Multiple Learned Dictionaries based Clustered Sparse Coding for the Super-Resolution of Single Text Image

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***Abstract*—This paper addresses the problem of generating a super-resolved version of a low-resolution textual image by using Sparse Coding (SC) which suggests that image patches can be sparsely represented from a suitable dictionary. In order to enhance the learning performance and improve the reconstruction ability, we propose in this paper a multiple learned dictionaries based clustered SC approach for single text image super-resolution. For instance, a large High-Resolution/Low-Resolution (HR/LR) patch pair database is collected from a set of high quality character images and then partitioned into several clusters by performing an intelligent clustering algorithm. Two coupled HR/LR dictionaries are learned from each cluster. Based on SC principle, local patch of a LR image is represented from each LR dictionary generating multiple sparse representations of the same patch. The representation that minimizes the reconstruction error is retained and applied to generate a local HR patch from the corresponding HR dictionary. The performance of the proposed approach is evaluated and compared visually and quantitatively to other existing methods applied to text images. In addition, experimental results on character recognition illustrate that the proposed method outperforms the other methods, involved in this study, by providing better recognition rates.**

I. Introduction

Low-resolution scanning presents a source of degradation that affects text embedded in document images. Consequently, degraded characters are not only disagreeable to view on a display device, but they also pose serious challenges to document processing systems such as Optical character recognition (OCR). Indeed, the performances of these applications depend critically on the image quality. For better visualization and interpretation, poorly resolved textual image needs to be reconstructed via a Super-Resolution (SR) process. The goal of such process is to recover a HR image from one or more observed LR images. According to the number of LR input images, there are mainly two kinds of SR: multi-images SR and Single-Image SR (SISR). The basic idea of the first kind is to combine the non-redundant information present in multiple LR images of the same scene that should be aligned with a sub-pixel accuracy. The SISR kind (known also as image up-scaling, up-sampling and zooming) suggests that the observed LR image is assumed to have been generated from the original HR image by a blur and down-sampling process.

This paper focuses on the SISR task that has become a very active research topic mainly with the rapidly increasing need of high quality images and videos. Multiple SR methods have been proposed in the last two decades to solve this task. Most of these methods have been concentrated on the natural images with no real application on the textual ones. Thus, this work aims to tackle this lack by proposing a SISR method for printed text in document images. The proposed method is based on a recently learning based approach known as Sparse Coding (SC) which suggests that image patches can be sparsely represented from a suitably chosen dictionary. Toward this principle, a generic training HR/LR patch pair database is collected from high-quality character images allowing the SR of text images. Motivated by the key role of the dictionary in SC theory, we propose a learning strategy based on unsupervised clustering of the training database in order to find more appropriate dictionaries adapted to the properties of characters. Given multiple learned dictionaries, a clustered SC scheme is proposed to enhance the SR process. The impact of the given contributions is studied on the visual text image quality and even on the character recognition accuracy. Interesting results have been thus achieved.

The rest of this paper is organized as follows: Section 2 presents a brief review of related works on SISR. Then, section 3 details the multiple learned dictionaries based clustered SC approach proposed for single text image SR. Experiments and comparative studies with results generated by other SR approaches are provided in section 4. Finally, conclusions and some perspectives are given in Section 5.

II. Related Works

The main approaches proposed in the literature for SISR are those based on interpolation, regularization and learning. The interpolation based approaches are the simplest ones and relies on the convolution of the image with kernels such as linear, cubic or higher order. Non-adaptive interpolation algorithms, which treat the whole image in the same way, suffer from generating artifacts along sharp edges. In order to improve the images sharpness, several adaptive interpolation algorithms have been proposed treating every image part differently. Examples of related works can be found in [2, 9]. However, such treatment process is very limited while generating high frequency components or fine details.

The regularization based approaches, such as [3, 8], enable the inclusion of a priori reconstruction constraints which requires that the smoothed and down-sampled version of the HR image should be close to the LR one. This category of approach overcomes most artifacts mentioned above, but is still suffering from other non-natural artifacts and its performance decreases when the scaling-up factor increases.

Rather than relying on heuristically derived information, learning based approaches have been proposed to model the relationship between LR input image and HR output image from a training database. The goal of these methods is not only to maintain the sharpness and details of the image, but also to recover new missing HR details that are not explicitly found in the LR image and assumed to be available in the training database. For instance, Sun et al. introduced the gradient profile prior learned from a large number of images to estimate the local image structures and hence to maintain the sharpness of the resulted image [16]. Freeman et al. developed a learning based approach where the prediction between LR and HR image patches is trained via Markov Random Field [6]. In [15], the authors designed neural networks with a spatial error feedback as interpolators to recover HR pixels. A common drawback of these above SR methods is that they heavily rely on enormous databases of millions of HR and LR patch pairs and therefore have an intensive computation.

More recently, a SC learning based approach has attracted increasing interest due to its effectiveness in various reconstruction tasks like SISR. Using the SC strategy, more patches can be represented using a smaller training database than the above learning approaches. However, the choice of the dictionary is a key for the successful of the SC based SISR. The authors of [21] constructed prototype dictionaries by randomly sampling raw patches from training images of similar statistical nature to the input image. Such dictionaries leaded to a state-of-the-art result. In [1, 9, 20], dictionary learning algorithms was developed to reduce the complexity of SC under prototype dictionaries. Recently, multiple dictionaries learning approach based on clustering training image patches is introduced. For example, Yang et al. [23] learn several dictionaries from K-means clustered patches. In [22], geometric dictionaries are learned after classifying training patches into several groups of geometric patches. These works have been successfully applied to natural, human face and synthetic aperture radar images.

While the methods mentioned above were proposed for generic image SR, other methods have been tailored to specific applications such as SR of document text images. For instance, Freeman et al. [6] proposed an exemplar-based approach which mapped blocks of the LR image into predefined HR blocks. This approach was applied to text image SR in [5]. Nevertheless, the results depend heavily on the examples of the training set and, more precisely, on the type font which must be known in advance. Luong and Philips [11, 12] demonstrated that the estimation of the restored pixel intensity can be based on information retrieved from the whole image, thereby exploiting the presence of repeating characters in the image and then applying the multi-image SR principle. To collect match similar character segments, Luong's method started with character segmentation which is not usually evident in LR text images. In [17], the authors proposed to solve SR problem by using factor graph. The unobserved patches in the HR image are modeled as nodes in the graph and the characteristic distribution of the derivatives of training images are used to define the constraint functions between nodes in the factor graph. A recent method based on SC is proposed to the SR of text image [18]. This method is based on single dictionary learned from a generic HR/LR patch pair database and adapted to the character properties.

In this paper, we propose a learning based approach for the SR of single text image using clustered SC and multiple dictionaries. The following section details the proposed method.

III. SISR Via Multiple Learned Dictionaries Based Clustered Sparse Coding

To address the SISR task by using SC, we divide the issue into two phases: the training phase and the reconstruction phase detailed in the following.

A. Training Phase

The training phase begins by collecting several images which are considered to be the HR examples. To produce high-quality character images, a graphic library called FreeType which implements a highly efficient font engine is used in this work. Via this library, HR character images are automatically obtained by discretizing vector fonts. We use for each character a large variety of sizes, styles (italic, non-italic) and fonts (serif, sans-serif) currently used in textual documents, signs, labels, bills, etc. After that, several HR patches are selected from each HR character image. Notice that we are interested only in patches localized along the edges of characters because the shape of edges is a very interesting reference to describe characters. For each HR patch, we generate the corresponding LR patch by blurring and down-sampling. This leads to the collection of a generic HR/LR patch-pairs database.

Training database contains numerous patterns which are very different due to their shapes, sizes, orientations and positions in the image patches. Single HR dictionary learned from all these data is not guaranteed to be suitable for the SR reconstruction task even if it has large number of atoms. Moreover, this leads to an intensive computation complexity. To overcome these limitations and to take full advantage of large training database, we propose to learn multiple dictionaries from a clustered database. We haven't prior knowledge about the database to guide the clustering process such as the number of clusters. Therefore, we partition the training database into C clusters in unsupervised fashion. In fact, an intelligent version of the K-means method, referred as iK-means [13], is applied to gather similar patterns in the same cluster. This clustering method determines the number of clusters and initial centroids for K-Means using the so-called anomalous pattern algorithm.

Given HR and the corresponding LR image patches of each cluster, two coupled HR/LR dictionaries are learned by using joint SC method [20]. The goal of this learning method, which is based on the SC algorithm proposed in [9], is to have the same sparse representation for each HR/LR image patch pair. Figure 1 displays some examples of the HR learned dictionaries which can describe the intrinsic geometrical structure of the corresponding training cluster. Thus, the proposed learning strategy can provide more appropriate dictionaries representing each cluster.

B. Reconstruction Phase

This phase is based on the SC principle which suggests that an input signal $X \in \Re^N$ can be well represented as a sparse linear combination of atoms from a suitably chosen dictionary D. This principle can be mathematically written as:

$$(P_0) : min_{\alpha} \|\alpha\|_0 \;\; s.t. \;\; \|X - D\alpha\|_2^2 \leq \rho \qquad (1)$$

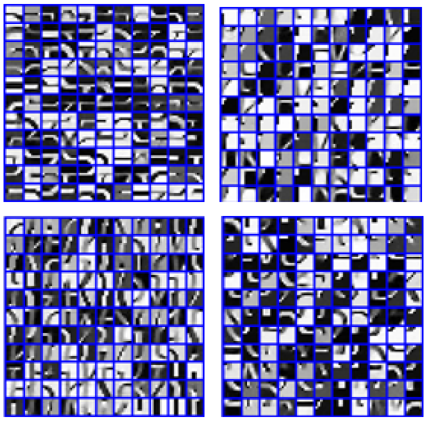

Fig. 1. Examples of HR dictionaries generated by the proposed learning strategy based on unsupervised clustering.

where α is the sparsest representation of X in D and ρ characterizing an allowable reconstruction error. Because of solving the optimization problem (P_0) is often difficult, Chen *et al.* [4] proposed that as long as α is sufficiently sparse, the problem (P_0) can be substituted by instead minimizing the l_1-norm as follows :

$$(P_1) : min_{\alpha}\|\alpha\|_1 \;\; s.t. \;\; \|X - D\alpha\|_2^2 \leq \rho \qquad (2)$$

The starting point of the reconstruction phase is the input LR image. The classical way of beginning a SR process is by up-sampling the input LR image via the bicubic interpolation. The interpolated image is considered as the LR image to be processed. LR patches (respectively the corresponding HR patches to construct) are processed from the upper-left corner with overlapping between adjacent patches. Instead of applying on each LR patch a feature extraction operator to represent it by a set of features (like in [20, 21]), we rely in our setting directly on pixels values composing the LR patch. The first step is to subtract the mean pixel value m from each local LR patch. Based on the theory about sparse coding, a LR patch y_j can be sparsely represented over a learned dictionary D_l, i.e. the solution of the problem (P_1) presented above. Given multiple learned LR dictionaries $\{D_l^k, k = 1..C\}$ prepared by the proposed learning strategy, every LR patch y_j is sparsely coded over each LR dictionary. This leads to the generation of multiple sparse representations $\{\alpha^k, k = 1..C\}$ for the same patch. In this contest, (P_1) is written as :

$$(P_1) : min_{\alpha^k}\|\alpha^k\|_1 \;\; s.t. \;\; \|y_j - D_l^k\alpha^k\|_2^2 \leq \rho \qquad (3)$$

Several algorithms have been proposed in the literature to solve (P_1). In our implementation, the feature-sign search algorithm [9] is selected because of its efficiency and significant speedup. After that, instead of using all the sparse representations weighted and summarized according to the coding errors (like in [22, 23]), we propose to select only the representation $\widehat{\alpha}$ that minimizes the local reconstruction error according to the appropriate LR dictionary $\widehat{D_l}$:

$$\widehat{\alpha} = min_{\alpha^k}\{\|y_j - D_l^k\alpha^k\|_2^2, \; k = 1..C\} \qquad (4)$$

The optimal solution $\widehat{\alpha}$ is then applied to generate a local HR patch x_j from the corresponding HR dictionary based on : $x_j = \widehat{D_h}\widehat{\alpha} + m$. Subsequently, the initial HR image X_0 is obtained by simply averaging the values in the overlapped regions to enforce compatibility between adjacent patches. Next, we apply on X_0 a global reconstruction constraint to eliminate the reconstruction errors and to ensure consistency with the LR input image. In fact, this constraint is that an observed LR image Y consists of a blurred and downsampled version of a HR image X of the same scene: $AHX = Y$, where A and H represents respectively a downsampling operator and a blurring filter. To enforce the global reconstruction constraint, we should solve the following optimization problem:

$$\widehat{X} = argmin_X\|X - X_0\| \;\; s.t. \;\; DHX = Y \qquad (5)$$

To finalize this task, we use Back-Projection method originally developed in computer tomography and applied to SR in [8, 20, 21]. Finally, a bilateral filtering is performed on the recovered HR image to better preserve edges and hence to further enhance the global reconstruction.

Based on the above description, the proposed reconstruction phase can be summarized as algorithm 1. We conclude this section by summarizing the main characteristics of our proposed method compared with the available SC based SISR methods. In fact, an intelligent and unsupervised clustering of the training database is introduced into the learning of multiple dictionaries. Such learning strategy doesn't require prior knowledge about the number of clusters and then differs from those of the existing SISR methods which have recourse to a supervised clustering. In addition, the use of multiple dictionaries is already defined in the literature, but our contribution differs in generating a clustered SC scheme via multiple dictionaries that minimizes as much as possible the local reconstruction errors and subsequently enhances the SR process. As such process is, to the best to our knowledge, an original approach never applied before for the processing of textual document images.

Algorithm 1:
SISR via multiple learned dictionaries based clustered SC.

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1. Input: a LR image Y, the multiple coupled LR/HR dictionaries $\{D_l^k, D_h^k, k = 1..C\}$ learned from the clustered database.

2. Using a sliding window to scan the input LR image and to construct the HR image from the upper-left corner with overlapping in each direction,

For each LR patch y_j of Y,

- Subtract the mean pixel value m of y_j.
- Perform the SC under each LR learned dictionary D_l^k to find the solution α_k of the problem (3).
- Select the optimal solution $\widehat{\alpha}$ of (4) according to the appropriate LR dictionary $\widehat{D_l}$.
- Compute the corresponding HR version x_j of the LR patch y_j by $x_j = \widehat{D_h}\widehat{\alpha} + m$.
- Put the resulting HR patch x_j into the HR image X_0.

End.

3. Merge the overlapped HR patches to generate the initial HR image X_0.

4. Generate the HR image $\widehat{X}$, which satisfies (5).

5. Apply a bilateral filtering on the HR image $\widehat{X}$.

6. Output: HR image $\widehat{X}$.

IV. Experiments and Evaluations

In this section, experimental SR results achieved by applying the proposed SR method and other SR methods on different LR text images are given. Results are evaluated both visually and quantitatively on text image quality and on character recognition performance.
In the proposed training phase, we generate 2480 high-quality training character images from which 124000 HR patches of size 7×7 and the corresponding LR patches are collected to form the HR/LR patch-pairs database. By performing the intelligent clustering iK-means method [13], this database is divided into 13 clusters. The multiple HR/LR dictionaries learned from the clustered database are of size 49×128. In fact, each dictionary has 128 atoms and each atom is represented by 49 pixel values. In the proposed reconstruction phase, a sliding window of size 7×7 with 5 pixels overlap is selected to scan the input LR image and then to construct the HR image.

A. Experimental Results: Text Image Quality

To investigate the performance of the proposed method, we compare it with bicubic interpolation and other recently published SR methods based on SC [18, 20] that differ from our method in important aspects. Indeed, unlike our method which is based on multiple coupled HR/LR dictionaries learned from a clustered database, the authors of [18, 20] use single coupled HR/LR dictionaries learned from the whole training database. By doing so, their reconstruction of a LR patch is based on a single sparse representation, but our reconstruction relies on multiple sparse representations generated by clustered SC for the same LR patch. From the same database of HR character images prepared in this study, single coupled HR/LR dictionaries (each dictionary is composed by 512 atoms) are trained and used in Walha's method [18] and in Yang's method [20] which is hence adapted to text image SR.
In this experiment, tests are performed for the up-scaling factor 2 on the LR text images shown in figure 2. These images, which are generated by blurring and down-sampling by a factor of 2 of the HR ground truth images, contain different texts size (10, 12), style (italic, non-italic, bold, non-bold) and font (serif, sans-serif). Results are evaluated based on the widely used metrics in image processing for recovery including the Root Mean Square Error (RMSE), the Peak SNR (PSNR) and the Structural SIMilarity index (SSIM) [19]. Table 1 compares quantitatively the RMSE, PSNR and SSIM results of the super-resolved images recovered by bicubic interpolation, the proposed method and the other SR methods [18, 20]. According to this table, we can see that images reconstructed by the proposed clustered SC method achieve higher measures result than [18], [20] and bicubic interpolation. More precisely, we conclude that under the same training database of character images, our method performs better than the other SC based methods involved in this study. In order to have a closer look, we specify a region in the LR image and in the reconstructed images and we enlarge it as shown in figure 4.
Compared to the original LR image in figure 4(a), we can notice clearly significant improvements in visual quality in the result produced by each SR method. Indeed, the letters are much better readable and blur is heavily reduced. On the other hand, results of [18], [20] and the proposed method have better visual quality than those of the bicubic interpolation which generates blur effects. Moreover, when we compare visually results in figure 4(c)-(d) versus those in figure 4(e), we can observe that image produced by the proposed method is clearer and sharper at edges than images recovered by [18] and [20] that have significant artifacts appearing near edges.

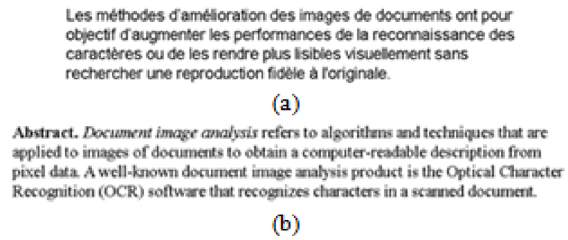

Fig. 2. Illustration of LR text images.

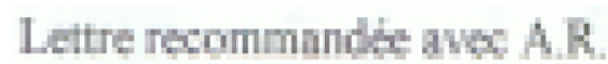

Fig. 3. Enlarged text line of the LR image scanned at 72 dpi.

B. Experimental Results: Character Recognition

Recognizing a LR text image is a challenging task and involves several difficulties to OCR systems. An efficient SR process performed before recognition can improve the character recognition performance. Hence, the goal of this section is to evaluate the influence of the SISR methods involved in this study on character recognition performance. As a realistic experimentation, tests are performed on a LR text image of small font size scanned at 72 dpi. For instance, a text line of this image is enlarged and shown in figure 3. The LR image and the corresponding HR images, that are super-resolved with a factor of 2 by bicubic interpolation, [20], [18] and the proposed SR method, are fed into two popular OCR systems: FreeOnlineOCR [26] and AbbyFineReader 10 [24]. Results, exposed in table 2, are investigated in terms of character OCR accuracy percentage defined as: $(R - L)/R \times 100$, where R is the total number of the correct character and L is the Levenshtein distance which is the total minimum cost of transforming one string into the other using the following edit operations: insertions, deletions and substitutions [14].
As shown in table 2, accuracies of the OCR engines are well

TABLE I. RMSE, PSNR and SSIM Results Of Text Images Recovered By Different SR Methods

Image	Measures	Bicubic	Yang et al. [20]	Walha et al. [18]	Proposed method
(a)	RMSE	39.581	34.541	33.541	**28.462**
	PSNR	16.180	17.364	17.619	**19.045**
	SSIM	0.805	0.825	0.855	**0.912**
(b)	RMSE	42.739	38.488	37.880	**35.034**
	PNSR	15.514	16.424	16.562	**17.240**
	SSIM	0.746	0.771	0.801	**0.846**

TABLE II. The Character Recognition Rates Over Different OCR Systems Performed On The Original LR Image And The HR Images Recovered By Several SR Methods.

OCR	LR image	HR image recovered by			
		Bicubic	*[20]*	*[18]*	*Proposed method*
FreeOnlineOCR	76.36	58.64	91.24	89.27	**91.46**
AbbyFineReader	84.46	92.34	88.62	89.49	**92.99**

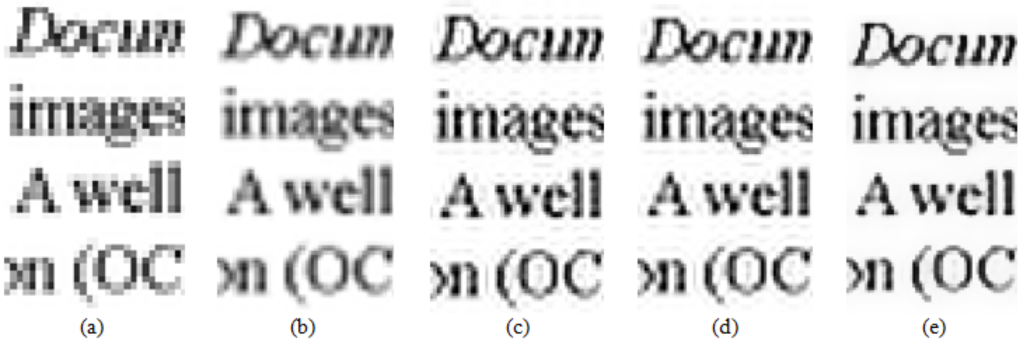

Fig. 4. Visual comparison of enlarged regions from LR and magnified text images recovered by different SR methods. (a) LR image. (b) Bicubic interpolation. (c) Method of [20]. (d) Method of [18]. (e) The proposed SR method.

improved by preprocessing the LR text image with the proposed SR method before recognizing it. Indeed, a significant accuracy increase of up to 15.1% in the case of FreeOnlineOCR and up to 8.53% in the case of AbbyFineReader is achieved when recognizing the text image super-resolved via our method, as compared to the original LR image. In addition, the proposed SR method combined with any OCR system consistently generates the most significant improvements in term of character recognition rate compared with the use of bicubic interpolation, [20] or [18] as preprocessing. This is due to the improved ability of our SR method in preserving edges and thus in distinction between characters.

V. Conclusions

In summary, we mention the main contributions of this paper. Firstly, a generic HR/LR patch pair database useful for finding a dictionary adapted to the characters properties was established and then partitioned into several clusters by performing an intelligent clustering algorithm. Secondly, the proposition of multiple learned dictionaries based clustered SC method was applied to the SR of LR document text images. The performance of this method was evaluated visually and quantitatively on different text images and compared to other SR methods. Experimental results showed the effectiveness of the proposed SR method which produced clearer and sharper characters than those obtained by the other methods. As a third contribution, such improvements lead to a significant improvement of the OCR systems accuracy.
A proposed extension to our work is to combine the proposed clustered SC based SR method with multi-images SR techniques in order to improve text images quality in video applications.

References

[1] M. Aharon, M. Elad, A. Bruckstein, *K-SVD : An algorithm for designing overcomplete dictionaries for sparse representation*, IEEE Trans. signal processing, 54(11):4311-4322, 2006.

[2] S. Battiato, G. Gallo, F. Stanco, *Smart interpolation by anisotropic diffusion*, ICIAP, Italy, pp 572-577, 2003.

[3] M. Ben-Ezra, Z. C. Lin, B. Wilburn. *Penrose pixels: Super-resolution in the detector layout domain*, ICCV, 2007.

[4] S. S. Chen, D. L. Donoho, M. A. Saunders, *Atomic decomposition by basis pursuit*, SIAM Review, 43(1):129-59, 2001.

[5] G. Dalley, W. Freeman, J. Marks, *Single-frame text super-resolution: a bayesian approach*, ICIP, pp 3295-3298, 2004.

[6] W. Freeman, T. Jones, E. Pasztor, *Example-based super-resolution*, IEEE Computer Graphics and Applications. 22(2):55-65, 2002.

[7] W. T. Freeman, E. C. Pasztor, O. T. Carmichael, *Learning low-level vision*, IJCV, 2000.

[8] M. Irani and S. Peleg, *Motion analysis for image enhancement: Resolution, occlusion and transparency*, JVCL, 4(4):324-335, 1993.

[9] H. Lee, A. Battle, R. Raina, A. Y. Ng, *Efficient sparse coding algorithms*, Neural Information Processing Systems (NIPS), 2007.

[10] X. Li, M.T. Orchard, *New edge-directed interpolation*, IEEE Trans. Image Process., (10):1521-1527, 2001.

[11] H. Luong, W. Philips, *Non-local text image reconstruction*, ICDAR, Vol. 1, pp 546-550, Brazil, 2007.

[12] H. Luong, W. Philips, *Robust reconstruction of low-resolution document images by exploiting repetitive character behavior*, IJDAR, 11(1):39-51, 2008.

[13] B.G. Mirkin, *Clustering for data mining: a data recovery approach*, Vol. 3, CRC Press, 2005.

[14] S. Rice, *Measuring the Accuracy of Page-Reading Systems*, PhD thesis, University of Nevada, 1996.

[15] C. Staelin, D. Greig, M. Fischer, R. Maurer, *Neural network image scaling using spatial errors*, Tech. Rep. HPL-2003-26R1, HP Labs, Israel, 2003.

[16] J. Sun, Z. Xu, H. Shum, *Image super-resolution using gradient profile prior*, CVPR, 2008.

[17] M. F. Tappen, B. C. Ruseel, W. T. Freeman, *Exploiting the Sparse Derivative Prior for Super-Resolution and Image Demosaicing*, Workshop on Statistical and Computational Theories of Vision, ICCV, 2003.

[18] R. Walha, F. Drira, F. Lebourgeois, A. M. Alimi, *Super-resolution of single text image by sparse representation*, Workshop on Document Analysis and Recognition (DAR), ICVGIP, pp 22-29, 2012.

[19] Z. Wang, A. C. Bovik, H. R. Sheikh, *Image quality assessment: From error visibility to structural similarity*, IEEE Trans. Image Process., 13(4):600-612, 2004.

[20] J. Yang, J. Wright, T. Huang, Y. Ma, *Image super-resolution via sparse representation*, IEEE Trans. Image Process., 19(11):2861-2873, 2010.

[21] J. Yang, J. Wright, T. Huang, Y. Ma, *Image Super-Resolution as Sparse Representation of Raw Image Patches*, CVPR, 2008.

[22] S. Yang, M. Wang, Y. Chen, Y. Sun, *Single-Image Super-Resolution Reconstruction via Learned Geometric Dictionaries and Clustered Sparse Coding*, IEEE Trans. Image Process., vol. 21, no. 9, 2012.

[23] S. Y. Yang, Z. Z. Liu, L. C. Jiao, *Multitask dictionary learning and sparse representation based single-image super-resolution reconstruction*, Neurocomputing, 74(17):3193-3203, 2011.

[24] www.finereader.abbyy.com

[25] www.freetype.org

[26] www.newocr.com