Super resolution of license plate images: comparative analysis of dictionary-based and MAP-based approaches

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Why is it possible

Image super-resolution use additional knowelege about enviroment:

- Knoweledge of blur information, camera motion etc
- Knoweledge of imaging object(text, faces, car plates, etc)
- Using several images taked from different places

Adaptability:

- Preprocessing for another CV algorythm.
- Extract additional information from several images.

Superresolution methods

- Training algorithms
- Interpolation
- Spectral representation
- Regularization

Or any combination of methods from above

PSNR metric

$$\mathrm{MSE}(\tilde{x}, x) = \frac{1}{m\,n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [\tilde{x}(i,j) - x(i,j)]^2$$

$\mathrm{PSNR}(\tilde{x}, x)$.

$$\mathrm{PSNR}(\tilde{x}, x) = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}_I^2}{\mathrm{MSE}(\tilde{x}, x)}\right)$$

where MAX_i – maximum possible pixel value of the image.

Problem formulation

$$y_r = DH_R W_R x + n_r, \quad 1 \leq r \leq m$$

where:

- x original image
- y_r observation r
- D matrix downsampling
- W matrix of geometric distortion
- H_R matrix blur observation r
- n_r observation noise r
- m the number of observations

The task of finding:

$$\tilde{x} = \underset{\hat{x}}{\operatorname{argmax}}\ PSNR(\hat{x}, x)$$

Subpixel motion

For subpixel motion we use bicubic interpolation between image pixels.
In our experiments we use model with shift, gaussian blur and normal distributed noise.

Methods

- Couple Dictionary Training for Image Super-resolution (Jianchao Yang,Zhaowen Wang, Zhe Lin,Scott Cohen, and Thomas Huang)
  The main idea is very simple - learn dictionary of small patches in two resolutions LR and HR.
  - use two coupled dictionary
  - super-resolution by 1 image
- Superresolution of License Plates in Real Traffic Videos (K. V. Suresh, G. Mahesh Kumar, and A. N. Rajagopalan)
  Image to be superresolved is modeled as a Markov random field and is estimated from the observations by a graduated nonconvexity optimization procedure.
  - A discontinuity adaptive regularizer is used to preserve the edges in the reconstructed number plate for improved readability.

Couple Dictionary Training for Image Super-resolution

- learn couple dictionaries relate the low- and high-resolution image patch
- we using author's implementation of algorithm with our training and test data.

Superresolution of License Plates in Real Traffic Videos I

1. Calculate X^0 as the average of the bilinearly upsampled and aligned images
2. Choose a convex $\lambda = 2v$, where v is the maximum value of the gradient along the x and y directions in the initial estimate X^0
3. Do:
   - 3.1 $X^{(n+1)} = X^{(n)} - \alpha \cdot \mathrm{grad}(X^{(N)}, \gamma)$
   - 3.2 $n = n + 1$
   - 3.3 If $(\mathrm{norm}(X^{(n)} - X^{(n-1)}) < \varepsilon)$
     then $\gamma^{(n)} = \max\{\gamma_{\mathrm{target}}, k\gamma^{(n-1)}\}$

   Until $(norm(X^{(n)} - X^{(n-1)} < \varepsilon)$ and $(\gamma^{(n)} = \gamma_{\mathrm{target}})$
4. $\hat{x} = X^{(n)}$ where α, ε, k, γ_{target} experimentally selected parameters of the algorithm.

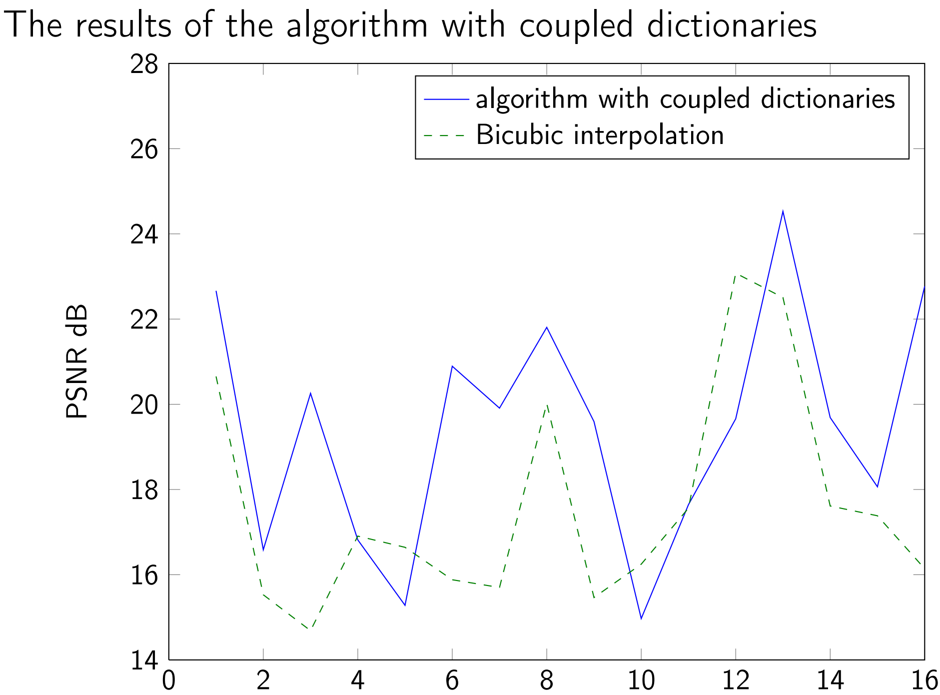
Superresolution of License Plates in Real Traffic Videos II

$$\mathrm{grad}(x,\gamma) = \frac{1}{\sigma^2}\sum_{r=1}^{m} W_R^T H_r^T D^T (DH_r W_r x - y_r) + \lambda \cdot G(x,\gamma)$$

где λexperimentally chosen regularization parameter and the gradient to the point (i,j) is given by the following formula:

$$\begin{aligned} G(i,j) &= 2\left[x(i,j) - x(i,j-1)\right] \exp\left(-[x(i,j) - x(i,j-1)]^2/\gamma\right) \\ &+ 2\left[x(i,j) - x(i,j+1)\right] \exp\left(-[x(i,j) - x(i,j+1)]^2/\gamma\right) \\ &+ 2\left[x(i,j) - x(i+1,j)\right] \exp\left(-[x(i,j) - x(i-1,j)]^2/\gamma\right) \\ &+ 2\left[x(i,j) - x(i-1,j)\right] \exp\left(-[x(i,j) - x(i+1,j)]^2/\gamma\right) \end{aligned}$$

The original images

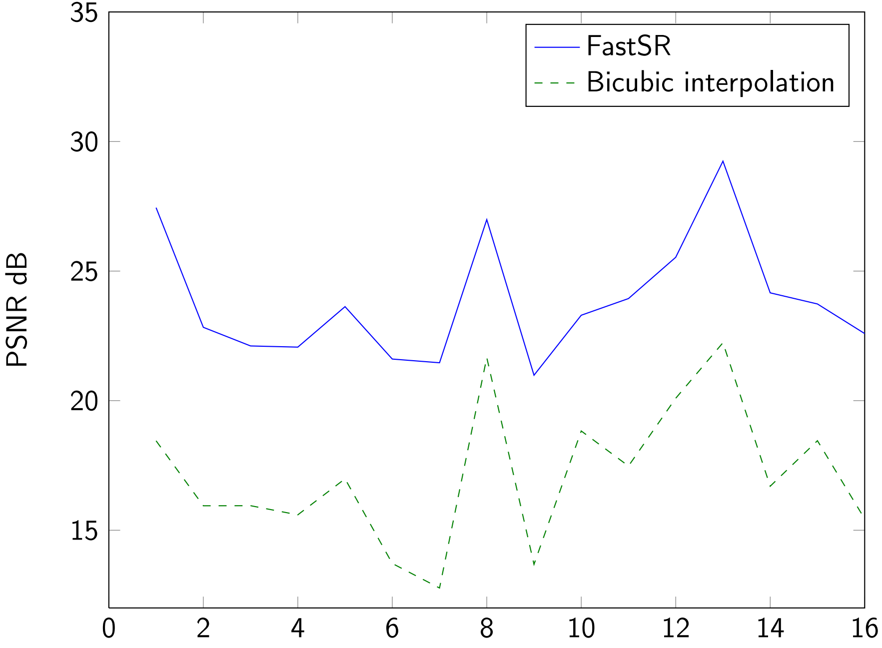

The results of the algorithm with coupled dictionaries
algorithm with coupled dictionaries
Bicubic interpolation
PSNR dB
28
26
24
22
20
18
16
14
0
2
4
6
8
10
12
14
16

The results of the algorithm with coupled dictionaries

Algorithm with coupled dictionaries

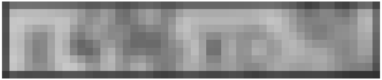
Source image

The results of algorithm FastSR

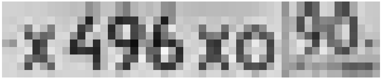


The results of algorithm FastSR

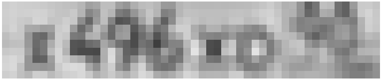
Initial estimation



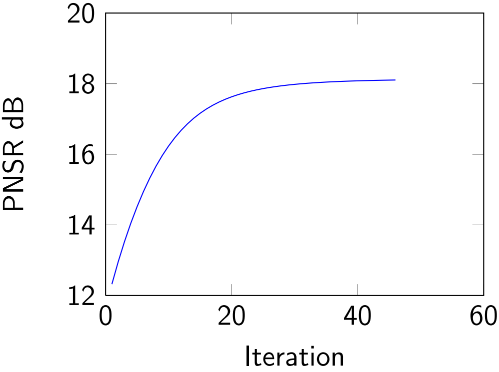
Original image



Result

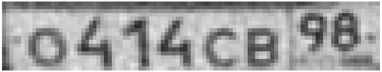


PSNR

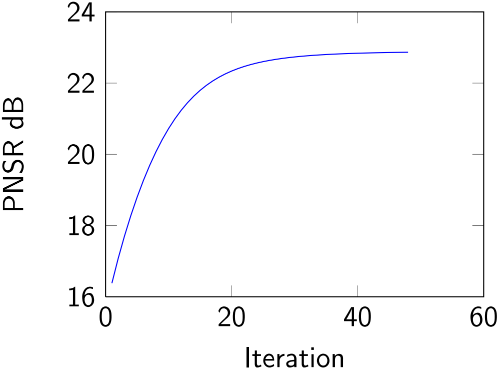


The results of algorithm FastSR

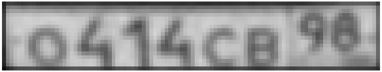
Result



PSNR



Initial estimation

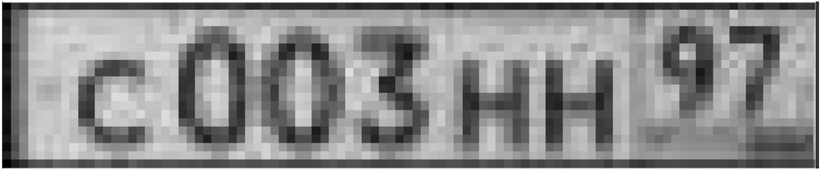


Original image

The results of algorithm FastSR

The results of algorithm FastSR

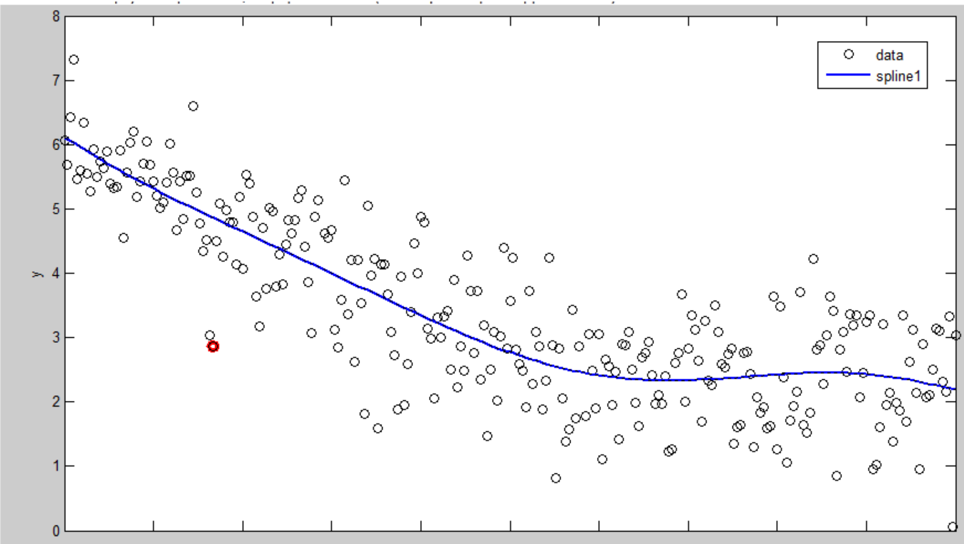
Initial estimation

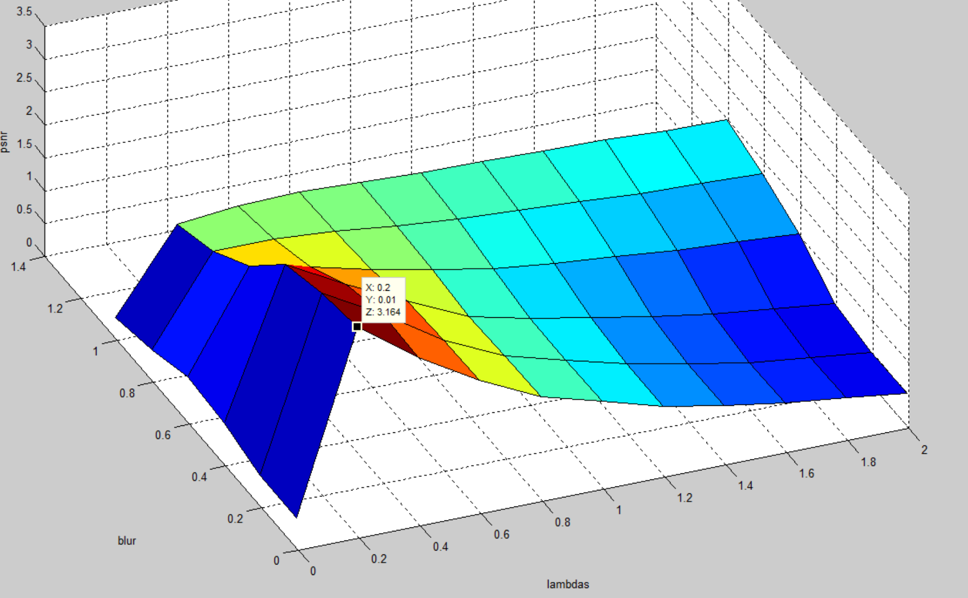


Motion estimation

In tests we use true information about shift LR images.
We research FastSR algorythm result with additive Gaussian noise in warps.

Warp noise test





psnr
3.5
3
2.5
2
1.5
1
0.5
0
1.4
1.2
1
0.8
0.6
0.4
0.2
0
blur
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
1.8
2
lambdas
X: 0.2
Y: 0.01
Z: 3.164

Conslusion

As a result of experiments, it was found that despite the fact that in most cases the firstalgorithmimproves PSNR, the results of his work is much worse than the second.
The second algorithm is resistant to noise at the following initial data:

- robustness shift (up to 0.2 pixel error does not change the result, an error of up to 2 pixels leads to an increase in PSNR in comparison with the initial approximation)
- robustness to noise on the original image (the normal noise with variance $\sigma = 25$ for luminance values from 0 to 255)
- robustness to blur on the original image($\sigma = 1$)