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Implementation of 3D Shapes by Using an Optimal and Efficient Shape Recovery Algorithm

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Abstract: This research work presents an optimal and efficient implementation of 3D shape recovery of objects based on image focus analysis. A modified SML operator known as Cross Sum Modified Laplacian (XSML) operator is employed which contains diagonal component and improves the quality performance as compared to conventional SML operator. The Gaussian interpolation technique is used to model the focus measure function. In order to analyze, accomplish and validate the proposed algorithm several synthetically refocused real objects with varying textures are used. An intensive analysis in carried out based on quantitative and qualitative evaluation by using conventional methods and statistical metrics. Both evaluated quantitative and qualitative frameworks ensure and validate the optimality and efficiency of suggested algorithm.

Keywords: Shape recovery, Shape from Focus, Focus measure operators, Image Quality Metrics

1. INTRODUCTION

Recovery of 3D structure of a scene from a set of images has been a key research issue in the field of computer vision. The recovered depth information is worth important and is widely used in medical and industrial applications such as 3D endoscopy, component inspection, autonomous vehicle guidance and robotic manipulations. In order to retrieve a 3D shape of objects from a collection of 2D images, a set of techniques known as shape form of X are presented, where X is one of visual clues such as stereo, focus, defocus, shading, texture, and motion. A large number of 3D shape recovery techniques model images acquisition process under the assumption that all depths in a scene are in focus simultaneously, however, in the practical optics system, only finite depths are in focus.

Shape from Focus (SFF) technique is a powerful and well-proven technique in the field of microscopy and other applications such as; robotics and the multi-media technology. It provides a reliable and comprehensive shape recovery and it can be compared with other shape recovery methods also due to its simplicity and ease in operation. SFF is a monocular (only one camera settings is involved) technique and therefore correspondence problem does not exist (Pertuz, *et al.,* 2013). In this technique, focus quality of images can be computed using any focus operator when images with different positions are presented which subsequently provides the utilization of focus profile for 3D shape restoration.

SFF method is a passive optical method needs to record an image set of an object at various focus levels. Change in focus level can be made either by varying the camera focus or object distance from the lens. The entire image series is processed by using the focus operator to determine the sharpest image of object. For accurate 3D reconstruction, object distance from the camera lens is required and can be computed from the camera parameters corresponding to the image frame containing the best focused image. In **(Fig.1)** the general image formation process is presented. If the image detector (ID) is positioned at an exact distance v, a sharp image P' of the object point P is produced. Conversely, placement of image detector by a distance s, results in a defocused image P'' of the point P.

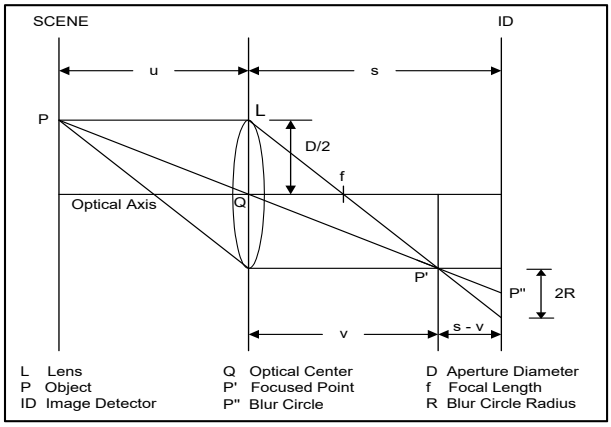


Fig-1: Geometry of basic image formation

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If f and v are known then by using the Gaussian lens formula the distance of the object u can be found as,

$$\frac{1}{f} = \frac{1}{u} + \frac{1}{v} \quad (1)$$

This research work aims to present a simple, optimal and efficient shape recovery algorithm using SFF approach to reconstruct the 3D shape of objects. The paper contains five sections. Section 2 gives the related work corresponding to the SFF method. In Section 3, proposed SFF algorithm is presented. Section 4 presents an experimental validation of the proposed algorithm, followed by concluding remarks in Section 5.

2. RELATED WORK

SFF method contains two key steps, focus operator and reconstruction technique (Pertuz, *et al.,* 2013). The first step measures the focus level of an image, whereas reconstruction technique generates precise 3D shapes (usually depth-maps) from the focus profile achieved using any focus operator. A significant work in literature has been reported on focus analysis of an image to acquire depth information from the scene under observation. Related work in this area is summarized as under.

2.1 Focus Measure Operators

The primary stage in SFF methods is the focus measure calculation. Generally, a focus measure produces maximal output when a particular area of the image is completely focused. In the literature, numerous focus operators are proposed in spatial and frequency domain (Krotkov, 1987; Malik and Choi, 2008; Subbarao, and Tyan, 1998; Horn, 1968). Amongst all, Tenenbaum gradient, Gray Level Variance (GLV) and Sum of Modified Laplacian (SML) are highly taken into account and applied extensively.

(Tenenbaum, 1970) has developed a gradient energy based focus operator. Tenenbaum function is a method of maximizing gradient magnitude using the Sobel operators described as;

$$\mathbf{FM_{Tenenbaum}(i,j)} = \sum_{\mathbf{p(x_0,y_0)\in\Omega(i,j)}} (\mathbf{I_{sx}}(x_0,y_0)^2 + \mathbf{I_{sy}}(x_0,y_0)^2)^2 \quad (2)$$

Where $I(x_0, y_0)$ represents the input image having subscripts sx and sy which denotes the Sobel operators in x and y directions, while $p(x_0, y_0)$ is a pixel around the local window $\Omega(i, j)$ of pixel(i, j).

To measure the image focus quality, (Nayar and Nakagawa, 1994) has proposed the focus measure based on Laplacian operator. The Laplacian is utilized for removing high frequency image variations, however, the x and y components may have opposite signs and can cancel each other. To overwhelm this issue, modified Laplacian is developed. Finally, for improving the robustness of weak-textured images, focus measure at point (i, j) is developed as the summation of modified Laplacian values in a local window around(i, j), which exceeds a threshold valueT.

$$\mathbf{FM_{SML}(i,j)} = \sum_{\mathbf{x=i-M}}^{\mathbf{i+M}} \sum_{\mathbf{y=i-M}}^{\mathbf{i+M}} \nabla^2_{\mathbf{ML}} \mathbf{I}(x_0,y_0) \mathbf{for}\ \nabla^2_{\mathbf{ML}} \mathbf{I}(x_0,y_0) \geq \mathbf{T} \quad (3)$$

Whereas, M defines the window size utilized to calculate the focus measure and $I(x_0, y_0)$represents the input image.

On the basis of variations in gray scale values, GLV focus measure is developed in (Krotkov, 1987) and can be obtained from the variance of the pixels gray scale values around a small window given as,

$$\mathbf{FM_{GLV}(i,j)} = \sum_{\mathbf{p(x_0,y_0)\in\Omega(i,j)}} (\mathbf{I}(x_0,y_0) - \boldsymbol{\mu}_{\mathbf{\Omega(i,j)}})^2 \quad (4)$$

Whereas, input image is $I(x_0, y_0)$, $\mu_{\Omega(i,j)}$ represents the components of gray values around the local window $\Omega(i, j)$and $p(x_0, y_0)$ the local window pixels.

2.2 Reconstruction Techniques

Once an image sequence is attained at various lens places and using some focus operator the focus profile for all images is calculated, second step in SFF applies a reconstruction technique that utilizes obtained profile in order to construct more accurate 3D shape of a scene. In the existing work, various scene reconstruction and refinement approaches have been proposed. Some researchers have utilized interpolation techniques (Nayar and Nakagawa, 1994; Zhang, *et al.,* 2000; Favaro, *et al.,* 2008) for surface approximation. (Subbarao and Choi, 1995) have proposed the focused image surface (FIS) based on piecewise planner approximation. They applied this FIS concept on the results of the SML operator. In (Choi and Asif, 1999), a piecewise curved surface approximation of FIS is proposed. A neural-network is applied on results of GLV operator in (Asif and Choi, 2001) to acquire the FIS shape through optimization of the focus operator around small 3D window. In (Ahmad and Choi, 2005) dynamic programming (DP) is applied on the SML results to cope the computational complexity of FIS. Instead of limiting to a small local window, this method searches for optimal focus measure in whole image volume. Furthermore, fuzzy-based approaches have also been utilized in shape based algorithms. (Pham, 1999) has developed a shape specification system based on fuzzy logic. While, (Malik and Nisar, 2011) have proposed the Fuzzy Inference System for 3D shape recovery. Though, these approaches produce better results compared to traditional methods; but they require high cost in calculation. Furthermore, their

performance is based on the initial estimate calculated using some focus measure.

In this work, a simple, optimal and efficient 3D shape recovery algorithm using SFF approach is proposed. The presented algorithm is based on work of (Nayar and Nakagawa1994). However, instead of using SML technique specified in (Nayar and Nakagawa, 1994), we determine the pixel which is most focused by XSML operator. The proposed XSML operator incorporates Laplacian for diagonal neighbor of pixel unlike conventional SML, in which the Laplacian only takes pixel neighbor inx and y directions.

Owing to presence of increments in calculated points, XSML operator improves and enhances the overall performance as compared to conventional approach SML. Firstly, the employed XSML operator calculates the XSML focus measure for image sequence, afterwards Gaussian approximation technique is applied on calculated focus measure values to acquire more accurate 3D shape and full focused image.

3. SHAPE RECOVERY ALGORITHM

Success of any shape recovery method depends on focus measure criteria which measures the each image pixel's sharpest value using a small local window. This measure can be expressed as;

$$f_i(x_0, y_0) = \max_i(FO_i(x_0, y_0)) \qquad (5)$$

Where$i = 1 \ldots . K,$ represents the total images in the series and $FO_i(x_0, y_0)$ is the focus operator applied using a small neighborhood around pixel(x_0, y_0) for i^{th} image.

In order to measure image focus quality, XSML operator (Thelen, *et al.,* 2009) is used, which is a modification of the SML operator. In SML operator, the Laplacian incorporates only direct neighbors in the x- and y-directions and it lacks central point distance measurement. On the other hand, when the diagonal neighbors are included weighted with a factor of $(\sqrt{2})^{-1}$ in order to provide compensation for their distance from the central point, the quality deliverance is improved and augmented. The XSML focus measure can be represented as;

$$\mathbf{FO_{XSML}(i,j)} = \sum_{\mathbf{p}(x_0,y_0)\in\Omega(i,j)} \nabla^2_{\mathbf{XSML}}\,\mathbf{I}(x_0, y_0) \qquad (6)$$

Where $I(x_0, y_0)$ represents the input image, $p(x_0, y_0)$ the neighborhood pixel $\Omega(i, j)$ of pixel $(i, j)$and $\nabla^2_{XSML}$is a XSML and given as,

$$\begin{aligned}\nabla^2_{\mathbf{XSML}}\mathbf{I}(x_0, y_0) &= |2\mathbf{I}(x_0, y_0) - \mathbf{I}(x_0 - 1, y_0) - \mathbf{I}(x_0 + 1, y_0)| \\ &\quad + |2\mathbf{I}(x_0, y_0) - \mathbf{I}(x_0, y_0 - 1) - \mathbf{I}(x_0, y_0 + 1)| \\ &+ \frac{1}{\sqrt{2}}|2\mathbf{I}(x_0, y_0) - \mathbf{I}(x_0 + 1, y_0 + 1) - \mathbf{I}(x_0 - 1, y_0 - 1)| \\ &+ \frac{1}{\sqrt{2}}|2\mathbf{I}(x_0, y_0) - \mathbf{I}(x_0 - 1, y_0 + 1) - \mathbf{I}(x_0 + 1, y_0 - 1)| \qquad (7)\end{aligned}$$

Using Equation (7), XSML focus measure is calculated in the sequence at each pixel of all images and a set of focus measures is obtained for every point of the image. After searching the maximum value for focus measures, the next step is a computation of the depth map. An interpolation method is applied on focus measure data to refine the position of a sharpest pixel and acquire a final depth map.

The proposed algorithm utilizes the Gaussian distribution (Nayar and Nakagawa, 1994) to model the focus measure function across the peak region and interpolates the calculated focus data to obtain accurate shape recovery.

The focus profile may be defined as;

$$\mathbf{F} = \mathbf{F_p}\,\mathbf{exp}\left(-\frac{(z-\bar{z})^2}{2\sigma^2}\right) \qquad (8)$$

The notation$\bar{z}$ismean and σis the standard deviation. The interpolation is performed by utilizing just three focus values, namely $\mathbf{F_{m-1}}$, $\mathbf{F_m}$ and $\mathbf{F_{m+1}}$ that lie on the highest area of $\mathbf{F}$, such that, $\mathbf{F_m} \geq \mathbf{F_{m-1}}$ and $\mathbf{F_m} \geq \mathbf{F_{m+1}}$**(Fig.2)**.

By applying natural logarithm Equation (9) can be transferred to,

$$\mathbf{lnF} = \mathbf{lnF_p} - \left(\frac{(z-\bar{z})^2}{2\sigma^2}\right) \qquad (9)$$

By putting the focus measures F_{m-1} , $F_m$and F_{m+1} and equivalent *z*values z_{m-1}, z_m, and z_{m+1}in Equation (10) , the position of the mean value is computed as,

$$\bar{\mathbf{z}} = \frac{(\mathbf{lnF_m} - \mathbf{lnF_{m+1}})\left(\mathbf{z_m^2} - \mathbf{z_{m-1}^2}\right)}{2\Delta\mathbf{z}((\mathbf{lnF_m} - \mathbf{lnF_{m-1}}) + (\mathbf{lnF_m} - \mathbf{lnF_{m+1}}))} - \frac{(\mathbf{lnF_m} - \mathbf{lnF_{m-1}})\left(\mathbf{z_m^2} - \mathbf{z_{m+1}^2}\right)}{2\Delta\mathbf{z}((\mathbf{lnF_m} - \mathbf{lnF_{m-1}}) + (\mathbf{lnF_m} - \mathbf{lnF_{m+1}}))} \qquad (10)$$

Where$\bar{z}$ is the approximated focus location of the best focused pixel.

Once this is processed for every point, a gray scale value is associated to each point corresponding to the sharpest pixel location to recover the 3D shape. Furthermore, the algorithm locates and merges all the best focused points in image sequence to recover a full focused image.

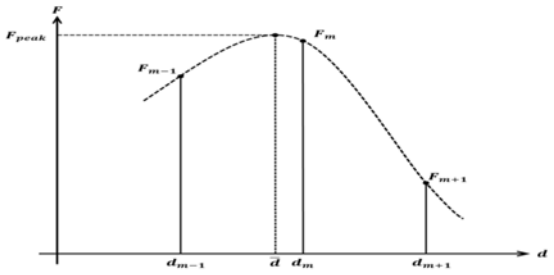


Fig. 2: Gaussian Interpolation technique for shape recovery

The work flow cycle and steps of proposed algorithm are summarized in **(Fig. 3)**.



Fig. 3: The block diagram of proposed 3D Shape Recovery Algorithm

4. EXPERIMENTAL VALIDATION OF THE PROPOSED ALGORITHM

In order to validate and verify the accuracy of proposed algorithm, several experiments have been performed. An8-bit gray levels data sets each having 25 images with details presented in **(Table-1)** are created synthetically and they are intensively analyzed based on qualitative and quantitative evaluation along with taking account the effect of window size. To generate synthetic image sets for experiments, a non-linear defocus model (Pertuz, *et al.,* 2013) is used. Some sample frames of all data sets with different focus positions are displayed in **(Fig-4)**.

Table 1: Construction specifications of synthetically created 8-bit data sets

No.	Image type	Description	Size (pixels)
01	IMAGE $_{SM-CN}$	Simulated cone	200 x 200
02	IMAGE $_{CO}$	Coins	200 x 200
03	IMAGE $_{LN}$	Lena	214 x 214
04	IMAGE $_{PP}$	Peppers	512 x 512

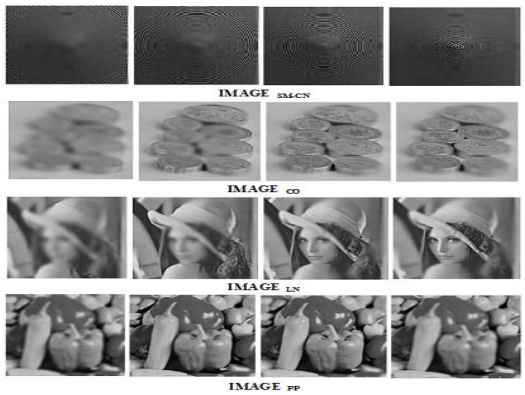


Fig. 4: Data sets with various focus settings

The proposed algorithm is experimented using various image data sets with different textures. Texture of objects plays a major role in the shape reconstruction. Therefore, four objects are selected with varying textures. The results of the proposed 3D shape recovery algorithm are benchmarked to focus measures SML, Tenenbaum and GLV in order to provide comparative analysis and validate the proposed algorithm. Theses focus measures have been chosen for comparison since they are extensively used Focus Measures for shape recovery in literature; SML is used by Refs. (Nayar and Nakagawa, 1994; Ahmad and Choi, 2005; Helmli and Scherer, 2001; Nayar and Nakagawa, 1990; Yun and Choi,1999), GLV by Refs. (Asif and Choi, 2001;Helmli and Scherer, 2001; Nayar and Nakagawa, 1990) and Tenenbaum by Refs. (Helmli and Scherer, 2001;Yun and Choi,1999). All the experiments are performed using window size of 15 x 15.

The reconstructed 3D shapes of IMAGE$_{SM-CN}$ computed with SML, Tenenbaum, and GLV, and proposed algorithm are shown in **Fig5 (a)–(d)** respectively. Due to compact texture of cone object, its reconstruction is easy but the rest of objects encompass areas which have weak textures, which consequences a challenging reconstruction task. It can be seen that, proposed approach recovers an accurate, vivid and smooth 3D shape than those recovered by SML, Tenenbaum, and GLV. The SML method provides a fair depth map, on the other hand, the results obtained from Tenenbaum, and GLV methods are degraded to some extent owing to spikes presence, but overall fully reconstructed shape is achieved.

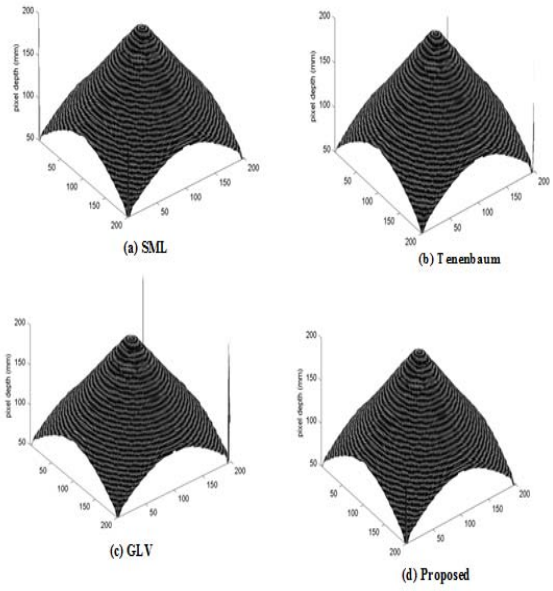


Fig. 5: Reconstructed 3D shapes for IMAGE$_{SM-CN}$

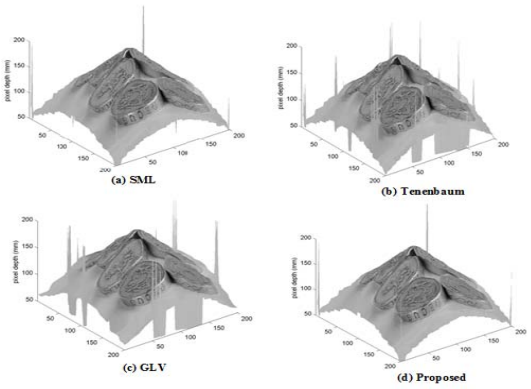


Fig. 6: Reconstructed 3D shapes for IMAGE_CO

Similarly, depth maps for the IMAGE_CO, IMAGE_LN and IMAGE_PP data sets are also computed. **(Fig. 6)** shows the 3D shapes reconstructed for the coins test data. It can be seen that, the acquired 3D shape by proposed algorithm provides more accurate and smooth shape as compared to aforementioned methods. On account of weak textured areas on the surface of the object, few spikes are produced but the original shape has remained unaffected in all cases. Likewise, 3D shapes reconstructed for IMAGE_LN and IMAGE_PP data sets by aforementioned methods along with proposed algorithm are shown in **(Fig7 and 8)**, respectively, which provides approximately similar information

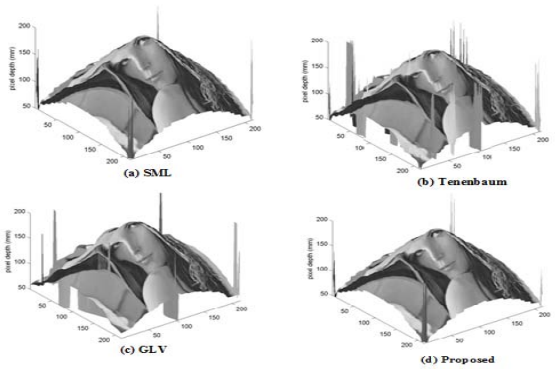


Fig. 7: Reconstructed 3D shapes for IMAGE_LN

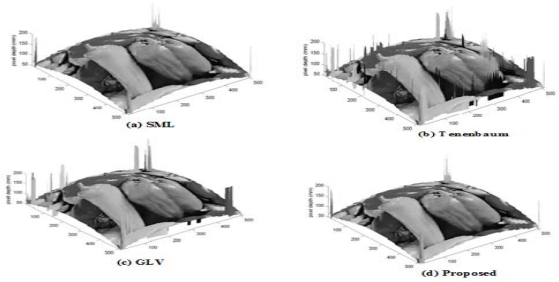


Fig.8: Reconstructed 3D shapes for IMAGE_PP

The composite 2D images of the simulated IMAGE_SM-CN, IMAGE_CO, IMAGE_LN and IMAGE_PP obtained through proposed approach are presented in **(Fig.9 (a-d)**. It can be seen that, all parts of the composite images are clear and in sharp focus. The reconstruction of focused images is carried out by taking the pixel's gray-level value at the position of the optimum focused image number obtained from the final focus map.

The simulation results ascertain the optimality and effectiveness of proposed algorithm. Furthermore, it is also apparent that despite varying and different textures, the proposed algorithm produces optimal results as compared to other aforementioned methods.



(a) IMAGE_SM-CN (b) IMAGE_CO (c) IMAGE_LN(d) IMAGE_PP

Fig. 9: The composite 2D images acquired using proposed algorithm

4.1 Quantitative Evaluation

To analysis the proposed algorithm quantitatively, four global statistical measures namely Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Universal Image Quality Index (UIQI) and Structural Similarity (SSIM) index are used. The lower the value of MSE is, the better the method will be (Eskicioglu and Fisher, 1995). A higher value of PSNR (Eskicioglu and Fisher,1995)represents the higher quality reconstruction. Universal Image Quality Index (UIQI) (Wang and Bovik,2002), measures the distortions between original and the reconstructed 3D shapes in the range (-1,1). The Structural Similarity index (Wang, *et al.,* 2004) is an extension of UIQI, measures the similarity between two images. The results of comparison in terms of MSE, PSNR, UIQI and SSIM index for all test image sets are depicted in **(Table 2)**. From the **(Table-2)**, it is observed that the proposed approach produces lower MSE value as compared to other methods for all data sets which ensures the accuracy and precision of proposed algorithm. The maximum value of PSNR is achieved through proposed approach, which shows that 3D shape is well reconstructed. Likewise, the proposed algorithm attains highest values for, UIQI, and SSIM. The obtained results show that the proposed algorithm provides the superior performance as compared to aforementioned methods.

Table 2: Performance Comparison

MSE Comparison				
SFF Methods	Test Images			
	IMAGE$_{SM-CN}$	IMAGE$_{CO}$	IMAGE$_{LN}$	IMAGE$_{PP}$
SML	3.308	11.080	7.661	5.911
Tenenbaum	3.210	46.601	86.462	158.865
GLV	6.480	67.267	68.183	204.667
Proposed	2.752	10.998	7.171	5.574
PSNR Comparison				
SML	42.935	37.685	39.288	40.413
Tenenbaum	42.945	31.447	28.762	26.121
GLV	40.021	29.852	29.794	25.020
Proposed	43.734	37.717	39.575	40.669
UIQI Comparison				
SML	0.9779	0.918	0.916	0.7159
Tenenbaum	0.9792	0.798	0.701	0.6180
GLV	0.9769	0.809	0.728	0.6376
Proposed	0.9805	0.922	0.921	0.7301
SSIM Comparison				
SML	0.997	0.990	0.991	0.990
Tenenbaum	0.998	0.946	0.915	0.908
GLV	0.997	0.955	0.943	0.912
Proposed	0.998	0.990	0.991	0.991

4.2 Effect of Window size

The size of evaluation window has been a main factor in the operation of SFF techniques. For shape recovery applications, the authors in (Malik and Choi, 2007) have addressed the issue of discovering the optimal window size for focus measures. They found that large size of window could produce inaccurate depth estimation due to over smoothing effects. Whereas, as mentioned in (Marshall, *et al.,* 1996) small windows are more noise sensitive and may become the cause of image blurring.

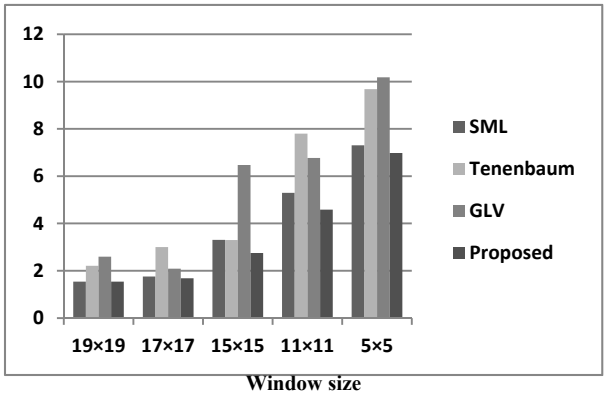


Fig.10: (a) MSE for IMAGE$_{SM-CN}$

In order to evaluate the effect of neighborhood, we conducted several experiments on simulated cone data set using various neighborhoods: 5×5, 11×11, 15×15, 17×17 and 19×19. In (**Fig-10 (a, b)** MSE and PSNR results are shown for IMAGE$_{SM-CN}$ test data using various window sizes. (**Fig-10 (a)** shows the MSE values obtained by proposed algorithm and the methods SML, Tenenbaum and GLV, which are used as benchmark. For instance, from **Fig-10 (a)**, it is found that, the reduction in window size results in increase of the MSE values. This is as usual since the neighborhood size directly affects the texture amount and image information that can detect changes in focus. **(Fig-10)** shows that SML works well at small neighborhoods, while GLV is mainly affected due to reduction of the window size.

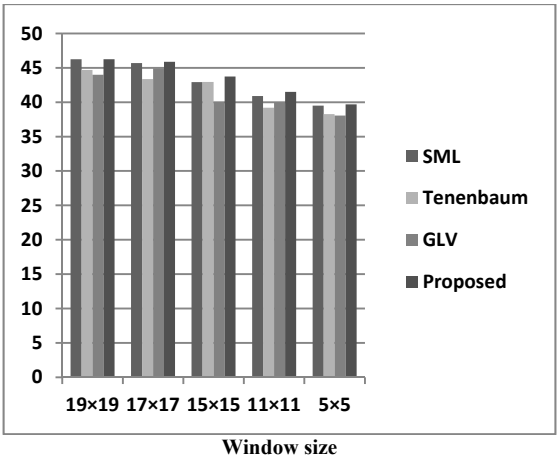


Fig.10: (b) PSNR for IMAGE$_{SM-CN}$

It is concluded that at small window sizes, our algorithm generates better results than other SFF methods. In addition, as the window size increases, error rates of proposed approach decreases rapidly as compared to other methods.

5. CONCLUSION

In this research an optimal and efficient shape recovery algorithm based on image focus is developed. For measuring the image quality and 3D shape reconstruction, XSML operator followed by Gaussian approximation technique is used. In order to validate results, the proposed algorithm is tested using image sequences of simulated cone (IMAGE$_{SM-CN}$), coins (IMAGE$_{CO}$), Lena (IMAGE$_{LN}$) and peppers (IMAGE$_{PP}$) and its performance is compared with SML, Tenenbaum and GLV focus measures. The experimental results demonstrate that proposed algorithm provides more accurate and optimum shape recovery as compared to existing methods. The algorithm fits very well and optimally for both small and large window sizes, however, for larger window size, it produces more accurate and smooth 3D shapes.

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