Low-Complexity Single-Image Super-Resolution based on Nonnegative Neighbor Embedding

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Super-resolution (SR) refers to problem of generating a single high resolution (HR) image, given one or several low resolution (LR) images as input. In this paper we propose a single-image SR algorithm that falls into the family of *example-based SR*. Taking inspiration from machine learning, it aims at learning the mapping from the LR image(s) to the HR image by using a dictionary: the learning process is performed locally, by trying to infer the HR details through the use of small "examples". For general SR purposes the examples used are patches (sub-windows of image); the dictionary is formed by pairs of patches conveniently learned.

In particular, our method follows the Neighbor Embedding (NE) approach [1, 2]. For each LR input patch $\mathbf{x}_t^i$, we construct the corresponding HR output each, by following these 3 steps.

1. *Nearest neighbor (NN) search*: find among the LR patches of the dictionary $\mathcal{X}_d = \{\mathbf{x}_d^j\}_{j=1}^{N_d}$ the K NN.
2. *LR patch estimation*: find a weighted combination of the selected neighbor that approximates $\mathbf{x}_t^i$.
3. *HR patch reconstruction*: keep the same weights with the corresponding HR patches to reconstruct the HR output patch $\mathbf{y}_t^i$.

The whole procedure is carried out in a feature space, i.e. each patch in represented by a vector of features computed on its pixels. In previous NE-based SR algorithms [1, 2], the weights of each linear combination (Step 2) are the result of the following constrained least squares (LS) minimization problem (*SUM1-LS*):

$$\mathbf{w}^i = \arg\min_{\mathbf{w}} \|\mathbf{x}_t^i - X_d^i \mathbf{w}\|^2 \quad \text{s.t.} \quad \mathbf{1}^T \mathbf{w} = 1 . \tag{1}$$

In the wake of the NE-based approach, we want to design a low-complexity and competitive algorithm for single-image SR. For this purpose, we analyze three key aspects:

1. the *features* used to represent the LR and HR patches
2. the method used to *compute the weights* of the patch combinations
3. the nature of the *dictionary* (external or "internal")

As for the feature representation, we propose to use centered luminance values (the straight luminance values of the pixels after subtracting the mean value of the patch) as unique features. This choice is in order to have consistency in the representation of the LR and HR patches, and to meet the low-complexity requirement (in fact, we have only one value per pixel). We show that, while keeping the usual *SUM1-LS* as a method to compute the weights, centered luminance values turn out to be good features, as they outperform gradient features (even more costly), if we observe the results for different values of the number of neighbors K.
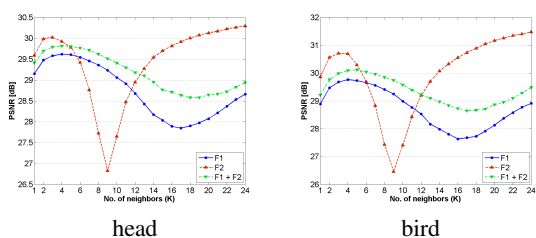

Figure 1: Comparison between LR features (*SUM1-LS*).

However, all the curves present a fall in the performance, that is even dramatic for our selected features. We explain this criticality with the fact that, for certain values of K, the LS solution is too fitted on the LR data and thus generates bad HR reconstruction. To try to overcome this problem, we propose another strategy to compute the weights, still based on the LS approximation of the input vectors, but with a more relaxed

non-negativity constraint. The problem in (1) thus becomes the following non-negative LS problem (*NNLS*):

$$\mathbf{w}^i = \arg\min_{\mathbf{w}} \|\mathbf{x}_t^i - X_d^i \mathbf{w}\|^2 \quad \text{s.t.} \quad \mathbf{w} \geq 0 . \tag{2}$$

We show that the combination of centered luminance values and *NNLS* weights gives the best results and presents monotonically increasing PSNR values (Figure 2). As for the dictionary issue, as we want to realize a single-step upscaling without iterating the algorithm for small scale factors, the external training is shown to be the obvious solution. By deriving the patch correspondences from a "self-pyramid" in the way of [3], in fact, we run the risk of having extremely poor (in size) dictionaries. Moreover, the external solution offers the possibility to build a dictionary in advance, so reducing the online running time.

The algorithm so designed is compared to some state-of-the-art methods: while presenting comparable results in terms of performance (much better if we consider the previous NE-based algorithms), we have a sensible reduction of the computational time. As future work, we plan to investigate other strategies for neighbor search (i.e. other metrics), in order to select "better neighbors" for the HR reconstructions and so improve the performance.
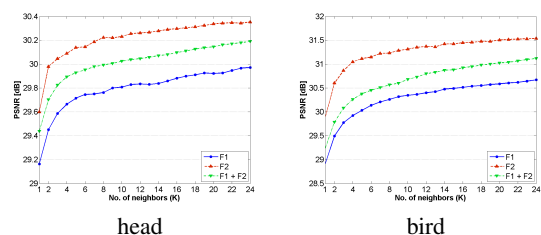

Figure 2: Comparison between LR features (*NNLS*).

Image	Scale	Our algorithm		Chang et al.		Glasner et al.	
		PSNR	Time	*PSNR*	Time	*PSNR*	Time
bird	2	34.69	18	32.94	110	34.42	406
head	2	32.88	18	32.34	145	32.68	367
woman	2	30.91	15	29.43	114	30.61	410
bird	3	31.37	9	29.71	47	32.16	281
head	3	31.46	12	30.82	68	31.69	370
woman	3	27.98	12	26.45	37	28.79	248
bird	4	28.99	6	27.37	21	30.07	475
head	4	30.26	6	29.57	26	30.86	379
woman	4	25.66	5	24.25	17	26.79	401

Table 1: Results (*PSNR* and running time in sec.) for different images.
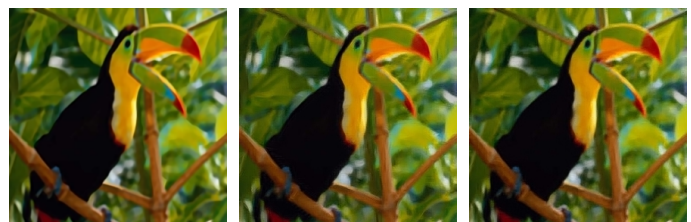
Glasner et al. [3]　　　Chang et al. [2]　　　Our algorithm

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[2] Hong Chang, Dit-Yan Yeung, and Yimin Xiong. Super-Resolution Through Neighbor Embedding. In *2004 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR)*, volume 1, pages 275–282, 2004.

[3] Daniel Glasner, Shai Bagon, and Michal Irani. Super-Resolution from a Single Image. In *2009 IEEE 12th International Conference on Computer Vision (ICCV)*, pages 349–356, 10 2009.