ICCV 2013 Supplementary Material
Super-resolution via Transform-invariant Group-sparse Regularization

October 4, 2013

1 Contents

This is the supplementary material for the paper *Super-resolution via Transform-invariant Group-sparse Regularization*. It contains the following experimental results that were not included in the main paper due to lack of space.

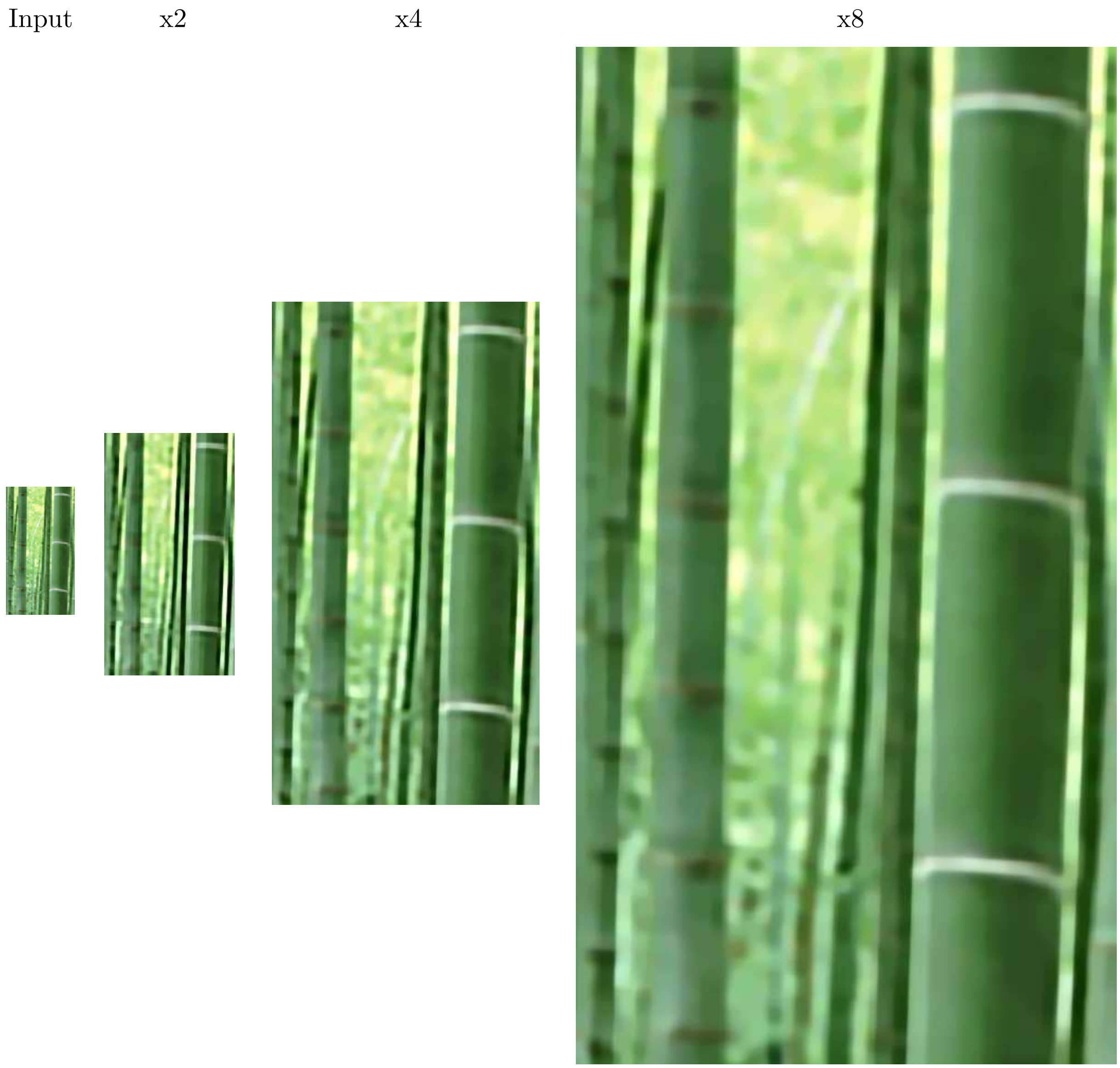
1. Comparisons between the proposed method, transform-invariant directional total-variation regularization abbreviated as TI-DTV, and three other methods: bicubic interpolation, total-variation regularization (TV) and sparse coding [16] for six additional examples taken from the SUN database [15].
2. Comparisons between the proposed method and the three methods mentioned above for the text examples shown in Figure 11 of the paper.
3. Results illustrating the effect of varying the different parameters in the proposed method.

2 Additional examples

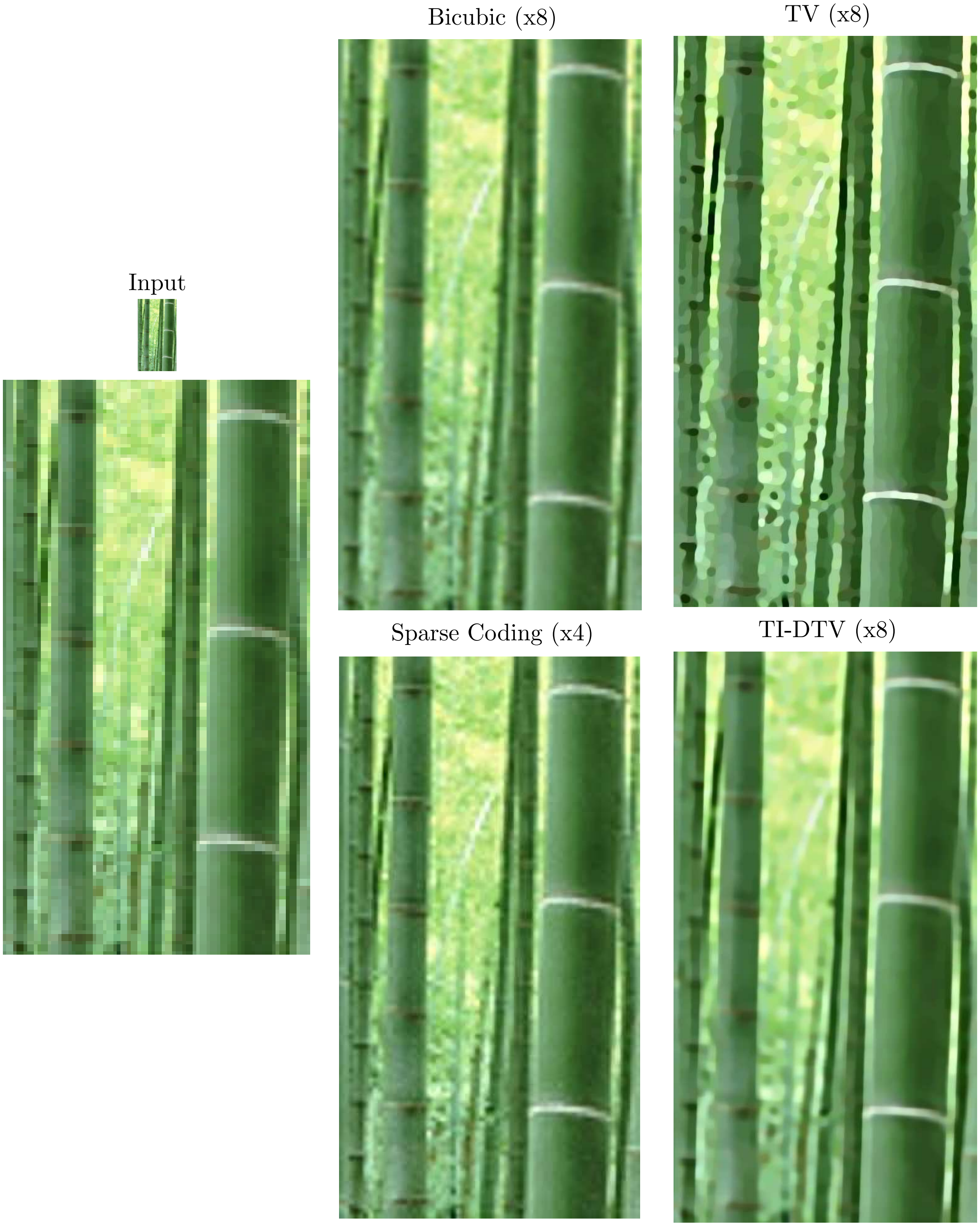
For six examples taken from the SUN database [15] we show comparisons to our method with bicubic interpolation, total-variation regularization (TV) and sparse coding [16]. The upsampling factor is eight for all examples, except the first figure for Example 1 and the results for the sparse-coding method because the available code only allows to use an upsampling factor of 4. The results seem to confirm that transform-invariant directional total-variation regularization is very effective in super-resolving edges at high upsampling factors without introducing additional artifacts. In comparison, bicubic interpolation produces overly smooth images, total variation generates artifacts that distort straight edges and the results of sparse coding are only slightly better than those of bicubic interpolation, although this method hallucinates some fine-scale random textures more effectively than the others (this is apparent in the foliage of Example 1).

2.1 Example 1: Bamboo forest

In the first figure for this example we show the result of super-resolving the image with our method for different upsampling factors. In the second we show comparisons to the other algorithms.



Super-resolution at different upsampling factors using TI-DTV regularization.

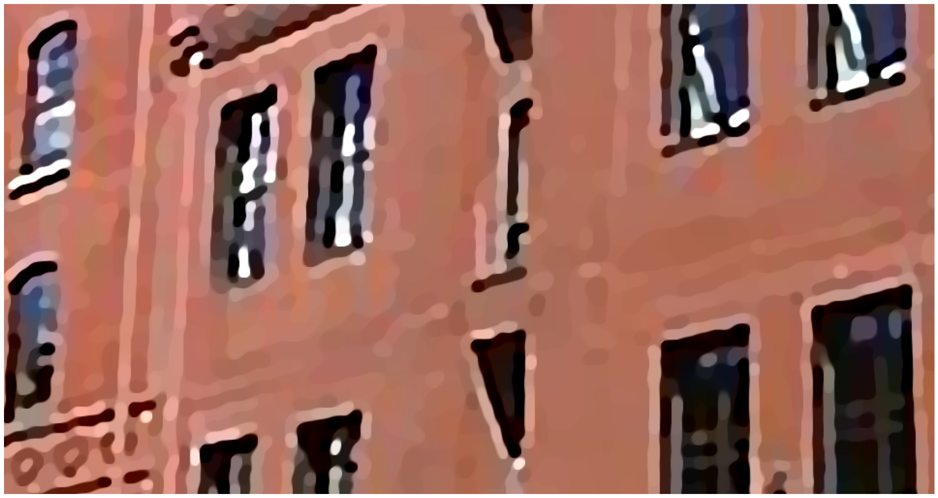

Input
Bicubic (x8)
TV (x8)
Sparse Coding (x4)
TI-DTV (x8)

2.2 Example 2: Building façade

Original

Bicubic (x8)

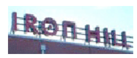
TV (x8)



Sparse Coding
(x4)

TI-DTV (x8)

2.3 Example 3: Sign



Original

Bicubic (x8)

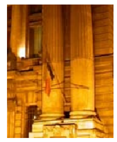
TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

2.4 Example 3: Palace façade

Original



Bicubic (x8)

TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

2.5 Example 4: Church façade

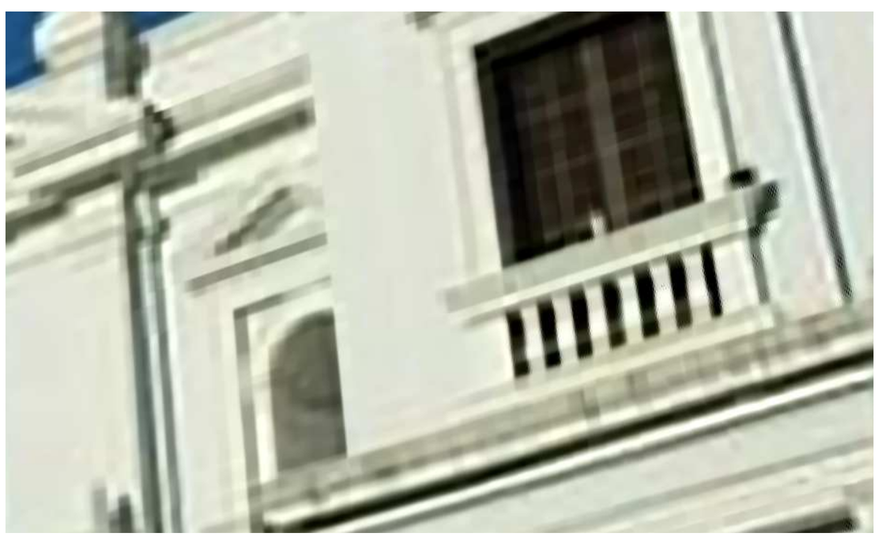
Original

Bicubic (x8)

TV (x8)

Sparse Coding (x4)

TI-DTV (x8)



2.6 Example 5: Columns

Original

Bicubic (x8)

TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

2.7 Example 6: Airport screens

Original

Bicubic (x8)

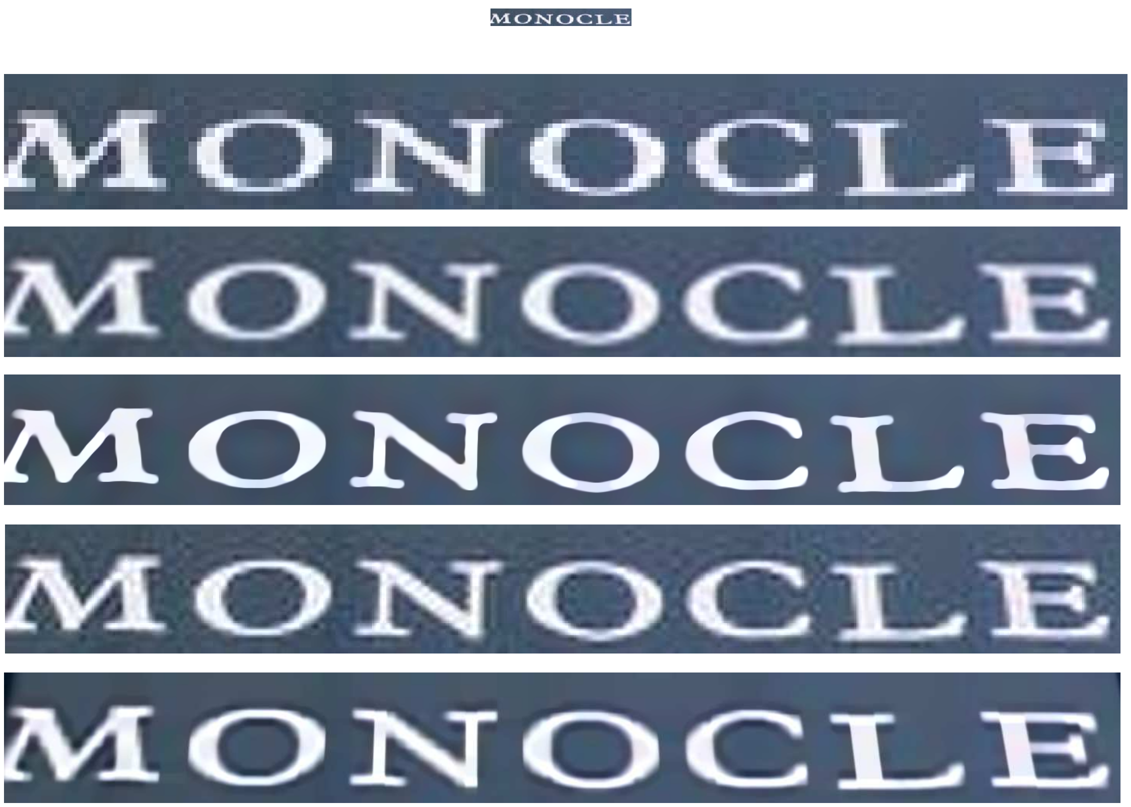
TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

3 Text examples: Comparison with other methods

For the four examples in Figure 11 of the paper we show comparisons to our method with bicubic interpolation, total-variation regularization (TV) and sparse coding [16]. TI-DTV and TV regularization produce significantly sharper results than bicubic interpolation and sparse coding. For letters with mostly horizontal and vertical strokes TI-DTV regularization is superior to TV regularization, since the latter generates some artifacts. For other letters, the performance between the two algorithms is similar.



Original

Bicubic (x8)

TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

Original

Bicubic (x8)

TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

Original

Bicubic (x8)

TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

Original

Bicubic (x8)

TV (x8)

Sparse Coding (x4)

TI-DTV (x8)

4 Sensitivity to Regularization Parameters

4.1 Parameter λ

We show the results of applying TI-DTV regularization to the first example in Figure 12 of the paper for differents values of λ but fixing $\sigma = 5.5$ and $\beta = 0.1$. Additionally, we also show the results after being rectified by the transformation learnt by TILT from the low-resolution data. When λ is small the result tends to be more blurred and similar to the original data. When λ is large the result does not correspond well to the data and some details may be suppressed. Finally, for values of λ around three, which was the value used for almost all examples in the paper and the supplementary material, the results are very stable.

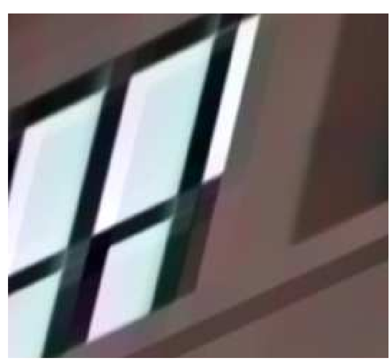
$\lambda = 0.1$

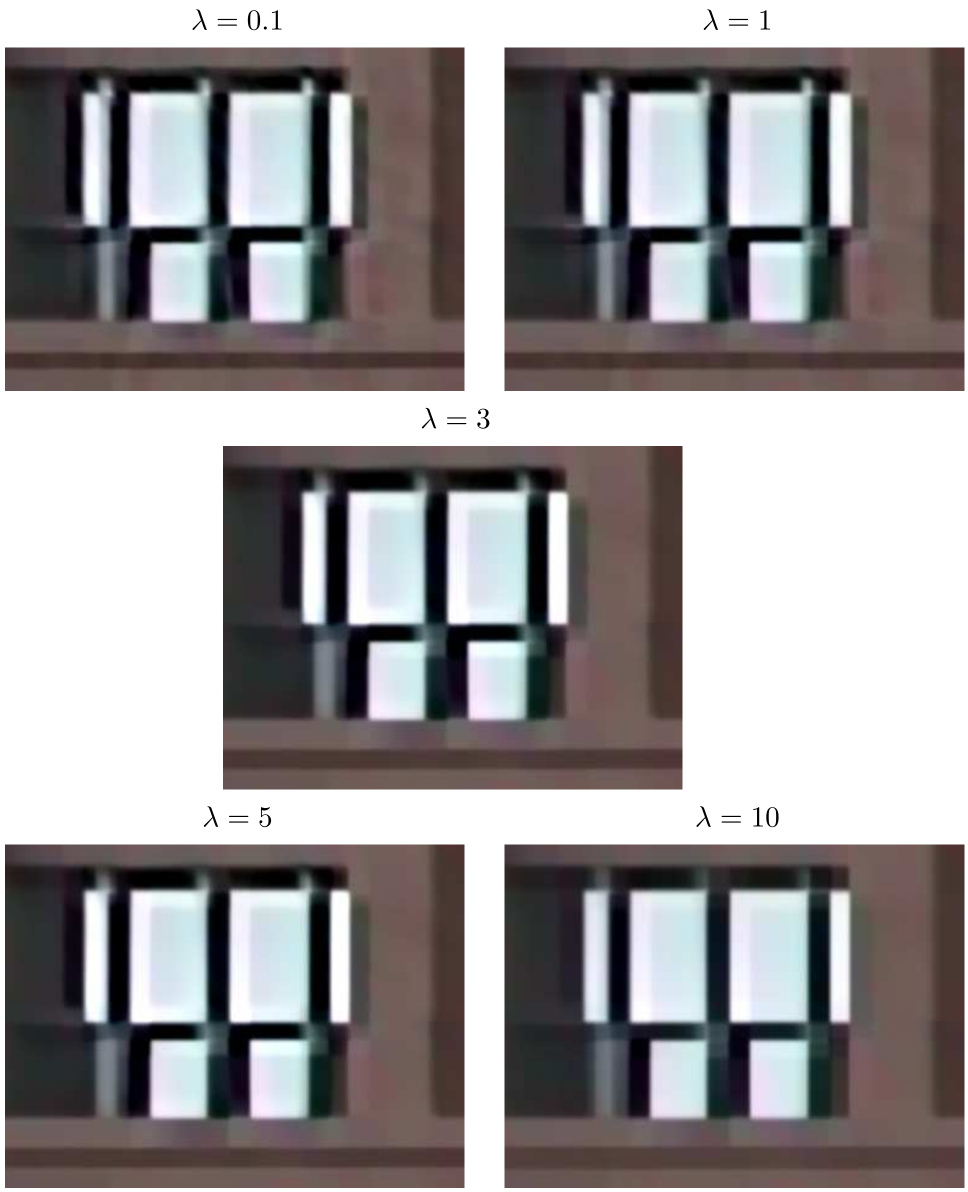
$\lambda = 1$

$\lambda = 3$

$\lambda = 5$

$\lambda = 10$

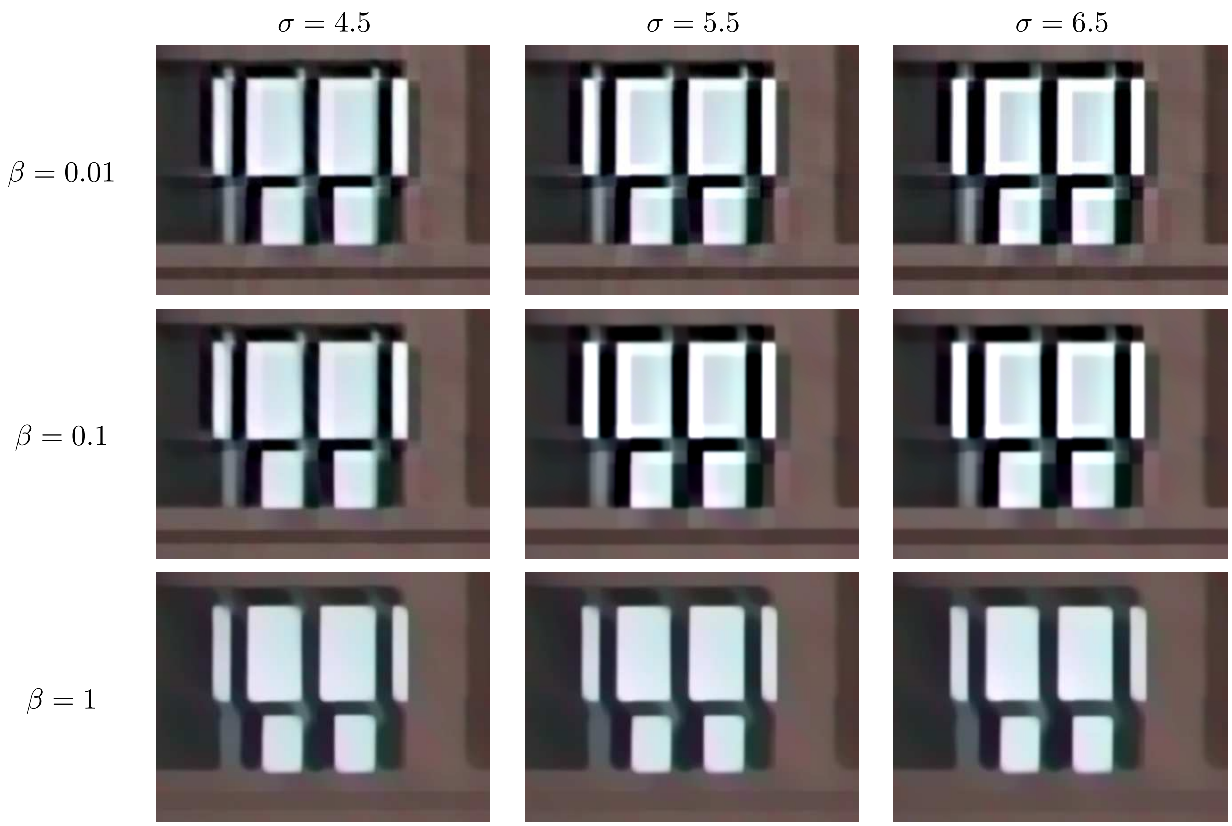




Results in previous figure after being rectified by the transformation learnt by TILT from the low-resolution data.

4.2 Parameters β and σ

We show the results of applying TI-DTV regularization with a fixed $\lambda = 3$ to the first example in Figure 12 of the paper for differents values of the parameters β, which controls the total-variation term in the cost function, and σ, which corresponds to the standard deviation of the Gaussian kernel used to model the relation between the low-resolution image and the super-resolved result. Additionally, we also show the results after being rectified by the transformation learnt by TILT from the low-resolution data. For small values of β the results are quite similar, although some small artifacts might appear. These artifacts are a consequence of the fact that the TI-DTV term in the cost function only acts in the transformed domain and this might not be enough to control the noise amplification caused by the ill-posedness of the inverse problem. When β is large, artifacts similar to those observed when only applying total-variation regularization are observed. The value of β used for almost all examples in the paper and the supplementary material is 0.1. Finally, the algorithm seems to be quite robust to small changes in σ. In fact, for all examples shown in the paper and in the supplementary material σ was fixed to 5.5.



Results in previous figure after being rectified by the transformation learnt by TILT from the low-resolution data.