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Trio Constrained Adaptive Noise Removal (TCANR) Mechanism for Salt and Pepper Noise in Image Classification

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Abstract: Noise removal (also called as denoising) of an image is a vital task in multi-class image classification. Three major shortcomings in Weighted Nuclear Norm Minimization (WNNM) are identified. Firstly, WNNM's patch matching based on the noisy data will considerably augment the risk of patch mismatching. This shortcoming is overcome by performing the grouping task based on noise contentment. Secondly, the fixed feedback percentage which keeps on feeds back ten percent of the residual image to the next iteration despite the consequences of noise levels. This shortcoming is ruled out by incorporating relative feedback mechanism. Finally, the unchanged / constant number of iterations for different noise not considering the distinctions in image content that which will certainly fails to deem the degree of detail in the image. For this variable termination criterion is used. The proposed work is named as Trio Constrained Adaptive Noise Removal (TCANR). Performance metric peak signal to noise ratio (PSNR) is chosen. Four existing methods are taken into account for comparing the proposed TCANR. Extensive simulations are conducted using MATLAB and the results prove that the proposed TCANR performs better in terms of PSNR when compared with the existing methods.

Keywords: WNNM, Classification, Multi-label, Noise Removal, Quality, Denoise, PSNR, TCANR, TV, FBF, LLSure, LAPB, Corel 5k, IAPR-TC12, PASCAL-VOC-2007, PASCAL-VOC-2010

1. INTRODUCTION

Classification of multi-label image is more muddled than the classification of single-label image because of the accompanying difficulties. Firstly, closer view protests in multi-label images are not adjusted as in single-label images. In few multi-label images, critiques are situated at unusual points with various range and postures. Surprisingly more dreadful, some closer view items are impeded by others. In spite of the difficulties, there are likewise extra prompts that could be used to help multi-label image classification.

Noise removal is one of the primary tasks in image processing and particularly in multi-label image classification. The nature of a computerized image always gets weakens by the impulse noise in the record or transmission. Images are definitely undermined by motive noise, brought about by failing pixels in camera sensors, accuse memory areas in equipment, diffusion in a filter which are noisy, and bit mistakes during transmission. There are two sorts of motive (or impulse) noise, which are random valued and salt-and-pepper noises. Salt-and-pepper noise can truly degenerate the images where the undermined pixel takes either the greatest or the lowest level of gray. This noise can altogether fall apart the nature of an image. The strategy of expelling this kind of impulse noise is capably a critical research task. Impulse noise is a choice like "on-off" that influences the image all of a sudden. Impulse noise is created at the period of receiving images through sensors, in the midst of the transmission of images or because of the barometrical varieties, for instance, lightening etc. At the point when an image is ruined due to the impulse noise, the nature of the image is corrupted at a substantial degree. Thus, the expulsion of impulse noise from the caught image is important to upgrade the nature of the image. Force of impulse noise has the inclination of being either moderately maximum or minimum; consequently, aspect of the image is extremely influenced because of high frequency of impulse noise. Safeguarding the image elements and weakening of noise are the two critical parts of image rebuilding. Overall, the linear filters are viable for added substance noises. In any case, their execution for evacuation of impulse noise will not be satisfactory. In this manner, non-linear filters are favored for expulsion of impulse noise. In this phase of research work, removal of salt and pepper noise is obtained. The proposed research work contributes mainly with the objective of removal of salt and pepper noise. Another important objective of the proposed research work is to reduce the peak signal to noise ratio when compared with the existing denoising algorithms. The next section presents the related works.

2. LITERATURE REVIEW

Xianquan Zhang et al.,2015 proposed a basic and proficient rebuilding calculation with the hypothesis of image inpainting. It takes the input as noisy pixels as missing the information for inpainting, attentively chooses complexity cover regarding points of interest of nearby region, and accomplishes rebuilding by repetitive complex

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process. Luis González Jaime et al.,2014 presented an approach in view of dealing with obscure noise models. To carry out this, distinctive refined images were acquired, and then it was consolidated utilizing multifuzzy sets and averaging total capacities. With a specific end goal to handle clashing issues of noise smoothing and depth protection, Muhammad Habib et al.,2016 proposed an approach by utilizing versatile fuzzy surmising framework for irregular esteemed impulse noise identification and evacuation, where its filter utilizes the strength based directional insights to develop versatile fuzzy enrollment capacities which assumes an essential part in fuzzy intruding framework.

V.P. Ananthi and P. Balasubramaniam.,2016 proposed a technique which explores image denoising by demonstrating this unclearness as deterioration. An IVIFS for an image was created by limiting entropy. At L/that point sort diminished IVIFS was acquired by taking probabilistic value of the enrolled interim. At long last, uproarious pixels were identified by utilizing the directional pieces and were filtered by utilizing fuzzy filter. Lianghai Jin et al.,2016 proposed a way to deal with impulse noise evacuation in shading images, where arrangement was a quaternion exchanging vector filter in which the impulse recognition comprises of more than one phase. Amarjit Roy et al.,2016 proposed a support vector machine (SVM) classification based Fuzzy filter (FF) for expulsion of impulse noise from dark scale images. At the point when an image was influenced by impulse noise, the nature of the image was contorted since the homogeneity among the pixels was broken. SVM was joined for identification of impulse noise from images.

Guorong Gao et al.,2015 presented two-phase denoising technique for the expulsion of arbitrary esteemed impulse noise (RVIN) in images. The principal phase of its calculation applies a impulse noise recognition schedule which was a refinement of the HEIND calculation and it was exceptionally precise in distinguishing the area of the noisy pixels, where its end phase was a image inpainting schedule that wass intended to reestablish the missing data at those pixels that have been distinguished amid the principal phase. Amarjit Roy and Rabul Hussain Laskar.,2016 proposed a multiclass support vector machine (SVM) based versatile filter for expulsion of impulse noise from shading images. The nature of the image gets corrupted because of the nearness of noise by impulse. Subsequently, the homogeneity among the pixels gets bended which should be reestablished. Examination of Ching-Ta Lu et al.,2016 exhibited a three-values-weighted technique for the expulsion of salt-and-pepper noise. At first, a variable-estimate neighborhood window was utilized to break down every outrageous pixel.

The target of a approach developed by Bin Zhou et al.,2012 was to diffuse the different values when measured in different direction and exclude the noise. Numerous methods were proposed for randomly varied models. The characteristics of the diffusion were controlled by nonlinear partial differential equation. Jian Lu et al.,2016 proposed a variety representation for rebuilding of images ruined by multiplicative noise, where it demonstration were figured in the logarithm transform space of the attractive images comprises of an data desirable style a quadratic style and an aggregate variety regularizer. In Xiang Guo et al.,2017 stationary wavelet transform (SWT) based technique was proposed to denoise the advanced image with the low noise, and the SWT denoising calculation was displayed after the investigating of the light noise.

Amarjit Roy and Rabul Hussain Laskar.,2017 proposed a non-causal linear prediction based adaptive vector median filter for removal of high density impulse noise from color images. In the proposed method, if the pixel under operation was found to be corrupted, the filtering operation will be carried out. In Sasan Mahmoodi.,2017 a nonlinear method based on anisotropic diffusion notion was proposed to remove noise from noisy signals modulated with multiple carrier signals by preserving carrier signals as well as discontinuities present in the original noiseless signals. The next section elaborates on the proposed research work with certain technical background and preliminaries.

3. TRIO CONSTRAINED ADAPTIVE NOISE REMOVAL (TCANR) MECHANISM FOR MULTI - LABEL IMAGES

3.1 Technical Background and Preliminaries

Weighted Nuclear Norm Minimization uses broad-neighbor ascetic-resemblance to concentrate associated area of a given reference into a grid to structure a grouping. Heaps of strategies have been created to play out the grouping function. In undeniable reality, a simple and adequate grouping strategy is made use with the assistance of WNNM and it is to be functioned by pair-wise ascertaining the closeness between the reference area and hopeful ones arranged at various spatial areas. It is critical that the closeness between two areas is enumerated by making utilization of the evaluation of more than a space. Minor parting means lifted closeness to resemblance. A blend of separation measures are most likely be utilized and the WNNM strategy utilizes the Euclidean separation measure for figuring the same. The resemblance between a indication area $\mathbf{P}_f$ of mass $n \times n$ and contestant P_i can be showed as:

$$Sim\left(P_f, P_i\right) = \frac{\left\| P_f - P_i \right\|_F^2}{n^2} \quad \ldots (1)$$

The WNNM mechanism arranges in descending order of all the similar patches based on the similarity values and then gathers the opening N patches as the similar patches that will form a matrix. In order to obtain a noise – free patch, nuclear norm minimization (NNM) is used as its convex respite, and is formulated as:

$$Xj = \arg\min_{X_j} \left\| Y_j - X_j \right\|_F^2 + \lambda \left\| X_j \right\|_* \quad \ldots (2)$$

where $\left\| X_j \right\|_*$ the nuclear norm of is X_j, Y_j is the observation matrix, and λ is a positive constant.
For shrinking every singular value with the same amount λ WNNM modeled a weighted nuclear norm of matrix X_j, by the below equation

$$\left\| X_j \right\|_{w,*} = \sum_i \left| w_i \sigma_i \left(X_j \right) \right| \ldots (3)$$

where $W = \left[w_1, w_2, \ldots w_n \right]$ and w_i is the non-negative weighted coefficient, and $\sigma_i \left(X_j \right)$ is the $i-$th singular value of X_j. Hence Eq. (2) gets rewritten as:

$$X_j = \arg\min_{x_j} \frac{1}{\sigma_n^2} \left\| Y_j - X_j \right\|_F^2 + \left\| X_j \right\|_{w,*} \quad ..(4)$$

Into the bargain, WNNM takes advantage of an iterative regularization technique that will nourish partial method noise back to the next denoising process which results in elevated denoising performance.

3.2 Proposed Work

First three important shortcomings in WNNM have been identified. First shortcoming is, WNNM's patch matching based on the noisy data that will considerably augment the risk of patch mismatching. Second shortcoming is the fixed feedback percentage which keeps on feeds back ten percent of the residual image to the next iteration despite the consequences of noise levels. Third shortcoming is the unchanged / constant number of iterations for different noise not considering the distinctions in image content that which will certainly fails to deem the degree of detail in the image.

3.2.1 Grouping based on Noise Containment

For overcoming the first shortcoming of WNNM, this sub-section presents the mechanism called grouping based on noise containment. Let P_f be a reference patch of size $n \times n$ in a noisy image, and P_i be a candidate similar patch. Here we only consider the additive Gaussian noise. Hence, P_j and P_i can be written as:

$$\begin{cases} P_f = P_f^0 + N_f^o \\ P_i = P_i^0 + N_i^0 \end{cases} \ldots (5)$$

where P_f^0 and P_i^o are the latent clean patches of P_f and P_i respectively , and N_f^o and N_i^o are the noise with mean 0 and standard deviation σ. Pertaining to clean images and noise are uncorrelated, the mathematical representation will be:

$$E\{Sim(P_f, P_i)\} \approx Sim(P_f^0, P_i^o) + \sigma^2 \ldots (6)$$

From the equation (6), it is observed that the similarity measure of noisy patches is a biased estimator when compared to clean ones which will categorize a dissimilar patch into the similar patch group by fault. For overcoming this pitfall and to restrain the noise effect on the matching of similar patches, a coarse prefiltering is used by using Discrete Cosine Transform (DCT).

3.2.2 Relative Feedback Mechanism

For overcoming the second shortcoming of WNNM, this sub-section presents the mechanism called relative feedback mechanism. Let Y be an original noisy image and J be a denoising operator. The denoised image outcome $\hat{X}$ will be:

$$\hat{X} = J(Y) \ldots (7)$$

Hence the noise ΔX will be,

$$\Delta X = Y - \hat{X} \ldots (8)$$

The relative feedback mechanism is performed using the below formula

$$f_n(i) = \frac{255 * \left(f(i) - f_{\min} \right)}{f_{\max} - f_{\min}} \ldots (9)$$

By taking into account of salt-and-pepper noise model the evaluation of the denoising performance via method noise is evaluated. If truth be told, it is impracticable to have clean images while performing the denoising process.

3.2.3 Variable Termination Criterion

For overcoming the third shortcoming of WNNM, this sub-section presents the mechanism called variable termination criterion. Based on the noise inducted in the image and quality of the image, it is imperative to resolve the number of iterations. Hence the correlation measure is carried out:

$$correl(k) = corr\left(H.* \hat{X}^{(k)}, H.* \left(Y - \hat{X}^{(k)} \right) \right) \ldots (10)$$

where H is a matrix that indicates the active regions of an image, and $\hat{X}^{(k)}$ is the denoised image after k iterations. H is obtained by dilating the result of edge detection $\hat{X}(1)$. So $H.* \hat{X}^{(k)}$ and $H.* \left(Y - \hat{X} \right)^{(k)}$ are the active regions of the k-th iteration denoised image and the method-noise image, respectively. The best iteration is the one that hits the minimum absolute value in the '*correl*' vector, which is used as the terminating criterion.
The proposed TCANR algorithm is portrayed below:

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Algorithm 1 Image Denoising with Trio Constrained Adaptive Noise Removal

Input: Noisy image Y

Initialize $\hat{X}^{(0)} = Y$, $Y^{(0)} = Y$;

Estimate noise level σ;

Map $\delta_{(\sigma)}$ according to σ ;

for $= t = 1 : K$ k **do**

  Iterative regularization $Y^{(t+1)} = \hat{X}^{(t)} + \delta_{(\sigma)} \Delta X^{(t)}$

  for each patch P_j of $Y^{(t+1)} = \hat{X}^{(t)} + \delta_{(\sigma)} \Delta X^{(t)}$ **do**

    Prefiltering for each noisy patch

    Form similar patch group Y_j

    Estimate weight vector w

    Perform singular value decomposition $Y_j = U \Sigma V^T$

    Recover $\hat{X}_j$ using $US_w(\Sigma)V^T$

  end for

  Aggregate $\hat{X}_j$ to reconstruct the denoising version $\hat{X}^{(t)}$

  if $t == 1$

    Compute H

  end if

  Compute $correl(t) = corr\left(H.*\hat{X}^{(t)}, H.*\left(Y - \hat{X}^{(t)}\right)\right)$

  if $correl(t) > correl(t-1)$

    break;

  end if

end for

Output: Denoised image $\hat{X}^{(t-1)}$

The next section explains the results and discussions of the proposed method named Trio Constrained Adaptive Noise Removal (TCANR).

4. RESULTS AND DISCUSSION

The performance of this TCANR is compared with 4 methods (Total Variation (TV) Method [L. Rudin et al.,1992], Fast Bilateral Filter (FBF) Method [Q. Yang et al.,2009], LL Sure (LLSure) Method [T. Qiu et al.,2013], Locally Adaptive Patch - Based (LAPB) Method [Minyoung Kim.,2015]) over four datasets (Corel 5k Dataset [P. Duygulu et al.,2002], IAPR – TC12 Dataset [M. Grubinger.,2007], PASCAL-VOC-2007 Dataset [M. Everingham et al.,2007], PASCAL-VOC-2010 Dataset [M. Everingham et al.,2010]). In this research work 10 images are taken from each of the four datasets.

4.1 Corel 5k Dataset

Corel-5K [35] is widely used for testing methods for image retrieval and annotation. The dataset is comprised of concepts manually annotated for about 5000 images. The concept keywords are mostly the object category names. The dataset provides the fixed splits of training/test sets, roughly taking 90%/10% proportions of the entire samples.

The obtained original images of Corel5k dataset are shown in the Fig.01. Then salt and pepper noise is added to the images of Corel5k dataset is shown in Fig.02. Then the denoised result image of the proposed TCANR is presented for the Corel5k dataset in Fig.03. The PSNR comparison for the dataset is presented in the Fig.04. The PSNR values for the Corel57 dataset is presented in the Table 1. From the results inferences made is, the maximum noise ratio for the dataset Corel5k is 19.2 dB and the minimum noise ratio is 14.7 dB. This projects the improved performance of TCANR in Corel5k dataset.

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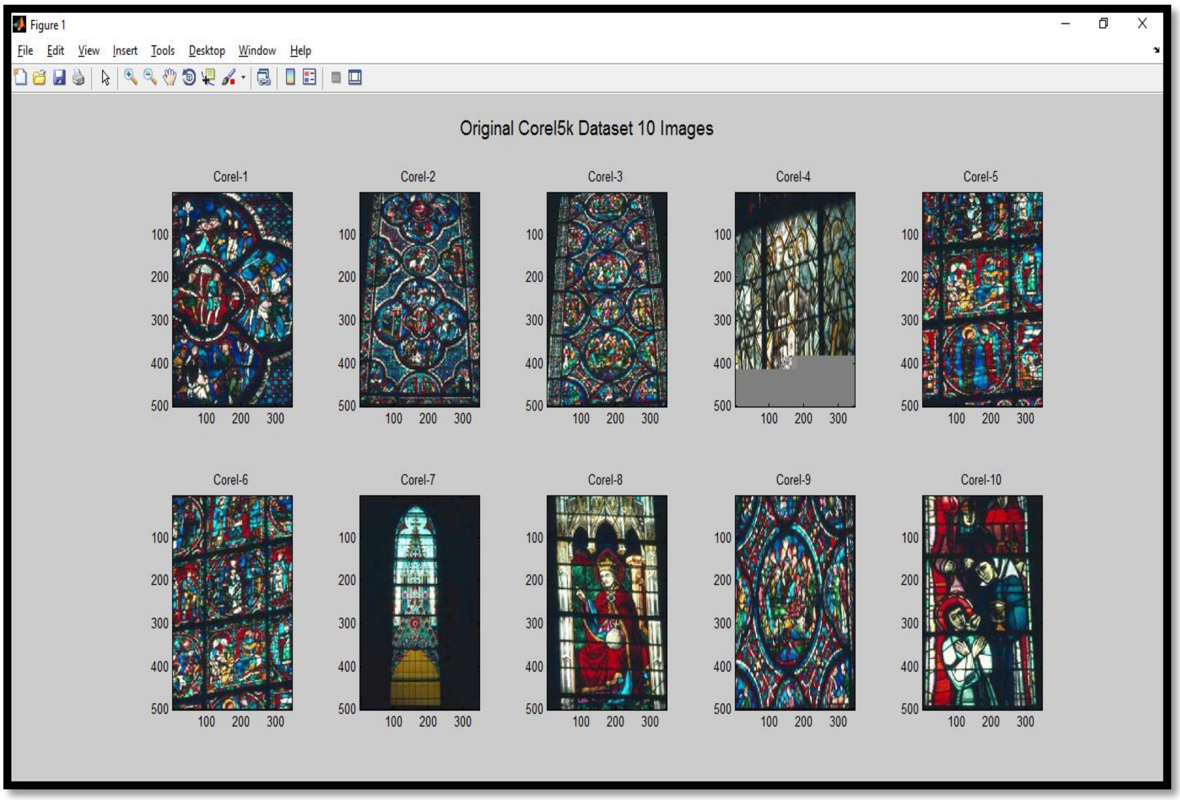

Fig. 01. Original Image of Corel 5K Dataset

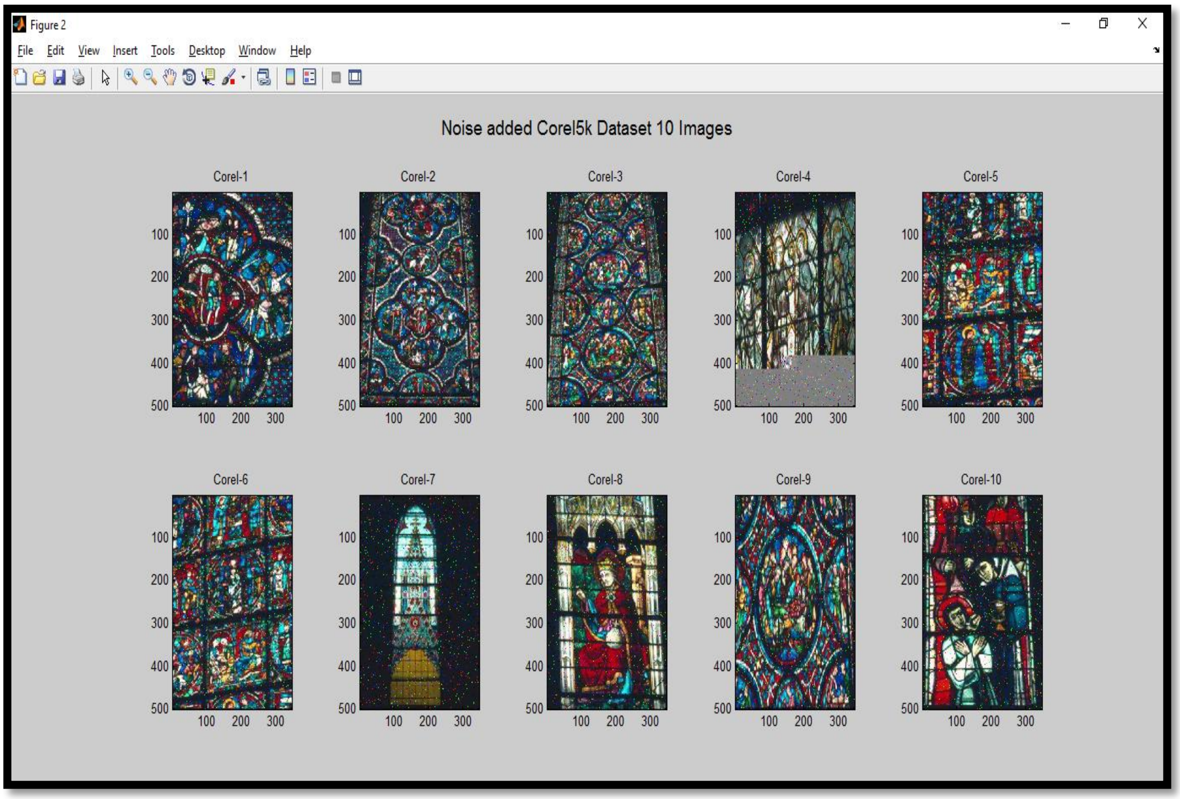

Fig. 02. Noise Added Image of Corel 5K Dataset

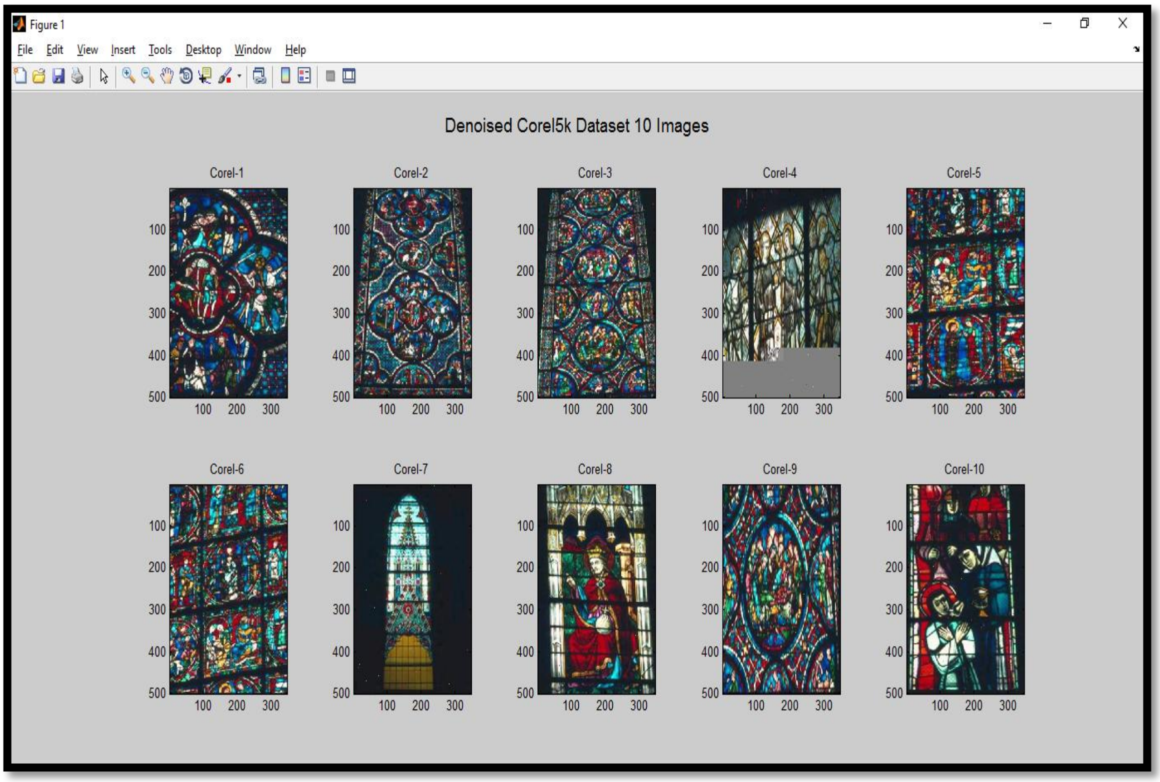

Fig. 03. Denoised Image for Corel 5K Dataset

Table 01. PSNR Comparison for the Corel 5K Dataset

Image Title	PSNR in dB				
	TV [#]	FBF [@]	LLSure [&]	LAPB [*]	TCANR
Corel - 01	30.1	27.9	24.2	18.1	17.5
Corel - 02	34.0	26.6	23.1	23.8	16.5
Corel - 03	28.7	27.9	26.3	20.0	16.6
Corel - 04	33.6	30.6	26.5	22.6	17.6
Corel - 05	33.2	27.7	22.1	23.6	16.8
Corel - 06	34.1	28.7	26.9	24.1	19.2
Corel - 07	32.1	27.0	25.7	22.3	19.0
Corel - 08	33.8	27.4	25.1	24.8	18.7
Corel - 09	28.6	25.3	22.9	18.9	14.7
Corel - 10	31.8	29.9	23.7	20.9	18.6

[where # → L. Rudin et al.,1992, @ → Q. Yang et al.,2009, &→T. Qiu et al.,2013, →Minyoung Kim.,2015]

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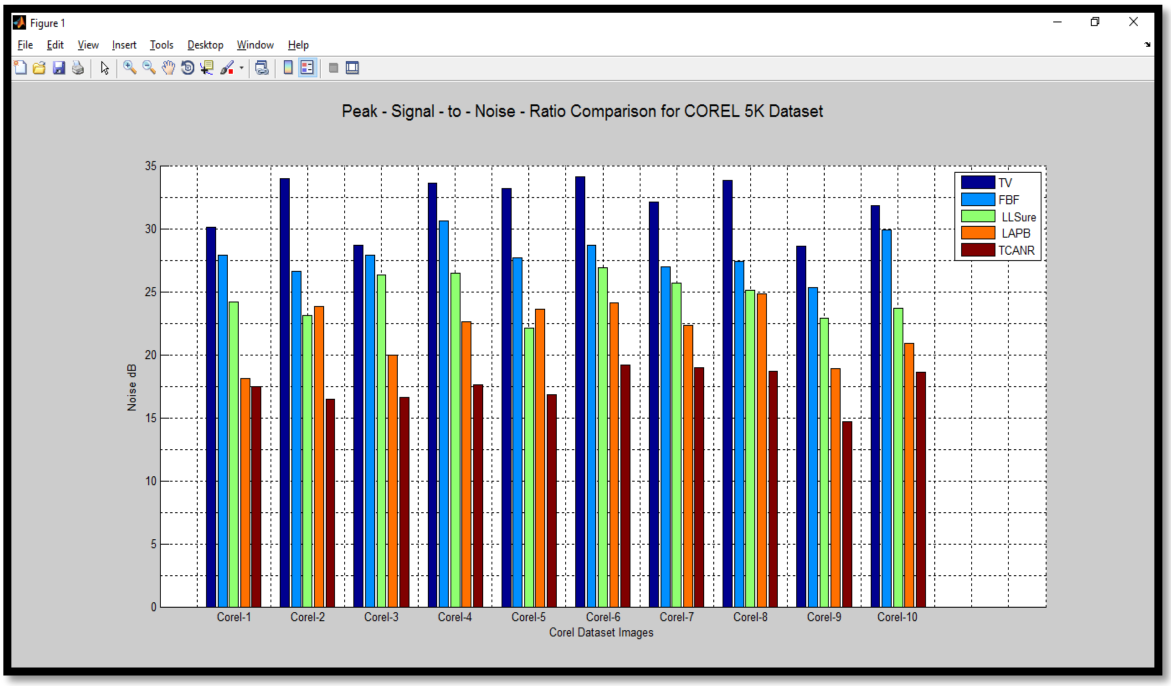

Fig. 04. Matlab Result - PSNR Comparison for COREL 5K Dataset

4.2 IAPR – TC12 Dataset

The image collection of the IAPR TC-12 consists of 20,000 images taken from locations around the world and comprising an assorted cross-section of images. This includes pictures of different sports and actions, photographs of people, animals, cities, landscapes and many other aspects of contemporary life.

The obtained original images of IAPR – TC12 dataset are shown in the Fig.05. Then salt and pepper noise is added to the images of IAPR – TC12 dataset is shown in Fig.06. Then the denoised result image of the proposed TCANR is presented for the IAPR – TC12 dataset in Fig.07. The PSNR comparison for the dataset is presented in the Fig.08. The PSNR values for the each of the four datasets are presented in the Table 2. From the results inferences made is, the maximum noise ratio for the dataset IAPR TC-12 is 17.3 dB and the minimum noise ratio is 12.9 dB. This projects the improved performance of TCANR in IAPR TC-12 dataset.

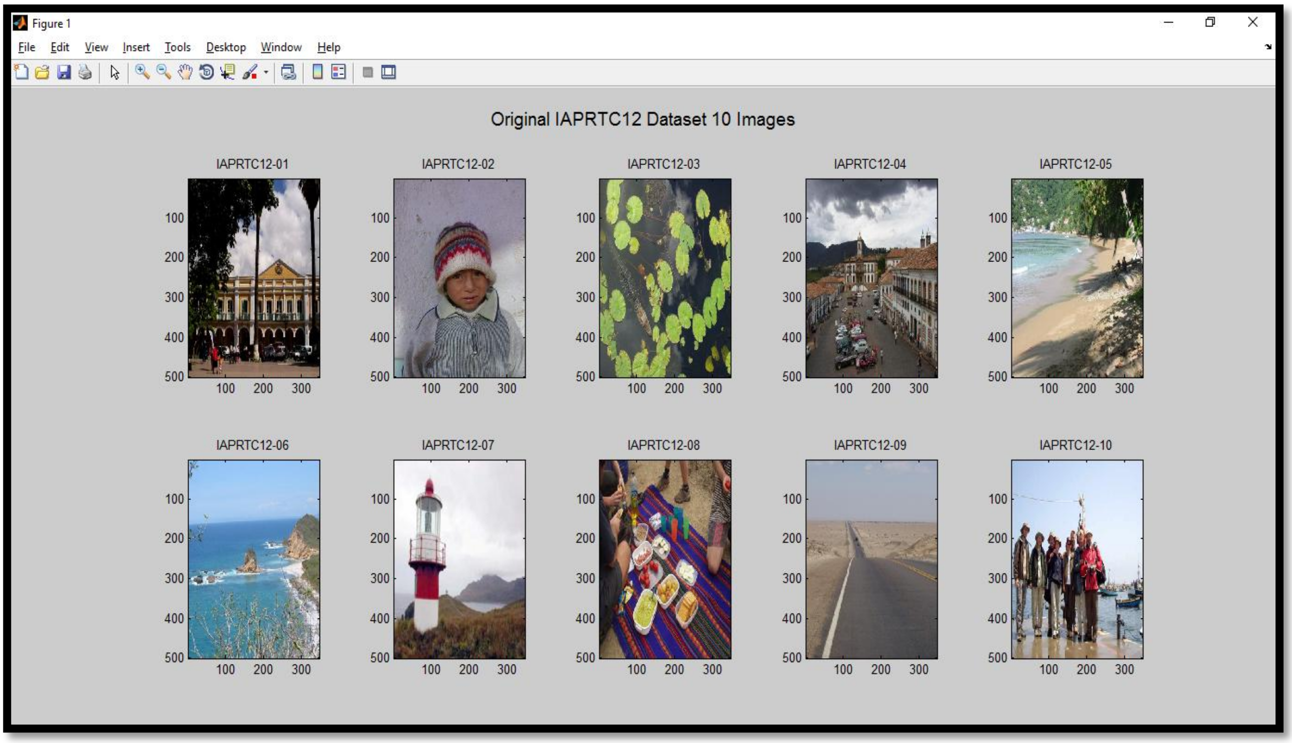

Fig. 05. Original Image of IAPR – TC12 Dataset

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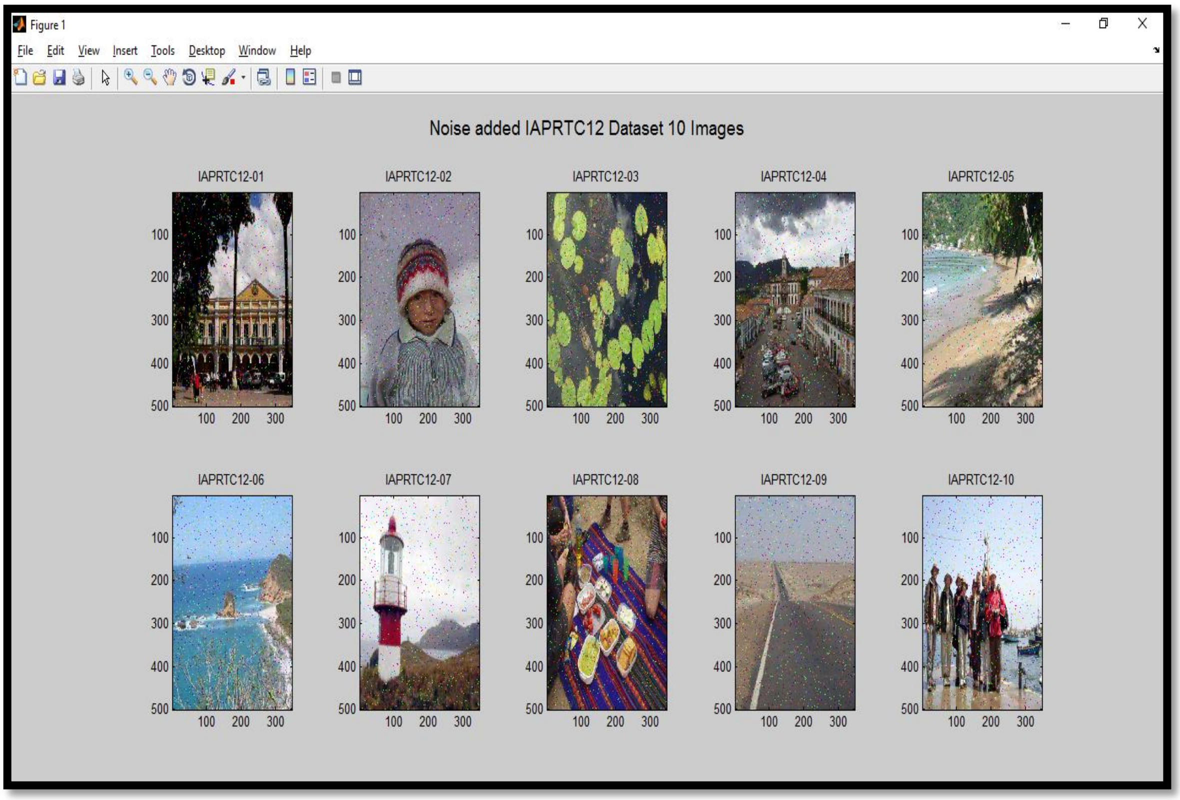

Fig. 06. Noise Added Image of IAPR – TC12 Dataset

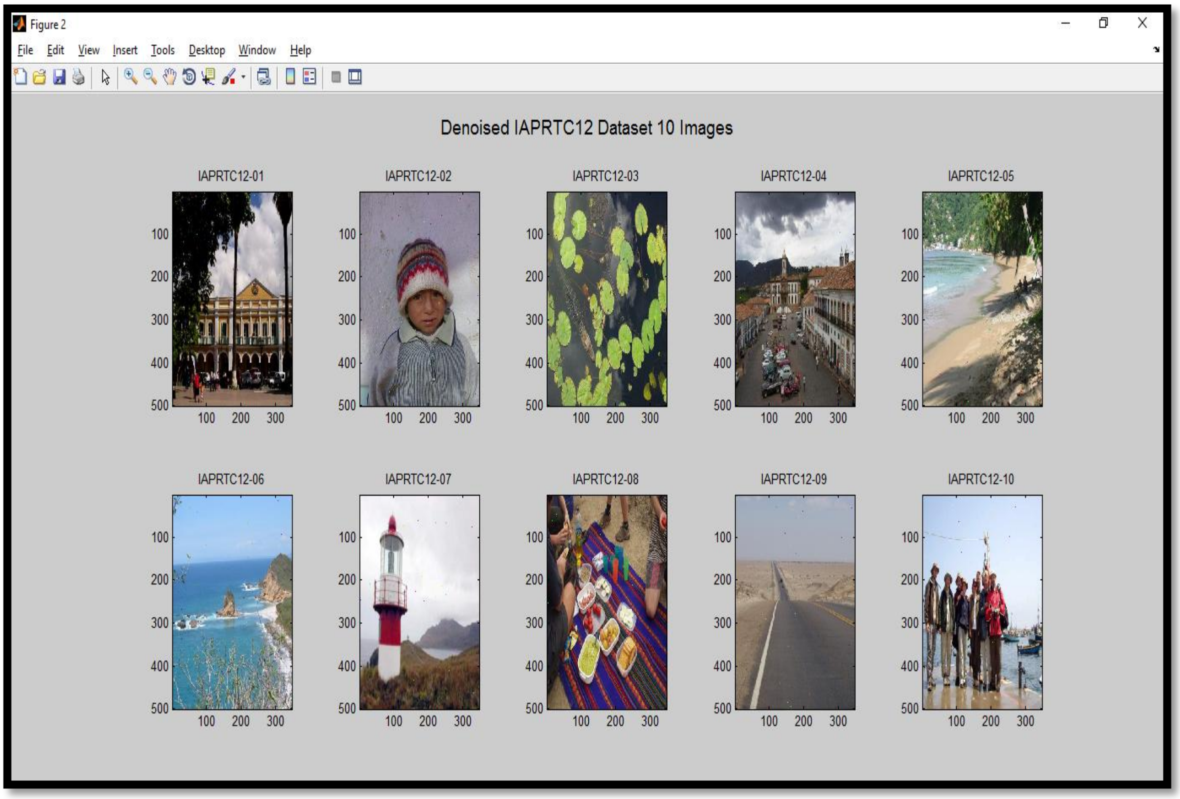

Fig. 07. Denoised Image for IAPR – TC12 Dataset

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Table 02. PSNR Comparison for the IAPR – TC12 Dataset

Image Title	PSNR in dB				
	TV [#]	FBF [@]	LLSure [&]	LAPB [*]	TCANR
IAPR – TC12 – 01	30.9	26.2	21.0	20.1	14.0
IAPR – TC12 – 02	32.0	26.9	21.6	17.6	15.1
IAPR – TC12 – 03	32.6	24.2	21.6	22.4	12.9
IAPR – TC12 – 04	32.1	24.3	25.3	18.6	17.1
IAPR – TC12 – 05	29.2	29.2	23.6	22.4	14.9
IAPR – TC12 – 06	31.7	24.4	22.5	22.7	15.7
IAPR – TC12 – 07	32.5	24.8	22.9	17.3	14.5
IAPR – TC12 – 08	32.5	28.1	23.9	19.1	17.2
IAPR – TC12 – 09	32.1	26.4	25.7	18.1	14.2
IAPR – TC12 – 10	29.5	27.8	23.0	17.4	17.3

[where # → L. Rudin et al.,1992, @ → Q. Yang et al.,2009, &→T. Qiu et al.,2013, →Minyoung Kim.,2015]

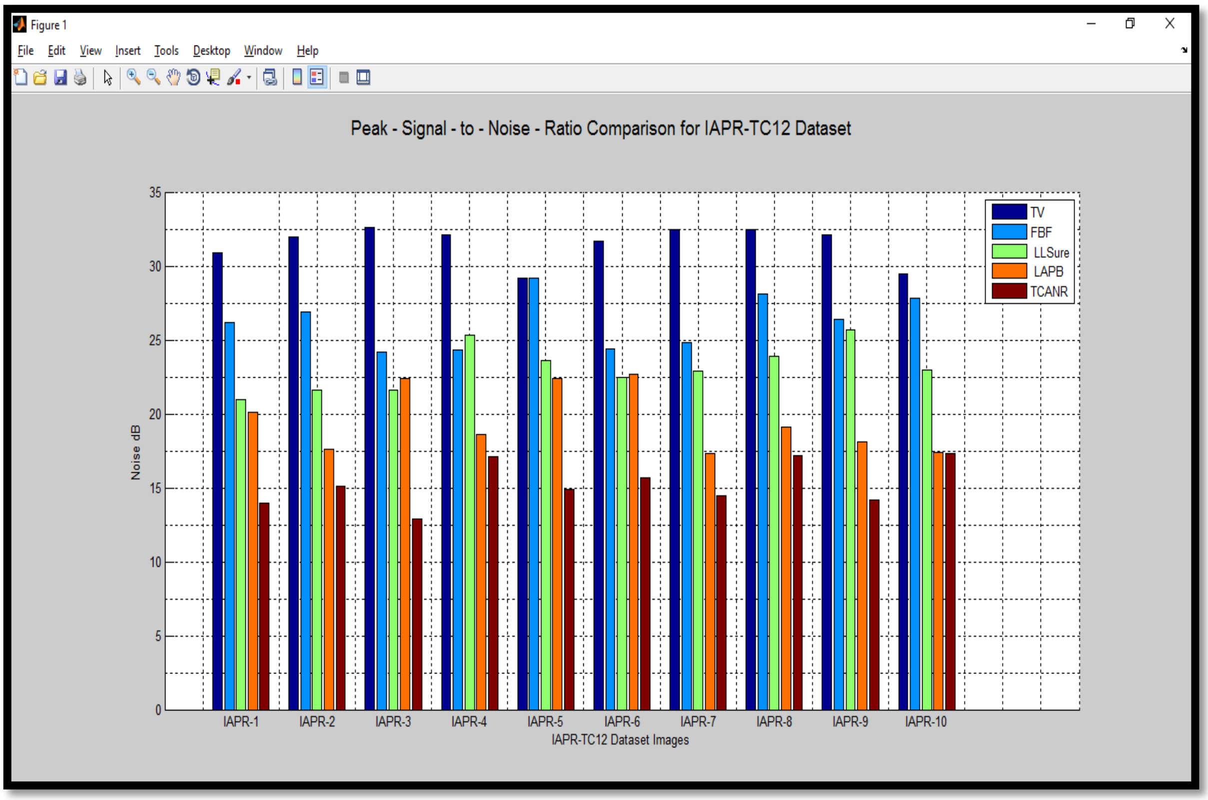

Fig. 08. Matlab Result - PSNR Comparison for IAPR – TC12 Dataset

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4.3 PASCAL – VOC - 2007 Dataset

The training data provided consists of a set of images; each image has an annotation file giving a bounding box and object class label for each object in one of the twenty classes present in the image. Note that multiple objects from multiple classes may be present in the same image. It contains 9963 images (VOC-2007) labeled with concepts including person, vehicle, dog, and so on.

The obtained original images of PASCAL-VOC-2007 dataset are shown in the Fig.09. Then salt and pepper noise is added to the images of PASCAL-VOC-2007 dataset is shown in Fig.10. Then the denoised result image of the proposed TCANR is presented for the PASCAL-VOC-2007 dataset in Fig.11. The PSNR comparison for the dataset is presented in the Fig.12. The PSNR values for the each of the four datasets are presented in the Table 3. From the results inferences made is, the maximum noise ratio for the dataset PASCAL-VOC-2007 is 19.7 dB and the minimum noise ratio is 15.7 dB. This projects the improved performance of TCANR in PASCAL-VOC-2007 dataset.

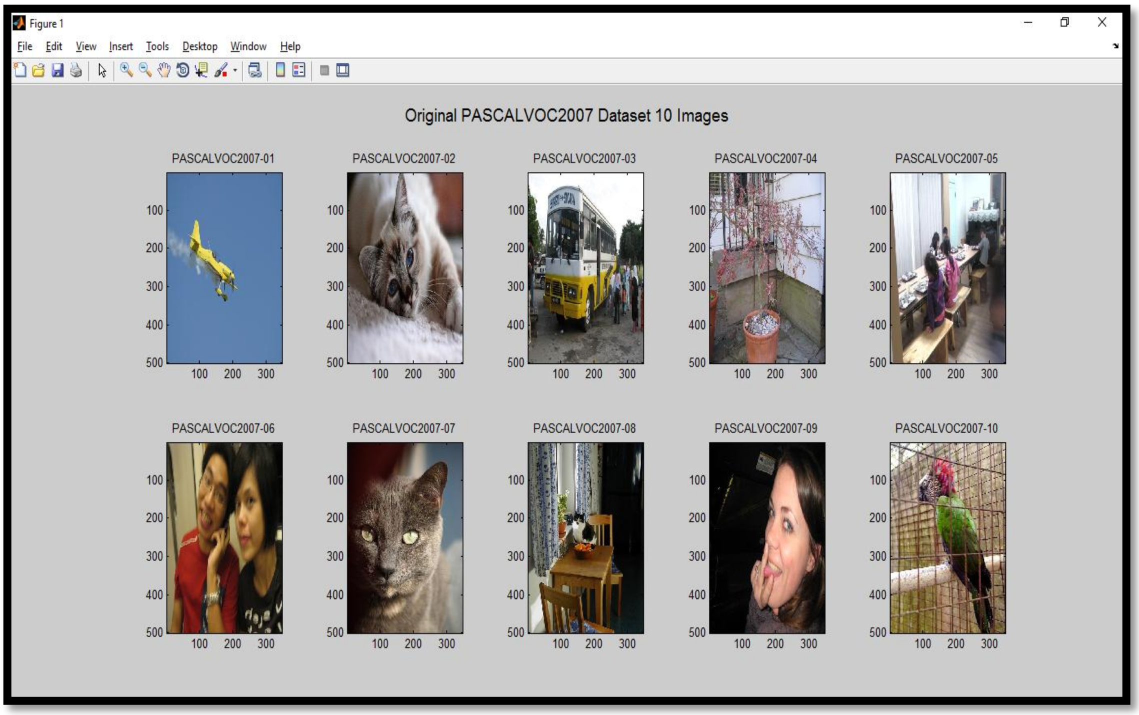

Fig. 09. Original Image of PASCAL – VOC - 2007 Dataset

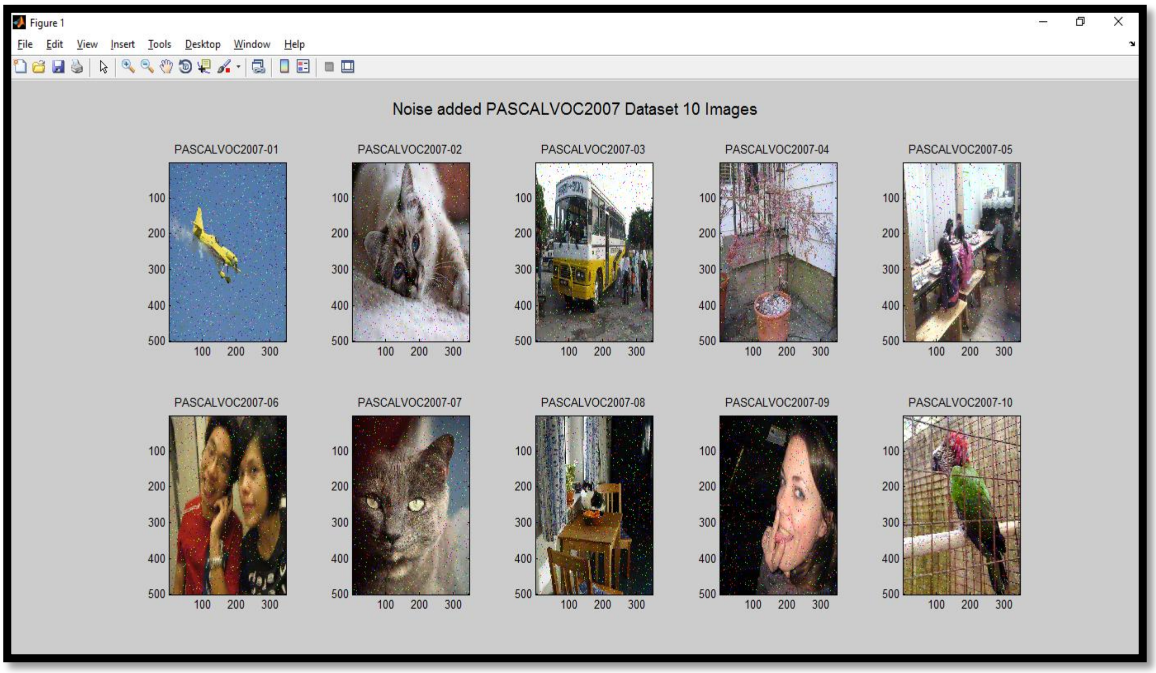

Fig. 10. Noise Added Image of PASCAL – VOC - 2007 Dataset

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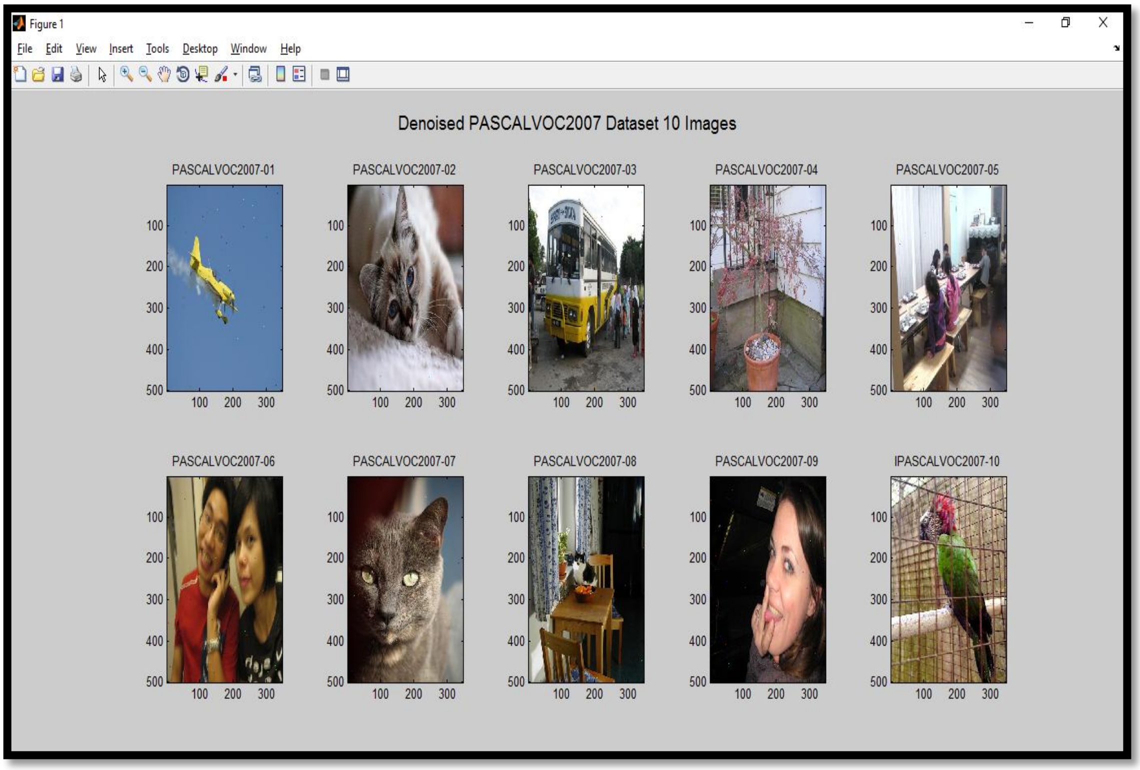

Fig. 11. Denoised Image for PASCAL – VOC - 2007 Dataset

Table 03. PSNR Comparison for the PASCAL – VOC - 2007 Dataset

Image Title	PSNR in dB				
	TV [#]	FBF [@]	LLSure [&]	LAPB [*]	TCANR
PASCAL-VOC-2007 – 01	31.7	29.2	24.3	19.7	19.4
PASCAL-VOC-2007 –02	31.3	28.3	24.4	22.8	16.9
PASCAL-VOC-2007 –03	31.1	28.7	24.4	21.9	17.9
PASCAL-VOC-2007 –04	31.0	30.5	24.2	23.6	16.1
PASCAL-VOC-2007 –05	30.7	31.4	27.3	21.7	19.0
PASCAL-VOC-2007 –06	34.1	30.1	26.9	24.1	19.7
PASCAL-VOC-2007 –07	33.5	30.6	26.1	24.7	18.0
PASCAL-VOC-2007 –08	30.3	27.0	27.8	20.8	15.7
PASCAL-VOC-2007 –09	31.5	30.4	28.0	24.2	18.6
PASCAL-VOC-2007 –10	32.2	29.5	26.9	23.2	16.4

[where # → L. Rudin et al.,1992, @ → Q. Yang et al.,2009, &→T. Qiu et al.,2013, →Minyoung Kim.,2015]

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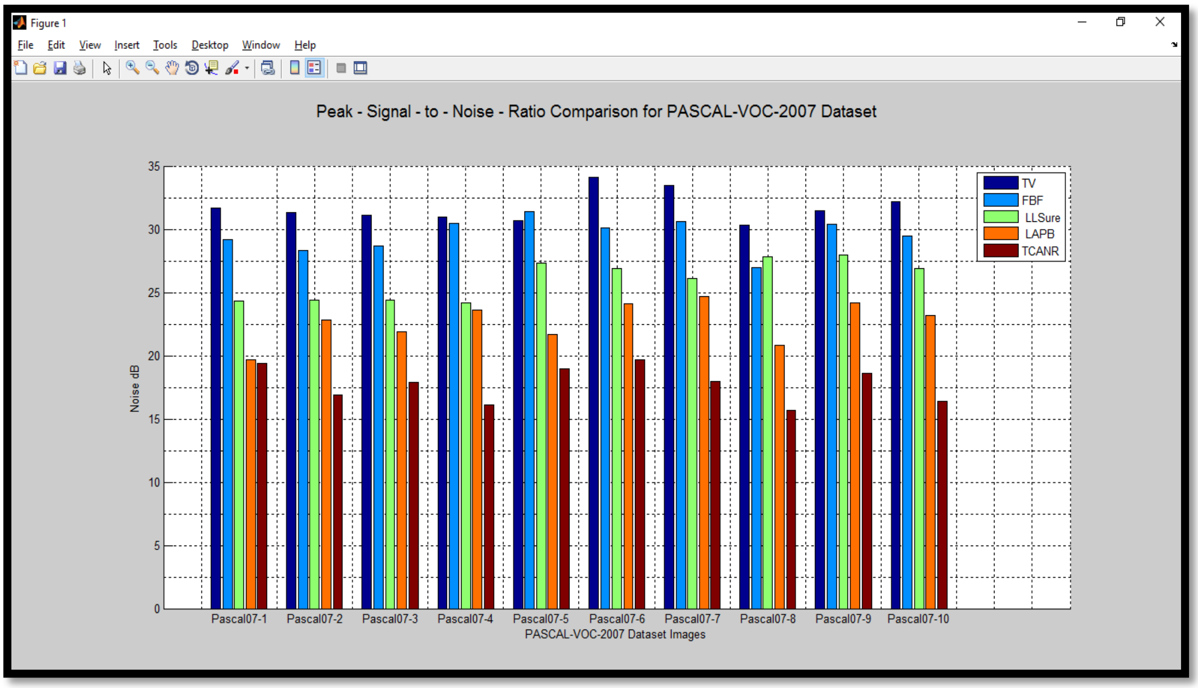

Fig. 12. Matlab Result - PSNR Comparison for PASCAL – VOC - 2007 Dataset

4.4 PASCAL – VOC - 2010 Dataset

It is the extension of PASCAL-VOC-2007 dataset with the following developments: (a) Action Classification taster introduced (b) Associated challenge on large scale classification introduced based on ImageNet (c) Amazon Mechanical Turk used for early stages of the annotation.
The obtained original images of PASCAL-VOC-2010 dataset are shown in the Fig.13. Then salt and pepper noise is added to the images of PASCAL-VOC-2010 dataset is shown in Fig.14. Then the denoised result image of the proposed TCANR is presented for the PASCAL-VOC-2010 dataset in Fig. 15. The PSNR comparison for the dataset is presented in the Fig.16. The PSNR values for the each of the four datasets are presented in the Table 4. From the results inferences made is, the maximum noise ratio for the dataset PASCAL-VOC-2010 is 14.9 dB and the minimum noise ratio is 18.9 dB. This projects the improved performance of TCANR in PASCAL-VOC-2010 dataset.

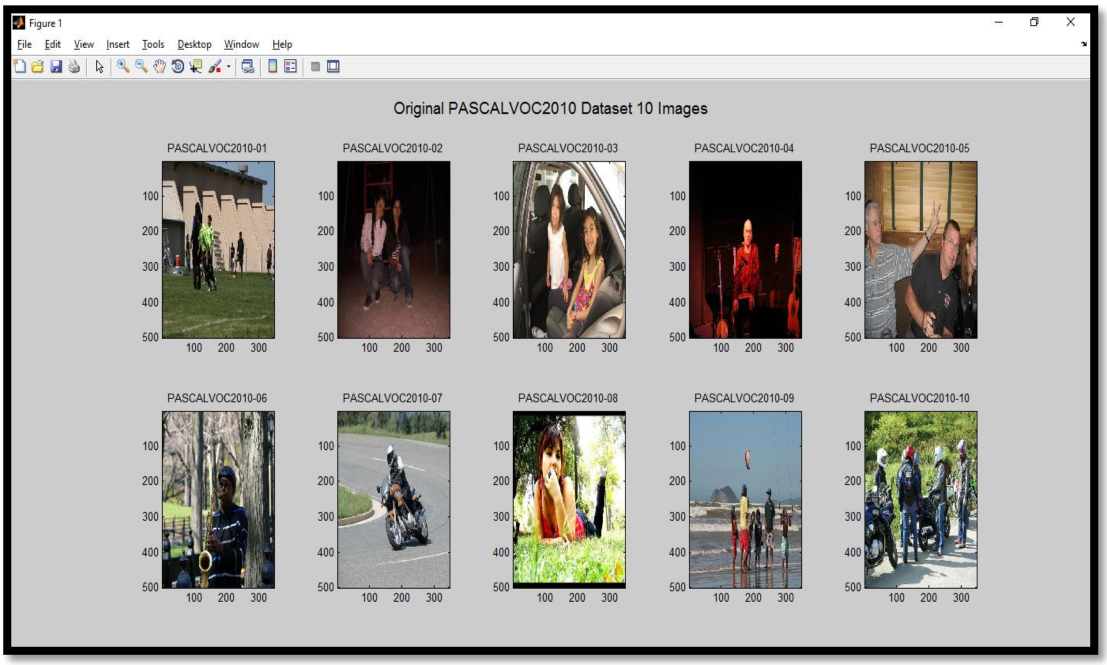

Fig. 13. Original Image of PASCAL – VOC - 2010 Dataset

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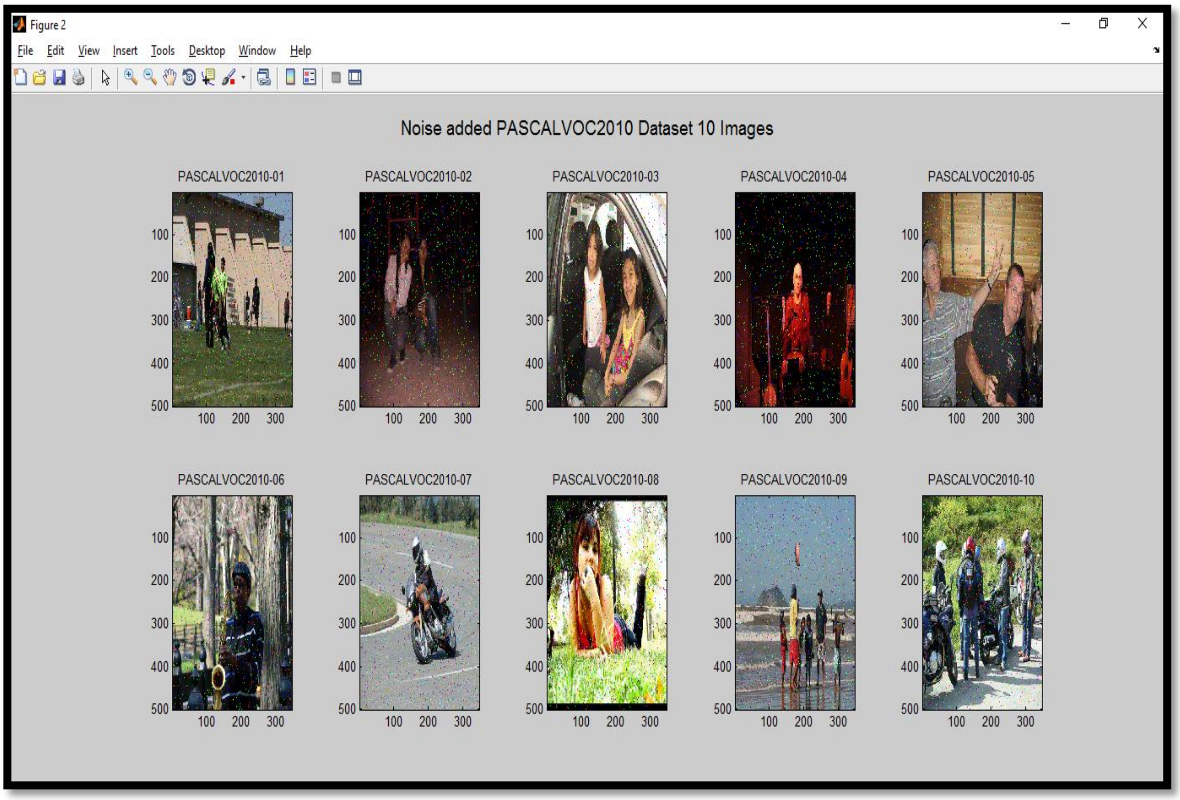

Fig. 14. Noise Added Image of PASCAL – VOC - 2010 Dataset

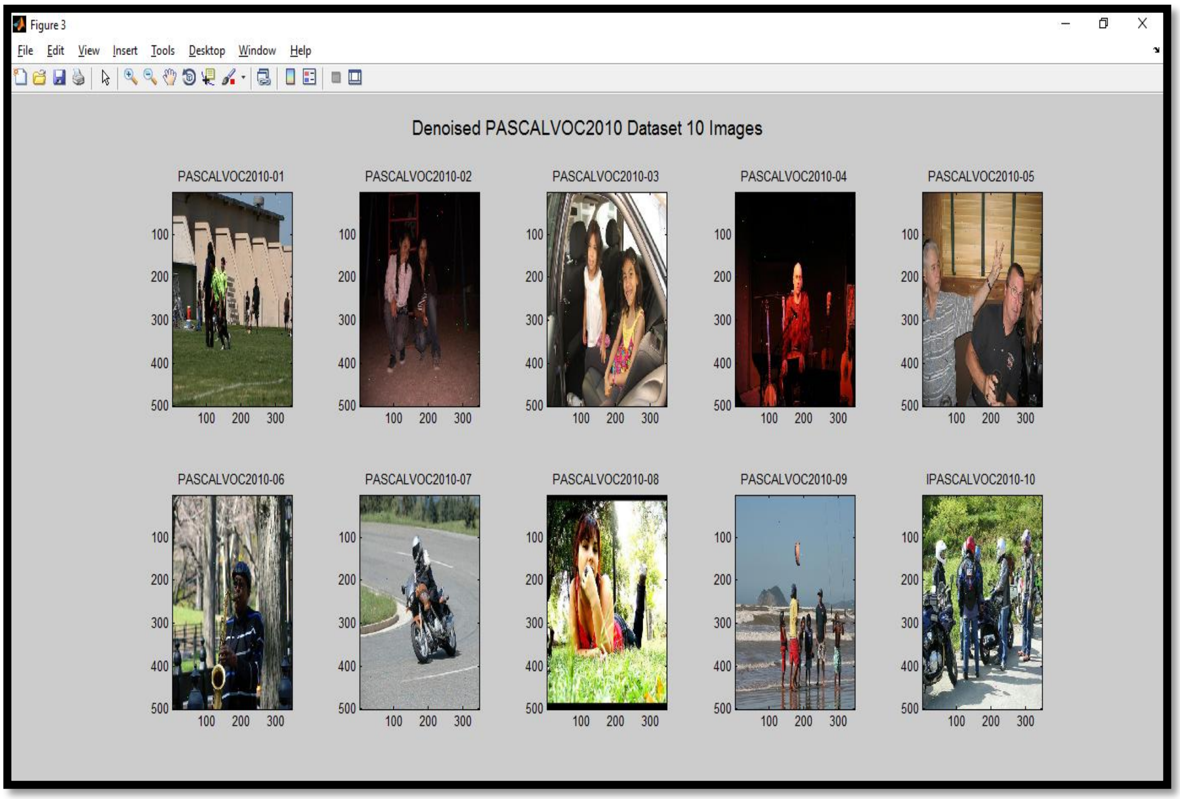

Fig. 15. Denoised Image for PASCAL – VOC - 2010 Dataset

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Table 04. PSNR Comparison for the PASCAL – VOC - 2010 Dataset

Image Title	PSNR in dB				
	TV [#]	FBF [@]	LLSure [&]	LAPB [*]	TCANR
PASCAL-VOC-2010 – 01	30.2	29.0	24.6	21.4	16.1
PASCAL-VOC-2010 –02	30.8	26.2	27.2	22.7	15.3
PASCAL-VOC-2010 –03	31.7	27.0	27.1	19.3	18.1
PASCAL-VOC-2010 –04	33.5	26.6	27.2	19.0	17.4
PASCAL-VOC-2010 –05	33.1	29.2	27.2	18.8	18.9
PASCAL-VOC-2010 –06	29.7	30.3	23.2	23.5	14.9
PASCAL-VOC-2010 –07	31.0	28.5	24.6	22.3	16.3
PASCAL-VOC-2010 –08	31.3	29.8	24.5	19.2	17.6
PASCAL-VOC-2010 –09	33.9	27.4	22.9	23.3	16.7
PASCAL-VOC-2010 –10	29.4	30.4	27.3	19.0	17.0

[where # → L. Rudin et al.,1992, @ → Q. Yang et al.,2009, &→T. Qiu et al.,2013, →Minyoung Kim.,2015]

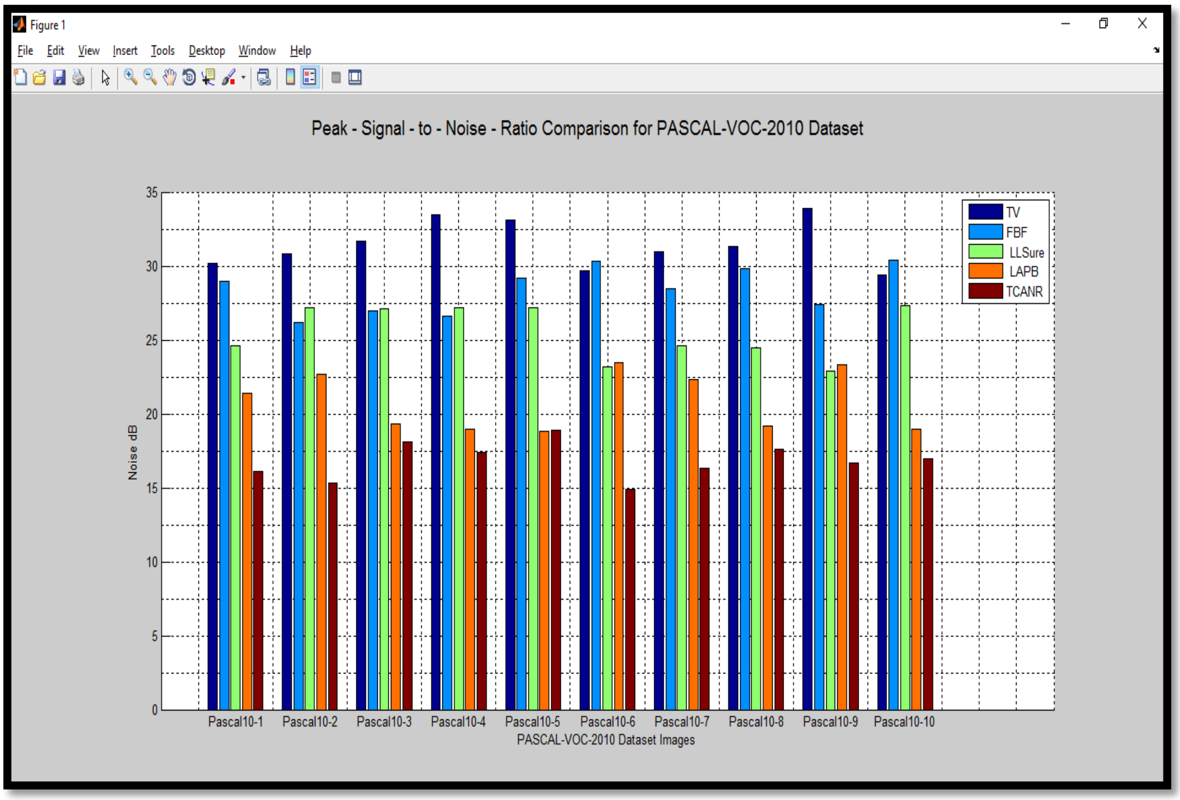

Fig. 16. Matlab Result - PSNR Comparison for PASCAL – VOC - 2010 Dataset

From the results (Fig.4, Fig.8, Fig.12 and Fig.16.) it is evident that the proposed TCANR obtains better performance than the existing methods (TV, FBF, LLSure and LAPB).

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CONCLUSIONS

Weighted Nuclear Norm Minimization makes use of broad-neighbor ascetic-resemblance to concentrate associated area of a given reference into a grid to structure a grouping. Three shortcomings in the existing WNNM method have been identified. In order to overcome these shortcomings Trio Constrained Adaptive Noise Removal (TCANR) is proposed in this research work. The performance of this TCANR is compared with 4 methods (Total Variation (TV) Method, Fast Bilateral Filter (FBF) Method, LL Sure (LLSure) Method, Locally Adaptive Patch - Based (LAPB) Method over four datasets namely Corel 5k Dataset, IAPR – TC12 Dataset, PASCAL-VOC-2007 Dataset and PASCAL-VOC-2010 Dataset. Widened simulations are conducted in MATLAB tool and the results affirms that the proposed TCANR performs better in terms of reducing the noise which is measured by PSNR. Future research may be performed by enhancing the proposed TCANR with other noise models.

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BIOGRAPHIES

G.Muthukrishnan, done his Under-Graduation in Madurai Kamaraj University and Post-Graduate in Bharathidasan University. He is currently pursuing his Ph.D in Computer Science in Dravaidian University, Kuppam, AndraPradesh. Also he is working as a Senior Project Manager in IT services company. He is having more than one year of research experience and teaching experience as well.

Capt..Dr.S.Santhosh Baboo, aged forty six, has around Twenty Five years of postgraduate teaching experience in Computer Science, which includes Six years of administrative experience. He is a member, board of studies, in several autonomous colleges, and designs the curriculum of undergraduate and postgraduate programmes. He is a consultant for starting new courses, setting up computer labs, and recruiting lecturers for many colleges. Equipped with a Masters degree in Computer Science and a Doctorate in Computer Science, he is a visiting faculty to IT companies.