RESEARCH ARTICLE OPEN ACCESS

A Modified Teaching Learning Based Optimal Smooth Ordering for Image Enhancement

Ahila.C, N.A.Vidya Mol
M.Tech (Information Technology) in, Vins Christian College of Engineering. e-mail:ahilac1990@gmail.com,
2Ms.N.A.Vidya Mol M.E., Asst.prof.of Vins Christian College of Engineering.

Abstract:
In image processing, input is an image such as photograph or video frame and output may be either image or set of characteristics or parameters related to image. A new image processing scheme is proposed which is based on smooth 1D ordering of the pixels of the image. The proposed scheme is based on reordering of its patches. For a given corrupted image extract all patches with overlaps and order them such that they are chained in the "shortest possible path," to solve using traveling salesman problem. Apply advance modify Teaching learning algorithm for solve travelling salesman problem and to select best filter coefficient. The obtained ordering shortest path is applied to the corrupted image means a permutation of the image pixels. This allows obtaining good recovery of the clean image by applying filtering or interpolation to the reordered set of pixels. The proposed scheme can be used for image denoising and inpainting, to achieves high quality results. Simulation results shows that the proposed algorithm is better than that of the existing algorithm in terms of visual quality and peak signal to noise ratio (PSNR).
Keywords— Patch-based processing, Modified Teaching Learning Optimization, Pixel permutation, Denoising, Image enhancement.

I. INTRODUCTION

Image processing using local patches has become very popular and was shown to be highly effective for representative work. The core idea behind these and many other contributions is the same: given the image to be processed, extract all possible patches with overlaps; these patches are typically very small com-pared to the original image size a typical patch size would be 8 × 8 pixels. The processing itself proceeds by operating on these patches and exploiting interrelations between them. The manipulated patches are then put back into the image canvas to form the resulting image.

There are various ways in which the relations between patches can be taken into account weighted averaging of pixels with similar surrounding patches as the NL-Means algorithm clustering the patches into disjoint sets and treating each set differently as performed seeking a representative dictionary for the patches. A To used a plain 1D wavelet transform and adapted it to the image by operating on a permuted order of the image pixels. Thus propose a very simple image processing scheme that relies on patch reordering. To start by extracting all the patches of size $\sqrt{n} \times \sqrt{n}$ with maximal overlaps. Once these patches are extracted disregard their spatial relationships altogether and seek a new way for organizing them.

Therefore, if the image mentioned above is of high-quality the new ordering of the patches is expected to induce a highly regular 1D ordering of the image pixels, being the center of these patches. When the image is deteriorated the above ordering is expected to be robust to the distortions thereby suggesting a reordering of the corrupted pixels to"what should be" a regular signal. Thus applying relatively simple one-dimensional (1D) smoothing operations such as filtering or interpolation to the reordered set of pixels should enable good recovery of the clean image.

A new image processing scheme is used which is based on smooth 1D ordering of the pixels of the image. The proposed scheme is based on reordering of its patches. For a given corrupted image extract all patches with overlaps and order them such that they are chained in the shortest possible path to solve using traveling salesman problem. Apply advance modify Teaching learning algorithm for solve travelling salesman problem and to select best filter coefficient. The obtained ordering shortest path is applied to the corrupted image means a permutation of the image pixels. This allows obtaining good recovery of the clean image by applying filtering or interpolation to the reordered set of pixels. The proposed scheme can be used for image denoising and inpainting to achieves high quality results.

II. RELATED WORKS

The permutation matrices and simple and intuitive 1D operations such as linear filtering and interpolation the proposed scheme can be used for image denoising and inpainting where it achieves high quality results. The for a given corrupted image reorder its pixels operate on the new 1D signal using simplified algorithms and reposition the resulting values to their original location. The proposed image reconstruction scheme to image denoising and shows that it achieves better results than the ones obtained with the K-SVD algorithm for medium and high noise levels and generally performs better than the BM3D algorithm for high noise levels.

A. Structured Sparse Model Selection (SSMS)

A structured sparse model selection (SSMS) signal model that reduces tremendously the degree of freedom as well as the computational complexity in signal estimation and on the top of that provides state-of-the-art image enhancement results.

B. Expected Patch Log Likelihood (EPLL)

The basic idea behind the method is to try to maximize the Expected Patch Log Likelihood (EPLL) while still being close to the corrupted image in a way which is dependent on the corruption model [2]. EPLL is the expected log likelihood of a patch in the image. Since it sums over the log probabilities of all overlapping patches it double counts the log probability. Rather it is the expected log likelihood of a randomly chosen patch in the image

C. Patch-Based Image Interpolation

Motivated by recent advances in adaptive sparse representations and nonlocal image modeling propose a patch-based image interpolation algorithm under a set theoretic framework. An algorithm [4] alternates the projection onto two convex sets. One is given by the observation data and the other defined by sparsity based nonlocal prior similar to BM3D. A Monte-Carlo based algorithm is proposed to optimize the randomness of sampling patterns to better approximate homogeneous Poisson process. Image interpolation and coding applications are reported to demonstrate the potential of the proposed algorithms.

D. Image Denoising Using NL-Means via Smooth Patch Ordering

Image denoising scheme based on reordering of the noisy image pixels to a one dimensional (1D) signal and applying linear smoothing filters on it. This algorithm had two main limitations such as, it did not take advantage of the distances between the noisy image patches, which were used in the reordering process.

The smoothing filters required a separate training set to be learned from. An image denoising algorithm [11] applies similar permutations to the noisy image but overcomes the above two shortcomings. To eliminate the need for learning filters by employing the nonlocal means (NL-means) algorithm.

To estimate each pixel as a weighted average of noisy pixels in union of neighborhoods obtained from different global pixel permutations the weights are determined by distances between the patches. It can show that the proposed scheme achieves results which are close to the state-of-the-art. The obtained ordering shortest path is applied to the corrupted image means a permutation of the image pixels.

E. Adaptive Sparse Domain Selection and Adaptive Regularization

As a powerful statistical image modeling technique sparse representation has been successfully used in various image restoration applications. First, a set of auto regressive (AR) models are learned from the dataset of example image patches. The best fitted AR models to a given patch are adaptively selected to regularize the image local structures. Second, the image non-local self-similarity is introduced as another regularization term. In addition, the sparsity regularization parameter is adaptively estimated for better image restoration performance.

III PROPOSED METHOD

The proposed scheme is based on reordering of its patches. For a given corrupted image extract all patches with overlaps and order them such that they are chained in the shortest possible path to solve using traveling salesman problem. Apply advance modify Teaching learning algorithm for solve travelling salesman problem and to select best filter coefficient. The obtained ordering shortest path is applied to the corrupted image means a permutation of the image pixels. This allows obtaining good recovery of the clean image by applying filtering or interpolation to the reordered set of pixels.

A. Preprocessing

Image pre-processing is the term for operations on images at the lowest level of abstraction. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. First resize the image using bicubic interpolation- balances image quality against performance. After resizing, divide the image into overlapping blocks of 8x8 pixels, and use DCT to transform each block into DCT coefficients and then add additive noise for getting a suitable dictionary for denoising. The denoising process includes a sparse coding of each patch of size 8×8pixels from the noisy image. Finally divide the patches separately.

B.Teaching Learning-Based Optimization

This optimization method is based on the effect of the influence of a teacher on the output of learners in a class. It is a population based method and like other population based methods it uses a population of solutions to proceed to the global solution. A group of learners constitute the population in TLBO. In any optimization algorithms there are numbers of different design variables. The different design variables in TLBO are analogous to different subjects offered to learners and the learners result is analogous to the fitness as in other population-based optimization techniques. As the teacher is considered the most learned person in the society the best solution so far is analogous to Teacher in TLBO. The process of TLBO is divided into two parts. The first part consists of the "Teacher phase" and the second part consists of the "Learner phase". The "Teacher phase" means learning from the teacher and the "Learner phase" means learning through the interaction between learners.

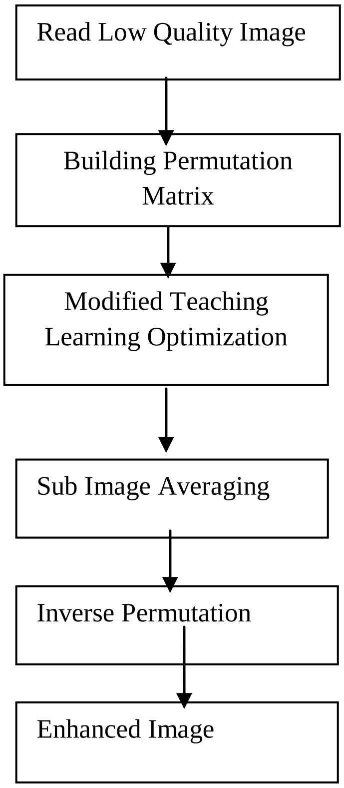


Figure 1: Proposed System Architecture

1) Initialization

Following are the notations used for describing the TLBO

N: number of learners in class i.e. "class size"

D: number of courses offered to the learners

MAXIT: maximum number of allowable iterations

The population X is randomly initialized by a search space bounded by matrix of N rows and D columns. The jth parameter of the ith learner is assigned values randomly using the equation (1)

$$x^0_{(i,j)}=x_j^{min}+\text{rand}\times(x_j^{max}-x_j^{min})\ldots\ldots (1)$$

where rand represents a uniformly distributed random variable within the range (0, 1), x_j^{max} and x_j^{min} represent the minimum and maximum value for jth parameter. The parameters of ith learner for the generation g are given by eqn (2),

$$X^g_{(i)}=[x^g_{(i,1)},x^g_{(i,2)},x^g_{(i,3)},\ldots\ldots,x^g_{(i,j)},\ldots\ldots,x^g_{i,D}]\ldots(2)$$

2) Teacher phase

The mean parameter M^g of each subject of the learners in the class at generation g is given as,

$$M^g= [m^g_1,m^g_2,\ldots\ldots,m^g_j,\ldots\ldots,m^g_D]\ldots\ldots (3)$$

The learner with the minimum objective function value is considered as the teacher $X^g_{Teacher}$ for respective iteration. The Teacher phase makes the algorithm proceed by shifting the mean of the learners towards its teacher. To obtain a new set of improved learners a random weighted differential vector is formed from the current mean and the desired mean parameters and added to the existing population of learners.

$$Xnew^g_{(i)}=X^g_{(i)}+\text{rand}\times (X^g_{Teacher}-T_F M^g)\ldots\ldots (4)$$

TF is the teaching factor which decides the value of mean to be changed. Value of TF can be either 1 or 2. The value of TF is decided randomly with equal probability as eqn(5),

$$T_f=\text{round } [1+\text{rand } (0, 1) \{2-1\}]\ldots\ldots\ldots\ldots\ldots (5)$$

where TF is not a parameter of the TLBO algorithm. The value of TF is not given as an input to the algorithm and its value is randomly decided by the algorithm. After conducting a number of experiments on many benchmark functions it is concluded that the algorithm performs better if the value of TF is between 1 and 2. However, the algorithm is found to perform much better if the value of TF is either 1 or 2 and hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria.

3) Learner phase

In this phase the interaction of learners with one another takes place. The process of mutual interaction tends to increase the knowledge of the learner. The random interaction among learners improves his or her knowledge. For a given learner $X^g_{(i)}$, another learner $X^g_{(r)}$ is randomly selected ($i \neq r$). In this approach, termed OTLBO each learner in the class of learners can be divided into several partial vectors where each of them acts as a factor in the orthogonal design.

Procedure for generating an orthogonal array L

Algorithm 1: Procedure for generating an orthogonal array L.

input: The number of levels Q

output: An orthogonal array L

Initialize an zero matrix L with M rows and P columns.

for i=1 to M do

$L_{i,1}$=**mod ([$\frac{i-1}{q}$],q)**

$L_{i,2}$=**mod (i-1,q)**

for j=1 to P-2 do

$L_{i,2+j}$=**mod ($L_{i,1} \times j + L_{i,2}$, q)**

end

end

A teaching learning based optimization approach based on orthogonal design (OD). In this approach, termed OTLBO, each learner in the class of learners can be divided into several partial vectors where each of them acts as a factor in the orthogonal design. Orthogonal design is then employed to search the best scales among all the various combinations.

Each solution to the optimization problem is represented as a learner. For an objective function with N variables, a learner is encoded in the form of

$$X_i = [x_{i,1}, x_{i,2}, x_{i,3}, \ldots, x_{i,N}], i = 1, 2, 3, \ldots\ldots\ldots, S$$

where S is the population size. The standard TLBO algorithm updates the current learner by comparing with best learner (i.e. teacher) in teacher phase and with a randomly select learner in learner phase. It lacks the interaction between neighboring learners and it may easily trap into local minima.

One technique to address this problem is to employ the multi-parent crossover during evolution and this technique has been shown to improve the convergence rate when applied to GAs. Given m learners, the question is how to execute the multi-parent efficiently. Since each learner consists of N factors, there are mN combinations. Consequently, the orthogonal design method is employed to select m (if a Lm (QP) orthogonal array is considered, where P = N and Q = m) representative sets of combinations to shorten the computational time.

Algorithm 2: OD-based operator for m learners

input: m particles $X_{i,j}$,i$\in [1, m]$ $and\ j \in [l, N]$

output: A new set of m learners $P_{i,j}$

Construct the orthogonal array $L_{m\times m}(M^m$+1) using algorithm 1.

Delete the last (m+1-n) columns of $L_{m\times m}(M^m$+1) to get $A = L_{m\times m}(m^n)$

Generate m new learners:

for i=1 to m do

for j=1 to N do

Index=Ai,j

$P_{i,j}$=$X_{index,j}$

end

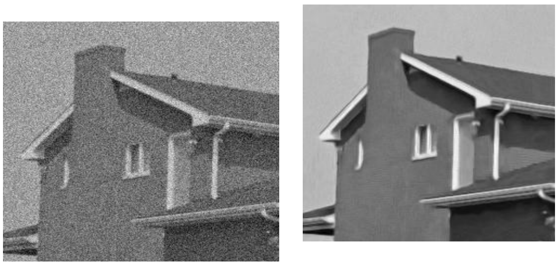
end

4) Steps of OD-based TLBO

To obtain a more precise solution compared to the standard TLBO, the OD-based operator is employed. The elitism preservation strategy for upgrading the current population is proposed, in which the learner is updated only if its fitness is improved. The procedure for the OD-based TLBO is shown in Algorithm 3. A convergence criterion or the maximum run can be used as the termination condition.

5) Elitist TLBO algorithm

The concept of elitism is utilized in the original TLBO algorithm to identify the effect on exploration and exploitation capacity of TLBO algorithm. In Elitist TLBO the duplicate solutions are modified by mutation on randomly selected dimensions of the duplicate solutions before executing the next generation. The effect of common controlling parameters of the algorithm, i.e., population size, number of generations and elite-size on the performance of the algorithm are also investigated by considering different population sizes number of generations and elite sizes.



PSNR=20.18dB PSNR=32.54dB

Figure 2: Denoising Result

C. Sub Image Averaging

Let Np=(N1-√n+1)(N2-√n+1)denote the number of overlapped patches in the image Z, and let X be an n × N_p matrix, containing column stacked versions of these patches. When calculated P assumed that each patch is associated only with its middle pixel. Therefore P was designed to reorder the signal composed of the middle points in the patches which reside in the middle row of X. However it can alternatively choose to associate all the patches with a pixel located in a different position. This means that the matrix P can be used to reorder any one of the signals located in the rows of X. These signals are the column stacked versions of all the n sub images of size (N1-√n+1)(N2-√n+1) contained in the image Z.

D. Inverse Permutation

First calculate the $N_p \times N_p$ matrix P using the patches in X and apply it to each subimage $\tilde{z}_j$.Then apply the operator H to each of the reordered sub images $\tilde{z}^p_j = P\tilde{z}_j$, apply the inverse permutation P^{-1} on the result and obtain the reconstructed sub images. Reconstruct the image from all the reconstructed sub images by plugging each subimage into its original place in the image canvas and averaging the different values obtained for each pixel.

E. Image Enhancement

Image enhancement is the process of adjusting digital images so that the results are more suitable for display. To make an image lighter or darker or to increase or decrease contrast. Simulation results shows that the proposed algorithm is better than that of the existing algorithm in terms of visual quality and peak signal to noise ratio (PSNR).

IV. EXPERIMENTAL RESULTS

A. Image Denoising

The problem of image denoising consists of the recovery of an image from its noisy version. The proposed image denoising scheme by applying it to a test set containing noisy versions of 4 images with 8 different noise standard deviations. The results are shown in Table I and it can be seen that using a learned filter instead of a simple smoothing filter improves the results for all images, with an average increase in PSNR of 2.32 db. Also, performing patch Classification further improves the results for all images, with an average increase in PSNR of 0.54 db. PSNR values obtained for the noisy test images with our scheme including patch classification and filter learning, with and without subimage averaging as a function of the number of employed permutation matrices.

TABLE I

DENOISING RESULTS (PSNR IN dB) OF NOISY VERSIONS OF 4 IMAGES

Image	Patch Reordering	Proposed 1	Proposed 2
Boats	30.1	31.32	36.5
Barbara	29.5	32.7	37.2
House	29.8	34.5	35.2
Tiger	30.2	33.4	34.9

The performance of proposed scheme on corrupted versions of the images Boats, Barbara and House, tiger obtained by zeroing 80% of their pixels, which are selected at random.

B. Image Inpainting

The problem of image inpainting consists of the recovery of missing pixels in the given image. The results reported for these algorithms for the case of 80% missing pixels. A patch-based sparse representation reconstruction algorithm with a DCT over complete dictionary to recover the image patches. When a patch does not share pixels with any of the unvisited patches the next patch in the path is chosen to be its nearest spatial neighbour.

PSNR=6.65dB

PSNR=28.9dB

PSNR=31.96dB

Figure 3: Inpainting result

V. CONCLUSION

The proposed scheme can be used for image denoising and inpainting where it achieves high quality results. The first is to make use of the distances between the patches not only to find the ordering matrices but also in the reconstruction process of the sub images. These distances carry additional information which might improve the obtained results. Improvements can also be made to the patch ordering scheme itself. A different direction is to develop new image processing algorithms which involve optimization problems in which the 1D image reorderings act as regularizers. Simulation results shows that the proposed algorithm is better than that of the existing algorithm in terms of visual quality and peak signal to noise ratio (PSNR).

REFERENCES

[1] G. Yu, G. Sapiro, and S. Mallat, “Image modeling and enhancement via structured sparse model selection,” in Proc. 17th IEEE Int. Conf. Image Process., Sep. 2010, pp. 1641–1644.

[2] D. Zoran and Y. Weiss, “From learning models of natural image patches to whole image restoration,” in Proc. IEEE Int. Conf. Comput. Vis.,Nov. 2011, pp. 479–486.

[3] W. Dong, X. Li, L. Zhang, and G. Shi, “Sparsity-based image denoising via dictionary learning and structural clustering,” in Proc. IEEE Conf.Comput. *Vis.* Pattern Recognit., Jun. 2011, pp. 457–464.

[4] X. Li, “Patch-based image interpolation: Algorithms and applications,”in Proc. Int.

[5] W. Dong, L. Zhang, G. Shi, and X. Wu, "Image deblurring and super resolution by adaptive sparse domain selection and adaptive regularization,"*IEEE* Trans. Image Process., vol. 20, no. 7, pp. 1838–1857,Jul. 2011.
[6] P. Chatterjee and P. Milanfar, "Clustering-based denoising with locally learned dictionaries," IEEE Trans. Image Process., vol. 18, no. 7,pp. 1438–1451, Jul. 2009.
[7] A. Buades, B. Coll, and J. M. Morel, "A review of image denoising algorithms, with a new one," Multiscale Model. Simul., vol. 4, no. 2,pp. 490–530, 2006.
[8] I. Ram, M. Elad, and I. Cohen, "Generalized tree-based wavelet transform,"IEEE Trans. Signal Process., vol. 59, no. 9, pp. 4199–4209,Sep. 2011.
[9] D. Heinen and G. Plonka, "Wavelet shrinkage on paths for denoising of scattered data," Results Math., vol. 62, nos. 3–4, pp. 337–354, 2012.
[10] R. R. Coifman and D. L. Donoho, "Translation-invariant de-noising,"Wavelets and Statistics. New York, NY, USA: Springer-Verlag, 1995, pp. 125–150.
[11] I. Ram, M. Elad, and I. Cohen, "Generalized tree-based wavelet transform,"IEEE Trans. Signal Process., vol. 59, no. 9, pp. 4199–4209,Sep. 2011.
[12] I. Ram, M. Elad, and I. Cohen, "Redundant wavelets on graphs and high dimensional data clouds," IEEE Signal Processing Letters, vol. 19, no. 5, pp. 291–294, May 2012.
[13] G. Plonka, "The easy path wavelet transform: A new adaptive wavelet transform for sparse representation of two-dimensional data," Multiscale Model. Simul., vol. 7, no. 3, pp. 1474–1496, 2009.
[14] T. H. Cormen, Introduction to Algorithms. Cambridge, MA, USA: MIT Press, 2001.
[15] M. Elad, Sparse and Redundant Representations: From Theory to Applications in Signal and Image Processing. New York, NY, USA: Springer-Verlag, 2010.

.