Improvement of the Reconstruction Quality of Multi Frame Using Super Resolution Method

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***Abstract* - OCT (optical coherence tomography) images rely on interferometry, which explains images suffer from a high level of noise. Noise in image is any degradation in an image signal, caused by external disturbance while an image is being sent from one place to another place via satellite ,wireless and network cable. Image noise is an undesirable by product of image capture the desired information. In existing system, A super resolution algorithm can be used to generate a high-resolution image or image sequence .The algorithm has been proposed to estimate sparse co-efficient using joint MAP estimator. A non-local sparse model-based Bayesian framework is proposed for OCT restoration. The Laplacian distribution, normalized vector and GEV distribution is used for best good fit for modeling super resolution method is not fast as MAP solution. In proposed system, to overcome the existing drawback on single super resolution algorithm we are going to explore multi frame super resolution to gain more improvement in reconstruction quality. A multi frame super resolution produces a superior quality, high resolution image from multiple numbers of blurred noisy low-resolution images.**

***Index Terms* - Multi-frame MAP Estimator, Image registration, MAP Estimator, Optical Coherence Tomography, SR Super Resolution.**

I.INTRODUCTION

Image Restoration can be defined as the process of removal or reduction of degradation in an image through linear or nonlinear filtering. Images with higher resolution are required in most electronic imaging applications such as remote sensing, medical diagnostics, and video surveillance. For the past decades, considerable advancement has been realized in imaging system. However, the quality of images is still limited by the cost and manufacturing technology [1]. Super-resolution (SR) is a promising digital image processing technique to obtain a single high-resolution image (or sequence) from multiple blurred low-resolution images. The basic idea of SR is that the low-resolution (LR) images of the same scene contain different information because of relative subpixel shifts; thus, a high-resolution (HR) image with higher spatial information can be reconstructed by image fusion. Subpixel motion can occur due to movement of local objects or vibrating of imaging system, or even controlled micro-scanning [2, 3]. Numerous SR algorithms have been proposed since the concept was introduced by Tsai and Huang [4] in the year of 1984. Most of them operate in batch mode, i.e., a sequence of images are co-processed at the same time. Thus, these algorithms require a high memory resource to store the LR images and temporary data and need a high computing resource as well. These disadvantages limit their practical application. There are a variety of SR techniques, including multi-frame SR and single-frame SR. Readers can refer to Refs. [1, 5, 6] for an overview of this issue. Our discussion below is limited to work related to quality multi-frame SR method, as it is the focus of our paper.

II. LITERATURE SURVEY

The basic assumption for increasing the spatial resolution is the availability of multiple LR images captured from the same scene [5]. The LR images represent different “looks” at the same scene, so LR images are sub sampled as well as shifted with sub pixel precision. If the LR images are shifted by integer units, then each image contains the same information and thus there is no new information that can be used to reconstruct an HR image. If the LR images have different sub pixel shifts from each other and if aliasing is present, then each image cannot be obtained from the others.[3] Here new information contained in each LR image can be exploited to obtain an HR image. If we combine these LR images, SR image reconstruction is possible. There is a natural loss of spatial resolution caused by the optical distortions because of out of focus, diffraction limit, motion blur due to limited shutter speed, noise that occurs within the sensor or during transmission and insufficient sensor density in the process of recording a digital image.

Existing system observed images of a real scene usually are in low resolution. This is due to some degradation operators. Moreover, in practice, the acquired images are decimated, corrupted by noise and blur [13]. We assume that all low-resolution images are taken under the same environmental conditions using the same sensor. A super resolution algorithm can be used to generate a high-resolution image or image sequence .The algorithm has been proposed to estimate sparse co-efficient using joint MAP estimator. A non-local sparse model-based Bayesian framework is proposed for OCT restoration. The Laplacian distribution, normalized vector and GEV distribution is used for best good fit for modeling super resolution method is not fast as MAP solution. The aim of Super resolution (SR) is to generate a higher resolution image from lower to resolution images. Super resolution is based on the Laplacian + GEV model which shows the best goodness fit for modeling the images.

- The disadvantage is that Image quality is not perfectly restored.
- Existing feature-based image registration methods include joint MAP estimator.
- Although these methods do not have processing of feature points.
- They cannot detect a sufficient number of feature points when the multifare image has appearance differences or when the detected feature points contain serious abnormal values.
- Registration effect is poor, and the algorithm is less robust.

A related problem to SR techniques is image restoration, which is a well-established area in image processing applications [6]. The goal of image restoration is to recover a degraded image, but it does not change the size of image. Restoration and SR reconstruction are closely related theoretically, and SR reconstruction can be considered as a second-generation problem of image restoration. One more problem related to SR reconstruction is image interpolation that has been used to increase the size of a single image. Comparisons between various SR techniques have been primarily concerned with what assumptions are made in modeling the SR problem. Some of these assumptions include assuming the blurring process to be known or that regions of interest among multiple frames are related through global parametric transformations [7]. Signal-to-noise ratio, peak signal to noise ratio (PSNR), root mean squared error, mean absolute error, and mean square error (MSE) of super-resolved images versus interpolated images have all been used as objective measures of SR accuracy; however, the prominent method of presenting results in literature has clearly been subjective visual quality. Figure -1 shows the basic work process of super resolution image reconstruction.

Figure 1: Common Super Resolution Flow Diagram

Detailed study of existing techniques in Super-Resolution was done with the help of different literatures available in journals and books. A Proliferation of literature is available in Super-resolution. Here highlight some of the key contributions. Super-resolution (SR) can be achieved using a single image or multiple images (image sets). In single image the input is single LR image. But in the case of multiple we take the different images of same scene it will give different looks of same scene. Based on the taxonomy of super-resolution technique based on the transformation domain super-resolution techniques are classified as two 1)spatial domain and 2)frequency domain. In spatial domain it is the normal image space. We perform operations directly on pixels. In frequency domain apply transforms (Fourier transform) convert it as frequency components and perform mathematical operations on this frequency components and again transform it into spatial domain for display purpose. Glasner et. al [20] combined the above two methods so as to obtain super - resolution from a single image. These single-frame super-resolution methods are also called Example based super-resolution described by Freeman et al. in [21] which states that to generate an up scaled image with desired number of pixels. The main aim of this paper is to check the performance of single-image and multiple image learning based super resolution method [22] and compare it with the existing methods. Our aim is to achieve the good performance of the super-resolution algorithms by reducing the computational time and cost of the system and getting a good quality image. In order to do so we are extending previous method which was described in [23]. Also, it has to be checked that the artifacts are reduced while a super-resolved image is reconstructed. We call image super-resolution as image up scaling, image zooming, image magnification, image up sampling etc. Li et al in [24] proposed a non-iterative adaptive interpolation scheme for natural image sources. Sun et al in [6] proposed a Bayesian approach to image super resolution. Primal sketch priors are constructed and used to enhance the quality of the reconstructed high-resolution image. Chang et al [25] have generated a high-resolution image from a single low-resolution image, with the help of a single or multiple training images from scenes of the same or different types. Various methods are used to recover or obtain a high resolution (HR) image from one or more low resolution (LR) images. Pixel replication and nearest Neighbour interpolation are the standard interpolation techniques that tend to increase the pixel count or repeat the pixels without actually adding the image details. These techniques blur edges and other sharp details of the images but perform well in smoother regions. In conventional multi frame super-resolution methods, many low-resolution images of the same scene with varying pixel shifts are taken as inputs and correspondence between high- and low-resolution patches is learned from a database which consists of LR and HR image pairs and then by applying this knowledge to a new low resolution (LR) image and reconstruct the corresponding high-resolution image. Purkait et al in [26] have proposed image zooming technique using fuzzy rule-based prediction. In [27] , single image super-resolution algorithm based on spatial and wavelet domain is presented. In [28], a survey on techniques and challenges in image super resolution reconstruction are discussed. Regularization literally means to remove the noise from an image. Total variation regularization methods lead to reduction in the artifacts while maintaining the sharp edges and textures. In this method, learning based method using single image is combined with Intermediate Dictionary Learning in order to get an improved image quality. It is different from in the fact that in this case a single image is used for learning. Thus, a large database of images is not needed for checking co-occurrence between the image patches so there is no problem of data redundancy as only high-resolution patches constitute its database.

III. BACKGROUND METHODS

Resolution techniques can be broadly classified into interpolation-based, reconstruction-based, and learning-based techniques. Interpolation-based methods such as bicubic interpolation remain the bulwark of digital zoom in consumer software and devices but produce blurring or ringing artifacts. Reconstruction-based techniques produce watercolor like artifacts. As the performance has been achieved using learning-based, reconstruction based and interpolation-based techniques, comparing with other methods learning based method give high quality image as output. In learning-based SR methods, a mapping from LR patches to their corresponding HR patches is learnt using set of LR-HR patch pairs. Most of them are memory and computation intensive due to formation of an LR-HR patch database or searching LRHR patch pairs within the same image. Direct nonlinear regression mapping between LR and HR patches gives good results with memory and time efficiency. According to technique principle and input and output data form, current super resolution algorithms can be divided into various types. The division standards also include transformation domain, the number of input image, color space and so on. Frequency domain and spatial domain are divided from the perspective of signal transformation domain. Based on input number of image, we can obtain single image based super resolution and multiple images based super resolution. According to technique principle, super resolution can be divided into three types, namely, interpolation based, reconstruction based, and learning based. And among existing super resolution methods, reconstruction-based method and learning based method are the most popular ones.

Most multiple images based super resolution algorithms are reconstruction-based methods. These algorithms assume that there is a target high resolution image and the low-resolution observations have some relative geometric displacements from the target high resolution image. They usually exploit these differences between low resolution observations and the targeted high-resolution image, and hence are referred to as reconstruction based super resolution algorithms. Super-Resolution techniques are mainly classified as

A. INTERPOLATION BASED SUPER-RESOLUTION:

This method try to recover missing information from neighboring pixels. It is quite straightforward but the quality is not tolerate when the scaling factor is getting larger. Interpolation is a method of constructing new set of data points within the range of a discrete set of known data points. Disadvantage is produce blurring or ringing artifacts. Mainly used Interpolation based techniques are

a. Bilinear Interpolation :

Bilinear interpolation is an extension of normal mathematical linear interpolation for interpolating functions of two variables (e.g.,x and y) on a rectilinear 2D grid. The main idea is to perform linear interpolation first in one direction(row), and then again in the other direction (coloumn). Bilinear interpolation is performed by finding linear interpolation between adjacent pixels. This can be done by finding the average gray value between two pixels and use that as the pixel value between those two. We can do this for the rows first, and then we take that result and expand the coloumns in the same way.

b. Bicubic Interpolation :

This is the Godzilla of pixel interpolation algorithms. It gives absolutely good results with negligible artifacts. But it requires an extreme number of complex calculations, and it is very hard to understand. Bicubic Interpolation takes a weighted average of the 16 pixels to calculate its final interpolated value. Bicubic gives sharper images than other two methods. These techniques take more computational time. When time is not an issue then this technique gives the best result among all other techniques.

c. Nearest Neighbour:

This method is performed by repeating pixel values. Pixel replication is used to increase the size of an image an integer number of times. It only considers one pixel: that is the closest one to the interpolated point. Requires the least processing time of all the interpolation algorithms. This has the effect of simply making each pixel bigger. Disadvantage: It produce jagged results

Images obtained through photography are affected by various real-world factors, such as noise inherent to the camera imaging system, or blurring caused by the subject of the image being out of focus or in motion. These factors degrade important details, negatively impacting image quality. Super-resolution (SR) image reconstruction is specifically the technique of constructing high resolution (HR) images using single, multiple, or sequential low-resolution (LR) images in the case of degradation. It is widely used in security surveillance, medical imaging, remote sensing imaging, image processing research and public safety. Generally, the use of sequential images for SR reconstruction provides a better reconstruction effect than that of a single image. This difference is due to the relative motion between frames in image sequences, as information observable from different angles in a single scenario is non-redundant and complementary. In the field of digital image research, many researchers are committed to traditional image reconstruction [1]. Although the use of single-frame images for reconstruction has been extensively studied, use multi-frame images to achieve higher resolution reconstructed images than single-frame images [2]–[4].

The advantage of multi-frame reconstruction is to use not only in-frame correlation in a single frame image, but also inter-frame correlation between multiple images. In order to take advantage of multi-frame images, generally involves image registration, fusion, and other techniques to compensate for the displacement between images. There are three main methods: frequency domain method, spatial domain method, and learning method: The benefits of the frequency domain method include it being easier to understand, as the algorithm model is based on the relationship between the image frequency domain, its calculating speed, as the computing hardware requirements are low, and its ease of application in practical engineering.

Though the traditional frequency domain method is based on the sequence of image pixels [5]–[7], the relationship between displacement interpolation reconstruction [8], [9] does not account for the optical system dispersion effect on imaging quality reduction, as the registration model didn’t consider factors such as spectrum aliasing effect on the sub-pixel displacement estimation. Spatial domain methods, which include projection on convex sets [10], the maximum a posteriori method [11], the variational method [12], and neural networks are mostly based on the theory of statistical or collection. These methods have high precision, but in cases for which the research target is the spatial domain method with convex optimization, is it more complex, and the solving model contains large-scale matrix operations that require high performance computing equipment support, high power consumption, high costs. These limitations mean the method can only be practically used in scientific research. In fields that generally do not use spatial domain information, such as remote sensing observation, it is limited to apply the spatial domain method widely due to the limitations of consumer and industrial cameras.

Among the learning methods, the deep learning method shows great potential in digital image processing and receives increasingly deep study for multi-frame SR image reconstruction technology. Studies by Kappeler et al. [13] and Dong et al. [14] show that by improving motion compensation methods, such as extension of the network input, SR reconstruction of multi-frame images can be achieved by using sequential frames in video. Shi et al. [15] improved the process of low-resolution image sampling by augmenting the sub-pixel convolution layer, thereby increasing the efficiency of SR image reconstruction. Caballero et al. [16] further improved its efficiency by extending the Efficient Sub-pixel Convolutional Neural Network with spatio-temporal networks and motion compensation. Seokhwa et al. [17] proposed a hyper-resolution reconstruction algorithm based on local self-similar multiframe images oriented locally, improving matching accuracy with less calculation. Compared with the frequency domain and spatial domain methods, the learning-based method has made great progress and can effectively improve image quality. However, it is difficult to use in real-world applications due to its complex structure and long recovery time. As a result, making significant progress for the SR algorithm of multi-frame images is challenging. Wang et al. proposed an SR image reconstruction algorithm based on gcForest [18]. In this paper, we build upon this method to further solve the problems of multi-frame image restoration.

We propose a novel multi-frame SR image reconstruction process based on the Multi-grained Cascade Forest reconstruction algorithm (SRMCF), which is a learning method using chunking. First, a convolutional neural network is used to process image registration in advance, and then a simple deep forest model is used for recovery to fuse images and reach the final SR restoration.

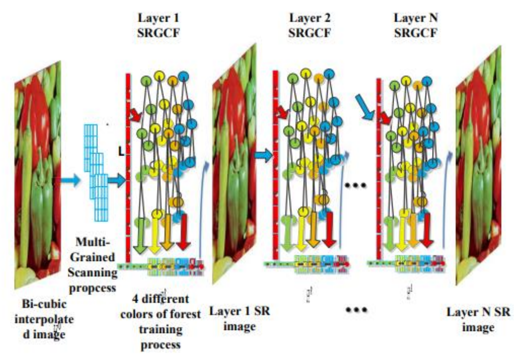

Figure 2: Flowchart showing Super Resolution Framework

Figure 2 showing the image layer activity for improving reconstruction quality of multi frame using super resolution method in which layer 1 gets different colors with training process and layer 2 re constructs and end giving super resolution image.

First, multi-grained scanning is performed on the bicubic interpolated edge images. Then, the feature vectors obtained through scanning are used to repeatedly train the completely random forests and the ordinary random forests. As discussed above, the classification result of each layer, excepting the final layer, joins in the training of the next layer. In our method, the depth of the cascade forest is not a constant and is instead generated automatically according to the quality of the recovered image. When we finish training one layer, the recovered image is automatically evaluated. If the quality is not optimal, a new layer is constructed for training until an optimal restored image is obtained.

Image registration algorithm based on convolutional neural network

In the reconstruction of multi-frame images, due to camera shooting, lighting and other factors, a certain motion blur is generated during the imaging. In order to solve these problems, we need to register each image frame to compensate for displacement. The purpose of image registration is to solve the optimal coordinate transformation relationship between images and transform the registration image to spatially align it with the reference image [19]. There are three kinds of image registration methods: region-based image registration, transform domain-based image registration and feature-based image registration. The feature-based image registration algorithm is the most mature and most widely used method among the three types. Its primary function is the detection and extraction of feature points. Existing feature-based registration methods include SIFT, SURF, ORB, etc. Although these methods have greatly improved the processing of feature points, they cannot detect a sufficient number of feature points when the multiframe image has appearance differences or when the detected feature points contain serious abnormal values. As a result, the registration effect is poor, and the algorithm is less robust. In order to guarantee the efficiency and effect of registration, this paper adopts a registration algorithm based on a convolutional neural network to register LR images. Image frame feature points are extracted by convolutional neural network. By making full use of the image frame information, the effect of registration is enhanced, and the robustness of registration is improved. Image registration algorithms based on convolutional neural network are mainly used to transform LR images to align with a reference image. First, a frame is selected from the LR image sequence as the reference frame, where the set of points detected from the reference frame is X, and the set of points detected from the LR image is Y. Then, the maximum expectation method (EM) is used to process Y to get the transformation position Z of Y, denoted as ZY . ZY and Z are then used to solve the image conversion using thin plate spline (TPS) interpolation. The algorithms mainly consist of four parts, as follows: • First,to detect and generate the set of feature points, a convolutional neural network is first used to extract the features of reference frames and LR images, generating corresponding point set X and vertex set Y according to the extracted features using threshold θ (where θ is a random value greater than 1) . • Second, for the pre-matching of feature points, preliminary pre-registration is conducted by using a distance matrix of features.

SRMCF-based super-resolution reconstruction algorithm for single frame images

Here, the SR reconstruction algorithm based on SRMCF is discussed, and then the SR algorithm based on SRMCF is constructed. The single-frame image reconstruction based on SRMCF is based on the Multi-grained Cascade Forest algorithm proposed according to Zhou [20], which simplifies the computational complexity by using its cascading forest structure, greatly reducing the time required for reconstruction. The quality of its image reconstruction is also higher than that of other reconstruction algorithms due to its first-level multiple training. The main step of this algorithm is to input a pair of HR images. If there is a corresponding LR, it will be input directly into the multi-particle scan for feature enhancement training. When the feature extraction training is completed, the model training will be carried out with the cascade forest, and then restored according to the model obtained from the training.

Reconstruction and Fusion

After registration of the low-resolution images, hyper resolution reconstruction was performed for each image according to the method in subsection B. Many HR images are obtained, and the final HR image frames are obtained by fusing these images. Image fusion refers to extracting useful information from two or more images with differences, removing the redundant information, and merging them to create a high-quality image. For existing fusion methods, most use local filtering, which is designed to extract a high frequency detail activity level measurement using the comparison of different source computing definition information in advance, to design fusion rules. This task is difficult to complete, so here we adopt a new image fusion algorithm that studies direct mapping between source images and focus figures, using high quality image blocks and fuzzy version training of convolutional neural networks for map coding. This process is mainly comprised of focus detection, initial segmentation, consistency verification, and fusion. For focus detection, two source images are first sent to the pre-training convolutional neural network model to output a score diagram, which contains the focus information of the source image. In particular, each coefficient in the score map represents the focusing characteristics of a pair of corresponding blocks from the two source images. Then, by averaging the overlapping patches, a focus map of the source image with the same size is obtained from the score map. Second, the focus diagram is divided into binary images with a threshold of 0.5. Third, we use two popular consistency verification strategies to refine the binary segmentation map (i.e., small area removal and guiding image filtering), to generate the final decision map. Finally, the pixel weighted average strategy is used to obtain the fusion image using the final decision graph.

IV. OBJECTIVE WITH ALGORITHM

The main objective is to eliminate the noise and need to recover the original image. Image is divided into number of patches & apply the PCA technique. Noise levels & the data levels are perfectly enhanced with PCA technique.

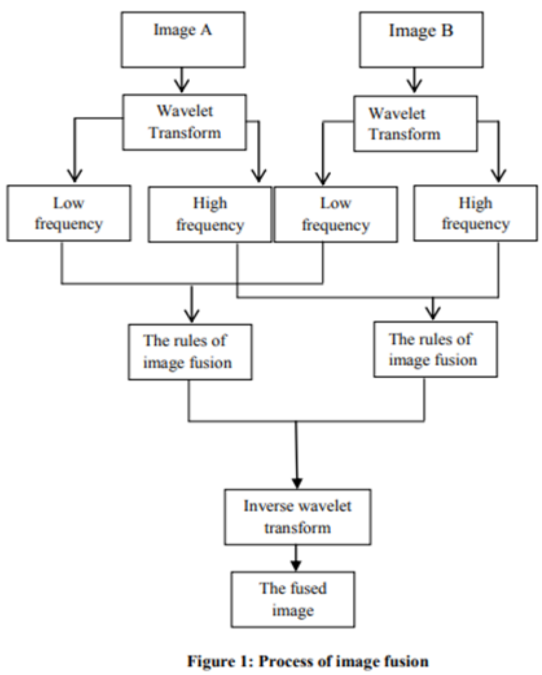

Figure 3: Block Diagram Showing Process of Image Fusion

In order to better solve the problem of super-resolution reconstruction, the process of low-resolution image acquisition needs to be modeled [12]. The degradation of an ideal high-resolution image to a low-resolution image is simulated, and Fig. 3 shows the process of image degradation.

The specific causes of motion deformation, blurring, down sampling, and additive noises in Fig. 3 are as follows:

1)Motion deformation: there are global motion and local motion. The global motion is generated according to the motion of the camera. After the global motion, the image is deformed. After the deformation, each object in the image has the same motion characteristics and parameters, and the motion can be compensated by estimating the parameters of the two-dimensional or multi-dimensional model. The local motion is generated by the motion of each object in the scene. After local motion, the image is deformed. After the deformation, each object in the image has its own motion characteristics and parameters, which are relatively complicated to handle [13].

(2) Blurring: there are mainly three types: the motion blur caused by the relative motion, the optical blur caused by the defocus of the optical imaging system and the diffraction limit and other factors, and the blurring of the low-resolution sensor. In the application of single-image super-resolution reconstruction, these blurs are usually characterized by point spread functions [14].

(3) Sampling: the light emitted by the object is converted into an electric signal on the sensor. In order to display and store the electric signal, it needs to be sampled. The sampling process may cause signal distortion, resulting in a decrease in the sharpness of the image and output of a low-resolution image [15].

(4) Additive noises: there are noises formed by mutual interference of various originals in the system, and noises in the sampling process.

Let X be an ideal high-resolution image. It can be seen from Fig. 1 that after X undergoes motion deformation, blurring, sampling, and noises during imaging, the quality of the image obtained actually decreases, resulting in a low-resolution image. The low-resolution image may be the result of one imaging or multiple imaging.

Using Laplacian based histograms and gaussian based histograms noise levels in the image will be identified. KNN & PCA algorithms are used in proposed methodology. Super resolution method mainly focuses on LSM and GEV model. GEV model will identify the noise probabilities and calculate noise levels. By using the optimization algorithm all the successive noise will be eliminated and restore the image.

Algorithm 1 LSM+GEV Based OCT Restoration

Initialization:

1) For image denoising set an initial image $\hat{x}^{(0)} = y$; or set $\hat{x}^{(0)}$ by bicubic interpolation for image super-resolution.
2) Set parameters: number of similar patches, GEV parameters, patch size, iteration number and regularization parameter.
3) Block matching: implement kNN search, and group a set of similar patches for each exemplar patch (construction data matrices $\{X_l\}$'s from $\hat{x}$)

for k =1, 2…, k_{max} **do**

1) Image-to-patch transformation: create data matrices $\{X_l\}$'s for each exemplar;
2) Estimate means γ utilizing (18) for each $\{X_l\}$.
3) Compute the PCA basis $\{\psi_l\}$ for each X_l;
4) **for** J =1, 2, ……, J_{max}
 (a) Compute θ_l for fixed B_l using (19).
 (b) Compute B_l for fixed θ_l using (26).
 End for
5) Restore each X_l by θ_l and B_l using (32).
6) If mod (k, k_0) =0, update the block matching;
7) Patch-to-image transformation: obtain reconstructed from $\hat{x}^{(k+1)}$ from $\{X_l\}$'s using (33).

End for

Output: $\hat{x}^{(k+1)}$.

Algorithm 1: LSM+GEV Based OCT Restoration Algorithm

A summary of the OSR algorithm using adaptive step size is provided in Algorithm 1. Other update strategies can also be used within a similar framework. The motion vector is estimated by a very fast subpixel image registration technique based on cross-correlation which is proposed by Feng et al. [23]. The registration result is verified by a measurement validation method based on Mahalanobis distance [10]; thus, the LR images with large registration error are eliminated. At each time step t, we align the current LR image with the initial LR image rather than the current HR image estimate because the first several HR image estimates may contain large amount of artifacts. Experiments show that multiple iterations on xt at each time step do not yield much improvement, so xt is updated only once when adaptive step size update is adopted. Aiming at the problem of slow reconstruction speed and general reconstruction effect of traditional multi-image SR reconstruction algorithm, a multi-image SR reconstruction algorithm based on SR is proposed. Firstly, the LR image sequence is calibrated based on a convolutional neural network, and then each image is reconstructed by SR. Finally, the reconstructed image is fused based on the convolutional neural network to obtain an HR image. Based on the results of experimental simulations, the reconstruction effect of the SR-based multi-image SR reconstruction algorithm is greatly improved compared with that of SR-based single image SR reconstruction. Additionally, the reconstructed algorithm exhibited better reconstruction quality and faster reconstruction speed when compared with other algorithms. In the experiment, the running time of the algorithm in this paper was about 4 times that of the SR-based single image reconstruction algorithm, as the algorithm performs SR reconstruction for each low-resolution image. In subsequent research work, the reconstruction process can be optimized to further improve the speed of SR reconstruction, reducing the time required for reconstruction.

Benefits:

- Image preprocessing is used for high level of noise removal.
- Effective high-resolution clean OCT output image.
- Efficiency increased by Gaussian and Laplacian distributions.

V. METHODOLOGY

We first test our multi frame super resolution method with simulated data to study the performance under different conditions. Then, we apply our method to real-image sequences generated by different cameras. Our algorithm is implemented using MATLAB R2014b, and all the experiments are carried out using an Intel Core i9-4790 CPU PC with 16GB RAM. In order to verify the effectiveness of the SR reconstruction method of multi-frame images proposed in this paper, multiple comparison experiments were conducted. The single-frame restoration and multi-frame restoration of SR were compared first, which was used to prove whether the image quality restored by multi-frame images was higher than that restored by single frame images. In summary, the multi-frame image SR restoration algorithm based on deep forest firstly conducts the registration of LR image sequences based on a convolutional neural network, and then performs SR reconstruction of each image after registration. Finally, the reconstructed image is fused based on multi frame super resolution to obtain HR images. The steps of the algorithm are as follows:

1. Input LR images;
2. Register the image sequence based on the convolution
neural network.

3. Perform single SR hyper-resolution reconstruction on n images after registration.
4. Performed multi frame super resolution network fusion on then HR images obtained after reconstruction.
5. Output a fused HR image.

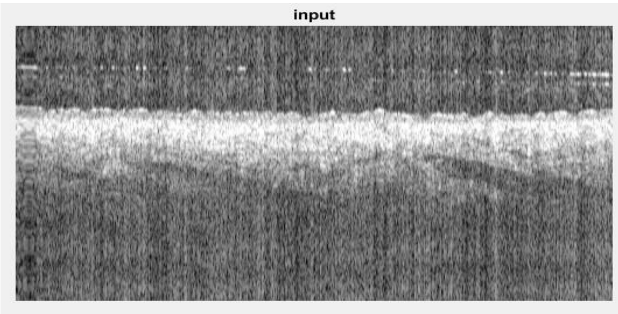

Figure 4: Input of LR Image to remove blur using multiframe SR Technique

```
#counts of top 10 drugs
sns.set(style="whitegrid")
plt.figure(figsize=(10, 5))
ax = sns.countplot(x="Class_label", data=data, palette=sns.color_palette("cubehe
lix", 4))
plt.xticks(rotation=90)
plt.title("Class Label Counts", {"fontname":"fantasy", "fontweight":"bold", "fon
tsize":"medium"})
plt.ylabel("count", {"fontname": "serif", "fontweight":"bold"})
plt.xlabel("Class_label", {"fontname": "serif", "fontweight":"bold"})
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Algorithm 1: Showing Matplotib line activities to perform

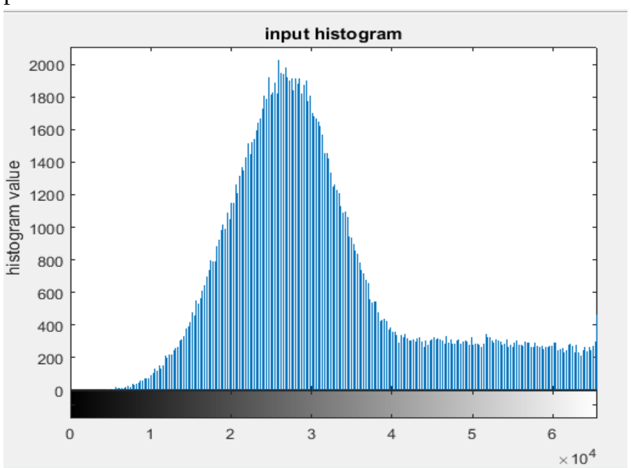

Chart 1: c

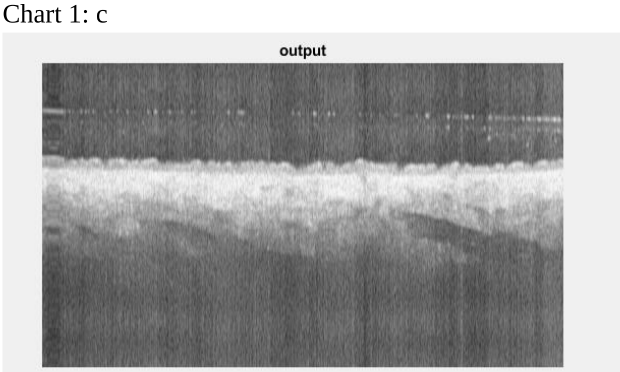

Figure 5: Output Showing blurs and noisy removed using multiframe SR Technique

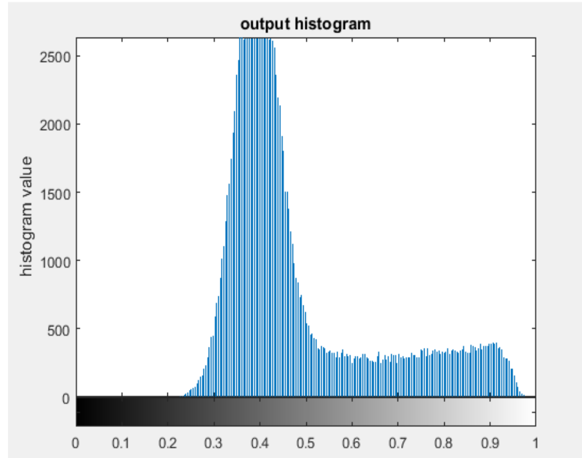

Chart 1: Bar Graph showing noisy Histogram of SR Image

Reconstructed HR images for different noise levels. Bar Graph showing histogram values raning from 500 to 2500 respectively from left to right and from maximum to minimum showing from 2500 to 0.

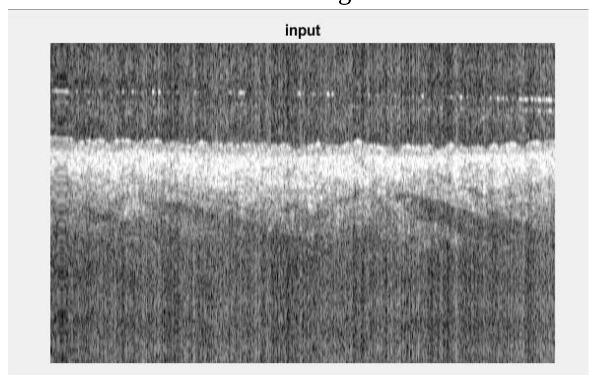

Figure 6: Input of LR Image to remove blur using multiframe SR Technique

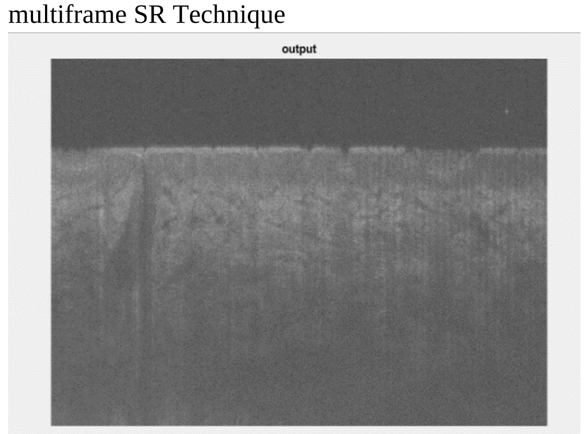

Figure 7: Output Showing blurs and noisy removed using multiframe SR Technique

```python
# print the test accuracy
score_1 = model_1.evaluate(X_test, y_test, verbose=0)
print('Test accuracy:', score_1[1])
```

```
Test accuracy: 0.95333331823349
```

```python
file_name = '/content/drive/MyDrive/Ensemble_model/vgg-16.h5'
```

```python
# Save the model
tf.keras.models.save_model(model_1,file_name)
```

```python
model_1 = tf.keras.models.load_model('/content/drive/MyDrive/Ensemble_model/vgg-16.h5')
```

```python
#plot confusion matrix
from sklearn.metrics import confusion_matrix
class_names = enc.classes_
df_heatmap = pd.DataFrame(confusion_matrix(model_1.predict_classes(X_test),np.argmax(y_test,axis=1)),c
olumns=class_names, index = class_names)
heatmap = sns.heatmap(df_heatmap, annot=True, fmt="d")
```

Algorithm 3: Algorithm describing VGG 16 Module

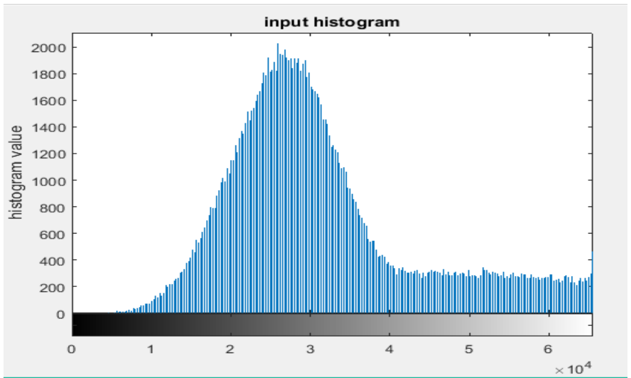

Chart 3: Bar Graph showing noisy Histogram of LR Image

Reconstructed HR images for different noise levels. Bar Graph showing histogram values raning from 0 to 2000 respectively from left to right and from maximum to minimum showing from 2500 to 0.

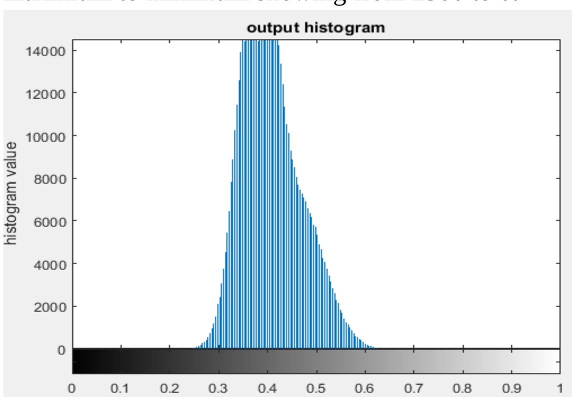

Chart 4: Bar Graph showing noisy Histogram of SR Image

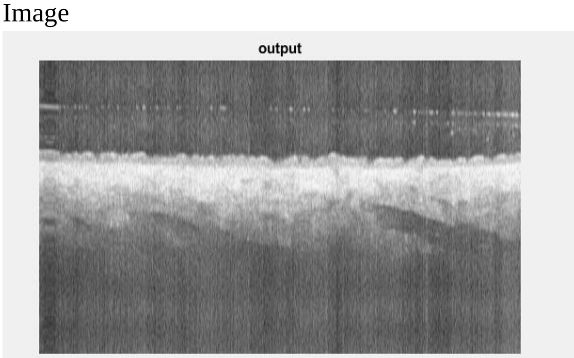

Table 3: Output Showing blurs and noisy removed using multiframe SR Technique

TABLE I
COMPARISON OF THE RESTORATION EFFECTS ON SINGLE-FRAME AND MULTI-FRAME IMAGES USING THE SRMCF ALGORITHM

Parameter	Reconstruction algorithm	
	Single frame SRMCF	Multi frame SRMCF
time(s)	0.05	0.62
PSNR(dB	34.24	35.69
SSIM	0.93	0.932

VI. CONCLUSION

In this paper, we propose a multi-frame super-resolution algorithm which operates in online mode. The algorithm is simple and memory efficient and needs much less computing resource compared to batch-mode methods. Additionally, we employ a noise-adaptive parameter in classical steepest gradient optimization algorithm to avoid noise amplification and the over fitting of LR images. Our method is also compatible with color images. Experimental results on simulated and real-image sequences show that our online SR method has a good performance in restoring the details and missing information in LR images and has a real-time application prospect. Image super-resolution naturally requires large computing resources. A good choice is to just process the region of interest which can also simplify the motion model. The work to incorporating a tracking system and more complex motion model into the online SR framework is ongoing.

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