# Regularization technique to restore woven biomedical fabrics using sparsity

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***Abstract***
*Biomedical fabrics are now widely used in advanced clinical applications. The woven biomedical fabrics are parts of medical products like vascular grafts, hernia mesh, orthopedic and so on. A new approach, Reconstruction of woven fabrics from a sequence of samples focus of this work. Latest Trends includes Sparsity Technique, which compels the use of minimum values of pixels. Herein a Work Satisfying the Expected problem has been proposed where the noisy image is treated with wavelet transforms and then the image is restored with the sparse restoration. The simulation results are being displayed and the values are tabulated.*

## Introduction

Biomedical fabrics form the platform for various medical devices used in cardiovascular, tissue, orthopedic products. The biomedical fabric must be flexible, porous, with conformability and compaction characteristics. Woven fabrics are created by interlacing yarns and are shaped as flat, tubular or net shaped as desired for the application. The weave of the fabric is critical for specific application. This work deals with the investigation of restoring woven biomedical fabrics. Image Restoration is a wide area of image processing applications, including biomedical images, astronomical images. The work deals with the image restoration techniques based on different aggressive models, such as the total Variation Framework, Wavelets, Minimization Regularization, etc. The major IR is narrowed down to the formulation of a regularization framework in sparsity through wavelet decomposition. The main aim is to restore the image effectively using minimal number of pixels through sparse technique, which are selected through higher value decomposition having the most important information. Among various applications the work is tested with the samples of images of woven fabrics, to detect the defects in woven fabrics so that it can be implemented in the quality check of that fabric.

**Sparsity:** Compressive sensing is a technique related to sparse representation, in application with signal acquisition, and sensing application. The common steps in all typical applications include (1) acquire the signal length greater than or equal to the Nyquist sampling rate, (2) calculation of transform coefficients (3) encoding the largest or most meaningful coefficients and their locations. This generally provides the ability to reconstruct the image with reduced dimensions [9].

In compressed sensing there is good accuracy because of signal reconstruction from nonlinear measurement procedure. Small number of signal sample is defined as the signal value measures limited number of arbitrary linear combinations. There should be a known transform domain, the aliasing artifacts in transform domain, and a nonlinear reconstruction for a sparse representation with a desired signal which is the requisite of compressed sensing approach.

A sparse vector is operator mapped with image data which is called sparsity. Extensive research is going on sparse image representation currently. Finite effective results have been produced by sparse representation in many optimization problems, where boundaries are the salient features. In two domains natural real-life images are known to be sparse. They are: The Discrete Cosine Transform (DCT), and Wavelet Transform Domains. Important role is played by DCT in JPEG image Compression Standard, MPEG Video Compression. Similarly, Wavelet Transform is used in the JPEG_2000 image compression standard.

Image is represented in a multi-scale form in Wavelet transform. Coarse scale Wavelet Coefficients are used for low-resolution image components and Fine Scale Wavelet Coefficients are used by high-resolution components. Wavelet Coefficient simultaneously carry both spatial position and Spatial Frequency Information. Fine Scale Wavelet Transform are also computed by finite differences in Transform. There is limitation with regards to parity only to spatial domain. The percentage of transform coefficients are defined through the sparsity of images which is needed for quality reconstruction [8].

Sparse representation can be assumed that natural signals represent a linear combination of few atoms from a dictionary. . Consider a signal $\Gamma \subset R^n$ then as per sparse representation theory the existence of a dictionary $D \in R^{n\,X\,T}$ where T, prototype signals that is referred to as atoms. For this signal, there exists a linear combination of atoms from D, that has many approximations. Generally, $x \approx Ds$. The vector 's' contains coefficients of x, in D (Dictionary). Usually $T > n$ implies that the Dictionary D is redundant.

The general optimization problem to be solved is as follows$\min_\alpha \parallel s \parallel_0 \text{ s.t } \parallel Ds - x \parallel < \in$, where $\parallel s \parallel_0$ denotes the non-zero components of s. [9].

**Relevant Algorithms:** A new sparse prototype representing the Centralized Sparse Representation has been proposed considering sparse coding coefficients very close to original image which is not recognized with the assumed dictionary of values. To make the sparse coding technology more accurate Centralized Sparse constraint has been developed in this work [3],

The conventional approach of Blind image restoration, including classifier has been proposed in this work, which treats restoration and recognition both simultaneously using sparse representations, including all low-quality images. [4]. Sparse representation, modelling with linear combinations of a few atoms in a specified dictionary has been represented where, x is the signal, and D gives the Dictionary on Ortho-normal basis, replacing both convex $l_0$ with $l_1$ norm, which propagates the use of Lagrange multiplier.

$$\min_{\alpha} \parallel \alpha \parallel_0 \ \text{s.t} \ \parallel x - D\alpha \parallel^2 \leq \in \quad (1)$$

As described in this work has been focused on both restoration and recognition approach. Now the formulation for Image restoration has been achieved with regularization using sparsity as follows, D giving the Orthonormal sparse transformation, k describing the Kernel matrix, r yields the solution with the training set D.

$$\{r.k\} = \text{argmin}_{\alpha,k} \parallel k * D\alpha - y \parallel_2^2 + \lambda \parallel \alpha \parallel_1 + \ \gamma \parallel k \parallel_2^2 \quad (2)$$

For Recognition, a new set of training samples has been represented in the whole training set, for a set of training samples D, with test sample x, using class c with the coefficients of α.

$$\alpha = \text{argmin} \ \parallel \alpha \parallel \text{s.t} \ \parallel D\alpha - x \parallel_2^2 \leq \in_i \quad (3)$$

The Joint blind image representation and recognition with kernel matrix K, class C, and with sharpened image X have been given as:

$$\{X, K, C\} = \arg \min_{X,K,C} E(x, k, c) \quad (4)$$

Blur kernel estimation has been derived from giving an overall efficiency for the optimization problem, to make it converge to a local minimal point.

$$k = \text{argmin} \parallel x^n * k - y \parallel_2^2 + \gamma \parallel k \parallel_2^2 \quad (5)$$

The optimization problem has been solved efficiently with suitable auxiliary variables, and henceforth the Energy function has been derived as:

$$E(x.y) = \parallel x * k - y \parallel_2^2 + \eta \parallel x - D\alpha \parallel_2^2 + \beta \sum_{l=1}^{L} \parallel e_l * x - u_l \parallel_2^2 \quad (6)$$

Thus, a combined approach for restoration and recognition has been proposed giving satisfactory results on the approach recovering the optimization problem with better energy efficiency.

Discriminative learned dictionaries for local image analysis, has been proposed to yield an energy formulation combining the sparse reconstruction and class discrimination components optimized through dictionary learning, which has been obtained for natural images with $x_l$ giving the image patch column wise, D is giving the learned dictionary in unit vector of $l_2$ norm [5].

$$min_{\alpha,D} \sum_{l=1}^{m} \parallel x_l - D\alpha_l \parallel_2^2 \quad (7)$$

For the single value decomposition to obtain non-zero coefficients the same dictionary D is updated which has been converged with minimum iterations.

$$min_{D\in R^{n*k}} \sum_{l=1}^{m} R(X_l, D, \alpha_l) \quad (8)$$

With $S_i$ training patches and 'i' being different classes, a reconstruction based approach has been proposed by choosing discriminative dictionaries, where $\lambda(y_i - y_{i)}$ produces the asymptotic linearity. This has solved different optimization technique difficulties.

$$c_i^{\lambda}(y_1, \ldots., y_n) = \log(\sum_{j-1}^{n} e^{-\lambda(y_i - y_{i)}}) \quad (9)$$

The declared dictionary update can be converted into proposed Single Value Decomposition method, which has allowed each coefficient to change or improve at the same time. The convergence has been obtained faster, the reconstruction is made through SVD, and the dictionaries have been updated.

$$b = \sum_{p=1}^{n} \sum_{L\in Sp} W_L(r_l + \alpha_{li}\,[i]d)(r_l + \alpha_{li}[j]d)^2 \quad (10)$$

Hence local sparsity values are obtained for the reconstruction approach. This has produced an effective optimization technique involving an update of dictionaries, through key patches, performing local discrimination such as segmentation and reconstruction. These image patches are discriminant and has ensured supervised feature selection which has performed effective iterations to produce better results.

This work Fast wavelet based image convolution using the EM algorithm has been proposed using the wavelet coefficients. This work has been a convolution over Discrete Wavelet Transform and Fast Fourier transform. This work has been formulated between E-step FFT (Fast Fourier transform) and M-step DWT (over Discrete Wavelet Transform) producing effective iterative results.

The E-step of Fast Fourier transform computes condition expected of likelihood of complete data, and has been estimated through $\theta$, being the DWT coefficients, z as the missing data of the de-noising problem, y as the complete data, w being the inverse wavelet transform.

$$logp(y,z|\theta) \propto \frac{\|w\sigma - z\|^2}{2\alpha^2} \propto \frac{\theta^T w^T (w\theta - 2z)}{2\alpha^2} \quad (11)$$

$$-Q\left(\theta, \hat{\theta}(t)\right) \propto \frac{\theta^T W^T (W\theta - 2\hat{z}(t))}{2\alpha^2} \propto \frac{\|w\sigma - z\|^2}{2\alpha^2} \quad (12)$$

M-step update value based on wavelet based de-noising for a direct de-noising problem corresponding to Laplacian applying soft thresholding technique over wavelet coefficients

$$\hat{\theta}(t+1) = arg\min_{\theta}\{\, \| w\theta - z(t) \|^2 + 2\alpha^2\, pen(\theta)\} \quad (13)$$

Hence this combination has been proposed to produce effective results through E-Step and M-Step coefficients using Fourier and Wavelet Transforms.

**Decomposed Sparsity- Wavelet Transformation:** The Discrete Wavelet Transform is used to treat and solve more advanced problems since it provides both scale frequency and the spatial timing of the analyzed signal. The discrete wavelet transform (DWT) algorithms have a firm position in the processing of signals in several areas of research and industry. [16]. The main goal of decomposition is to scale the images to have ease of processing.

Consider an image to be represented by the square matrix A, then the transformation is performed by constructing special matrices W and $W^T$ and then computing $WAW^T$, the process is the construction of W, $W^T$ and how $WAW^T$ concentrates most of the nonzero values (nonblack pixels) in the upper left-hand corner of the transformation, hence reducing the number of bits. [17]

The transformation has created large regions that have pixel values ‘0’ or near to ‘0’ (i.e., regions where most of the representations are either black or nearly black).

The resulting image is transformed by quantization, then encoded and hence the resultant will be a scaled decomposed image which needs only lesser information to process than the original image. The wavelets or wavelet transformation abounds in many image processing applications involving compression of digital images of fingerprints by The Federal Bureau of Investigation (FBI), identification of edges, image morphing, digital watermarking. Wavelets have proved its ruing in the field of image denoising.

The proposed work is formulated to restore the sample of textile images through sparse restoration using wavelet transforms. The Discrete Wavelet Transform is used to perform a single-level two-dimensional wavelet decomposition with respect to either a particular wavelet or particular wavelet decomposition filter.

**Sparse Representation Based Restoration:** A common dictionary ‘B’ is produced. Let’s consider an observation vector $y \in R^N$, of unknown class as a linear combination of training vector. The common dictionary of the unknown class ‘B’ has been combined with the unified Variational Framework, here ‘$B_S$’ is a linear self-adjoint and positive operator. Now with the class of ‘$B_S$’ the minimum value of unique point can be reached

The function to be minimized is:

$$\frac{1}{2\lambda}||g - Au||^2_{X1} + J(u) \quad (14)$$

Let $\mu > 0$; so$\mu \parallel A * A \parallel < 1$, and $B_S = \mu A * A$.

Combining the minimization with the dictionary ‘$B_S$’, the samples of $k_{th}$ class, $B_k$ with a new test image $y \in R^N$ belonging to the same class will lie approximately in the linear space of training samples from the class k. This implies most coefficients (α) not associated with k will be close to zero.

Here ‘α’ implies the sparse vector. To represent the observed vector y in sparse vector ‘α’, the following equation $y = B_S\alpha$ must be solved. For ‘α’ to be sparse ‘$B_S$’ should satisfy certain properties and ‘α’ can be recovered by CSR technique.

An effective CSR has been proposed which overcomes the local and non-local redundancy to produce effective results in image restoration techniques. The general formulation of image restoration for the proposed work using degradation model can be given as:

$$y = Hx + v \quad (15)$$

Where the H is the degradation matrix, x is the original image, v is the noisy image. This regularization technique moves with the processing of all raw images in reality. Sparse technique is one of trendy approach which can deal with all these problem formulations.

The centralised sparse representation model has used two parameters to balance the local and non-local redundancy. This has produced an improving convergence speed and good image restoration quality. The main parameter has been determined using Bayesian Interpretation, producing the relation between the Bayesian and Wavelet Interpretation. Using the Laplacian Distribution, the parameters are determined as given below:

$$\alpha_y = \mathrm{argmin}_\alpha\{\| y - H\emptyset\alpha \|_2^2 + \textstyle\sum_i \lambda_i \| \alpha_i \| + \sum_i \Upsilon_i \| \emptyset_i \|\} \quad (16)$$

**Proposed Algorithm:**

- Compute the observation vector, ‘y’.
- Perform Wavelet transformation for the input observation vector
- Initialize the training vector

$y = B\alpha$, where $\alpha$ is

$\alpha = [\alpha_{11}, \ldots \alpha_{1n} \,|\alpha_{21}, \ldots \alpha_{2n}| \ldots |\alpha_{L1}, \ldots \alpha_{Ln}]^T$

- Initialize the regularization function

$$\frac{1}{2\lambda}||g - Au||^2_{X1} + J(u)$$

- Determine the sparse code through non-local means as $\alpha_y$
- Perform the final step of deblurring

for i=1 to k, calculate $\alpha_y$

$$\alpha_y = argmin\left\{\| y - B\phi.\alpha \|_2^2 + \sum_i \lambda_i \| \alpha_i \|_1 + \sum_i \gamma_i \| \theta_i \|_1\right\}$$

Where $\lambda_i = \frac{\sqrt[2]{2}\sigma_n^2}{\sigma_i}, \gamma_i = \frac{\sqrt[2]{2}\sigma_n^2}{\delta_i}$

Update the value of $\alpha_y$ to obtain the final result.

**Simulation Results:** The simulation results for the proposed work can be given in this segment describing the image results and the iteration values. The PSNR values for uniform blur matrix and the Gaussian blur has been computed for various Standard Deviation value being $\sqrt{2}$ and 2.

**Table 1**
**PSNR Values of various S.D Values**

| | Proposed (Decomposed Sparsity) | CSR |
|---|---|---|
| For uniform Blur $\sigma^n = \sqrt{2}$ | | |
| PSNR | **31.00** | 31.04 |
| For uniform Blur $\sigma^n = 2$ | | |
| PSNR | **30.33** | 30.12 |
| For Gaussian Blur $\sigma^n = \sqrt{2}$ | | |
| PSNR | **29.1192** | 29.13 |
| For Gaussian Blur $\sigma^n = 2$ | | |
| PSNR | **29.088** | 29.10 |

The image Sample has been obtained from SITRA (South Indian Textile Research Association), Coimbatore. Fig (1). Shows the original Input Image.

**Figure 1: Original Input Image**

The second figure is the processed output of the wavelet transform. Here decomposition is made for the L1 Transformation focussing on the most informative pixel region.

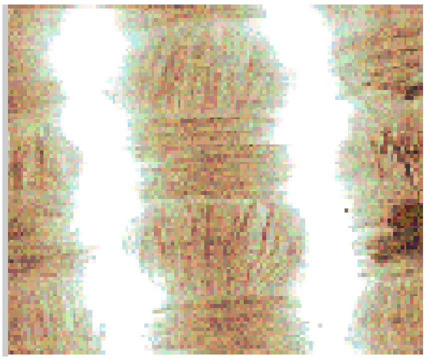

**Figure 2: Decomposed L1 image**

The transformed image has been processed with the sparse concept where the pixels are again filtered for the highest priority information. The resultant image of the final step of restoration has been displayed in the Fig (3).

**Figure 3: Restored Image**

## Conclusion

Hence a novel effective approach has been proposed where the most important pixel values are considered, which results in increased PSNR range and quick response of the output when compared to the generalized technique. The much needed information of the image is being calculated using transforms for further concentrated through sparsity. Hence the values are precise for the proposed formulation. Finally, the sample images are displayed and the PSNR values are tabulated for the proposed approach for various S.D values. Thus, the work has been proven to be time efficient, with promising number of iteration values.

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