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Image Resolution Enhancement Using Sparse-Neighbor Embedding

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***Abstract*— Obtaining a High-Resolution (HR) image of a scene from a single or multiple Low-Resolution (LR) images is known as image Super-Resolution (SR). A lot of applications like Computer Vision, Medical Imaging, Pattern Recognition, Satellite imaging, a robust performance can be achieved if the Low-Resolution input is super-resolved to a high-resolution image. Generally Neighbor-Embedding (NE) based super-resolution, first a neighbour search is performed using Euclidean distance after that optimal weights are determined using constrained-least square problem. In this paper a sparse-neighbor selection process is used for super-resolution reconstruction. Histogram of oriented Gradients (HoG) method is used to extract the features of Bicubically interpolated (BI) LR image patches. Then the whole training data set is partitioned into set of subsets by clustering the histogram of oriented gradients (HoG) using fuzzy C-means method. A Sparse neighbor selection algorithm (SPNS) is used to search by incorporating Robust-SL0 algorithm and classification-regression based super-resolution criterion. SPNE algorithm simultaneously searches the neighbors and estimation of weights is done.**

***Index Terms*– HoG, IBP and Super Resolution**

I. INTRODUCTION

SUPER-RESOLUTION (SR) refers to the task of producing a high-resolution (HR) image from one or more low-resolution (LR) images. Resolution-enhancing technology may prove to be essential in medical imaging and satellite imaging where diagnosis or analysis from low-quality images can be extremely difficult. Electronic imaging devices like cell phone camera, portable digital cameras etc., resolution is an important factor which generally depends on sensors. High-resolution imaging devices are more expensive and can't be used for practical applications. Methods for SR can be broadly classified into two families of methods: (i) The classical multi-image super-resolution, and (ii) Example-Based super-resolution. Conventional approaches to generating a super-resolution image normally require as input multiple low-resolution images of the same scene, which are aligned with sub-pixel accuracy. Super Resolution image reconstruction is generally a severely ill-posed problem because of the insufficient number of low resolution images, ill-conditioned registration and unknown blurring operators and the solution from the reconstruction constraint is not unique. In example-based SR, correspondences between low and high resolution image patches are learned from a database of low and high resolution image pairs (usually with a relative scale factor of 2), and then applied to a new low-resolution image to recover its most likely high-resolution version.

As a first step of any example-based SR algorithm, the target image is divided into patches of the same size of the LR patches in the dictionary; then, each LR input patch is compared to the stored LR patches and, once the nearest patch among these is found, the corresponding HR patch is finally taken as the output. SR methods based on sparse representations instead of selecting from the dictionary only one patch, several patches are taken into account and contribute simultaneously to the generation of a single HR output patch. In Locally Linear Embedding (LLE) basic assumption is that a patch in the LR target image and the corresponding HR unknown patch share similar neighborhood structures: as a consequence of that, once the LR patch is expressed as the linear combination of a certain number of its neighbors taken from the dictionary, the output patch can be reconstructed by using the HR patches in the dictionary corresponding to the neighbors selected, and combining them in the same way. But its performance is sensitive to the number of neighbors chosen, that appears as a parameter difficult to properly set.

The reconstruction framework of the proposed method takes place in the following stages: 1) Both the HoG and the first and second-order gradient features are extracted in a raster-scan order from the upscaled version of the LR input by using the bi-cubic (BI) interpolation; 2) subset selection that the HoG feature of each LR input matches the centroids of clusters is performed to find a medium-scale subset close to the LR input for synthesis process. Both K-NN classifier and classification regression based super resolution trained by k-means clusters and fuzzy c-Means clusters respectively using here to partition the whole training data into a set of subsets; 3) SpNE is applied to synthesize the HR image patch of the LR input, in which searching neighbors and estimating weights are simultaneously conducted; and 4) after constructing all the HR patches and obtaining the initial HR image, the total-variation-based (TV) deblurring and the iterative back-projection (IBP) algorithm are sequentially performed to obtain the final HR outcome.

Here we are comparing K-NN classifier trained by k-means clustering and classification regression based super resolution trained by c-means clustering. The major difference between classification regression based super resolution and K-NN classifier is regression tree is a decision tree based technique but KNN works on distance based technique. As regression tree is decision tree based, the number of comparisons made on the gallery images will be limited but in K-NN the number of comparisons made on the gallery image cannot be limited. Also fuzzy C-means deals with fuzzy based approach governed by membership values and objective function but K-means is governed by random centroid values. Through c-means clustering, a group of medium-scale subsets can be constructed, which can effectively reduce computational time while preserving SR quality and SR quality is improved as its neighborhood patch calculation is accurate and stable. This system is proposed mainly to minimize reconstruction error while searching the required k- candidates also to establish optimal subsets. The system will maximize the computational speed and minimize the computational cost.

II. PROPOSED METHOD

The proposed system develops a sparse neighbor selection (SpNS) algorithm to search neighbors with the help of robust-SL0 algorithm and classification-regression based super-resolution criterion. To accelerate the super-resolution process, characterization of local geometric structure of low-resolution image patches are extracted using HoG feature matrix. Then whole training data set is partitioned into a set of medium-scale subsets by clustering (Fuzzy C-means clustering) the histogram of oriented gradients (HoG). To overcome the limitation of previous method fuzzy C-means clustering is used instead of k-means clustering and a classification-regression method for super-resolution.

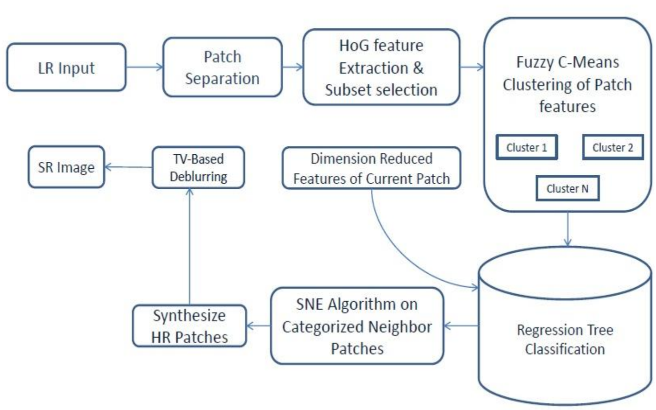

Fig. 1: Proposed Super-Resolution System

A. Patch Separation and Feature Extraction

Normally Example-learning based super-resolution gathers a large no of samples for training purpose, which is necessary for representing variety of image patterns. As the number of training data in database increases computational complexity also increases and will take a lot of time to process. To alleviate this problem, an alternate approach is to search the k-NN of a given sample within a subset close to input. Low level but efficient features are used to characterize the local structure of image patches to obtain the objective. For this purpose we use HoG, a good geometric descriptor that uses the distribution of local intensity gradients or edge directions. Local object appearance and shape can often be characterized rather well by the distribution of local intensity gradients or edge directions. Other low-level features like pixel intensities, gradient information or a combination of both have their own disadvantages, pixel intensities exhibit their variance to intensity difference between image patches, whereas gradient features are sensitive to noise. By contrast, the HoG feature does not have either problem.

The implementation of the descriptors can be achieved by dividing the image into small connected regions, called cells, and for each cell compiling a histogram of gradient directions or edge orientations for the pixels within the cell. First step of calculation is the computation of the gradient values by applying a discrete mask in one or both of horizontal and vertical directions. Gradients of each pixel can be represented by a vector $\overrightarrow{p_i} = \{dx_i, dy_i\}$, where dx_i and dy_i represents respectively the horizontal and vertical derivatives of pixel point i. For the gradient direction that falls into the range of $-\pi/2 - \pi/2$ in radian form can transform it into $0^0 - 180^0$ via $\left(\left(arctan\left(dy_i/dx_i\right) + \pi/2\right) * 180\right)/\pi$.

Next, the discrete directions should be determined. We specify the orientation bins evenly spaced over $0^0 - 180^0$ at intervals of 5^0 and round the continuous angle of each pixel to a discrete value, i.e downward or upward. Each pixel within the cell casts a weighted vote for an orientation-based histogram channel based on the values found in the gradient computation. As for the vote weight, pixel contribution can either be the gradient magnitude itself, or some function of the magnitude; in actual tests the gradient magnitude itself generally produces the best results. Finally, the number of pixels falling into the same bin is calculated for edge orientation histograms. By linking the edge orientation histograms of each cell in an LR image patches and by normalizing the patch to the unit l_2-norm HoG feature is constructed.

B. Clustering On HoG Using Fuzzy C-Means Clustering

In early methods of super-resolution with sparse-neighbor embedding follows k-means clustering that has certain disadvantage, unable to handle noisy data and the algorithm fails for non-linear dataset. Also choosing initial cluster center randomly may not produce a good result. Fuzzy clustering gives the idea of partial membership belonging, among the fuzzy clustering methods fuzzy C-means clustering is one of the important and widely used. In FCM, based on the distance measure the vector space of sample point is divided into a number of sub-spaces. In the previous step with the help of HoG we can segment the image patch pairs in the whole training dataset into set of sub-sets, where each subset shares a similar geometric structure. Specifically, all training samples comprise a union of such clusters as:

$$\begin{cases} X_s = \bigcup_{c=1}^{C} X_s^{(c)} = \bigcup_{c=1}^{C} \{X_s^i \mid i \in \Omega_c\} \\ Y_s = \bigcup_{c=1}^{C} Y_s^{(c)} = \bigcup_{c=1}^{C} \{Y_s^i \mid i \in \Omega_c\} \end{cases}$$

Where X_s and Y_s denote the matrices of the training data set $\{X_s^i\}_{i=1}^N$ and $\{Y_s^i\}_{i=1}^N$by stacking the features of LR and HR image patches in column form C and represents the number of clusters. Correspondingly, $X_s^{(c)}$ and $Y_s^{(c)}$ denote the data matrices consisting the features of the LR and HR image patches in the Cth cluster. In addition Ω_c stands for the index set of X_s^c or Y_s^c.

Fuzzy C-means algorithm partitions a set of object data $X = \{X_1, X_2, \dots, X_n\}$ into a number of C clusters by minimizing the objective function:

$$J_{FCM} = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m \, d_{ik}^2$$

Where the membership $u_{ik} \in [0,1]$ represents the degree of pixel $X_k (k = 1,2, \dots, n)$ belonging to cluster i$(1 \leq i \leq C)$, the fuzzy parameter $m \in (1, \infty)$ determines the amount of the resulting classification, and $d_{ik} = \|X_k - V_i\|_A$ is the distance between pixel X_k and the centroid V_i of cluster i. By the definition of fuzzy theory, the memberships satisfy the constraint that $\sum_{i=1}^{c} U_{ik} = 1$ for each pixel X_k. First step in FCM is to calculate the cluster centers, which is a matrix v of dimension c rows and m columns. Second step is to calculate the distance matrix D, Euclidean distance between every pixel and every cluster center. From the distance matrix a partition matrix U is calculated, if the difference between initial partition matrix and the calculated partition matrix is greater than convergence value then the entire process is repeated. Then the final partition matrix is used for reconstructing image.

The clustering problem can be defined as the minimization of J_{FCM} under the probabilistic condition:

$$\sum_{i=1}^{c} U_{ik} = 1$$

The fuzzy C-means (FCM) algorithm consists in the iteration of the following formulas. The cluster center are calculated,

$$V_i = \frac{\sum_{k=1}^{n} (U_{ik})^m X_k}{\sum_{k=1}^{n} (U_{ik})^m}$$

Fuzzy C-means algorithm gives good results for overlapped data set and comparatively better than k-means algorithm.

C. Sparse Neighborhood Selection

General sparse representation of an over complete dictionary can be specified with the help of Robust-SL0 algorithm. Suppose that the matrix $X \in \mathbb{R}^{d\,X\,N}$ is an over complete dictionary, where each column vector is a d-dimensional atom. The number of columns in the matrix X is far greater than the number of rows, which make sure that the dictionary is over complete. Consider a signal $x \in \mathbb{R}^d$, its sparse representation can be seen as finding a sparse vector $w = [w_1, \dots, w_N]^T \in \mathbb{R}^N$ by solving the optimization problem:

$$\min_w \|w\|_0 \;\; s.t \; \|x - Xw\|_2^2 \leq \varepsilon^2$$

Where $\|.\|_0$ denotes the ℓ_0 – norm, which counts the number of non-zero elements in the vector. Due to the requirement of combinatorial search the above problem cannot be solved directly, moreover a small amount of noise completely changes the ℓ_0- norm of the solution. To alleviate this problem LASSO ℓ_1-norm regularization can be used.

In sparse neighborhood selection using Robust SL0 algorithm with regression tree; we divide the whole index set w_i into two subsets. With the help of gradient descent algorithm the solution vector w_i^* can be obtained. Consider t as the number of iterations, then minimum ℓ_2-norm solution $w_i^{(0)}$ can be obtained from pseudo inverse X^+ of X.

$$w_i^{(0)} = X^+ x_i$$

With the constraint condition $supp(w_i) \subset N_K(i)$, reset the jth element in the solution $w_i^{(t)}$ to zero if $j \in N_K^{(i)}$ and will keep the rest unchanged. Then $w_i^{(t+1)}$ can be updated via

$$w_i^{(t+1)} = w_i^{(t)} + \eta \nabla \mathcal{F}_\delta (w_i^{(t)})$$

Where η is a constant term that specifies the iteration steps. After the specified number of iterations have finished, indexes of top k non-zero elements of $w_i^{(T)}$ are selected as the desired neighbors $N_K^{(i)}$ for linear embedding.

D. Iterative Back Projection (IBP)

In this algorithm, the HR image is estimated by back projecting the difference between simulated LR images and the observed LR images. Starting with an initial estimate for the HR image, the back-projection process is repeated iteratively for each incoming LR image. IBP model has two important steps; first step is to construct a model for the imaging process and the second step is image registration process. The relation between a lexicographically ordered LR observation and the original HR image can be expressed as:

$$Y_r = DH_rW_rx + n_r$$

Starting with an initial estimate for the HR image, back projection process is repeated iteratively. The iterative process consists of two important steps: simulation of the observed images, and back projection of error to correct the estimate of the original scene. A small residual error means that the scene estimate is an accurate one; whereas a significant residual error indicates that the estimate is poor so the error information can be used to improve the scene estimate. Back projection process is iterative and reduces the simulation residual error to a minimum.

III. EXPERIMENTAL RESULTS

The Super-Resolution approach based on sparse-neighbor embedding with the help of regression tree classifier and iterative back-projection has been evaluated. Experimental results shows that Super-Resolution with sparse neighbor embedding with the help of regression tree classifier followed by iterative back projection can achieve a better performance compared to k-means and k-NN classification method. Histogram of Oriented Gradient (HoG) method is used as the feature extraction method, which is free from pixel intensity variations and noise occurrences. Input LR image and the reconstructed images using k-NN classification method and that of Regression tree method is given below (Fig. 1 – Fig. 4):

Fig. 2. Input Image

Fig. 3. K-Means and K-NN Based SR

Fig. 4. FCM and Regression Tree Based SR

TABLE 1: COMPARISON

Image	k-means and k-NN based Super-Resolution		FCM and Regression tree based Super-Resolution	
	MSE	PSNR	MSE	PSNR
1	109.5268	27.7356	77.4066	29.2430
2	289.4780	23.5146	233.4096	24.4496
3	15.2513	36.2977	10.8109	37.7922
4	76.6771	29.2841	57.3195	30.5478
5	43.1937	31.7766	30.3356	33.3113

The Table 1 shows the results of k-NN based SR and Regression tree based SR. Here Mean Squared Error (MSE) and Peak Signal to Noise Ratio are considered for evaluation purpose. It is seen that MSE values of the proposed method is lesser compared to k-NN based Super-Resolution and the PSNR value is increased, which indicates that proposed method is better than the existing method. PSNR is most commonly used to measure the quality of reconstruction, higher PSNR generally indicates that the reconstruction is of higher quality.

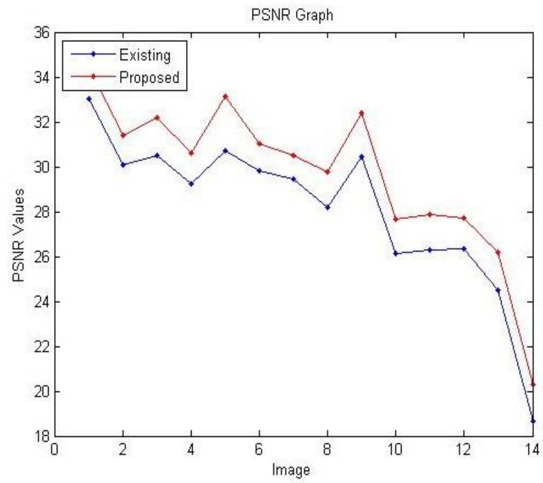

Fig. 5. PSNR Graph

Above graph (Fig. 5) shows the comparison results of k-NN with that of Regression tree PSNR values for fourteen images are represented.

IV. CONCLUSION

In this paper we have presented an efficient method for Super-Resolution using Sparse Neighbor Embedding Algorithm and a classification-regression based classifier. To accelerate the speed of execution clustering on HoG features are done initially with the help of Fuzzy C-means (FCM) clustering method, which divides the entire training data set into a medium subset. Neighbor selection and updating of weights during iteration is done by Robust SL0 algorithm with the help of regression tree classifier. Finally an iterative back projection algorithm is used to obtain an optimal image in case of incompatibility exists.

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REFERENCES

[1]. S. Park, M. Park, and M. Kang, "Super-resolution image reconstruction: A technical overview," IEEE Signal Process. Mag., vol. 20, no.3, pp. 21–36, May 2003.

[2]. Xinbo Gao, Kaibing Zhang, Dacheng Tao, and Xuelong Li,"Image Super-Resolution With Sparse Neighbor Embedding", IEEE Trans Image Processing, Vol. 21, no. 7, July 2012

[3]. Jianchao Yang, John Wright, Thomas Huang, and Yi Ma,"Image Super-Resolution Via Sparse Representation", IEEE. Trans. Image Process., vol. 19, no. 11,pp. 2861–2873, Nov. 2010.

[4]. T.-M. Chan and J. Zhang, "An improved super-resolution with manifold learning and histogram matching," in Proc. IAPR Int. Conf. Biometrics, 2006, pp. 756–762.

[5]. H. Chang, D.-Y. Yeung, and Y. Xiong, "Super-resolution through neighbour embedding," in Proc. IEEE Conf. Comput. Vis. Pattern Recog., Jul. 2004, pp. 275–282.

[6]. A. Eftekhari, M. Babaie-Zadeh, C. Jutten, and H. Abrishami Moghaddam, "Robust-SL0 for stable sparse representation in noisy settings," in Proc.IEEE Int. Conf. Acoust., Speech, Signal Process., Apr. 2009, pp. 3433–3436.

[7]. M. Irani and S. Peleg, "Improving resolution by image registration," CVGIP: Graph. Models Image Process., vol. 53, no. 3, pp. 231–239May 1991.

[8]. S. Osher L. Rudin and E. Fatemi, "Nonlinear total variation based noise removal algorithms," *Physica D.*, vol. 60, pp. 259-268, 1992.

[9]. Esmaeil Faramarzi, Dinesh Rajan, and Marc P. Christensen, " A Unified Blind Method for Multi-Image Super-Resolution and Single/Multi-Image Blur Deconvolution", IEEE TRANSACTIONS ON IMAGE PROCESSING, DEC. 2012.

[10]. B SOWMYA and B SHEELARANI, "Land cover classification using reformed fuzzy C-means", Indian Academy of Sciences, Vol. 36, Part 2, April 2011, pp. 153–165.

[11]. Wang F 1990 Fuzzy supervised classification of remote sensing images. IEEE Trans. Geosci. Remote Sens. 28(2): 194–201.

[12]. Shashi Rathore, Y. Harshalatha / International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622 ,Vol. 2, Issue 6, November- December 2012, pp.1449-1454.

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