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# Orthogonal Locality Preserving Projection Based Image Denoising for Restoration and Inpainting

**A.Gayathri[1], A.Rama[2], P.V.Pramila[3]**

[1]Associate Professor, Department of Computer Science and Engineering,
Saveetha School of Engineering, SIMATS, Chennai, India, gayathribala.sse@saveetha.com
[2]Assistant Professor (SG), Department of Computer Science and Engineering,
Saveetha School of Engineering, SIMATS, Chennai, India, ramaa.sse@saveetha.com
[3]Associate Professor, Department of Computer Science and Engineering,
Saveetha School of Engineering, SIMATS, Chennai, India, pramilapv.sse@saveetha.com

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**Abstract**

Inadequate portrayals utilizing change space methods are generally applied for better understanding of the raw information. Symmetrical Locality Preserving Projection (OLPP) is a straight strategy that attempts to save nearby structures of the information. Vectorised nature of OLPP require high-dimensional information to be changed over to vector design, consequently leading to loss of spatial neighbourhood data of raw information. Then again, handling 2D information legitimately, jelly spatial data, yet in addition improves the computational productivity significantly. The 2D OLPP is relied upon to take in the change from 2D information itself. This paper infers scientific establishment for 2D OLPP. The proposed method is utilized for picture in painting through denoising task. The proposed approach plays out a few cutting edge image denoising approaches for dark scale, shading, and surface effects in pictures. The Concept of In painting has been executed in the Proposed System. In painting is the concept where a rough picture is smoothened with the goal that the PSNR esteem increments thereby improvement in the Quality of the Images were also obtained. The experimental results show a higher PSNR values when contrasted with the denoised picture and the nature of the images were like wise also improved.

***Keywords:*** *Orthogonal Locality Preserving Projection (OLPP), Principal Component Analysis (PCA), Neighborhood Preserving Embedding (NPE), Locality Preserving Projection (LPP)*

## 1. Introduction

Inadequate portrayals utilizing space changes have gotten gigantically famous in a decade ago. Applications, for example, object recognition, information dimensionality decrease, image reclamation like denoising, deblurring, inpainting, compressive detecting and so forth utilize inadequate portrayals of information. A portion of the area change procedures take in premise from given information itself. Principle Component Analysis (PCA), Neighborhood Preserving Embedding (NPE), Locality Preserving Projection (LPP) are a portion of the broadly utilized change area methods [1-5].

LPP targets saving nearby structure of information in the change area too. As the premise picked up utilizing LPP isn't symmetrical, which might be alluring in numerous applications, Orthogonal Locality Preserving Projection (OLPP) having symmetrical premise vectors was proposed.

All the methods talked about so far procedure just a single dimensional information for example vectors. At least two dimensional information, for example,

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image initially must be changed into vector group. So as to process two dimensional information legitimately, Two Dimensional PCA (2D-PCA), here figure Two Dimensional Orthogonal Locality Preserving Projection (2D-OLPP). The methodology legitimately forms pictures in two dimensional (2D) position (i.e.) framework group, thus the overhead of changing them in vectors gets decreased and the spatial neighborhood data stays unblemished. Because of 2D information preparing, the premise lattice ends up being significantly more conservative than the one acquired by OLPP, lessening the existence complexities of the calculation impressively. Symmetrical nature makes the methodology simpler to be utilized in numerous applications that require symmetrical premise. Up until this point, LPP and its variations have been for the most part utilized for object acknowledgment and dimensionality decrease related applications.

In this paper proposed 2D-OLPP approach for image denoising. Commotion in pictures gets presented during obtaining process and henceforth denoising turns into an indispensable piece of picture age process if clean pictures are wanted. High relationship among the neighboring pixels of the picture is one of the main properties that was utilized for picture denoising undertakings with spatial space channels. These separating strategies utilized pixel based nearby relationships. Idea of 'non-neighbourhood self-similitude' indicated auxiliary likenesses between fixed measured patches from various spatial areas of the picture. To show the redundancies of the picture, direct changes, for example, Fourier Transform, Discrete Cosine Transform (DCT), Wavelet Transform, Block DCT have been broadly utilized.

## 2. Literature Survey

Latest state of art edge procedures for picture denoising depend on two insights of normal pictures: (1) There exists self-similitude between the patches from various areas of a similar picture (2) Image patches can be scantily spoken to by straight mixes of the premise vectors. Assortment of these premise vectors of same or diverse straight changes is known as 'word reference'. It can include the fixed all inclusive premise expressed above or can be adaptively taken in utilizing patches from the picture itself.

Principle Component Analysis (PCA) and Independent Component Analysis (ICA) have been utilized to adaptively take in word references from loud info pictures. Collective sifting is performed utilizing hard thresholding on the changed coefficients followed by reverse change and conglomeration of the patches. Worldwide word reference for sub-picture or an enormous bit of the picture is found out utilizing Orthogonal Locality Preserving Projection (OLPP) from all the covering patches present in that part and picture denoising is acted in the OLPP area.

Expected Patch Log Likelihood (EPLL) is augmented to locate a recreated picture in which each fix is likely under the earlier while keeping the picture despite everything near the debased picture. EPLL and strategy proposed utilize Gaussian Mixture Model (GMM) for learning the word reference and boisterous coefficients are denoised by organized meager estimation. K-Singular Value Decomposition (K-SVD) ('K' signifies number of bunches) and its variations get familiar with an over-complete word reference for whole loud picture and inadequate direct blends of the word reference vectors are chosen for each fix. Non-neighborhoodmeager models are created in by gathering comparative fixes in a framework and utilizing the idea of low position lattice consummation. The framework standardization is punished dependent upon a hard imperative overwhelming coupled sparsity on the coefficients. In the greater part of the methodologies examined up until this point, a word reference is acquired for each fix or a bunch of patches subsequent to gathering fundamentally comparative patches [6-8].

A word reference is gotten for each fix or a bunch of patches in the wake of collection together basically comparable patches. A worldwide word reference learning plan (2D-OLPP) is proposed, which deals with both, (i.e.) the premise are found out while dealing with the basic likeness between patches. The OLPP based picture denoising approach additionally utilizes the guideline of likeness protection keeps up basic comparability while learning the premise, however it requires the patches to be changed over in vector organization and chips away at an enormous window of the picture at once, rather than the entire picture.

In 2D-OLPP, patches from the whole info picture are considered all things considered (in grid position) and gauged by their basic closeness during the premise learning process. Henceforth, a worldwide word reference is found out from the boisterous info picture, which astoundingly diminishes the computational intricacy of the methodology, and simultaneously executes the fundamental thought of non-nearby self-likeness in word reference learning process. A changed Wiener channel update rule to dispose of clamor from two dimensional fixes in the change space is likewise recommended [9-13].

**Structural Inpainting:** Basic inpainting utilizes geometric methodologies for filling in the missing data in the locale which ought to be inpainted. These calculations center around the consistency of the geometric structure.

**Textural Inpainting:** Like everything else the auxiliary inpainting techniques have the two favorable circumstances and inconveniences. The principle issue is that all the basic inpainting strategies can't reestablish surface. Surface has a dreary example which implies that a missing bit can't be reestablished by proceeding with the level lines into the hole

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**Combined Structural and Textural Inpainting:** Consolidated basic and textural inpainting approaches at the same time attempt to perform surface and structure filling in areas of missing picture data. Most pieces of a picture comprise of surface and structure. The limits between picture locales amass basic data which is an intricate marvel. This is the outcome when mixing various surfaces together. That is the reason, the cutting edge inpainting strategy endeavors to consolidate auxiliary and textural inpainting. An increasingly customary technique is to utilize differential conditions, (for example, the Laplace's condition) with Dirichlet limit conditions for progression (a consistent fit). This functions admirably if missing data exists in the homogeneous part of an article region. Different techniques follow isophote bearings (in a picture, a form of equivalent luminance), to do inpainting. Model based inpainting follows the Bayesian methodology for which missing data is best fitted or assessed from the mix of the models of the fundamental pictures just as the picture information really being watched. In deterministic language, this has prompted different variational in painting models. Manual PC strategies incorporate utilizing a clone apparatus or mending instrument, to duplicate existing pieces of the picture to reestablish a harmed surface. Surface blend may likewise be utilized. Model based picture inpainting endeavors to computerize the clone device process. It fills "gaps" in the picture via scanning for comparable fixes in a close by source locale of the picture, and replicating the pixels from the most comparative fix into the gap. By playing out the fill at the fix level instead of the pixel level, the calculation lessens obscuring relics brought about by earlier methods. perform better in fix rebuilding. Propelled by this outcome, we propose a conventional system which takes into account entire picture rebuilding utilizing any fix based earlier for which a MAP (or inexact MAP) gauge can be determined. We tell the best way to determine a fitting cost work, how to enhance it and how to utilize it to reestablish entire pictures. At long last, we present a nonexclusive, shockingly straightforward Gaussian Mixture earlier, gained from a lot of common pictures. At the point when utilized with the proposed structure, this Gaussian Mixture Model beats all other conventional earlier strategies for picture denoising, deblurring and inpainting [14-16].

## 3. Proposed System

Image Denoising is a procedure that focuses on the expulsion of clamor which may degenerate a picture during its procurement or transmission, while holding its quality. Picture Denoising has gotten significant with the goal that the nature of the pictures can be upgraded. The Images are frequently influenced by irregular clamor emerging in the picture securing process. The nearness of clamor produces unfortunate visual quality as well as brings down the perceivability of low difference objects. The calculation utilized is Orthogonal Locality Preserving Projection with an additional idea of Cubic Interpolation. In the Proposed System, The Output from the Existing System is given as the Input and 80% of the pixels are missing at first, the Corrupted Patches are sifted through (i.e.) It is denoised in order to improve the nature of the Image. The Patches are then Re-built in order to actualize the idea of Inpainting [17-20]. At that point Various Iterations are done, Each Iteration has around ten Permutations. Three Iterations are done to finish the Inpainting Process. The Inpainted Image is gotten with a Higher PSNR esteem and the Quality of the Image is improved than the Original Image.

### System Description

Noised image is divided into sub-bands by constructing weight matrix using OLPP algorithm. These sub -bands are passed as input to modified inverse wiener filter. The filtered image is denoised efficiently by OLPP. PSNR and MSE are calculated for denoised image. This denoised image is passed as input inorder to attain interpolation. Missing pixels are extracted from the denoised image and then permutation is applied. Cubic interpolation technique is carried out inorder to attain inpainting.

### Proposed Architecture

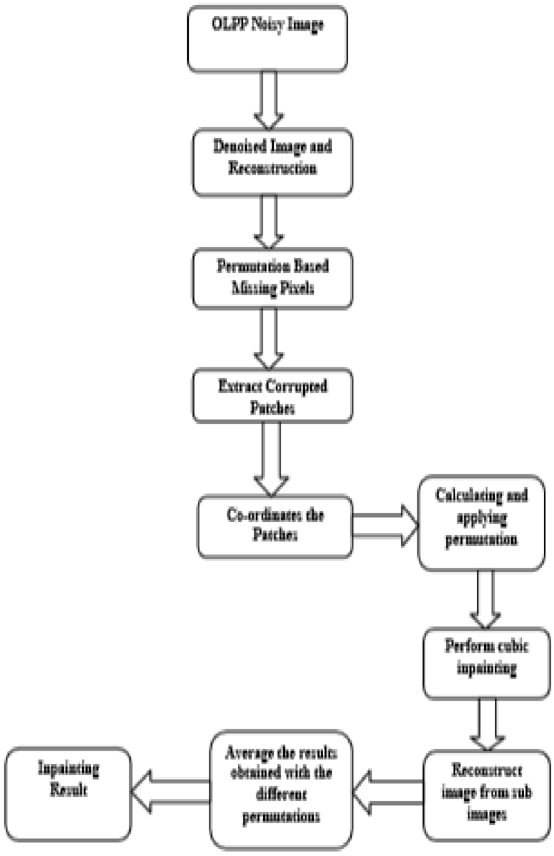


Figure 1: Proposed Architecture

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**Data Flow Diagram**


Figure 2: Data Flow diagram of proposed system

**Proposed Method Description**

Input Image: Extraction of corrupted patches and reconstruction of the patches Calculating permutation and applying cubic interpolation to the inpainted image. The Input Image for the Proposed System is the image that is obtained from the Existing System Output. The PSNR value of this Image is 30.4076 DB. The Process of Inpainting is going to be implemented in the Proposed System.

**Extraction of Corrupted Patches and Reconstruction of the Patches**

The Corrupted Patches are extracted from the Original Image and it is re-constructed. Then, the process of Permutation takes place. Permutation is the process in which the patches are re-ordered so that the patches canoccupy their original positions. The Patches are then co-ordinated so that the original Image is obtained.

Figure 3: Input Image and addition of noise by 80%

**Calculating Permutation and Applying Cubic Interpolation**

The Noisy Images are in the form of Rows and Columns. The Rows are indicated by N_m and the Columns are indicated by N_n. The Values of the Original image are obtained and then the values are converted to zero, So that when Interpolation is performed, new values are obtained when interpolation is performed. The corresponding Interpolation values can be Obtained. Interpolation is the Process in which the Image is smoothened, The quality of the image is enhanced and the PSNR value is also increased.

## 4. Experimental Analysis and Result

The Interpolation Process is carried out in the three Iterations, Each Iteration consists of ten permutations. Cycle Spinning is the process that is carried out during each iteration, It is a loop which continues to enhance the image during each Iteration.
The Iterations are given as follows:

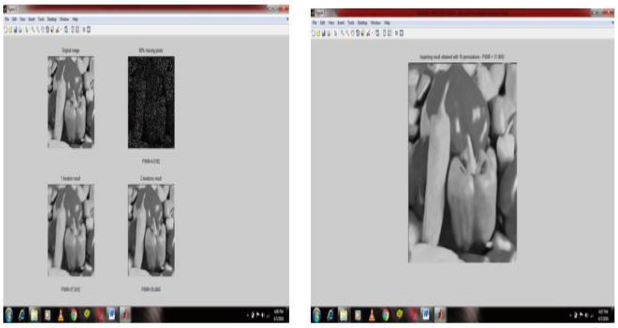

Figure 4: PSNR value after first iteration (27.24), second iteration (30.48), third iteration(31.06)

THE INPAINTED IMAGE:After various Iterations, the PSNR value increases when compared to the original image. This increases the quality of the Image and also the Image is smoothened when compared to the Original Image.

Table 1: (a) PSNR values for proposed system, (b) Comparison of Inpainting in OLPP with σ =40 (Proposed work)

| Data Sets | Denoised Value | Noisy Value | Iteration1 | Iteration 2 | Iteration 3 | SSIM |
|---|---|---|---|---|---|---|
| | | | PSNR | PSNR | PSNR | |
| Barbara | 28.41 | 6.96 | 29.14 | 31.36 | 31.66 | 11.35 |
| Lena | 29.07 | 6.68 | 30.15 | 32.48 | 32.76 | 15.41 |
| House | 30.99 | 5.87 | 31.26 | 34.79 | 35.41 | 14.10 |
| Boat | 27.08 | 6.36 | 28.50 | 29.99 | 30.22 | 15.03 |
| Pepper | 28.96 | 7.66 | 28.13 | 30.18 | 31.15 | 20.81 |
| Man | 26.44 | 8.73 | 26.74 | 28.95 | 29.32 | 12.20 |
| Elaine | 29.69 | 5.97 | 30.77 | 33.70 | 34.09 | 13.52 |

(a)

| Data Sets | Denoised Value | Noisy Value | Iteration 1 | Iteration 2 | Iteration 3 | SSIM |
|---|---|---|---|---|---|---|
| | | | PSNR | PSNR | PSNR | |
| Barbara | 26.87 | 6.98 | 29.61 | 31.57 | 31.77 | 11.31 |
| Lena | 27.47 | 6.70 | 30.62 | 32.78 | 32.95 | 19.47 |
| House | 29.38 | 5.88 | 31.67 | 34.50 | 34.97 | 18.74 |
| Boat | 25.75 | 6.39 | 29.35 | 30.79 | 30.99 | 19.87 |
| Pepper | 26.94 | 7.68 | 28.58 | 31.07 | 31.32 | 29.31 |
| Man | 25.05 | 8.77 | 27.49 | 29.76 | 30.04 | 13.33 |
| Elaine | 27.97 | 5.99 | 30.99 | 33.51 | 33.80 | 17.68 |

(b)

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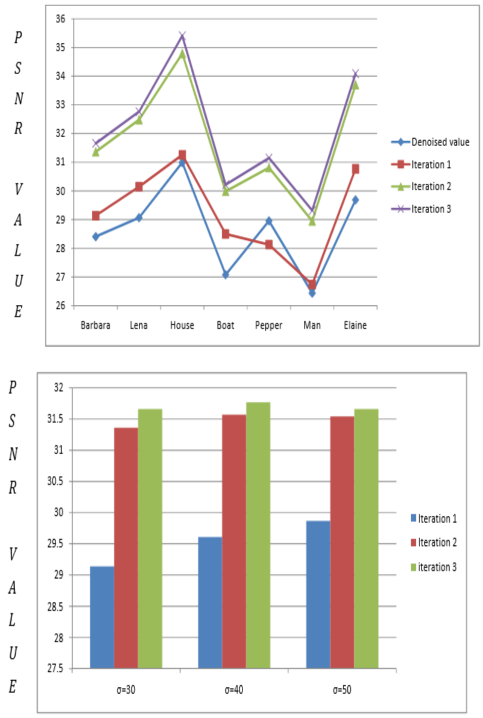


Figure 5: Graph Representing the comparison of all the data sets for the various iterations when σ is 30 and Graph for the Image Barbara for various σ value is 30,40,50

Table 2: (a) Comparison of In painting in OLPP with σ =50 (Proposed work)and (b) Comparative study between existing and proposed PSNR values for various sigma values

| Data Sets | Denoised Value | Noisy Value | Iteration 1 | Iteration 2 | Iteration 3 | SSIM |
|---|---|---|---|---|---|---|
| | | | PSNR | PSNR | PSNR | |
| Barbara | 25.41 | 7.00 | 29.87 | 31.54 | 31.66 | 10.38 |
| Lena | 26.26 | 6.71 | 30.70 | 32.56 | 32.63 | 23.61 |
| House | 28.35 | 5.89 | 31.78 | 33.92 | 34.16 | 23.98 |
| Boat | 24.62 | 6.41 | 29.93 | 31.18 | 31.31 | 24.27 |
| Pepper | 26.08 | 7.71 | 28.82 | 31.04 | 31.22 | 36.50 |
| Man | 24.02 | 8.81 | 28.07 | 30.18 | 30.39 | 15.55 |
| Elaine | 26.71 | 6.00 | 31.08 | 33.10 | 33.31 | 20.68 |

(a)

| Data Sets | σ= 30 | | σ= 40 | | σ= 50 | |
|---|---|---|---|---|---|---|
| | Existing PSNR Value | Proposed PSNR Value | Existing PSNR Value | Proposed PSNR Value | Existing PSNR Value | Proposed PSNR Value |
| Barbara | 28.41 | 31.66 | 26.87 | 31.77 | 25.41 | 31.66 |
| Lena | 29.07 | 32.76 | 27.47 | 32.95 | 26.26 | 32.63 |
| House | 30.99 | 35.41 | 29.38 | 34.97 | 28.35 | 34.16 |
| Boat | 27.08 | 30.22 | 25.75 | 30.99 | 24.62 | 31.31 |
| Pepper | 28.96 | 31.15 | 26.94 | 31.32 | 26.08 | 31.22 |
| Man | 26.44 | 29.32 | 25.05 | 30.04 | 24.02 | 30.39 |
| Elaine | 29.69 | 34.09 | 27.97 | 33.80 | 26.71 | 33.31 |

(b)

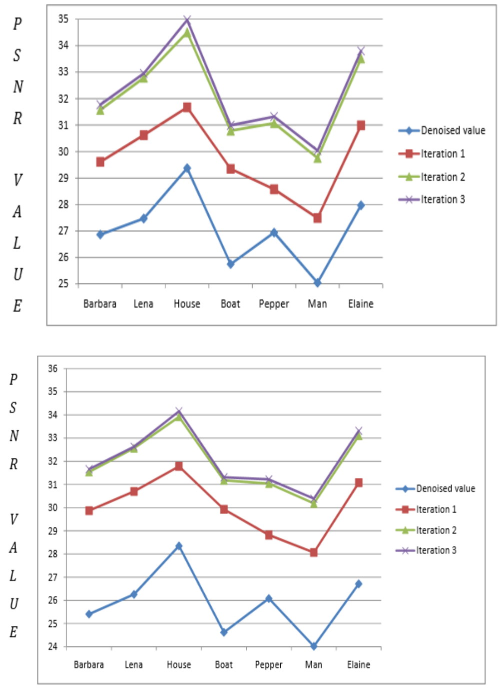


Figure 6: Comparison of all the data sets for various Iterations along with the denoised value when σ is 40 and Comparison of all the data sets for various Iterations along with the Denoised Value when σ is 50

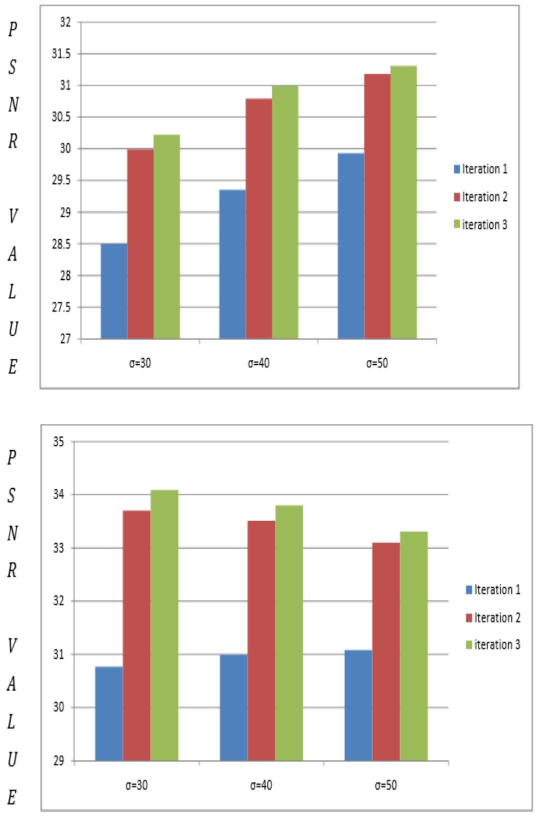


Figure 7: Graph for the Image of Lena and house for various σ value is 30,40,50

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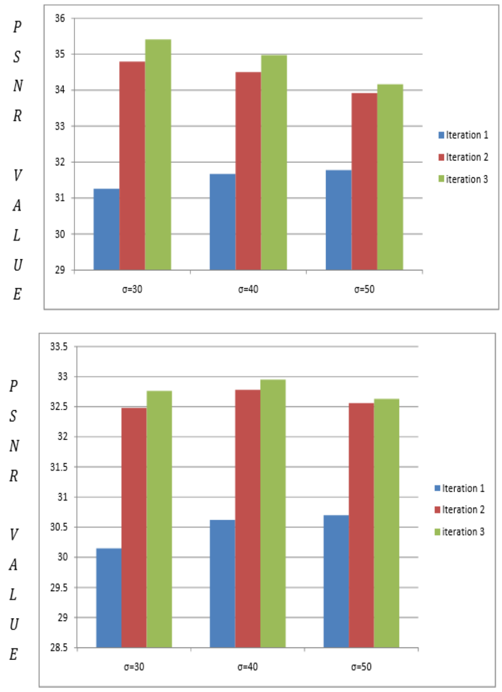


Figure 8: Graph for the Image of Boat and pepper for various σ value is 30,40,50

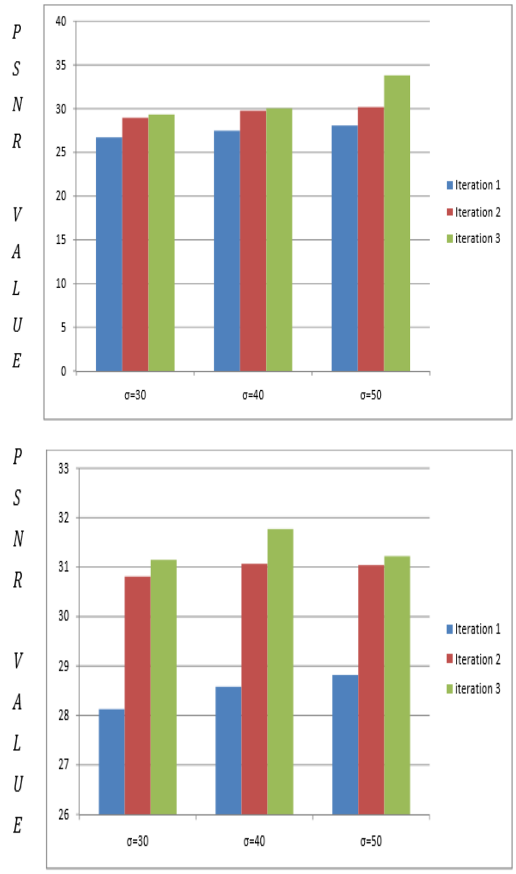


Figure 9: Graph for the Image of Man and Elaine for various σ value is 30, 40, 50

**Comparison between OLPP denoising and Inpainting**

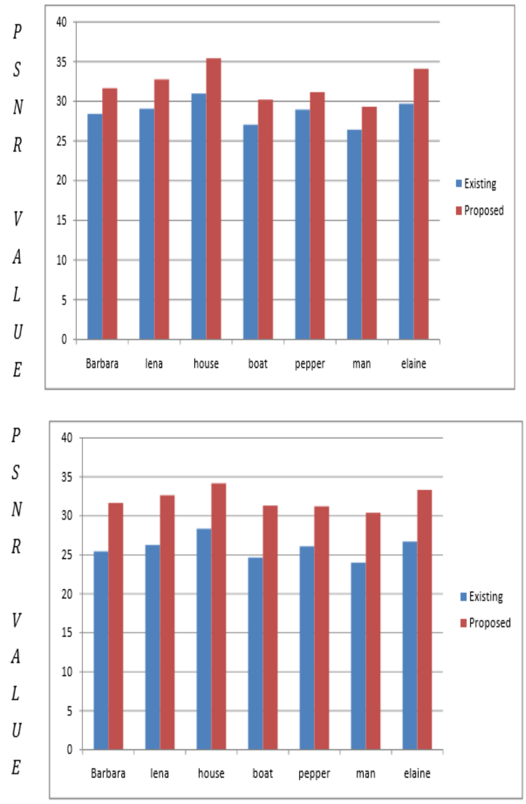


Figure 10: Comparison between existing and proposed when sigma value is 30 and 40

**Original Images**

Figure 11: Original image of Barbara, boat, house, lena, man, elaine and pepper

**Noisy Images**

Figure 12: Noisy image of Barbara, boat, house, lena, man, Elaine and peppers

**Denoised Images**

Figure 13: Denoised image of Barbara, boat, house, lena, man, Elaine and peppers

**Inpainted Images**

Figure 14: Inpainting experiment resultant image of Barbara, boat, house, lena, man, Elaine and pepper

## 5. Conclusion

Orthogonal Locality Preserving Projection (OLPP) put together with picture denoising are applied towards reclamation and inpainting alongside is presented. For denoising, 2D-OLPP forms two-dimensional picture fixes legitimately that protects the spatial data. The class calculations for denoising where premise are processed for each picture fix, a worldwide premise is adequate for whole picture in the 2D-OLPP.

The calculations relinquish even at higher densities. The exhibition of the calculation is better when contrasted with the current frameworks. With improvement witnessed in the visual quality, the presentation of the created calculation and other standard calculations were quantitatively estimated by the parameters, Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE). The methodology was tried broadly on few of the benchmark informational indexes. The outcomes acquired were extremely promising and gave off an impression of being tantamount with the trailblazer approaches of picture denoising.

The proposed approach can additionally be stretched out for picture deblurring and picture improvement errands.

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## Authors Profile

**Dr.A.Gayathri,** received the B.E degree in Electronics and Communication Engineering from Periyar Maniammai College of Technology for Women (Bharathidasan University, India) in 2001 and the M.Tech (CSE) degree in Computer Science and Engineering specialization from Bharath University, Chennai, India in 2005. She completed the Doctorate in the Department of Information and Communication Engineering at Anna University. She is currently working as Associate Professor in Saveetha School of Engineering (Department of CSE), SIMATS, Chennai, and Tamil Nadu. She is the member of CSI, IAENG and ACM.

**DrA.Rama,** Senior Assistant Professor, Department of Computer Science and Engineering, Saveetha School of Engineering,, Chennai, India.

**Dr.P.V.Pramila**, received the B.E degree in Electronics and Communication Engineering from Bharath Institute of Science and Technology, (Madras University, India) in 2001 and the M.Tech (VLSI) degree in Electronics and Communication Engineering specialization from Satyabama University, Chennai, India in 2008. She completed the Doctorate in the Department of Information and Communication Engineering at Anna University. She is currently working as Associate Professor in Saveetha School of Engineering (Department of CSE), SIMATS, Chennai, and Tamil Nadu.