Interactive Super-resolution through Neighbor Embedding

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Abstract. Learning based super-resolution can recover high resolution image with high quality. However, building an interactive learning based super-resolution system for general images is extremely challenging. In this paper, we proposed a novel GPU-based Interactive Super-Resolution system through Neighbor Embedding (**ISRNE**). Random projection tree (**RPtree**) with manifold sampling is employed to reduce the number of redundant image patches and balance the node size of the tree. Significant performance improvement is achieved through the incorporation of a refined GPU-based brute force **kNN** search with a matrix-multiplication-like technique. We demonstrate 200-300 times speedup of our proposed **ISRNE** system with experiments in both small size and large size images.

1 Introduction

Learning based super-resolution, which recovers the high resolution (HR) by learning the relationship between HR training images and low resolution (LR) counterparts, attracts much attention recently. Comparing with other methods, learning based super-resolution is capable of extracting more image/patch information from a collection of image pairs or image patch pairs and supports higher magnification factors with fewer LR images [1].

Freeman *et al.* [2] constructed a Markov network to connect the LR and HR image patches, followed by employing Bayesian belief propagation to allocate HR counterparts. However, artistic style is exhibited in the recovered HR image [3]. Assuming local geometry preservation for both high- and low-dimensional manifold, Chang *et al.* [4] proposed single image super-resolution through neighbor embedding (**SRNE**). Wei *et al.* [5] improved **SRNE** by extracting visual primitives and removing the noisy patches by validation (**NEVPM**). Yang *et al.* [6] investigated the selection of neighbor factors from the perspective of compressed sensing and Su *et al.* [7] studied the influence of patches from the viewpoint of neighborhood preservation. Furthermore, efficient face super-resolution methods has been proposed by employing a hallucination algorithm and its variants [8–10]. These

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algorithms are efficient because they employ linear PCA algorithm to project all the LR images into a low-dimensional subspace [8].

It is worth noting that although many refinements have been proposed, the performance issue of learning based super-resolution, which plays a crucial role in its practical applications, is not well studied yet. It is very challenging to build an interactive (a few frames per second) learning-based method which can learn from hundreds of thousands of image patches or training images.

To attack the aforementioned issue, we propose Random Projection tree (RPtree) [11] with manifold sampling to reduce the total number of image patches and balance the tree structure. Then a refined GPU-based kNN search is employed to find the neighboring patches from the nodes of RPtree. Thirdly, we perform SRNE for the recovery of high-resolution test image patches. Finally, we introduce a global reconstruction constrain for further improving the image quality of high-resolution images. We successfully build an interactive super-resolution with neighboring embedding system (ISRNE) without compromising the image quality, even achieving a slightly better quality than the previous SRNE. Our experiments indicate that ISRNE not only demonstrates a remarkable improvement over performance, but also shows a superior scalability to existing methods.

The rest of the paper is organized as follows. In Sect. 2, we describe our interactive SRNE in details. We report the experiment results and discuss the limitation of the ISRNE in Sect. 3, followed by a conclusion in Sect. 4.

2 Interactive Super-resolution through Neighbor Embedding (ISRNE)

To construct an interactive super-resolution system, we devote our efforts on the parallelization of two crucial steps of SRNE. These steps are: (1) All the image patches are separately reconstructed by neighbor embedding which has a closed-form solution; (2) The neighboring patches of each test patch are searched by kNN. It is worth noting that in this paper, we do not consider the parallelization of NEVPM, a refined version of SRNE since NEVPM comprises some steps which are hard to be paralleled [5]. For self-containness, we give a brief introduction on SRNE before the discussion of our approach.

2.1 Super-resolution through Neighbor Embedding

A key assumption in SRNE is that the local geometries of image patches are similar in two distinct HR and LR feature spaces. Therefore, an HR counterpart of an LR image patch can be recovered using a collection of HR training patches.

We denote $\mathbf{y}_s$ and $\mathbf{x}_s$ be the training patches from HR images and its LR counterparts respectively. The optimal reconstruction weights of each patch $\mathbf{x}_t$ from LR test images is obtained by minimizing the local reconstruction error [4]:

$$\epsilon = \min \|\mathbf{x}_t - \sum_{\mathbf{x}_s \in \mathcal{N}_{\mathbf{x}_t}} \omega_{ts} \mathbf{x}_s\|^2, \quad \mathbf{x}_t, \mathbf{x}_s \in \mathbb{R}^d \quad (1)$$

subject to the constraints $\sum_{\mathbf{x}_s \in \mathcal{N}_{\mathbf{x}_t}} \omega_{ts} = 1$ and $\omega_{ts} = 0$ for any $\mathbf{x}_s \notin \mathcal{N}_{\mathbf{x}_t}$, where $\mathcal{N}_{\mathbf{x}_t}$ is the neighborhood of $\mathbf{x}_t$ given neighbor factor k . Denote $\mathbf{G} = (\mathbf{x}_t \mathbf{1}^T - \mathbf{X}_s)^T (\mathbf{x}_t \mathbf{1}^T - \mathbf{X}_s)$, Equation (1) can be optimized by solving a linear system equation $\mathbf{G}\mathbf{W} = \mathbf{1}$, s.t. $\sum_{\mathbf{x}_s} \mathbf{w}_{ts} = 1$. Thus, the HR patch $\mathbf{y}_t$ is attained as follows:

$$\mathbf{y}_t = \sum_{\mathbf{x}_s \in \mathcal{N}_{\mathbf{x}_t}} \omega_{ts} \mathbf{y}_s, \quad \mathbf{y}_s \in \mathbb{R}^D. \quad (2)$$

where $\mathbf{y}_s$ is the HR counterpart of LR image patch $\mathbf{x}_s$.

In the last step above, we can either simply average the values in the overlapped regions between adjacent patches, or employ other more sophisticated methods (*e.g.* one pass algorithm) to enforce inter-patch relationship.

To achieve efficient parallelization of SRNE, we introduce **RPtree** with manifold sampling.

2.2 Random projection tree with manifold sampling

RPtree, a variant of the k -d tree, hierarchically partitions data of D dimension into pieces in a manner which only depends on the intrinsic low-dimensional manifold [11]. The advantages of utilizing **RPtree** are that: (1) **RPtree** consumes less time ($O(n)$) to construct than **PCA tree** ($O(n \log n)$) [11], given n data points; (2) Unlike k -d tree, **RPtree** can deal with high-dimensional data (≥ 30) which are often seen in super-resolution domain; (3) **RPtree** won't bring a detrimental effect on the **SRNE** performance, since the manifold assumption of **RPtree** is the same as that of neighbor embedding [4].

RPtree is built in a streaming manner [12] in which the following statistics at each internal node of the tree are maintained and updated as new data arrives.

$$\mu_i \leftarrow (1 - \alpha_i) \mu_{i-1} + \alpha_i x_i$$

$$\sigma_i^2 \leftarrow (1 - \alpha_i) \sigma_{i-1}^2 + \alpha_i (x_i - \mu_i)^2.$$

where μ_i and σ_i^2 denote the mean value and the corresponding variance in the i th iterative times, respectively. Parameter $\alpha_i (\leq 1/i)$ is a weighted factor, and x_i means a new sample. The details can be seen in [12].

With this way, Freund *et al.* [11] proved that if data in C are of intrinsic dimension d , the average diameter of any descendant cell ($\leq d$ levels below) of C will be less than half of the average diameter of C with constant probability, picking any cell C in the RP tree. However, this theorem is not sufficient to assure the even partition of **RPtree** especially when the data is distributed unevenly, which is the case in natural image patches. Since the background patches are quite similar, most of such patches will be assigned to few nodes. To reduce the difference of distribution density between the background and foreground patches, we introduce manifold sampling in order to balance the **RPtree**. Given d dimensional n data points $\mathbf{x}_i (i = 1, \dots, n)$, specifically, we approximate the geodesic distance between data points $\mathbf{x}_i$ and $\mathbf{x}_j$, which are lying close together (their Euclidean distances $\text{dist}(\mathbf{x}_i, \mathbf{x}_j)$ is less than a given threshold ϵ or one

of the K nearest neighbors of $\mathbf{x}_j$ of $\mathbf{x}_j$), can be approximated. For data points lying far apart, we then approximate the geodesic distance by the shortest path distance which is formulated as follows:

$$dist(\mathbf{x}_i, \mathbf{x}_j) = \min\{dist(\mathbf{x}_i, \mathbf{x}_j), dist(\mathbf{x}_i, \mathbf{x}_k) + dist(\mathbf{x}_k, \mathbf{x}_j)\} \quad \forall k, 0 \leq k \leq n$$

Once the approximated geodesic distances between sample pairs in the high dimensional space are calculated, we can directly use these distance values to decimate redundant points in the manifold. We also prove an error upper bound of manifold sampling for super-resolution as follows:

$$\frac{\|\Delta \mathbf{y}\|}{\|\mathbf{y}\|} \leq \frac{4\epsilon}{\|\mathbf{P}\|} + \frac{r\epsilon}{\|\mathbf{y}\|},$$

where $\mathbf{P}^T \mathbf{P} = \mathbf{G}$, and r denotes the super-resolution factor. It indicates that we can guarantee the difference between the original SR results and correspond one with manifold sampling is small by carefully choosing ϵ . Due to limited space, we put the proof into the supplementary.

2.3 GPU Acceleration

The complexity of the brute force kNN algorithm reaches an order of $O(nmd + nm \log m)$, where m represents for the number of query data points and, n for the number of reference data points, and d is the dimensionality of the data points. To reduce computational cost, Garcia *et al.* [13] proposed a fast kNN search scheme based on a brute force GPU algorithm and obtained a remarkable increase in performance. However, a naïve implementation of GPU acceleration has very low efficiency due to large amount of un-coalesced memory access and bank conflicts. In our approach, we develop a matrix-multiplication-like algorithm, to compute the distances.

Denoting the query points as $\mathbf{X}_t(x_{t_{ij}})_{m \times d}$ and the reference points as $\mathbf{X}_s(x_{s_{ij}})_{n \times d}$, the squared distance matrix $\mathbf{D}(dist_{ij}^2)_{m \times n}$ can then be calculated:

$$\mathbf{D} = \mathbf{X}_t \odot \mathbf{X}_s^T,$$

where $\odot$ denotes the operator between two matrices, and is defined by:

$$dist_{ij}^2 = \mathbf{x}_{t_i} \cdot \mathbf{x}_{s_j} = \sum_{k=1}^d (\mathbf{x}_{t_{i_k}} - \mathbf{x}_{s_{j_k}})^2.$$

Above approach is very similar to the matrix multiplication between $\mathbf{X}_t$ and $\mathbf{X}_s^T$, except that the computing kernel is modified. We can very conveniently cope with the computation utilizing currently available parallel matrix multiplication algorithms to obtain significant performance improvement. An illustration of this operation is shown in Fig. 1.

As the neighborhood number k is relatively small in our application, we employ insertion sort for best performance [13]. Unlike Bishop *et al.*'s method [14],

Fig. 1. Matrix-multiplication-like operation between $\mathbf{X}_t(x_{t_{ij}})_{m \times d}$ and $\mathbf{X}_s(x_{s_{ij}})_{n \times d}$. We follow the method of matrix multiplication to compute the distance matrix, with the computing “kernel” modified.

we needn’t perform dimension reduction which is required for k nearest neighbor search on k -d tree. We further propose a combination of GPU-based **kNN** and **RPtree** with manifold sampling to speed up queries. In Sect. 3, we show that there is no negative impact on the the quality of restoration.

2.4 Global Reconstruction Constrain

In super-resolution domain, there are two important criteria to evaluate the recovered HR quality. One is the recovery of high frequency, the other is the consistency of LR and HR images. To keep the consistency, generally speaking, a global reconstruction constrain which means the simulated downsampling of the reconstructed HR image $\mathbf{Y}$ is the same as the LR image $\mathbf{X}$ should be considered as follows:

$$\mathbf{X} = D_S H \mathbf{Y}$$

where H represents a blurring filter, and D_S the downsampling operator.

As the consistency of LR and HR images are not always satisfied when patch by patch restoration is employed, Liu *et al.* [15] first proposed a two step method to combine the local nonparametric and global parametric model. In **ISRNE**, we utilize the back-projection method (BP) which has been studied by Yang *et al.* [6] as a post-processing procedure to enhance the consistency.

Back-projection algorithm is an iterative procedure for estimating unknown scenes. Given an estimation of the super resolution image, a simulated imaging process yields a set of low-resolution images which are compared with the observed low resolution images. The super-resolution estimation is then modified so as to reduce the error between the observed and simulated images. The process is terminated when the error is less than a predetermined level, or after a given

number of iterations. The iterative procedure is formally described as follows:

$$\begin{aligned}\hat{\mathbf{Y}}^{(t+1)} &= \hat{\mathbf{Y}}^{(t)} + \mathbf{H}^{BP} \left(\mathbf{X} - \hat{\mathbf{X}}^{(t)} \right) \\ &= \hat{\mathbf{Y}}^{(t)} + \mathbf{H}^{BP} \left(\mathbf{X} - D_S H \hat{\mathbf{Y}}^{(t)} \right)\end{aligned}$$

where $\mathbf{H}^{BP}$ is a back-projection operator which is an approximation to the inverse of the operator $D_S H$, t is the iterative times.

3 Experiments

In order to evaluate the effectiveness of **ISRNE**, experiments are carried out on two image sets of different scales. The smaller training set is from Chang *et al.*'s paper [4] as in Fig. 2, and the larger one consists of 370 images are collected from a well-known COREL database.

In the experiments, we will magnify the input image by a factor of 4. In the LR images, we always use 3×3 LR patches, with overlap of 2 pixel between adjacent patches, corresponding to 12×12 patches with overlap of 8 pixels for the HR images. Like **SRNE** [4], the neighbor factor k is set to be 5 and the features (first-order and second-order gradient) are extracted directly from the illuminance component of LR images since humans are more sensitive to illuminance changes.

The computer used for the evaluation is an Intel Core 2 Duo E7200 2.53GHz with 2GB of DDR2 memory PC2-5300 (2×1GB dual-channel memory). The graphics card used is an NVIDIA GeForce 8800 GT with 512MB of DDR3 memory. NVIDIA CUDA 2.0 is employed for GPU computation.

We first evaluate the effectiveness of **RPtree** with manifold sampling using the small training set. The tree height is set to be 4, which is a tradeoff between the tree search and node search cost. To remove the randomness of **RPtree**, the output, *i.e.* the number of patches in each node, of 10 times are recorded. The sum of node frequencies of the 10 repetitions is reported as in Fig. 3. It is easy to see from Fig. 3 that the distribution of these patches on the tree nodes are highly imbalanced. Furthermore, there always exists a “big” node in the tree, which contains almost half of the total patches. For example, the frequency of a node owing the number of points in [4000, 6000] is equal to 10. It is not difficult to observe that such patches are sampled from the background. After manifold sampling is employed, the imbalance is greatly reduced as shown in Fig. 3. It indicates that the proposed **RPtree** with manifold sampling indeed remove redundant patches and improve the balance of **RPtree**.

As shown in Fig. 4, we compare our method with neighbor embedding (**SRNE**) [4] and back projection. It is easy to notice that the forehead hair and double eye of the girl utilizing **ISRNE** are more clear than those using **SRNE**. Furthermore, **ISRNE** has lower RMSE for the recovery of HR image than **SRNE**, and is comparable to **SRNE+BP** method and sparse representation method [6] which needs several hours to get the result. It indicates that while the main goal of the proposed

Fig. 2. Small training set.

Fig. 3. The distribution of data in **RPtree**. The vertical axis means the times of a node of **RPtree** owing the number of points in some interval.

ISRNE is to attain interactivity, the recovered image quality is not sacrificed, even better than that of the previous one (*e.g.* SRNE) in some cases.

Fig. 4. 4 $\times$ recovery of low resolution image. The root mean squared errors (RMSEs) are shown in the Brackets, from left to right: LR, SRNE (0.0387), SRNE + BP (0.0368), Sparse Representation (0.0357), ISRNE (0.0369), Ground truth.

To evaluate the performance of ISRNE, we compare it with several state-of-the-art acceleration methods including: Brute force **kNN** search (**BF**), **RPtree**, partial distance search acceleration (**PDS**) [16], and the combination of manifold sampling with the former three methods. Furthermore, we also study the performance of three variants of the proposed ISRNE algorithm by neglecting either manifold sampling or **RPtree**, or both. The training images are the small training set as in Fig. 2. The test images of increasing sizes include one image from Chang *et al.*'s paper [4] and three images downloaded from Internet. To remove the randomness of **RPtree**, all the methods related to **RPtree** are repeated 10 times and the corresponding means and standard deviations of the computational times are reported in Fig. 5.

It can be seen from Fig. 5 that compared with other methods, ISRNE has the best performance, and the acceleration ratio of **BF** is increased with the resolution of the test images. Furthermore, **RPtree** and manifold learning are two comparable and complementary methods which can further accelerate the refined GPU-based **kNN** procedure. When the size of images are smaller than 500×348 , the running time is less than 1 second which is a basic requirement to

Fig. 5. A performance comparison on the super-resolution with different search methods for images with different resolutions.

Fig. 6. 4 $\times$ recovery of low resolution image using the big training set. For each scene, the left one is the LR image and the right one is recovered by ISRNE. From left to right, top and bottom, the RMSE errors of these four test images are: 0.0827, 0.0583, 0.0643, and 0.0734, respectively. In the middle, there are close-ups of the four images.

build an interactive super-resolution system. While the “MS+RPtree+PDS” made a remarkable improvement in the aspect of acceleration, it is hard for PDS to design an alternatively parallelized one due to its serial computation nature.

	Test 1	Test 2	Test 3	Test 4
T_{pre} (s)	9.490	9.450	9.420	9.400
T_{kNN} (s)	1.930	1.890	1.760	1.870
T_w (s)	0.115	0.118	0.117	0.118
T_{resto} (s)	0.161	0.160	0.162	0.166
T_{post} (s)	0.107	0.107	0.103	0.107
Total	11.803	11.725	11.500	11.560

Table 1. Running time (RT) of **ISRNE** in seconds, from top to bottom: RT for preprocessing, RT for kNN search, RT for weights calculation, RT for reconstruction, RT for postprocessing and the total RT.

Finally, we attempt to figure out how many training/test patches will hinder the interactive property of **ISRNE**. Therefore, we extract 131,523 patches from 2,156,360 (5828×370) raw patches which are generated from the mentioned large training image set. The test set consists of four images from Corel test set without overlapping with the large training set. The HR test images (of size 384×256) recovered by **ISRNE** are shown in Figures 6, and running time analysis are tabulated in Table 1. Compared with the LR images, we can observe that (1) the wall of Roman relics becomes cleaner; (2) the faces of these horses become smoother and a little bit recognizable; (3) some buildings on the mountain are shown up; (4) the food details in the dish is distinguishable and the edges of the dish is cleaner. Note that most of the running time is spent on pre-processing, especially on transferring all the 131,523 patches into memory. The time for kNN search and neighbor embedding is only about 2 second, while other aforementioned learning methods for super-resolution never run through such tough tests.

4 Conclusion

With the combination of **RPtree** with manifold learning and the refined GPU-based kNN search, an interactive super-resolution through neighbor embedding is proposed. Experiments on both small-scale images and large-scale images indicate that the proposed **ISRNE** not only remarkably accelerates the procedure of super-resolution but also enhances the image quality of recovered high-resolution images well. Note that although the kNN search time grows with the training patches and test patches, a more powerful hardware will greatly neutralize the side effect. Meanwhile, this scheme can easily be applied to other patch based search and replace problems like image denoising, inpainting, texture transfer, and transparency separation.

There are a few issues that require a thorough investigation. Since **RPtree** can construct a tree much more efficient than other tree-based algorithms, we

will investigate how to dynamically update the training patches to further refine the performance of ISRNE in the future. Furthermore, we would like to generalize the proposed framework to other learning based super-resolution method.

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