

# Various Occluded Object Information Recovery in Urban High-Resolution Panchromatic Satellite Images

Kartik Ingole<sup>1</sup>, Shruti Golar<sup>2</sup>

<sup>1</sup>Assistant Professor, <sup>2</sup>PG Student,

ECE Department, T. G. P. C. E. T.

**Abstract** - The presence of shadows in very high-resolution panchromatic satellite images can obstruct some objects to cause the reduction or loss of their information, particularly in urban scenes. To recover the obstructed information of objects, shadow removal is a significant processing procedure for the image interpretation and application. Over the years many researchers have proposed various techniques for detection and removal of obstructed information. We have reviewed and analyzed different techniques which have been used over the years. The review includes research papers, publication and other available literature. We have tried to provide a comparative analysis of various schemes and we put forward the observations obtained from the review.

**Keywords:** panchromatic satellite images, shadow removal, spatial adaptive nonlocal sparse (SANS), bimodal histogram.

## I. INTRODUCTION

The high resolution Satellite imaging is recommended and necessary for the observation of space, earth and other planets has ability to obtain very high-resolution images. These high-resolution images exhibit more detail information to increase the object-oriented applications, like building detection and to spot out populated and non-populated areas. Unfortunately, most of the high-resolution satellite images contain shadows as undesired information which causes partial or total loss of information. In such a circumstance, the objects in the shadow regions are difficult to be extracted for further processing or applications. So, in order to restore obscured objects, shadow detection and shadow removal is an essential preprocessing step for panchromatic high-resolution satellite images. Many effective algorithms of shadow removal have been proposed for natural images or remote sensing multispectral images. However, there is a great lack of shadow removal method for panchromatic imagery, while these panchromatic images usually contain high resolution data to be useful for various applications. For the purpose of the information recovery of obscured objects, the characteristics of shadows and objects in the panchromatic images of urban areas should be analyzed and remove the shadows to obtain shadow-free images. Many current researches and studies indicate that shadow detection is the indispensable step in the complete processing chain of shadow removal.

In the proposed system, build novel shadow detection and removal method has been developed for the panchromatic satellite images. Multilevel image thresholding method and image matting technique are both used to obtain soft shadow detection results. In the initial step of shadow removal, the linear correlation method is used to enhance shadow areas roughly in global. In the second level refined process, the characteristics of intensity of objects and shadows are noted and patch intensity difference is calculated and it is used to remove the shadow portion. The linear radiometric correction and intensity adjustment are used to control the brightness. Finally the shadow free image is smoothed by applying Gaussian filter to obtain smoothed shadow free image.

## II. SYSTEM MODEL

The soft shadow detection will be performed. The shadow probability will be calculated accurately to show the distribution of umbra and penumbra. The proposed automatic method is expected to be effective to avoid the boundary effects after recovery, due to the presence of the penumbra. The proposed SANS shadow removal method is expected to restore the obscured information of objects in shadow areas effectively. We will analyze two cases of the spatial relationship between the objects and shadows. The shadow areas will be restored by similar structure patches based on the group sparse representation, and the smooth results are expected to be obtained. Based on group matrix of our SANS method, we will try to present a twice line correction method to control the brightness of the recovered areas. First correction will use the whole image parameters to enhance shadow areas roughly. Second correction will use the parameters of similar patches in the group matrix to correct each patch in shadow areas, and uniform shadow-free images will be obtained.

## III. PREVIOUS WORK

W. Liu and F. Yamazaki, "Object-based shadow extraction and correction of high-resolution optical satellite images", in this study, a radiance measurement was carried out to investigate the spectral characteristics of sunlight. Then a method has been proposed for shadow detection and correction of optical imagery. First, building shadow areas

are detected using an object-based classification method that employs brightness values and their relationship with the neighboring area. Next, the detected shadow areas are corrected using a linear function to produce a shadow-free image. The shadow pixels with different darkness levels have been corrected by using different ratios to obtain a smoothly restored image. The proposed semi-automated method was applied to a Quick Bird and a World View-2 image of Tokyo, Japan, to demonstrate the effectiveness of the method.

#### IV. PROPOSED METHODOLOGY

The proposed framework involves the two main procedures as shown in Fig.1: shadow detection and shadow removal.

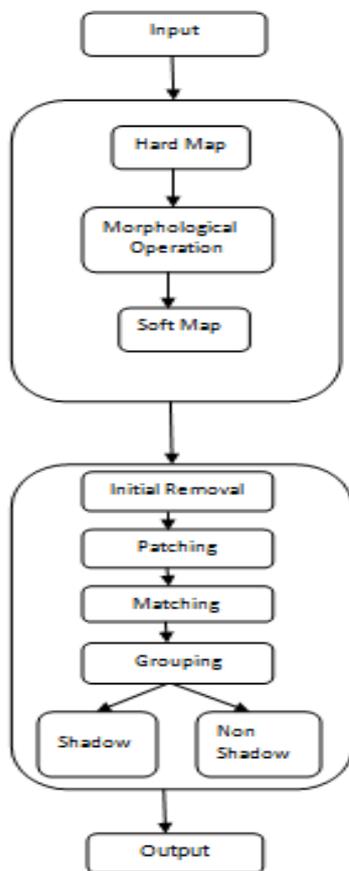


Fig. 1: Flow Chart of Proposed System

#### 4.1 Shadow Detection

Shadows are formed because of something blocking the light source, as shown in Fig. 2. The phenomenon frequently occurs in dense urban areas. Solving the shadow problem is very important issue for urban object applications in the high-resolution satellite images. Shadows can be classified into self-shadow and the cast shadow. The self-shadow is formed when a face of the object is not directly illuminated by the light. The cast shadow is formed when some objects block the light source to fall on other objects. And the cast shadow is of two

types: the umbra and the penumbra. The umbra is not directly illuminated by the light source, while the penumbra is only partly blocked by light source. The penumbra is obvious in very high-resolution images. In addition to shadow areas, other areas under the direct light are called non shadow areas or sunlit areas in this paper. In this work, we mainly research the cast shadow areas, and distinguish the umbra and the penumbra in the shadow detection.

Fig -2: Formation of shadow.

#### 4.1.1 Hard shadow detection

Initial detection is used to locate the shadow areas. Shadow image is classified to shadow and non-shadow areas roughly by hard threshold. Multilevel image thresholding is used as thresholding method here. The result of hard thresholding is a binary image which is called hard map, shown in the fig 3

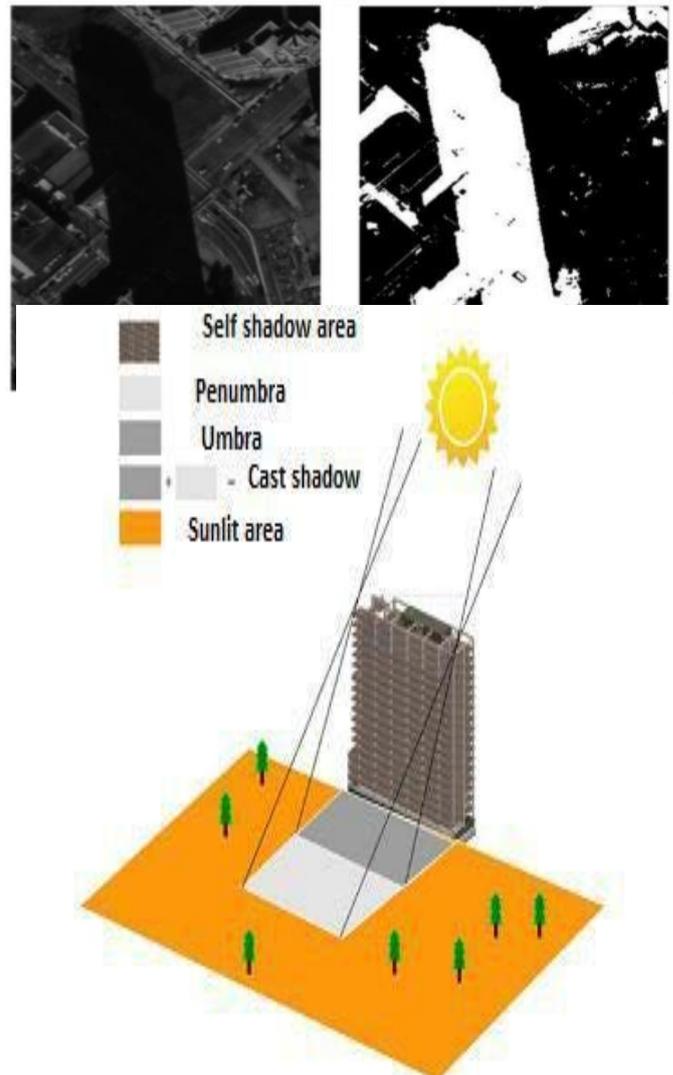


Fig -3: Result of hard shadow detection

#### 4.1.2 Applying morphological operations

The hard map of binary mask cannot provide the precise edges between shadow and non-shadow regions due to the presence of penumbra. So two morphological operations are applied to shadow areas. They are erosion and dilation. Erosion removes pixels on the object boundaries and dilation adds pixels to the boundaries of objects in an image.

These morphological operations are applied to locate penumbra. Shadow areas are eroded and dilated by these two morphological operators and the difference middle areas are filled with the original image.

$$Diff[x,y]=d(Bm[x,y])-e(Bm[x,y])$$

where Diff represents the difference image between dilation and erosion; d and e represent dilate and erode operations.



Fig- 4: Result after applying morphological operations.

#### 4.1.3 Soft shadow detection

An image matting technique is used to derive the probability value of each pixel belonging to the shadow or non-shadow. 0 and 1 represent the pixel belonging to non-shadow and shadow respectively. If the value is between 0 and 1 then pixel belonging to the penumbra in the soft shadow map. Image matting can accurately separate the foreground image from background image, representing shadow, and non-shadow.

Image matting technique calculate the shadow probability  $\theta$  for each pixel by minimizing the energy function based on the following,

$$E(\theta) = \theta^T L \theta + \lambda (\theta - \hat{\theta})^T D (\theta - \hat{\theta})$$

Where  $\theta$  is the predicted shadow probability represents laplacian matrix and D is a diagonal matrix. By all the above steps shadow detection process is completed. The detected shadow is yet to be removed next.

#### 4.2 Shadow Removal

The proposed removal method including two levels is the initial shadow removal or correction using linear correlation and final refined restoration with smoothening. The initial correction step compensates the intensity for shadow area by a global parameter, which makes the same brightness and smoothness across shadow area and non-shadow area belong roughly to the same category. The refined restoration step utilizes the patch intensity difference between the initial corrected image and non-shadow region to restore the shadow areas making same brightness and smoothness as that of non-shadow area.

##### 4.2.1 Initial Shadow removal

After soft shadow detection initial shadow removal is performed. Here linear correlation correction is used for restoring the brightness of shadow region. This procedure uses the mean value and standard deviation of all the sunlit areas to compensate the intensity of shadow areas in the whole image. The shadow-free image after initial shadow removal can be expressed as,

$$I_n[x,y] = (1 - \theta[x,y])I_s[x,y] + \theta[x,y] \times \left( \frac{\sigma_{sunlit}}{\sigma_{shadow}} (I_s[x,y] - \mu_{shadow}) + \mu_{sunlit} \right)$$

where,  $I_n$  is the intensity of shadow after the initial correction;  $I_s$  is the intensity of shadow in the original shadow image;  $\theta$  is the shadow probability of our soft detection.  $\mu_{shadow}$  represents the mean value of shadow areas,  $\mu_{sunlit}$  and  $\mu_{shadow}$  implies mean value of non-shadow area,  $\sigma_{sunlit}$  and  $\sigma_{shadow}$  represents the mean value and standard deviation of shadow areas and non-shadow areas.

##### 4.2.2 Refined restoration and smoothening

Initially restored shadow areas can be still noisy and non-uniform. So we recover the shadow area in detail with the information of the intensity. It makes uniform image quality between the recovered shadow areas and the non-shadow. For that initially we take the initially corrected image and non-shadow region and are divided into patches. Each patch has its own intensity. Patch intensity of corrected image is compared with patch intensity of non-shadow region. If the image patch intensity is less than non-shadow patch intensity, then patch intensity difference is calculated,

$$I_d = I[i]_{ns} - I[i]_{im}$$

Where  $I[i]_{ns}$  represents the patch intensity of non-shadow region and  $I[i]_{im}$  represents the patch intensity of initially corrected image. This intensity difference is added to each shadow patch to adjust the shadow region of the image. Then shadow and non-shadow regions are separately adjusted with the computed value of  $I_d$ .

After removing shadow in two levels, it is smoothed using Gaussian low pass filter. It is a final touch given to the shadow free image. Gaussian smoothing is used here to reduce the noise of image by applying Gaussian low pass filter. This smoothing obtains smoothed shadow free image.



Fig-5: finally smoothed shadow free image.

**Table – 1: The mean value and standard deviation of the recovered shadow area samples by to that of corresponding non-shadow area.**

	MEAN VALUE	STANDARD DEVIATION
Non-Shadow Region	53	2.5
Recovered shadow area by our proposed method	60	3.9

For quantitative analysis the samples of the recovered shadow areas are selected and the samples in the corresponding non-shadow areas are collected, and the mean value and standard deviation of both samples are computed. If the mean value and standard deviation are closer to those of non-shadow area samples, which indicates that the method is better. As can be seen from Table I, proposed method performed better. The results indicate that the proposed method can promise the brightness (mean value) and the smoothness (standard deviation) of recovered area to be the more or less similar to that of the similar non-shadow area. Efficiency of the system can also be estimated by computing no of shadow pixels removed out of total no of detected shadow pixels.

### 5. SIMULATION/EXPERIMENTAL RESULTS INPUT/OUTPUT

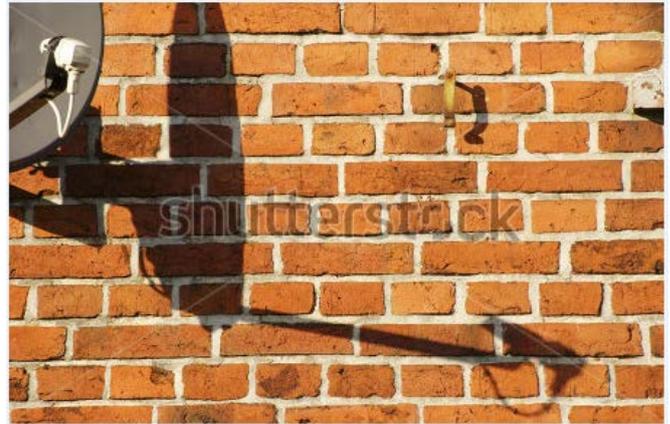


Fig-6: Snapshot of Input image

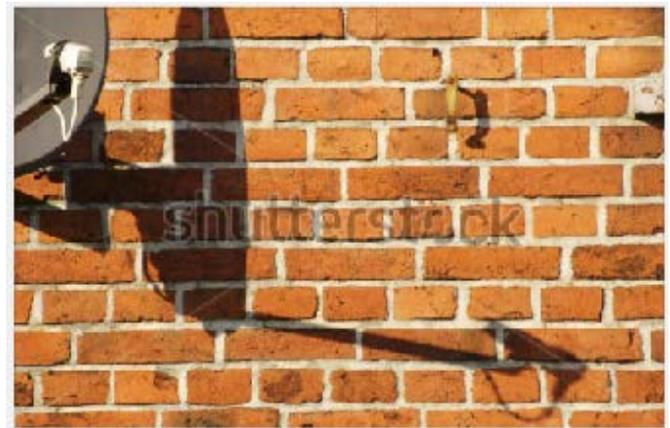


Fig-7: Snapshot of Filtered Image



Fig-8: Snapshot of Pre-Processing Image



Fig-9: Snapshot of Binary Image using Segmentation

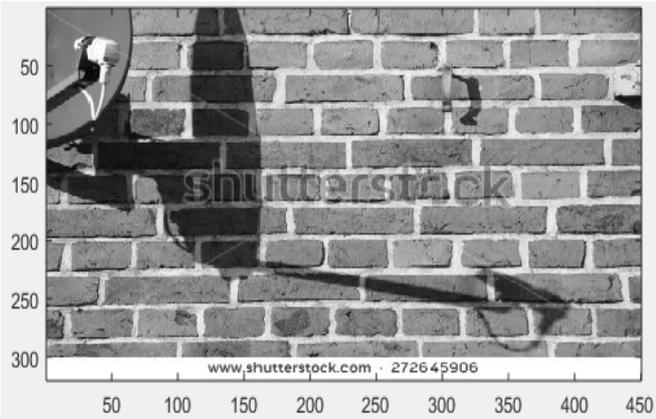


Fig-10: Snapshot of Original Image with varying background & foreground objects

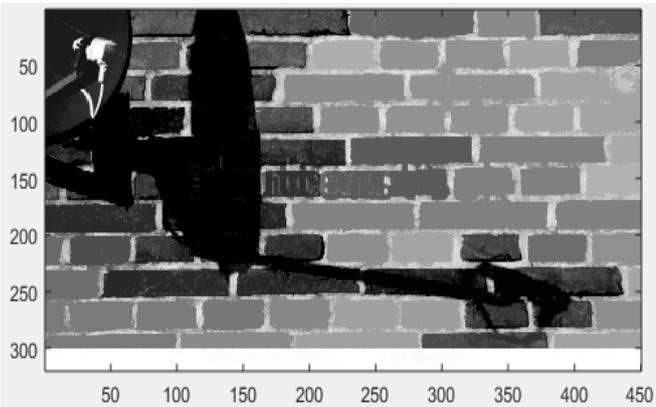


Fig-11: Snapshot of Reconstructed Image with circular regions removed



Fig-12: Snapshot of Different Image between original & reconstructed

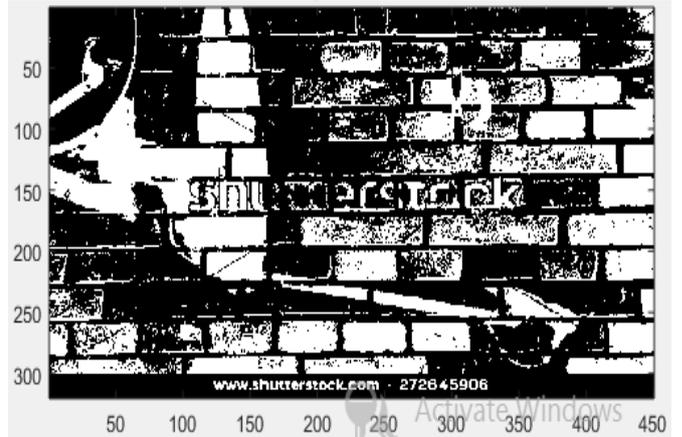


Fig-13: Snapshot of Segmentation Image



Fig-14: Snapshot of Shadow detection Image

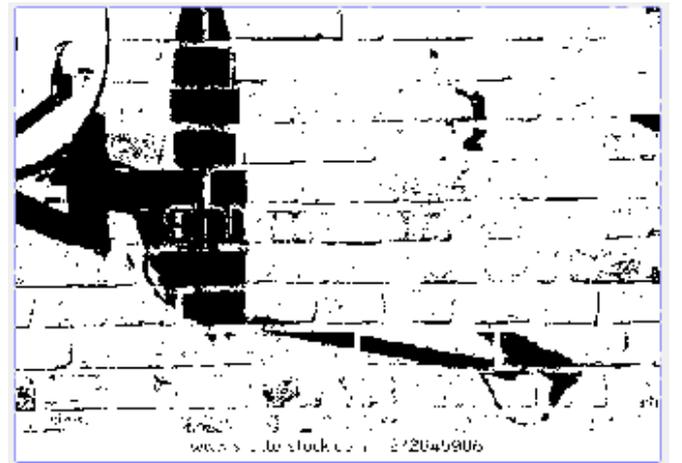


Fig-15: Snapshot of False Shadow Elimination Image



Fig-16: Snapshot of Boundary Extraction Image



Fig-19: Snapshot of shadow removal image



Fig-17: Snapshot of Inner & Outer Image using Red & Blue Channel

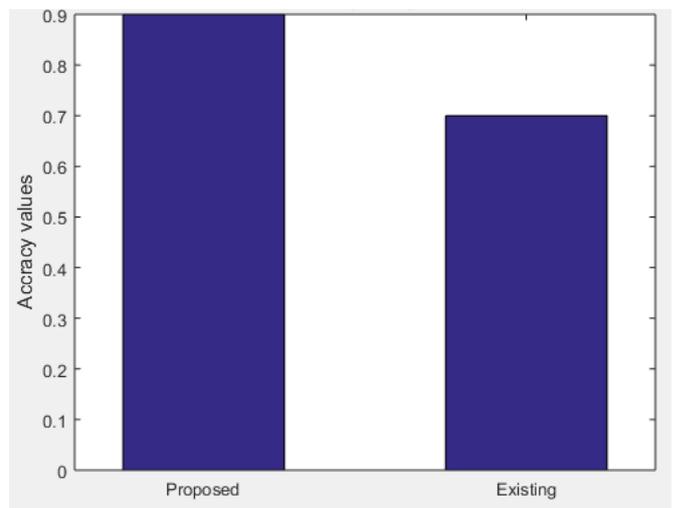


Fig-20: Snapshot of Accuracy Analysis

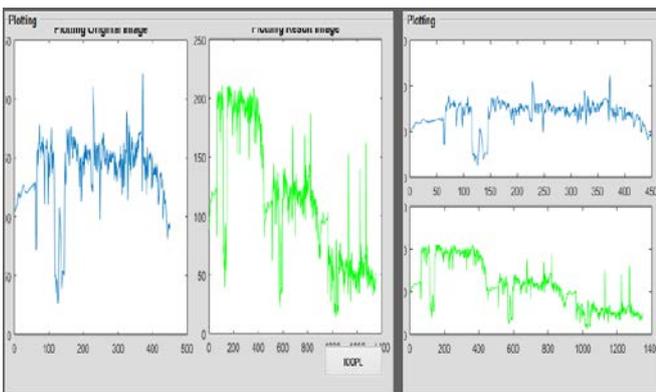


Fig-18: Snapshot of Object oriented shadow detection & removal using IOOPL

## 6. CONCLUSION

A novel framework for shadow detection and shadow removal method for the very high resolution panchromatic satellite images is proposed. This work has dealt with the challenging problem of the shadow removal in the panchromatic satellite images, to recover the obscured information of objects in the shadow containing images. For shadow detection, multilevel image thresholding and image matting technique are combined to obtain the soft detection results. The soft shadow detection results can show the probability value of each pixel belonging to the shadow, and helps to trace out the presence of penumbra portion. To restore the occluded information of objects, two levels of removal methods including the initial correction and the refined restoration are used. The initial correction step compensates the intensity for shadow areas by global parameter. In the refined restoration step utilizes the patch intensity difference between the initial corrected image and non-shadow region to restore the shadow areas making same brightness and smoothness as that of non-shadow

area. From the experimental results, our method to solve the main problems is summarized as follows:

The soft shadow detection is performed automatically. The shadow probability is calculated accurately to show the distribution of umbra and penumbra. The proposed automatic method is effective to avoid the boundary effects after recovery, due to the presence of the penumbra.

The proposed shadow removal method can restore the obscured information of objects in shadow areas effectively as comparing with existing methods. The shadow areas are restored by patch intensity difference and the brightness also adjusted, finally results are smoothed to reduce the noise.

## 7. FUTURE SCOPES

In future, object based image analysis has been accepted as an effective method for processing high spatial resolution multiband image. In future work will aim to implement the proposed algorithms in a Graphics Processing Unit (GPU) with parallel computing techniques to achieve a faster performance.

## REFERENCES

- [1] W. Liu and F. Yamazaki, "Object-based shadow extraction and correction of high-resolution optical satellite images," *IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens.*, vol. 5, no. 4, pp. 1296–1302, Aug. 2012.
- [2] A. Makarau, R. Richter, R. Muller, and P. Reinartz, "Adaptive shadow detection using a blackbody radiator model," *IEEE Trans. Geosci. Remote Sens.*, vol. 49, no. 6, pp. 2049–2059, Jun. 2011.
- [3] V. J. D. Tsai, "A comparative study on shadow compensation of color aerial images in invariant color models," *IEEE Trans. Geosci. Remote Sens.*, vol. 44, no. 6, pp. 1661–1671, Jun. 2006.
- [4] L. Luca, F. Melgani, and G. Mercier, "A complete processing chain for shadow detection and reconstruction in VHR images," *IEEE Trans. Geosci. Remote Sens.*, vol. 50, no. 9, pp. 3440–3452, 2012.
- [5] E. Mohamed and M. Khan Iftakharuddin, "Shadow detection of man-made buildings in high-resolution panchromatic satellite images," *IEEE Trans. Geosci. Remote Sens.*, vol. 52, no. 9, pp. 5374–5386, 2014.

## AUTHOR'S PROFILE

**Kartik Ingole** has received his Bachelor of Engineering degree in Electronics Engineering from G. H. R. I. I. T. Engineering College, Nagpur in the year 2008. He has received his M.Tech. degree with the specialization of Communication from P. C. Engineering College in the year 2012. His area of interest is Signal and Systems & Signal Processing.

**Shruti Golar** has received his Bachelor of Engineering degree in Electronics Engineering from Y. C. C. E. Engineering College, Nagpur in the year 2012. At present she is pursuing M.Tech. with the specialization of Communication from T. G. P. C. E. T. Engineering College. Her area of interest is Signal Processing and Image Processing.