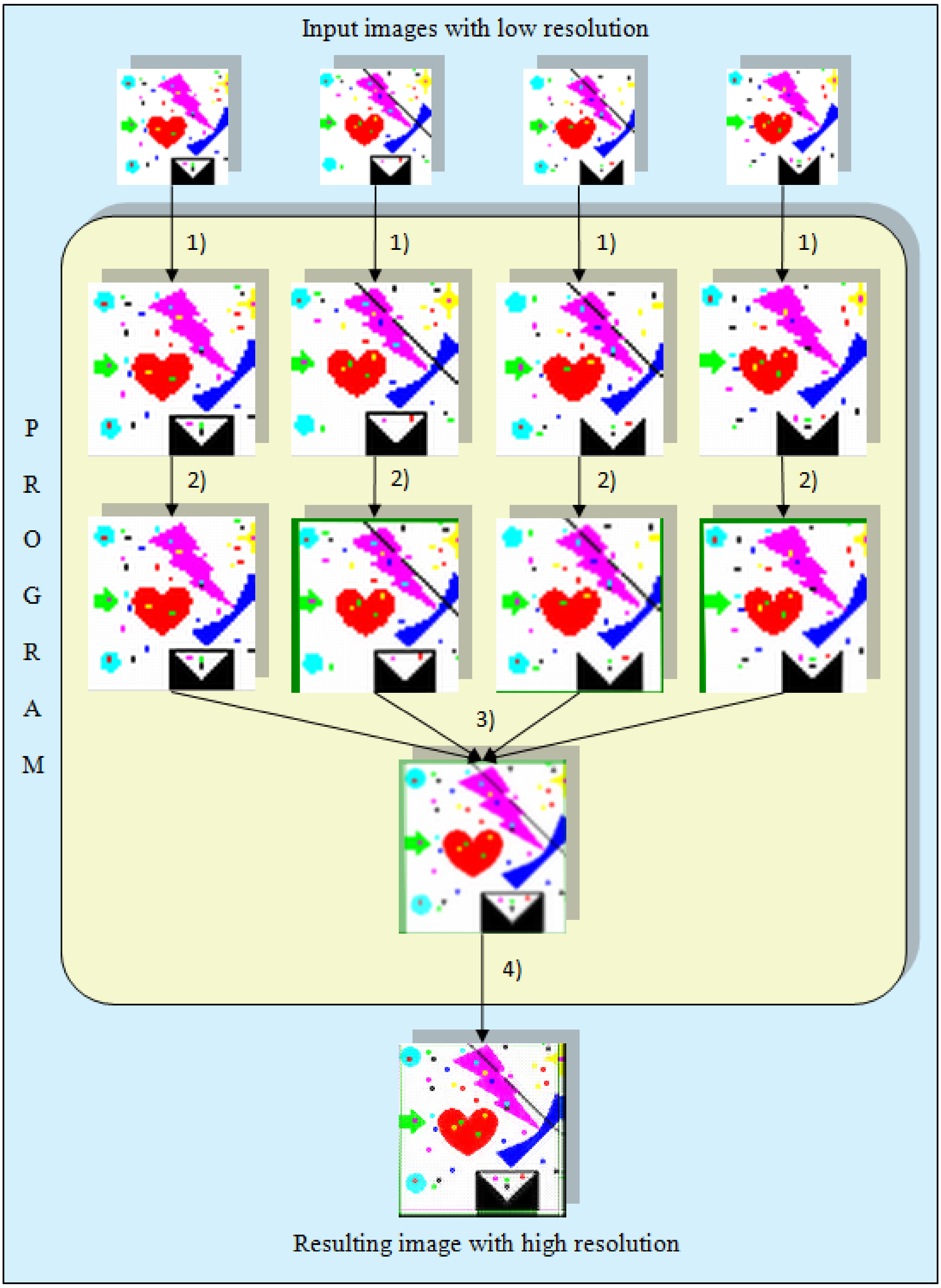



Figure 6.10: Computation of proposed super-resolution method. 1) Lanczos resampling, 2) registration and transformation, 3) merging of images, 4) PSF computation and deconvolution.

# Chapter 7

# Testing of proposed super-resolution method

There is described an optimal design of test data in this chapter. It is based on the front method for comparison of super-resolution methods' results. This is comparison of visual quality of results and is more described in chapter 5.

The optimal design of test data must satisfy certain conditions. The whole process of design optimal test data is described in section 7.1.

The first part of testing deals with images which contain only translational motion. These tests are described in section 7.2. The second part of testing deals with images which contain only rotation. Description of these tests can a reader find in section7.3.

Evaluation of test's results is described in section 7.4.

## 7.1 Creation of test data

Implementation of the proposed super-resolution method described in section 6.2.1 increases the resolution of input images twice. Therefore the design of testing data must accept this fact.

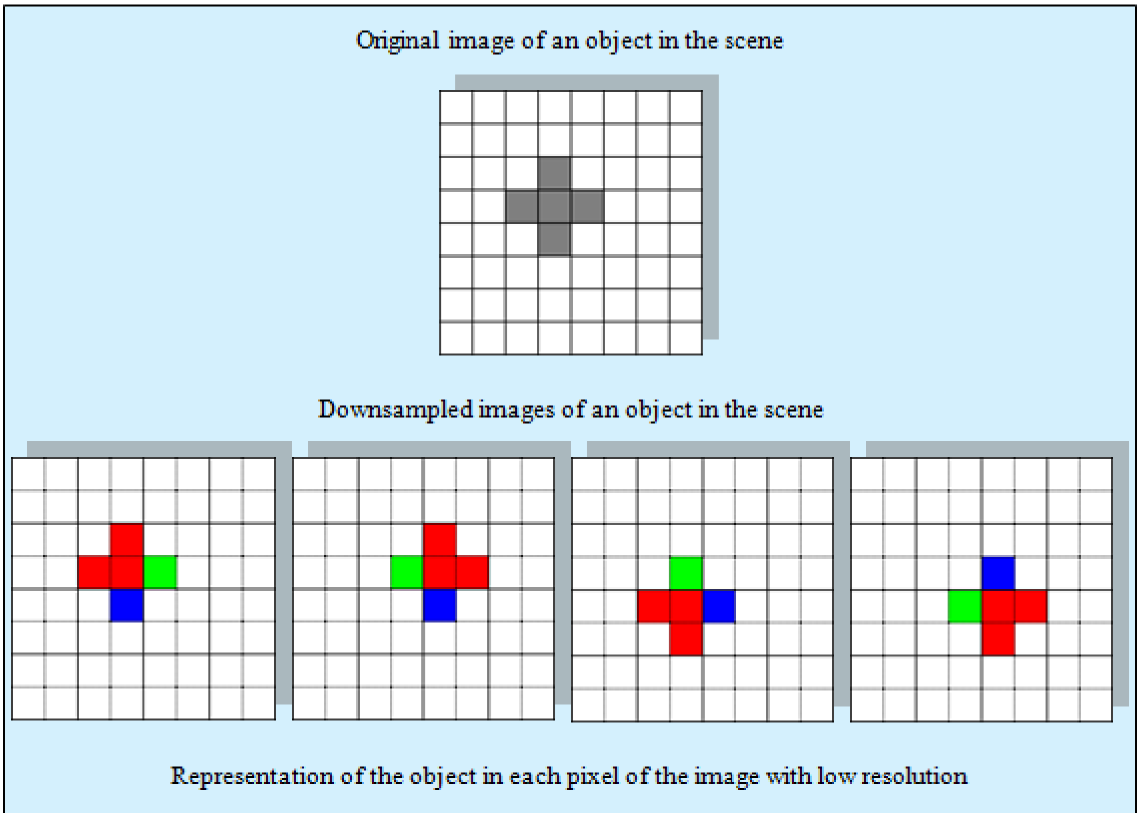
Test data are created from the image of the scene with high resolution. From this image are cut out different images. These images represent different viewpoints when capturing the scene. Then are these images downsampled to half size. Images created by this way represent input images of the super-resolution method (images with low resolution).

The last condition for good test data is that the images with low resolution must be subpixel shifted and that it must be available sufficient number of pictures in low resolution. This condition is based on basic requirements of the super-resolution method described in section 3.1.

Creation of good test data must satisfy all conditions described above. The test data thus must contain:

1. different viewpoints on the scene,
2. sibpixel shift between images with low resolution,
3. sufficient amount of images with low resolution.

The creation of test data which satisfy all of these conditions is as follows. Implementation of the method increases the resolution of input images twice. To easily compare the visual quality of result is appropriate to decrease the resolution of original image with low resolution also twice. Subsampling to the half size allows four different ways to obtain subpixel shifted images with low resolution that carries unique information about the image. First of them is only resizing of the original image. The second way is resizing of the original image which is shifted by an odd number of pixels in the horizontal direction. The third possible way is resizing of the original image which is shifted by an odd number of pixels in vertical direction. And fourth way is resizing of the original image which is shifted by an odd number of pixels in both directions (horizontal and vertical). The principle is shown in Fig. 7.1.




| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 0.75 | 0.25 | 0 |
| 0 | 0.25 | 0 | 0 |
| 0 | 0 | 0 | 0 |

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 0.25 | 0.75 | 0 |
| 0 | 0 | 0.25 | 0 |
| 0 | 0 | 0 | 0 |

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 0.25 | 0 | 0 |
| 0 | 0.75 | 0.25 | 0 |
| 0 | 0 | 0 | 0 |

| | | | |
|---|---|---|---|
| 0 | 0 | 0 | 0 |
| 0 | 0 | 0.25 | 0 |
| 0 | 0.25 | 0.75 | 0 |
| 0 | 0 | 0 | 0 |

Figure 7.1: Creation of the test data. Original image of the scene with high resolution (up). Images with low resolution (middle) - from left resized original image, resized original image shifted by an odd number of pixels in horizontal direction, resized original image shifted by an odd number of pixels in vertical direction, resized original image shifted by an odd number of pixels in both directions. Corresponding representation of the object in each pixel of the image with low resolution (down).

## 7.2 Test data that contain only translation

Test data that contain only translational motion of the original image are the simplest variation of test data. These images are created as follows:

- first input image represents only a part of the original image (the reference image),
- second input image compared to the reference image is shifted by 5px left and by 2px up (shifted by an odd number of pixels in horizontal direction),
- third input image compared to the reference image is shifted by 2px right and by 1px down (shifted by an odd number of pixels in vertical direction),
- fourth input image compared to the reference image is shifted by 3px left and by 3px up (shifted by an odd number of pixels in both directions).

Images created by this way are then downsampled to half size of the original image. Original image of the scene with high resolution, input images into super-resolution method with low resolution, merged image with high resolution and resulting image of the super-resolution method with high resolution are shown in Fig. 7.2.

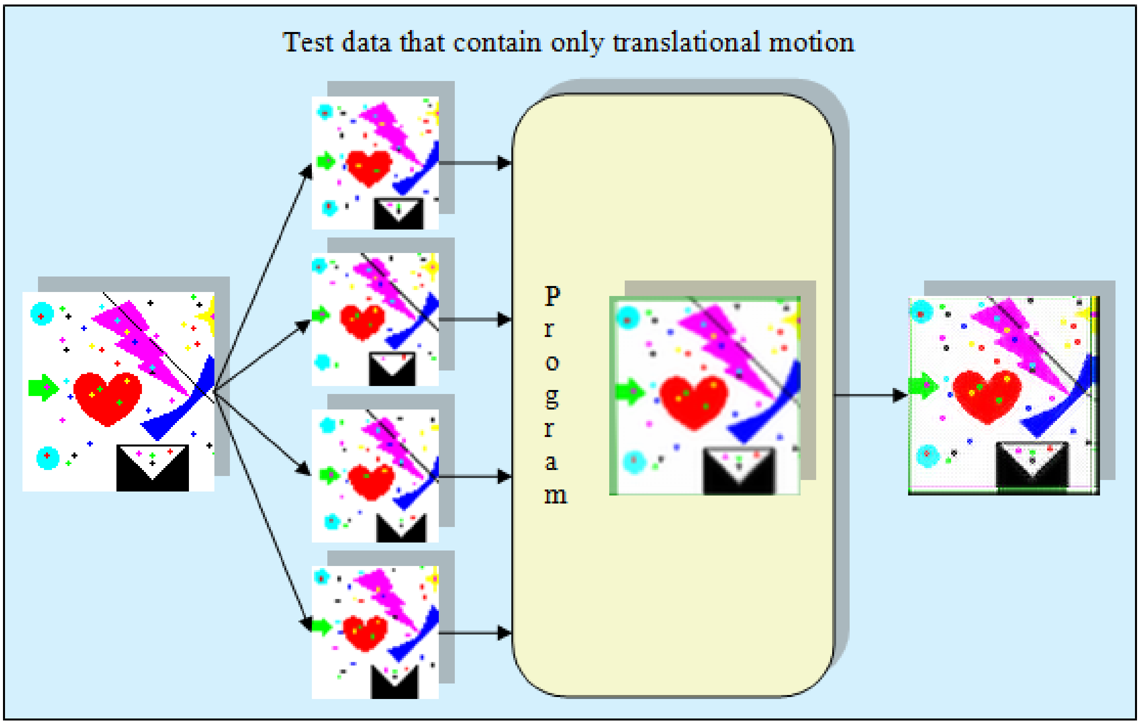



Figure 7.2: Test data that contain only translational motion. Original image of the scene (left), input images into super-resolution method (middle), merged image (in program block) and resulting image of the super-resolution method (right).

Testing of proposed super-resolution method for input data which contain only translational motion has got very good results.

## 7.3 Test data that contain only rotation

Tests which contain rotation already have not as good results as tests based on translational motion. This is true for almost all super-resolution methods. The same applies to the proposed super-resolution method. The test data are created as follows:

- first input image represents only a part of the original image (the reference image),
- second input image is the reference image rotated by 5 degrees the centre of rotation is in the middle of the image,
- third input image is the reference image rotated by 10 degrees the centre of rotation is in the middle of the image,
- fourth input image is the reference image rotated by 15 degrees the centre of rotation is in the middle of the image.

Images created by this way are then downsampled to half size of the original image. Original image of the scene with high resolution, input images into super-resolution method with low resolution, merged image with high resolution and resulting image of the super-resolution method with high resolution are shown in Fig. 7.3.

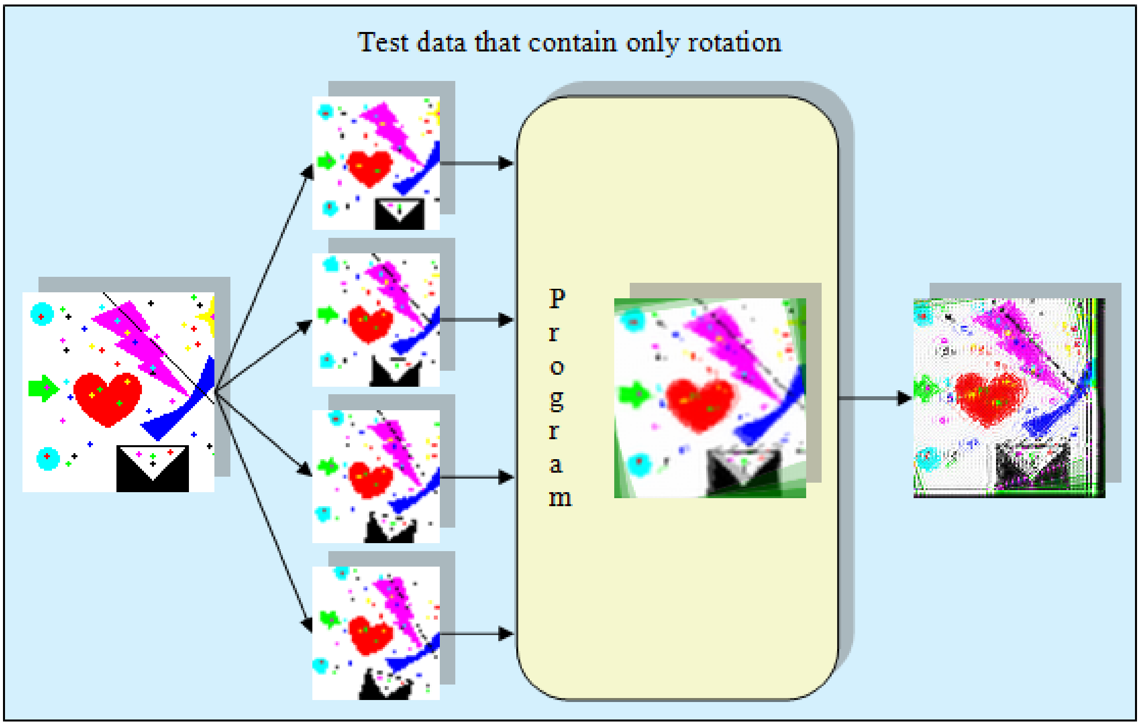



Figure 7.3: Test data that contain only rotation. Original image of the scene (left), input images into super-resolution method (middle), merged image (in program block) and resulting image of the super-resolution method (right).

Testing of proposed super-resolution method for input data which contain only rotation haven't got good results. These unsatisfactory results are caused especially by worse functionality of the step called registration and transformation 6.2.2 of proposed super-resolution method. This step used Lucas-Kanade algorithm 6.2.2 to determine matching points between two images.

The graph in Fig. 7.4 shows dependence of found matching points in percentage on the rotation between images in degrees. From this graph it is clear that if the image is rotated by more than 5 degrees then success of finding matching points decreases rapidly.

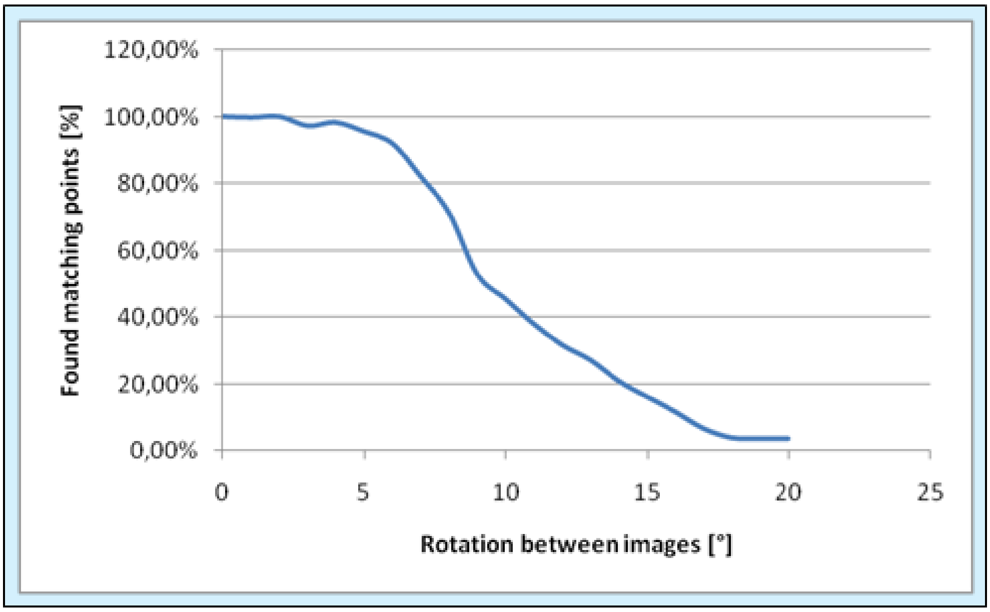



Figure 7.4: Dependence of found matching points on the rotation between images.

Testing of proposed super-resolution method for input data which contain only rotation have got thus unsatisfactory results for rotation bigger than 5 degrees. For this reason is the proposed super-resolution method applicable only to a limited range of image rotation.

## 7.4 Conclusion of testing

After examining the results of tests is evident that proposed super-resolution method is well applicable to input data which contain only translational motion.

Images which contain rotation generally represent a larger problem for super-resolution methods. The proposed super-resolution method is no exception. It is applicable only to a limited range of image rotation. However as the problem was identified block of registration and transformation 6.2.2 of proposed super-resolution method. This allows design of improvements of this method.

In order to save space in this thesis are all tests included only in electronic form on the enclosed storage media. Tests mentioned directly in this thesis serves only to create ideas about testing of super-resolution methods.

# Chapter 8

# Improvements of proposed super-resolution method

In chapter 7 is described testing of proposed super-resolution method. For images that contain only translation is the result very good. However the problem occurs in images which contain rotation.

Unsatisfactory results are primarily caused by inaccurate calculation of registration and transformation between images. The aim of improved super-resolution method is thus to substitute the existing calculating of registration and transformation between images by another algorithm.

As good solution it seems to be replacing of existing algorithm for detecting matching points between images. The proposed super-resolution method uses Lucas-Kanade optical flow algorithm 6.2.2. This algorithm uses correlation to determine corresponding points between images. This principle seems to be less suitable for super-resolution purposes. Better approach to computation matching points between images is described in section 8.1.

Because even the best algorithm for finding matching points between images is not without flaws it is necessary to adjust also the computation of transformation matrixes between images. Convenient way of computation transformation matrixes between images is to use some of the robust method. Chosen robust method for calculation transfrormation matrixes between images is described in section 8.2.

## 8.1 Matching points between images

Because the main problem in proposed super-resoution method is dealing with images containing rotation it is necessary to find an algorithm which is rotation-invariant. Well known rotation-invariant algorithm is Scale-invariant feature transform (SIFT) [24]. This algorithm can be used for detecting and describing local features in images. The big disadvantage of this algorithm is that it is patented. It means that this algorithm can not be used without an appropriate license.

Fortunately there is an algorithm which is partly inspired by the SIFT algorithm. This is the Speeded Up Robust Features (SURF) [26] algorithm. The advantages of SURF algorithm are that SURF is free for use, several times faster than SIFT and it is more robust against different image transformations than SIFT.

### 8.1.1 SURF algorithm

Information for describing SURF algorithm were taken from [7] and [4].

The surf algorithm is built on three basic building blocks. They are follows:

1. integral images,
2. Fast-Hessian detector,
3. and interest point descriptor

For the purpose of finding the matching points between images is important the second basic building block of the SURF algorithm. For this reason is this block described more in-depth in section 8.1.1. For the other blocks are described only their significant contribution to the SURF algorithm.

**The integral image** is computed very fast from an input image. This approach is particularly useful if input images have big dimensions because the computational time is independent of changes in size. SURF algorithm uses this feature to perform fast convolutions of varying size of filters.

**The interest point descriptor** describes how the pixel intensities are distributed within a scale dependent neighbourhood of each interest point detected by the Fast-Hessian detector. Integral images used in conjunction with filters known as Haar wavelets are used in order to increase robustness and decrease computation time. Haar wavelets are simple filters which can be used to find gradients in the horizontal and vertical directions.

#### Fast-Hessian detector

Fast-Hessian detector is based on the discriminant of the Hessian matrix. The value of the discriminant is used to classify the maxima and minima of the function by the second order derivative test. It is also possible to calculate the derivatives by convolution with an appropriate kernel. As a suitable filter's kernel is chosen the second order scale normalised Gaussian. Since the Gaussian filter is circularly symmetric is it possible rotation invariance of SURF algorithm.

In order to find extrema across all possible scales can be used the scale-space continuous function. The scale-space can be created by applying kernels of increasing size to the original image. This means that the original image is unchanged and varies only the filter size. This allows for multiple layers of the scale-space pyramid to be processed simultaneously and provides performance increase. In computer vision the scale-space is typically implemented as an image pyramid.

The task of accurate interest point localisation in the image can be divided into three steps:

1. the responses are thresholded such that all values below the predetermined threshold are removed,
2. after thresholding a non-maximal suppression is performed to find a set of candidate points,
3. the final step in localising the points involves interpolating the nearby data to find the location in both space and scale to sub-pixel accuracy.

### 8.1.2 Implementation of SURF algorithm

The implementation of SURF algorithm uses the OpenSURF library [3]. This library is also written in C++ programming language. This is the obvious advantage of OpenSurf library. The next advantage of this library is its linkage to the OpenCV library. There are some identical data types which leads to high time saving in implementation of different algorithms.

The whole process of finding the matching points between images is also straightforward. Just call two functions which are contained in above mentioned library.

Using the first of these functions - `surfDetDes()` - are calculated interesting points in the image. The parameters of this function are $octaves = 2$, $intervals = 4$, $init\_samples = 1$ and $thres = 1e-4$. These parameters were found empirically. Once are known the feature points in two images among which are searched matching points is called the function `getMatches()`. This function calculates the matching points between these images. The result of finding matching points between images is shown in Fig. 8.1.

Only one intervention into `getMatches()` function is needed. It is the expansion of function parameters for determining the match ratio for testing purposes.

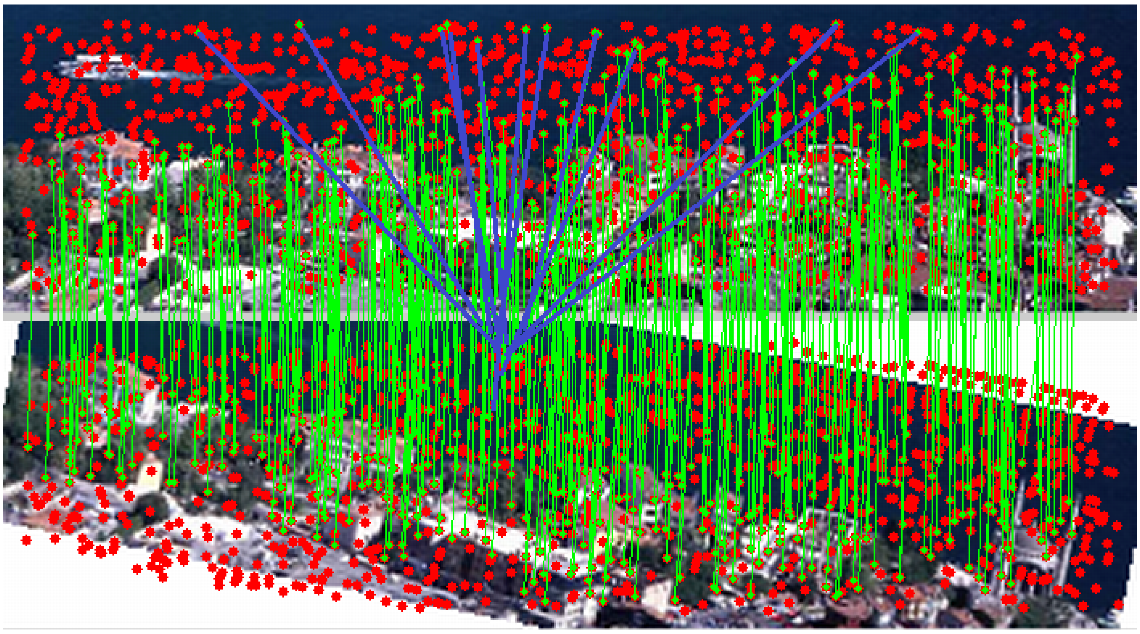


Figure 8.1: Matching points between two rotated images. Rotation angle is 11 degrees and the center of rotation is at the center of the image. Found 374 matching points between images. Found 1455 interesting points in the top image, 1345 interesting points in the bottom image. The blue line represents the incorrect matching points.

## 8.2 Computation of transformation matrixes and transformation of images

Transformation matrixes between images are computed by the same way as is described in section 6.2.2. There are used matching points between images to determine transformation matrix between images. Transformation matrix is computed using `cvFindHomography()` function from OpenCV library. Only one difference compared to previous technique is that the `cvFindHomography()` function use robust RANSAC algorithm when calculating transformation matrixes. This is done using of the parameter `CV_FM_RANSAC` in a function call. The RANSAC algorithm is described in section 8.2.1.

After calculating of transformation matrixes between images are these images transformed onto uniform high resolution grid of the reference image with high resolution. This approach is the same as the approach described in section 6.2.2 i.e. using `cvWarpPerspective()` function from OpenCV library.

### 8.2.1 RANSAC

As shown in Fig. 8.1 the SURF algorithm calculated matching points between images. However it is possible that this algorithm calculated bad matching points. These matching points are connected by a blue line in the figure. The green line represents correct matching points between images.

To eliminate the influence of poorly calculated matching points serves above mentioned algorithm RANSAC [22]. An abbreviation means Random Sample Consensus.

RANSAC is an iterative algorithm to estimate parameters of a model from a set of observed data (matching points between images). It produces a reasonable result only with a certain probability. This probability increasing as more iterations are allowed. A basic assumption is that the data consists of inliers, i.e., data whose distribution can be explained by some set of model parameters (points connected by green line), and outliers which are data that do not fit the model(points connected by blue line).

The principle of this algorithm can be summarized into following steps:

1. random choose of points that fit to the model,
2. points within some distance of model are considered as a hypothetical inlier (distance is represented by a threshold),
3. if sufficiently many points have been classified as hypothetical inliers the estimated model is reasonably good,
4. the model is reestimated from all hypothetical inliers,
5. the model is evaluated by estimating the error of the inliers relative to the model.

The greatest advantage of RANSAC is that it can estimate the parameters with a high degree of accuracy even when significant amount of outliers are present in the data set. A disadvantage of RANSAC is that the reasonable model can be produced by RANSAC only with a certain probability.

# Chapter 9

# Testing of improved super-resolution method

Testing of improved super-resolution method is also based on the comparison of visual quality of the results. There are used test data whose creation is described in section 7.1.

As in chapter 7 it is possible to divide the test data into two major groups. In section 9.1 are thus described tests on images which contain only translational motion.

The main reason for design of improved super-resolution method were unsatisfactory results of proposed super-resolution method for images that contain only rotation. The tests of improved super-resolution method for images that contain only rotation are described in section 9.2.

During the description of above mentioned tests can a reader find that the results of improved super-resoution method are in some cases worse than results of proposed super-resolution method . It is because the step of PSF computation and the step of deconvolution are designed for the proposed super-resolution method. In section 9.3 is described the reason why the step of PSF computation and step of deconvolution working incorrectly in some cases in connection with the improved super-resolution method.

There are summarized the results of improved super-resolution method in the section 9.4. These results are compared with results of proposed super-resolution method and results of comparisoun are briefly described.

## 9.1 Test data that contain only translation

Images used for testing are created by this way:

1. the reference input image represents a part of original image,
2. second input image is shifted by 5px left and by 2px up in comparison with the reference image,
3. third input image is shifted by 2px right and by 1px down in comparison with the reference image,
4. and the fourth input image is shifted by 3px left and by 3px up in comparison with the reference image

These images are then downsampled to half size of the original image. Fig. 9.1 shows images with which the program works.

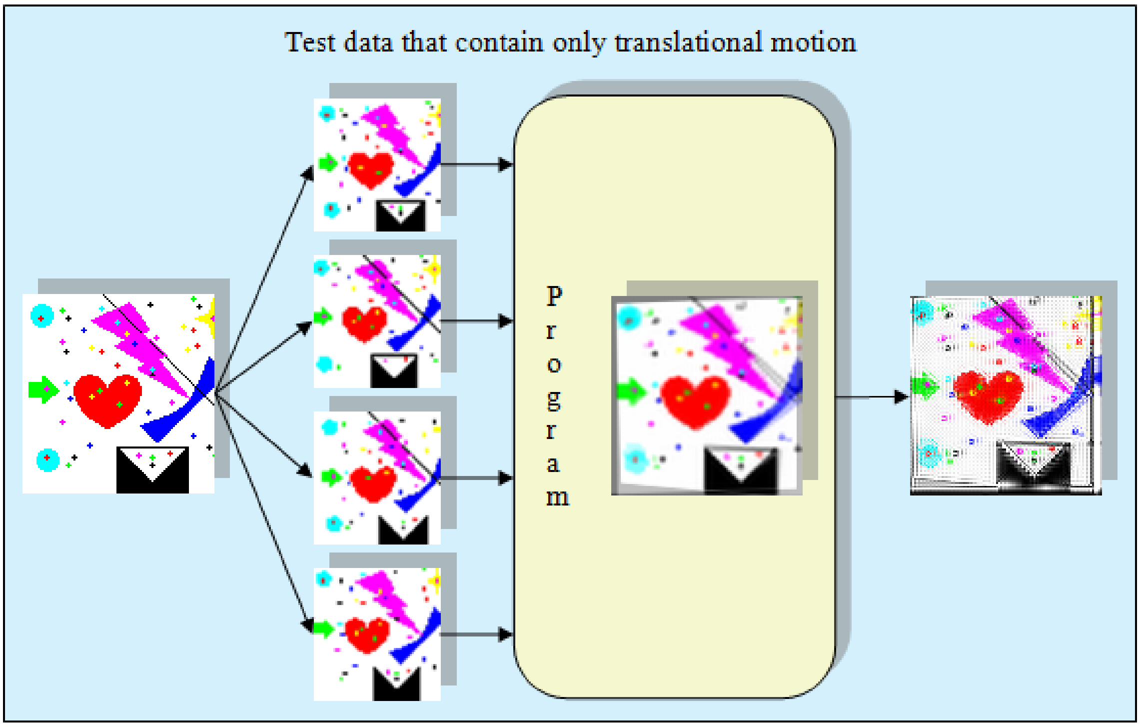



Figure 9.1: Test data that contain only translational motion. Original image with high resolution (left), input images into super-resolution method (middle), super-resolved image with high resolution before the step of inverse filtration (in program block) and the resulting image of improved super-resolution method (left).

## 9.2 Test data that contain only rotation

The main focus of improved super-resolution method is on images that contain rotation. In testing are used data which are created by following way:

1. the reference input image represents a part of original image,
2. second input image is the reference image rotated by 5 degrees,
3. third input image is the reference image rotated by 10 degrees,
4. and fourth input image is the reference image rotated by 15 degrees.

The center of rotation is in the middle of the reference image. These images are then downsampled to half size of the original image. Fig. 9.2 shows images with which the program works.

Improved super-resolution method is designed to avoid the rapid decrease of found matching points between images depending on the rotation of images. The graph in Fig. 9.3 shows dependence of found matching points in percentage on the rotation between images in degrees. From this graph it is apparent better functionality of improved super-resolution method in comparison to proposed super-resolution method for images containing the rotation.

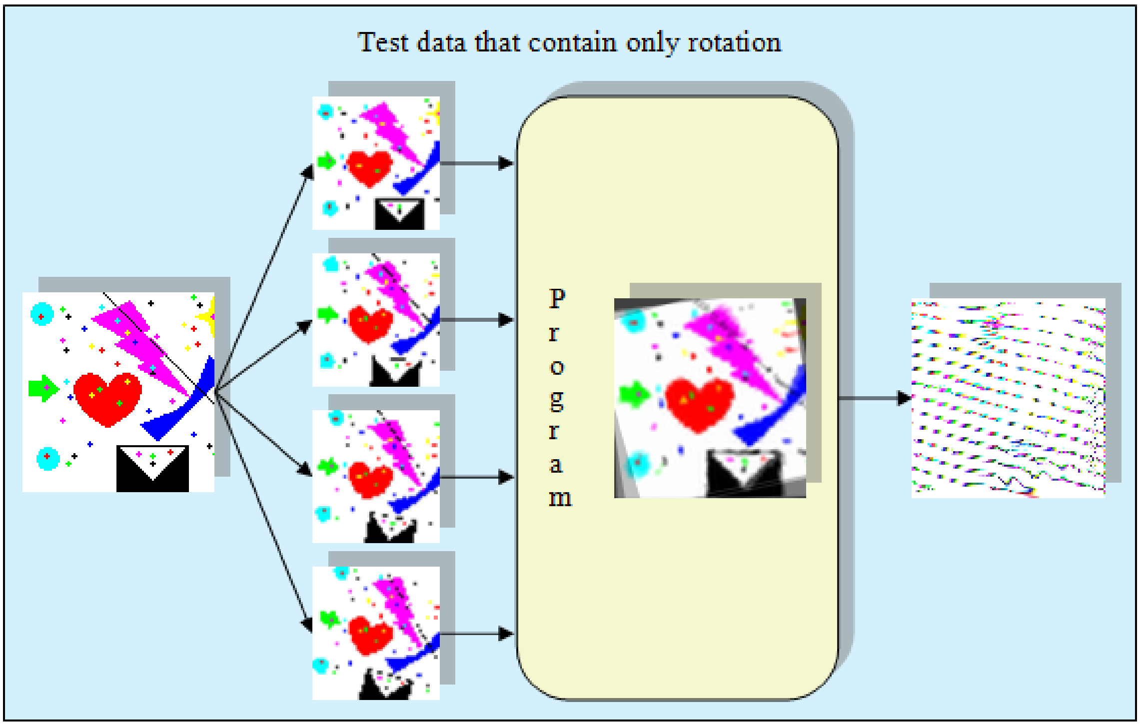



Figure 9.2: Test data that contain only rotation. Original image with high resolution (left), input images into super-resolution method (middle), super-resolved image with high resolution before the step of inverse filtration (in program block) and the resulting image of improved super-resolution method (left).

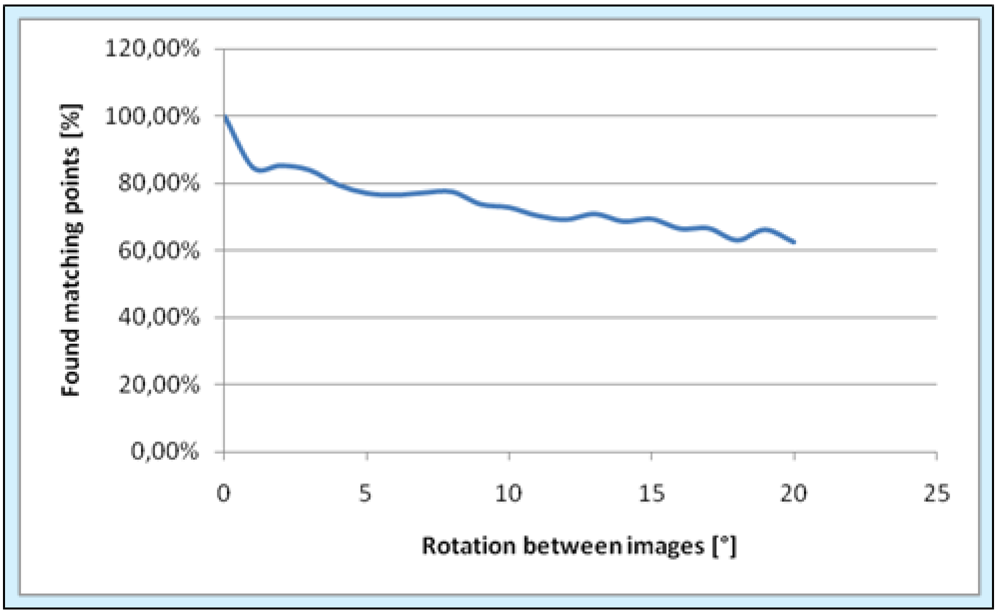



Figure 9.3: Dependence of found matching points on the rotation between images.

## 9.3 Testing of deconvolution and PSF computation

As it is described in section 6.2.5 the deconvolution is based on inverse filtering. It means that block of deconvolution computes the resulting image with high resolution using the image with high resolution which is affected by the errors incurred in the process of calculation and using the filter that represents the errors incurred in the process of calculation.

For correct calculation of the deconvolution is therefore crucial the computation of the PSF (inverse filter). The calculation described in section 6.2.4 is designed for proposed super-resolution method. For this reason works well for this method. For improved super-resolution method this calculation works also well in most situations.

There are two exceptions which can cause wrong computation of the inverse filter kernel and then wrong computation of the whole resulting image. The first of them is caused by using of robust methods for computation matching points between images 8.1 and transformation matrixes between images 8.2. Using of robust methods in these calculations may mean the use of incorrect points for computation of the inverse filter kernel. The incorrect points are points which are called outliers in terminology linked with robust methods. Outliers can cause the occurrence of multiple peaks in the inverse filter kernel. The inverse filtering algorithm described in section 6.2.5 is unable to work correctly with inverse filter kernels that contain multiple peaks.

The second exception may be in general caused by inaccurate calculations of the transformation matrixes between images. This has got the consequence that the resulting inverse filter kernel is flat. Kernel of flat inverse filter then influences relatively large part of the image and for this reason the inverse filtration has visually worse results.

In Fig. 9.4 are shown the kernel of sharp filter and the kernel of flat filter. It is clear that the kernel of flat filter has the amplitude twice bigger than the kernel of sharp filter. Both kernels have the size of 5x5 pixels.

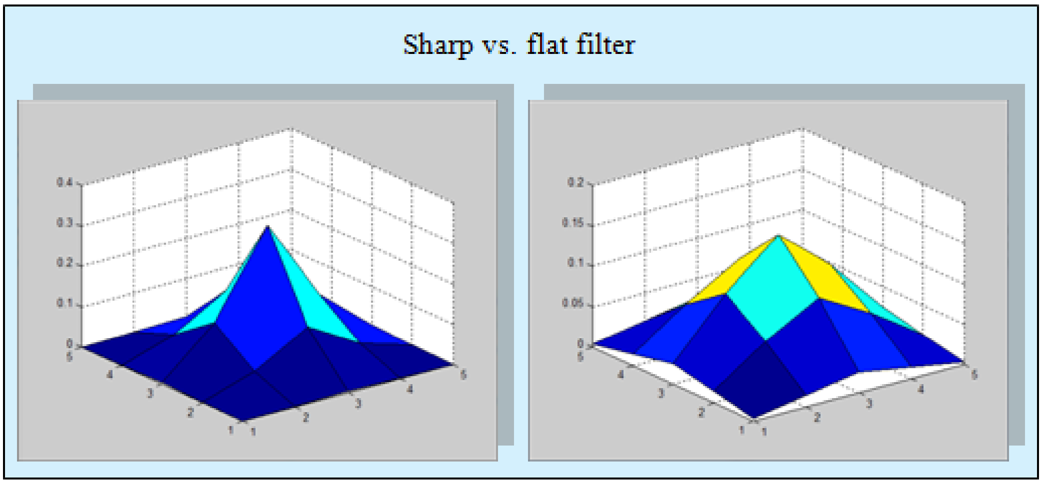



Figure 9.4: Kernel of sharp filter(left) and the kernel of flat filter(right).

In Fig. 9.5 are shown three types of filters. The first filter is sharp which means that is good for image filtering generaly. The second filter is flat which means that influences relatively large part of the image. It is not well suited in image processing applications. And the third filter contain multiple peaks which means that this filter is unusable in inverse filtering. There are also shown examples of images which are convolved and then deconvolved using the above mentioned filter's kernels.

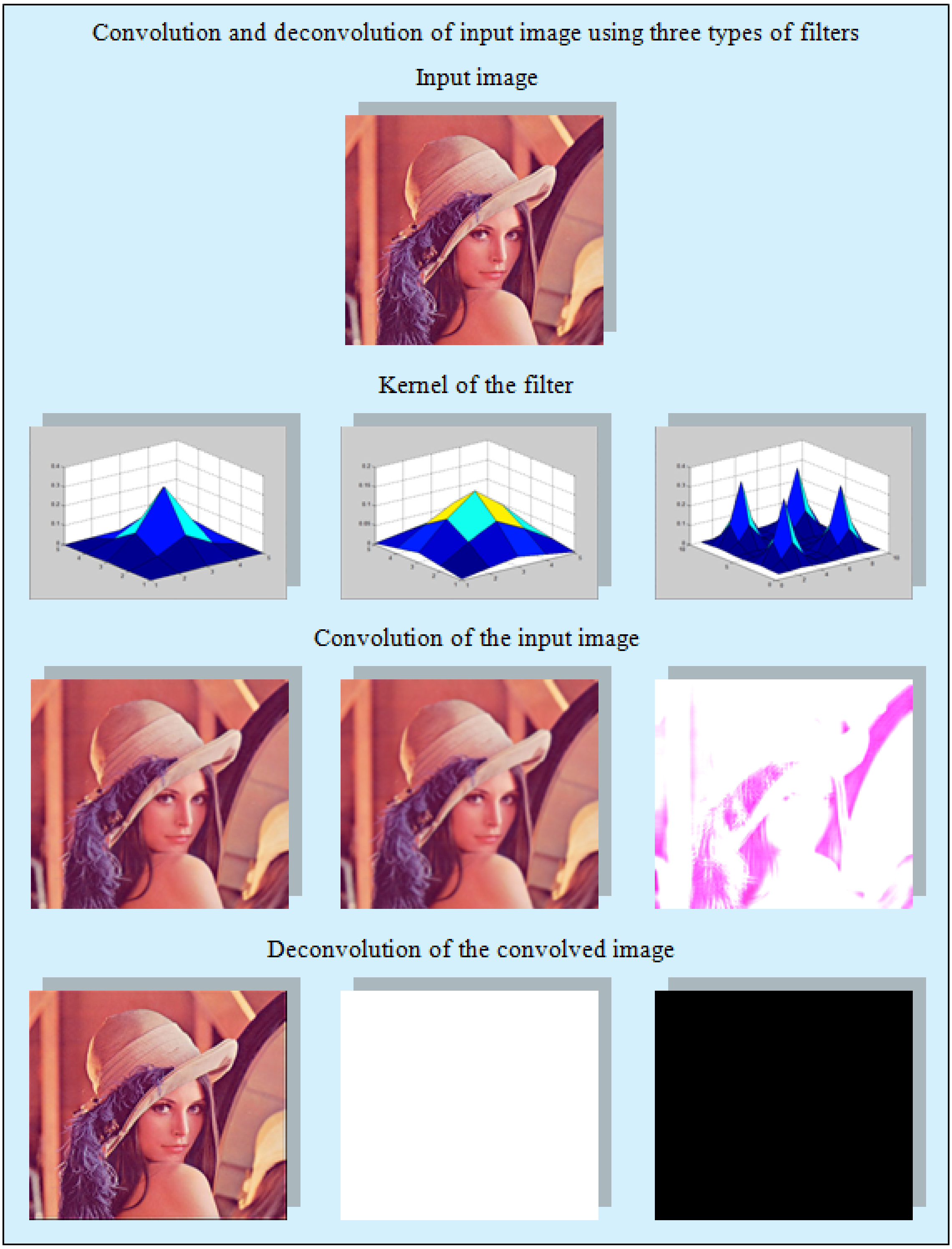



Figure 9.5: Convolution and deconvolution of images using sharp filter(left), flat filter(middle) and filter with multiple peaks(right).

## 9.4 Conclusion of testing

For comparison of proposed and improved super-resolution methods it is useful to show the results of these methods. These results are shown in Fig. 9.6. In the figure are shown as images with high resolution corrupted by errors incurred in calculating (i.e. resulting images of block of merging images 6.2.3) so resulting images of the whole super-resolution method. It is because the block of PSF computation 6.2.4 is not designed for improved super-resolution method and can cause worse results in some cases described in section 9.3.

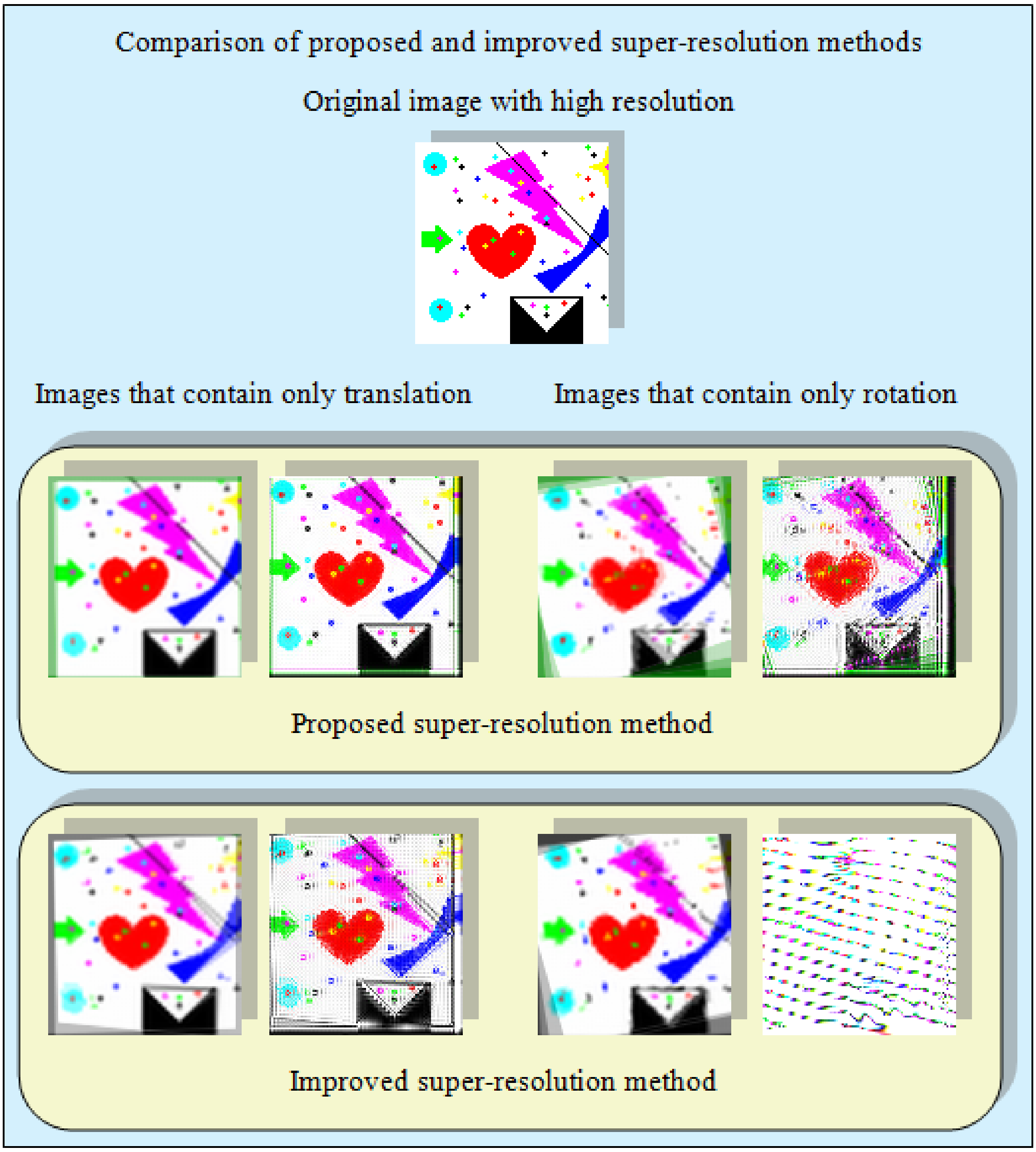



Figure 9.6: Comparison of proposed and improved super-resolution methods.

As shown in Fig. 9.6 the improved super-resolution method has better visual results for images that contain rotation. It is apparent particularly from images with high resolution corrupted by errors incurred in process of calculating. The kernel of inverse filter calculated in PSF computation step is flat and therefore the results of whole method are unsatisfactory. For this reason is proposed robust method for PSF computation in conclusion of this thesis.

As it is described in section 7 the proposed super-resolution method has got very good results for input images with low resolution which contain only translational motion. For images with low resolution which contain only rotation of the original image are the results satisfactory only for a limited range of image rotation. It is caused by using Lucas-Kanade algorithm 6.2.2 for finding corresponding points between images. After reaching a certain threshold of rotation between images provides this algorithm unsatisfactory results. The graph in Fig. 7.4 shows dependence of found matching points on the rotation between images for Lucas-Kanade algorithm.

The main task of improved super-resolution method is thus better results for images that contain rotation. The method is based on finding matching points using SURF algorithm and calculation of transformation matrixes using RANSAC algorithm. Both of these algorithms are robust.

The main advantage of improved super-resolution method is that the SURF algorithm is rotation invariant. This implies better ability to calculate matching points between images which contain rotation. The graph in Fig. 9.3 shows the dependence of found matching points on the rotation between images. Success rate in images which contain only rotation is much higher than for the proposed super-resolution method.

The main disadvantage of improved super-resolution method are in some cases worse results in calculating of the kernel of inverse filter. This is caused by outliers which may influence the result of each robust method.

Tests presented directly in this thesis serves to create ideas about results of proposed and improved super-resolution methods. In order to save space in this thesis are all tests included only in electronic form on the enclosed storage media. Next advantage of electronic form of tests is that the images are in full resolution and also it is simpler to work with this type of testing data.

# Chapter 10

# Conclusion

Different approaches for super-resolution of the images are presented in the theoretical part of this thesis. These approaches are briefly described and compared according to the optimal criteria.

The practical part of this thesis deals with design of super-resolution methods. The block diagram of proposed super-resolution method is shown firstly and then is described the internal functionality of each block. The entire calculation process is shown in the figure for a better idea of the calculations which are carried out within the implementation.

Testing of proposed super-resoloution method showed very good results of this method for input images with low resolution which contain only translational motion. However for input images with low resolution which contain rotation has got the proposed super-resolution method unsatisfactory results. This is caused by computation of corresponding points between images. Neither the subsequent step of calculating the transformation matrixes is not the best.

For this reason the improved super-resolution method is designed. This method uses for determining of matching points between images and transformation matrixes between images the computation based on the robust methods.

Testing of improved super-resoloution method show better results for input images with low resolution that contain rotation. Especially the merged image (resulting image of the block of merging images) is much more better than merged image of proposed super-resolution method.

The biggest disadvantage of improved super-resolution method is the calculation of resulting image from the merged image. The method uses the same technique as the proposed super-resolution method for this calculation. This is not the best approach.

The mutual comparison of both super-resolution methods has got the following result. The proposed super-resolution method is better for input images with low resolution that contain only translational motion between images. The computation time is also better. On the other hand the improved super-resolution method has got higher computational demands but it is rotation invariant.

For future work with improved super-resolution method it would be appropriate to involve some kind of robust method for estimating PSF. A very promising technique for PSF estimation seems to be the method described in [11].

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