Regularized selection: a new paradigm for inverse based regularized image reconstruction techniques

F. Kucharczak, C. Mory, O. Strauss, F. Comby, D. Mariano-Goulart

ICIP 2017

Summary

1. Contextualization
2. Non-additive imprecise Super-Resolution (SR) method
3. The proposed regularization method
4. Conclusion

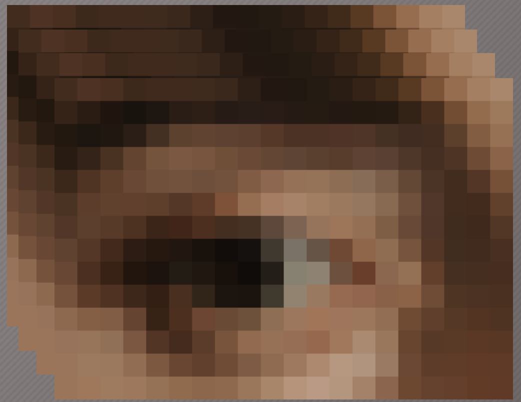
1. Contextualization

Single-image vs. Multi-image SR

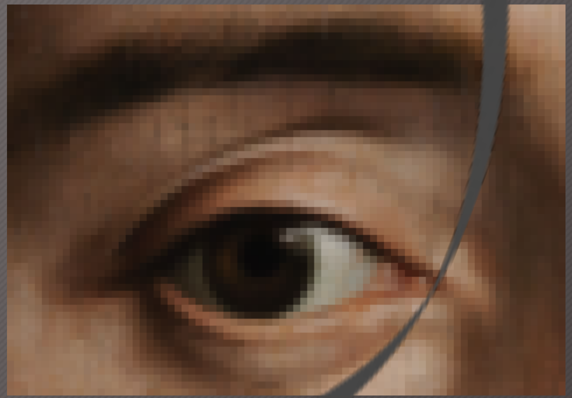
Single-image SR

Correspondance between
LR and HR patches

Multi-image SR



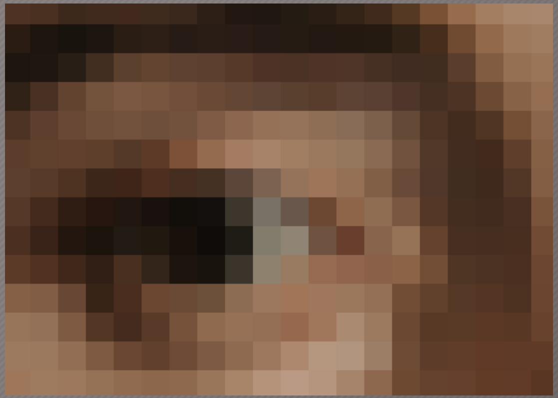
Stack of Low Resolution
(LR) Images



1. Contextualization

What is Super-Resolution (SR)?

Multiple low resolution images of the same scene acquired with sub-pixel shifts

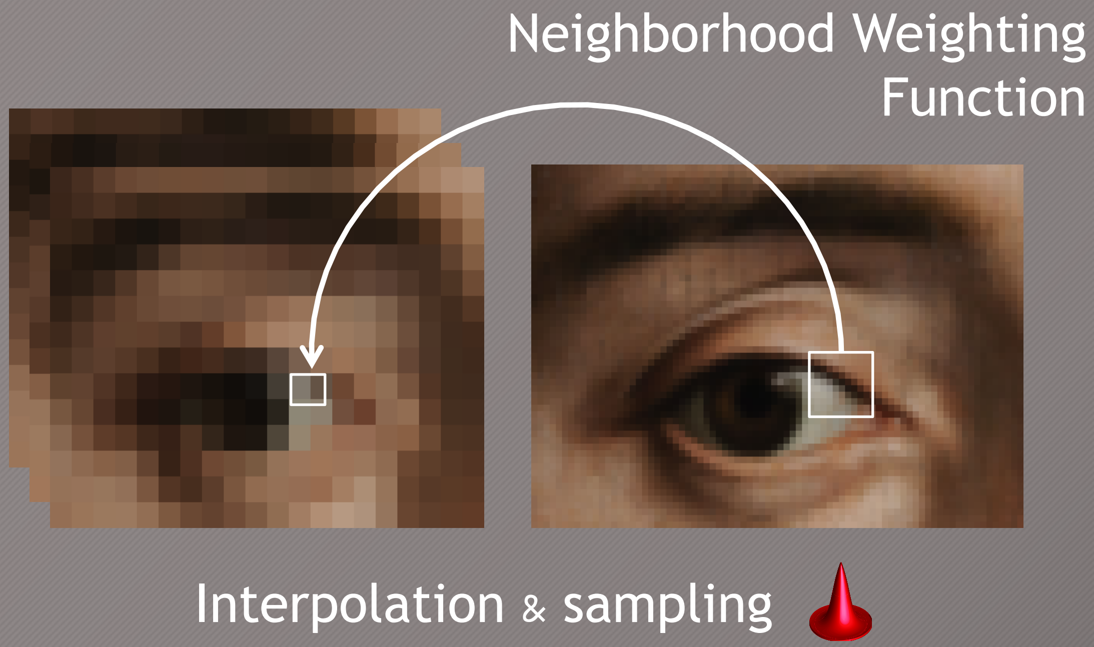


SR

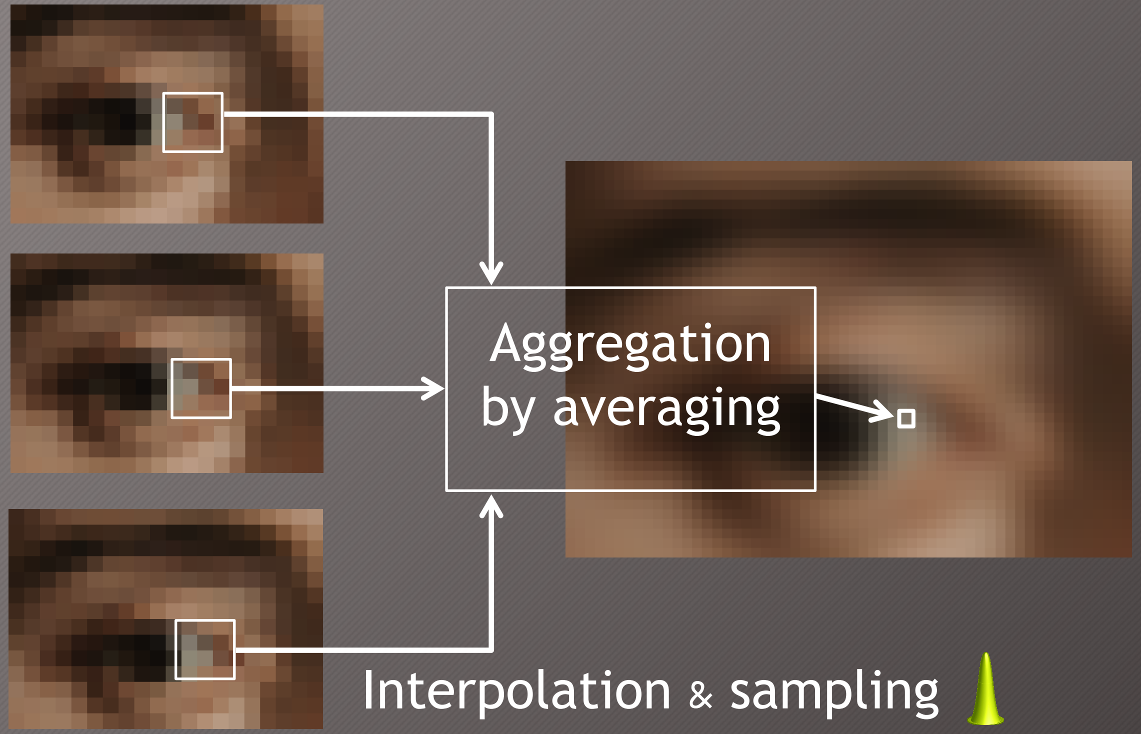
2. Non-additive imprecise SR method

Choice of the Impulse Response and imprecision

Projection

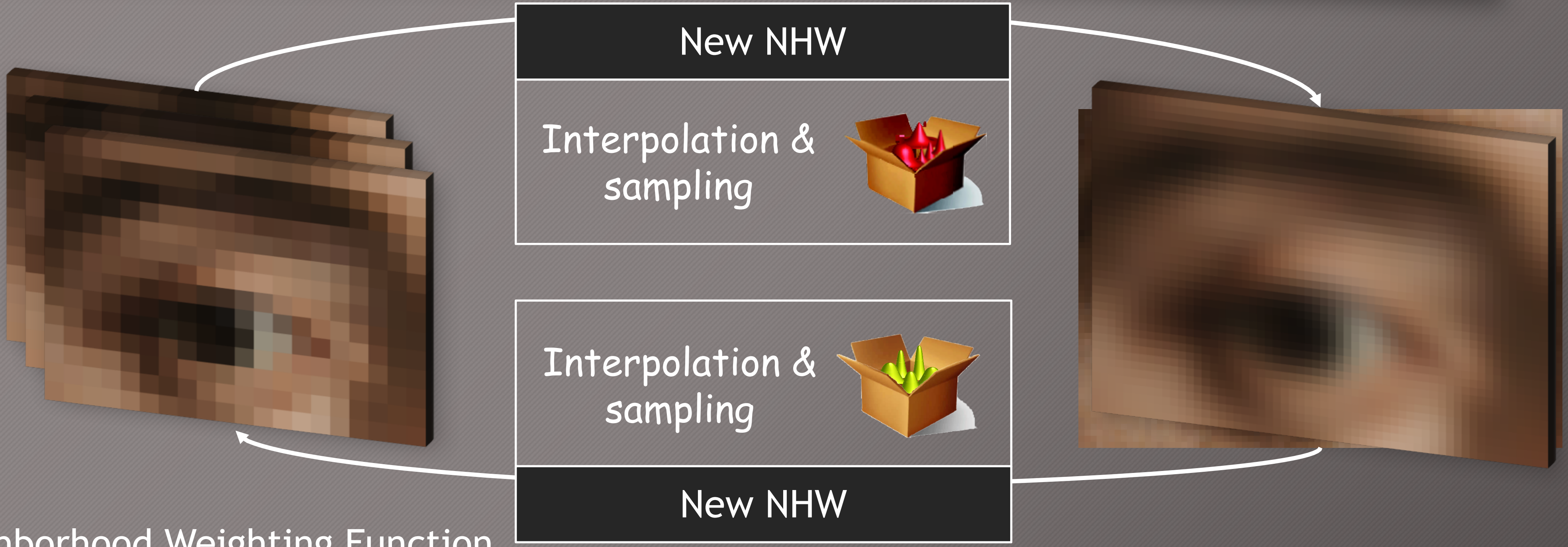


Back-projection



2. Non-additive imprecise SR method

Convex set of « acceptable » reconstructed images



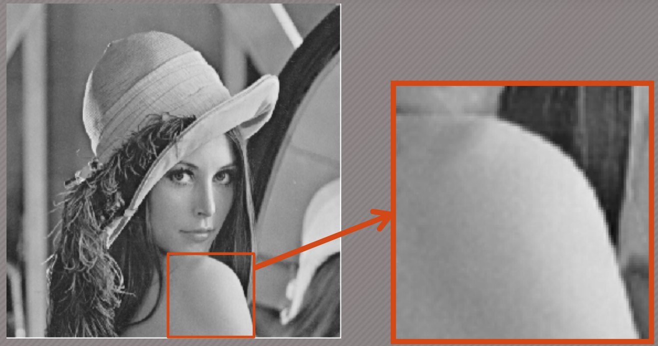
NWH : Neighborhood Weighting Function

F. Graba, F. Comby, O. Strauss, Non-additive imprecise image Super-Resolution. ICIP 2014: 3882-3886

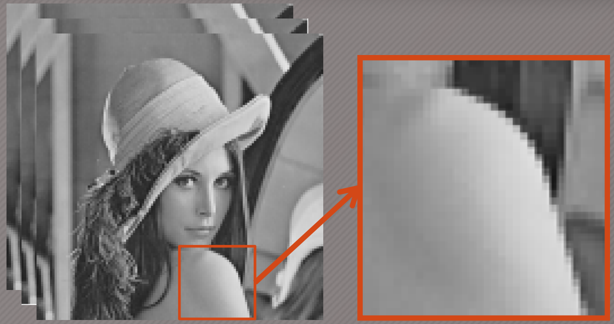
F. Graba, F. Comby, O. Strauss, Non-Additive Imprecise Image Super-Resolution in a Semi-Blind Context. IEEE Trans. Image Processing: 1379-1392 (2017)

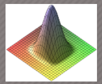
2. Non-additive imprecise SR method

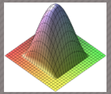
Illustration

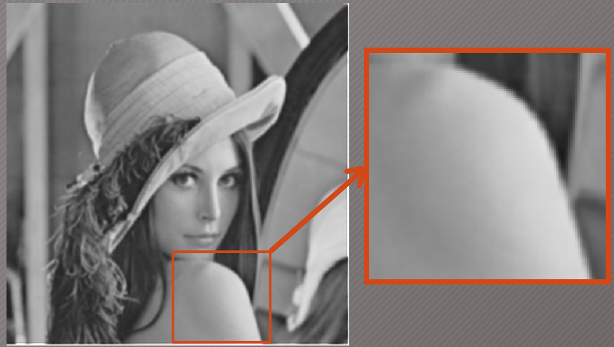


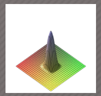
Original image



LR sequence generated with 

Reconstruction with 



Reconstruction with 

INF

SUP

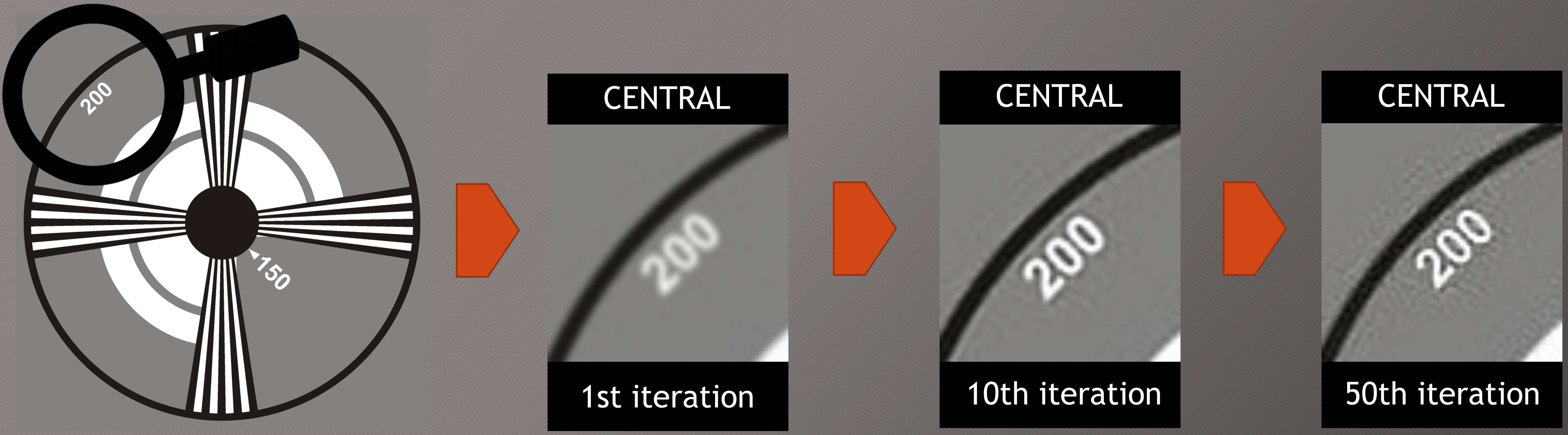
CENTRAL

Reconstruction with the interval-based algorithm of Graba et al. (2017)

3. Regularized selection (RS)

Why?

Until now, the presented method is regularized by early stop of the iterations



3. Regularized selection

How to regularize such an algorithm?

- Implicit regularization → ✗ Not sufficient (cf. last slide)
- Post-smoothing → ✗ Too much content dependent
  Doesn't preserve edges
- Integrated regularization
  Balance of the data fitting term and regularization term → ✗ Would modify the bounds
  Not coherent with the construction of the algorithm
- Think different → ✓

3. Regularized selection

Our proposition

A two step regularization process:

1 Convex-set of acceptable reconstructed HR images.
Graba et al. (2017)

2 Selection of the image that best fits a defined regularization criterion
Presented paper

2 Minimization of a regularization function (Total variation or L_2 norm of the gradient for example) under the constraint of inclusion inside of the reconstructed intervals.

Use of the Chambolle and Pock (2010) algorithm.

3. Regularized selection

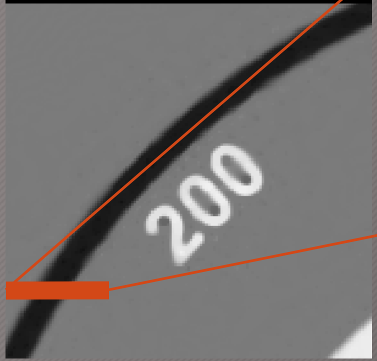
An iterative process - illustration

INF

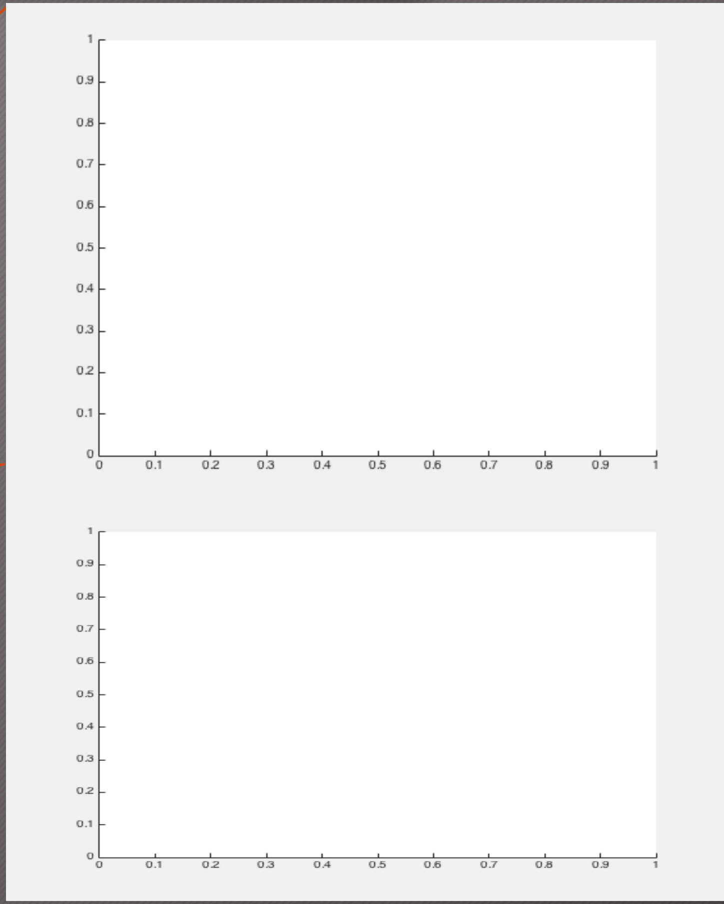
SUP

CENTRAL

RS - TV



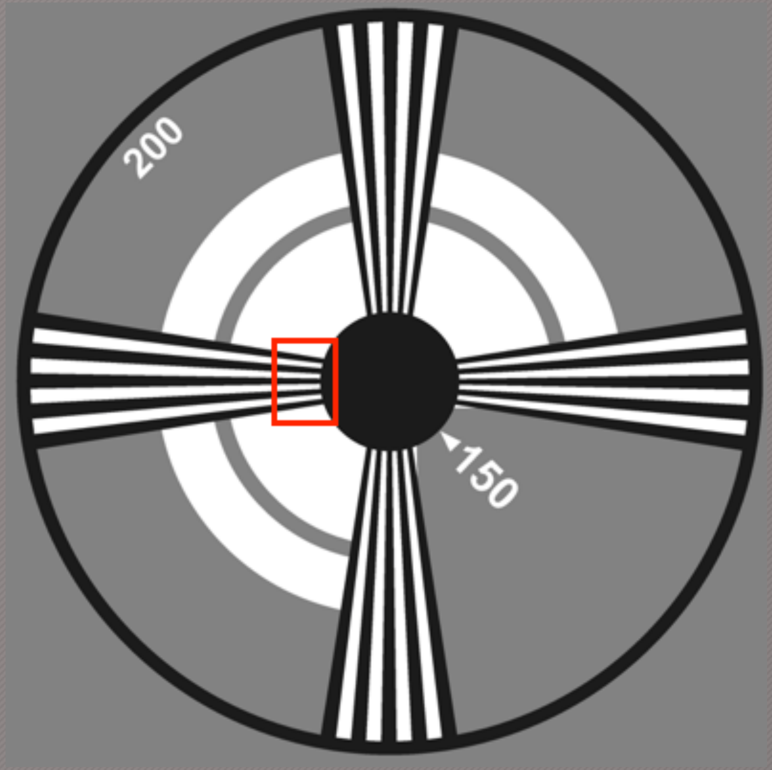
Profile of the orange line through iterations

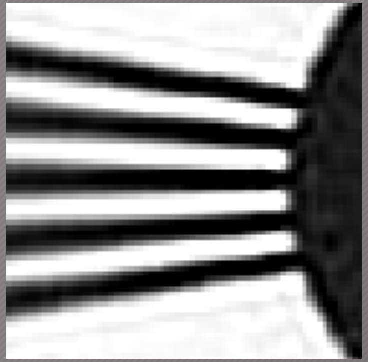


Convergency of the algorithm

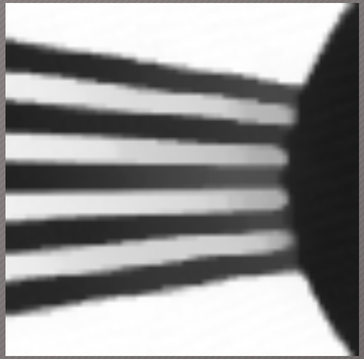
3. Regularized selection

Quantitative results on simulated data

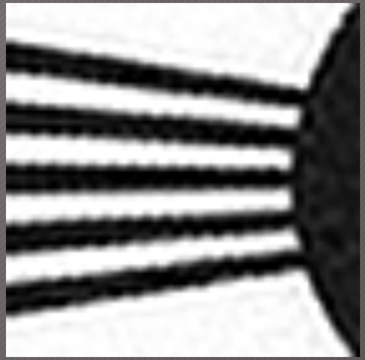




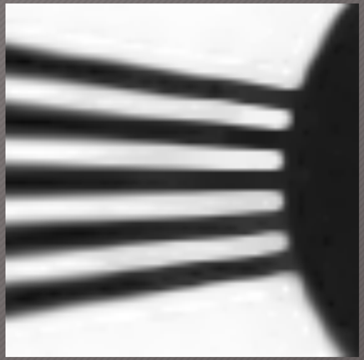
Central image



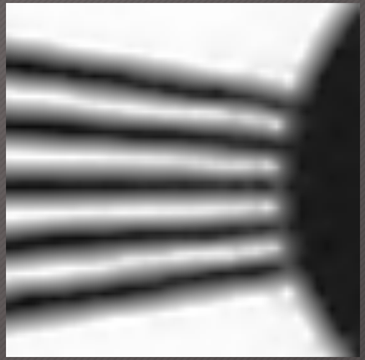
IBP L_1- PSNR: 19.6



IBP L_2- PSNR: 17.9



RS L_1- PSNR: 20.7



RS L_2- PSNR: 19.1

3. Regularized selection

A « data-content » independent method

IBP L_1 with a regularization term ponderation preserving details

3. Regularized selection

A « data-content » independent method

IBP L_1 with a regularization term ponderation smoothing uniform regions

3. Regularized selection

A « data-content » independent method

RS - L_1 independent of data-content : - smooth uniform regions

- preserve edges and details

3. Regularized selection

A « data-content » independent method

IBP L_1 - β_1

IBP L_1 - β_2

RS TV – without regularization parameter

4. Conclusion

<u>In this paper, we presented:</u>

- A new regularization paradigm based on
  - 1) a two step reconstruction : construction of a convex-set of acceptable HR images.
  - 2) selection of the image, in this set that best fits a pre-defined regularization criterion.
- A coherent regularization method for interval-based inverse problems.
- A regularization weighting parameter free method, content-independent.
- A scalable method, that can be used with plenty of different regularization criteria.

REGULARIZED SELECTION: A NEW PARADIGM FOR INVERSE BASED REGULARIZED IMAGE RECONSTRUCTION TECHNIQUES

Florentin Kucharczak[12], *Cyril Mory*[23], *Olivier Strauss*[2], *Frederic Comby*[2], *Denis Mariano-Goulart*[4]

[1]Siemens Healthineers
[2]LIRMM, Montpellier University/ CNRS, France
[3]Creatis, Univ. Lyon/ UMR 5220, France
[4]CHRU Lapeyronie, Montpellier University, France

ABSTRACT

In this paper, we present a new regularization paradigm for inverse based regularized image reconstruction techniques. These methods usually attempt to minimize a cost function expressed as the sum of a data-fitting term and a regularization term. The trade-off between both terms is determined by a weighting parameter that has to be set by the user since this trade-off is data dependent. In the approach we present here, we first concentrate on finding a set of eligible candidates for the data fitting term minimization and then select the most appropriate candidate according to the regularization criterion. The main advantage of this method is that it does not require any weighting parameter, and guarantees that no over-regularization can occur. We illustrate this method with a super-resolution reconstruction technique to show its efficiency compared to other competitive methods. Comparisons are carried out with simulated and real data.

Index Terms— Regularization, inverse problems, interval-based methods, imprecise modeling, super-resolution.

1. INTRODUCTION

In the traditional approach, inverse based regularized reconstruction techniques consist in minimizing a criterion ϵ of the form:

$$\epsilon(\mathbf{X}) = \epsilon_1(\mathbf{H}(\mathbf{X}, \mathbf{Y})) + \beta.\epsilon_2(\mathbf{X}), \quad (1)$$

that gathers a data-fitting term ϵ_1, that expresses how the output image $\mathbf{X}$ is linked to the input measurements $\mathbf{Y}$ via the observation model $\mathbf{H}$, and a regularization term ϵ_2 that aims at discarding inappropriate solutions, preventing over-fitting. Those two terms have to be balanced thanks to a parameter β used to control the regularization level of the solution. Once a post-regularization (i.e. a smoothing of the obtained image) rather than minimizing a regularized criterion. All these methods have in common that setting their regularization parameter (β or iteration number) is difficult and image content dependent.

In this paper, we propose an innovative solution to the problem of balancing data-fitting and regularization, which we call ”regularized selection”. We propose to first select a convex set of images that fully satisfy the first criterion ϵ_1, and then to select, in this convex set, the image that minimizes the regularization criterion ϵ_2.

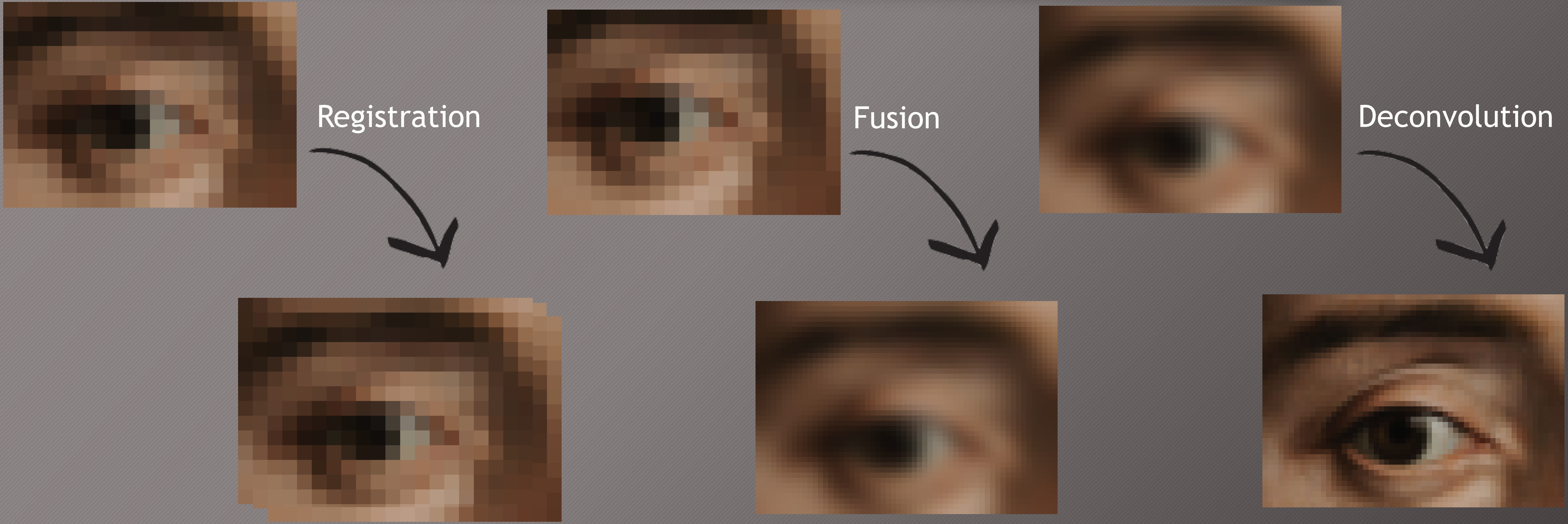
This method is based on previous works that consider more deeply the fitting term $\mathbf{H}$. In fact, digital signal-image processing usually relies on an underlying real-valued continuous model, while the processing is achieved by an algorithm working in the digital space, i.e. an integer-valued discrete space. This kind of methods make extensive use of kernels to ensure the interplay between continuous and discrete space. The choice of a particular kernel (e.g. bicubic) can have a major effect especially in inverse based image processing reconstruction techniques. In the last decade, a new generic approach has been proposed in the literature to lower the impact of the discrete-to-continuous interplay modeling in image processing (e.g. [4] in tomography, [5] in image upsampling, [6] in low-pass filtering or [7] in super resolution reconstruction). This approach mainly consists in modeling scant knowledge of the appropriate discrete to continuous interplay by using a non-additive neighborhood function [8] that models a convex set of conventional methods. Due to this modeling, the resulting image is interval-valued, i.e. each pixel value is a real interval. After convergence, this interval-valued image represents the convex set of images that satisfy the first criterion. Until now, the center image has been used to gather the information of the

Thank you for your attention

Any questions ?

1. Contextualization

3 main operations



1. Contextualization

Optimization approach

Observation model:

$$\boxed{\mathbf{Y}^{\mathrm{k}} = \mathrm{DHW}^{\mathrm{k}}\mathbf{X} + \mathbf{B}^{\mathrm{k}}}$$

Decimation

Impulse Response Effect

Motion

Noise

$$\boxed{\mathbf{Y}^{\mathrm{k}} = A^{\mathrm{k}}\mathbf{X} + \mathbf{B}^{\mathrm{k}}} \quad A^{\mathrm{k}} = \mathrm{DHW}^{\mathrm{k}}$$

Objective of SR: Find $\mathbf{X}$ knowing Y and A

Definition of an objective function:

$$\epsilon(\mathbf{X}) = \epsilon_1\big(H(\mathbf{X}, \boldsymbol{Y})\big) + \beta\epsilon_2(\mathbf{X})$$

Data-fitting term

Regularization weight

Regularization term

We want to find: $\boxed{\widehat{\mathbf{X}} = \underset{\mathbf{X}}{\operatorname{argmin}}\big(\epsilon(\mathbf{X})\big)}$

3. Regularized selection

A new paradigm for inverse based regularized techniques

Main families of methods for regularization:

- Early stop of an un-regularized reconstruction process.
- Post-smoothing as regularization.
- Use of a regularization function ϵ_2:

$$\epsilon(\mathbf{X}) = \epsilon_1(H(\mathbf{X}, Y)) + \beta\epsilon_2(\mathbf{X})$$

Examples :

$\epsilon_2(\mathbf{X}) = \|\nabla\mathbf{X}\|_1$, ∇: gradient operator

$\epsilon_2(\mathbf{X}) = \|\nabla\mathbf{X}\|_2^2$,

Main drawbacks of these methods:

Regularization parameter (β or number iteration) difficult to set and image content dependant.

New paradigm: Regularized selection, a two step reconstruction process :

1. Reconstruction of a convex set of images that fully satisfy the first criterion ϵ_1.
2. Select, in this convex set, the image that minimizes the regularization criterion ϵ_2.