A NOVEL PROCESSING CHAIN FOR SHADOW DETECTION AND PIXEL RESTORATION IN HIGH RESOLUTION SATELLITE IMAGES USING IMAGE IMPOSING

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Abstract— **High resolution satellite images may contain shadows due to the limitations of imaging circumstances and presence of tall-standing objects. These shadows cause problems in the exploitation of such images. This paper proposes a complete processing chain to mitigate these shadow effects. This processing chain has two parts. A shadow detection part bases on image imposing and a pixel restoration part based on Bayesian belief propagation algorithm. The shadow detection part executes a Binary conversion supervised by Support Vector Machine (SVM) algorithm and a Canny Edge Detector followed by Image Imposing. The pixel restoration part has two phases. An example-based learning phase and a conclusion phase. In the example-based learning phase, the positions of the shadow and nonshadow pixels are observed and stored in different libraries named as shadow and nonshadow library. By exploiting their Markov Property, the samples are connected by Markov Random Field (MRF). In the conclusion part, the relationship learnt from MRF is used for Decision Making by Bayesian Belief Propagation algorithm. In the end, the restored image is evaluated by comparing the Image Enhancement Factors (IEF) of the images which are shadow detected by image imposing and by morphological filtering. The results after the evaluation on the satellite images exhibit that the shadow detection part is fine and the recovered shadow regions are consistent with their neighboring nonshadow region.**

Keywords- Shadow Detection, Pixel Restoration, Support Vector Machine (SVM), Canny Edge Detector, Image Imposing, Example-based learning, Markov Random field (MRF), Bayesian Belief Propagation (BBP), Image Enhancement Factor (IEF).

I. INTRODUCTION

In aerospace technology, the earth observation commercial satellites are having very high resolution ranged from 0.4 to 5.0m. With this high resolution, the objects such as buildings, vegetations, roads, and cement in the scene of interest can be differentiated with fine details. This makes it easy for the researchers and officials on remote sensing applications such as Urban and Land Development, Crime Mapping, Agriculture, Oceanography, Geology, Disaster Management, Object Detection, Object Recognition, Object Mapping and Image Interpretation. In the Scene of interest, due to the poor lighting conditions, presence of high rise objects such as tall buildings, small scale hill and tall dense vegetations, shadows occur. These shadows lead to short of information. This insufficiency of information makes the applications unfavourable and even infeasible. To mitigate the lack of information, this proposal suggests the complete processing chain including a shadow detection stage and a pixel restoration stage.

As far as the shadow detection is concerned, number of approaches is discussed in the preceding literatures. Using artificial neural networks, the roads and backgrounds in the scene of interest are detected [7]. Detection is carried out in two steps.1.Learing and 2.Recalling.In the Learning phase all the nodes check for the network change and updates its table of information. In the Recalling phase, the updated information is broadcast to all its neighbouring nodes. This approach only focuses on the detection of objects and not on the Reconstruction. The shadow regions are segmented using Region Growing method [5]. This approach involves in two processes. 1. Seed selection and 2.Region growing. After the shadow detection, Refinement process is carried out via Morphological Filtering. But this too doesn't consider the Reconstruction for the problem detected and performs only on particular colour bands.

Some of the proposals also consider the reconstruction processes along with the detection in the previous literatures. By exploiting the Radiance ratio, the status of the image pixels are concluded by analyzing whether it is having a weaker sun light or a stronger sun light [4]. It uses histogram and thresholding for shadow detection. By implementing Land-cover classification and comparing the shadow pixel intensity with different land-cover pixels, the correlation is observed and the brightness is compensated. The requirement of visual inspection leads to poor accuracy and time consumption. Shadow detection and Restoration are accomplished using information from multiple colour bands [9]. This paper uses gamma correction, linear correlation and histogram matching for restoration process but considers the shadow as noise and doesn't analyze the true characteristics of the shadow. In a property based approach, the properties like Luminance and Chromaticity are analyzed [8]. This exploits the term Image ratio for shadow segmentation. Using morphological filtering, histograms and some logical operations, a Look Up Table (LUT) is created. With the reference of LUT, the luminance of pixels is adjusted. Linear regression method is used for shadow reconstruction, after the detection is accomplished [3].

Thresholding and morphological filtering are carried out for shadow detection [1]. This approach meets failure in maintaining the structure of the image. The above said approaches discussed in the previous literatures are not good enough in maintaining the structure of the original image and not powerful in the dynamic analysis of data.

II. PROBLEM DELINEATION

The problems in such high resolution satellite images are noises, shadows, elimination changes, poor lighting conditions and the degradation of sensors. Among these, this proposal investigates and suggests a methodology to mitigate the effects of shadows.

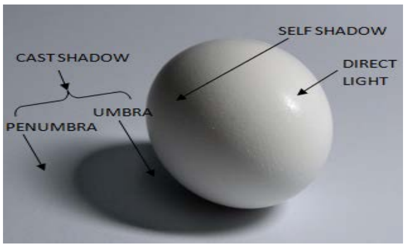

Fig. 1. Parts of Shadow

A shadow is simply the absence of information in an area due to the incomplete illumination of the light and the presence of tall-standing opaque objects in the scene of interest. Despite of the different types in shadow, they all are basically divided into two prime parts. 1. Cast Shadow and 2.Self Shadow. As shown in the fig.1, the shadow on the object itself is called as self shadow. The shadow behind the object on the background of the scene is referred to as cast shadow. Since self shadow doesn't influence the application of satellite images as much as cast shadow does, this paper focuses on the cast shadow. Cast shadows are further divided into two categories 1. Umbra and 2. Penumbra. Umbra is the deepest dark area. Penumbra is an area in the shadowed region where the light illumination is scattered and gets partial brightness. Such effects of penumbra can be dealt with proper edge detection. In this proposal the shadow and nonshadow regions are categorized using binary classification supervised by a machine learning algorithm termed as Support Vector Machine (SVM). The canny edge detector is the choice for the edge detection process. Image imposing is executed after the canny edge detector in order to get fine-tuned shadow detection.

From the detected shadow pixels P_s, the corresponding underlying nonshadow pixels P_n are required to be determined. This problem can be framed mathematically with the help of Bayesian Theorem (BT). BT computes priori and posteriori probabilities.

$$\text{Priori probability} = P(P_s).$$

$$\text{Posteriori probability} = P(P_s \mid P_n).$$

The second one is the conditional probability of the detected shadow and nonshadow pixels in the original scene. This posteriori probability carries the estimation for the brightness of the given shadow pixel to be updated.

III. PROPOSED SYSTEM

The fig.2 interprets the Overall block diagram of the Proposed System. The complete methodology involves in shadow detection and pixel restoration and is implemented on the multi spectral satellite image of a built-up, sub-urban area.

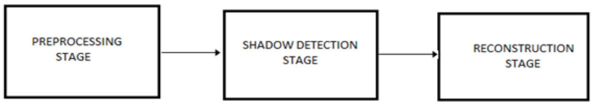

Fig. 2. Overall Block Diagram of the Proposed System

The entire methodology is divided into three phases. 1.Preprocessing, 2.Shadow detection and 3. Pixel Restoration.

A. Preprocessing

The review on [2] exhibits that preprocessing is an exercise in order to make the image of interest to be comfortable and processable for further proceedings. Preprocessing is classified into three steps. 1. Gray conversion, 2.Thresholding and 3.Binary Classification. In Fig.3, the flow chart for Preprocessing and Shadow Detection is described.

1) Grayscale Conversion: A gray scale conversion algorithm is implemented on the given multi spectral satellite image. After finding the positions of each and every pixel, its corresponding intensity value is observed and assured in a single band ranged from 0 to 255. The value '0' denotes the total absence and the value '1' denotes the total presence. There are 254 fractional values in between the range.

2) Thresholding: Thresholding is carried out in order to perform black and white conversion. In this segment the histograms are exploited to obtain threshold value. First of all, the histogram of the entire scene of interest is observed. From the plotted values, the minimum occurrence pixel value P_{min} is subtracted from the maximum occurrence pixel value P_{max} to set the threshold value T and the expression is given as

$$T = P_{max} - P_{min} \tag{1}$$

3) Binary Classification: As aforementioned, Machine Learning has been done in order to accomplish binary conversion. Since all the input samples are clearly identified (i.e., not variant) and the desired output labels are given (i.e., black or white), the machine learning algorithm which is being used here is Support Vector Machine algorithm. It is a supervised model with learning procedures. This categorizes the incoming input pixels into one of the two predestined output labels on the basis of threshold. The output image from this process will be containing pixels either as black or white.

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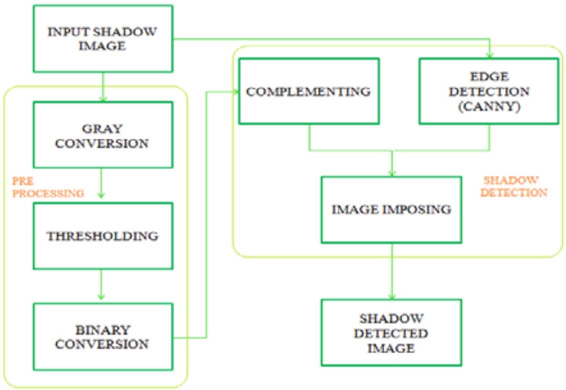

Fig. 3.The flow chart for Preprocessing and Shadow Detection

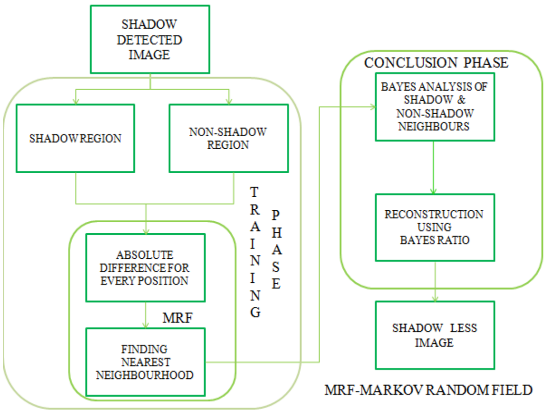

Fig. 4.The flow chart for Pixel Restoration

B. *Shadow Detection*

Though the shadow and nonshadow parts are categorized in the preprocessing stage, they are not accurate at the boundaries and edges, due to the presence of noise and penumbra effect. From the literature work in [2], we come to know that for a clear-cut shadow detection, detection phase should involve in two more processes called as 1.Edge detection and 2. Image imposing.

1) Canny Edge Detection: The traditional operators such as sobel, prewitt are only dealing with the magnitudes whereas the canny edge detector is computing the magnitude along with its direction. Edge detection is accomplished in four steps. 1. Noise reduction, 2.gradient computation, 3.nonmaximum suppression for linear edges determination and 4.hysteresis thresholding for curvy edges determination. As a result, a binary image is obtained. Each pixel in this output may be either an edge pixel (i.e., white) or a nonedge pixel (i.e., black).

2) Image Imposing: Emplacement of an image or a video on a previously existing image or a video one on another is set to be image imposing. In other words, it is described as the overall addition process of two different images or videos. The output from the binary conversion is complemented and then added with the edge detected image to get complete and fine-tuned boundary detection. The output will be a black and white image. ‘White’ represents shadow while ‘Black’ denotes nonshadow pixels.

C. *Pixel Restoration*

In order to recover the nonshadow pixels from the corresponding shadow region, this pixel restoration phase is sub divided into two stages. 1. Training phase and 2. Conclusion phase.

1) Training phase: The survey in [10] suggested an example-based learning approach for low level vision problems based on image training

By exploiting this concept, this proposal takes the detected shadow and nonshadow pixels to an example based learning procedure. In this, the positions of above said pixels are observed and stored in different libraries labelled as Shadow library and Nonshadow library respectively. The analysis on the pixels conveys that they all are having a Markov property. A pixel or a node which is said to be having Markov Property should have the future states depending only on the present states and not on the events preceding it. In other words, such nodes or pixels are statistically independent from each other except their direct neighbours. The network or arrangement of nodes or pixels having this property is referred to as Markov Random Field (MRF). The neighbours are defined by their minimum distances with the pixel of interest. So the absolute difference is manipulated for every shadow pixel with other nonshadow pixels in the image. Four nonshadow pixels in the nearest neighbourhood (i.e., having minimum distances) are selected and grouped.

2) Conclusion phase: The conclusion should be derived from the training samples observed in the previous phase. For that a decision making algorithm is required. The study in [1] recommends that Bayesian Belief Propagation algorithm (BBP) can solve the MRF. The MRF and BBP are complementing each other. While the MRF is determining the information, the BBP is concluding the uncertainty based on the observed evidence using probability theorem. The unknown shadow pixel in the scene of interest is denoted as Hypothesis ‘H’. The well-defined nonshadow pixels are referred to as Evidence ‘E’. The nonshadow pixels in the nearest neighborhood are labeled as ‘(E∩H)’. This paper performs two probability computations..1. Priori Probability. i.e., Probability of Hypothesis ‘H’ before the Evidence E is observed = P(H).2.Posteriori Probability (the conditional probability). i.e., Probability of Hypothesis ‘H’ after the Evidence E is observed = P(H|E). The Consistency of the Evidence ‘E’ with the observed Hypothesis ‘H’ is said to be

$$P(E|H) = \frac{P(E \cap H)}{P(H)} \quad (2)$$

The formulation for the posteriori probability P(H|E) is given by

$$P(H|E) = \frac{P(E|H).\,P(H)}{P(E)} \qquad (3)$$

The Hypothesis H i.e., the detected shadow pixel of interest is updated with this posteriori value P(H|E). With this the uncertainty is concluded.

IV. RESULTS ANALYSIS AND EVALUATION

In this section, two different Multi spectral (MS) satellite images are taken to evaluate the behaviour of the proposed methodology. The first image is a part of an MS satellite image of size 287×175 located in a sub-urban residential area as shown in fig. 5(a). The second image is an MS satellite image of size 356×358 as shown in fig. 6(a). The preprocessing results for the two images are illustrated in the figs. 5(b), 5(c), 5(d) and figs. 6.(b),6(c), 6(d). The shadow detection results for the two images are shown in figs. 5(e), 5(f) and figs. 6. (e), 6(f). The pixel restoration results for the two abovementioned images are interpreted in the figs. 5(g) and 6(g).To verify the effectiveness of the investigated method, Image Enhancement Factor (IEF) is considered. As far as our proposed system is concerned, the enhancement is to measure the quantity of the reconstructed pixels, the pixel deviation between input shadow image and output shadow less image is analyzed and calculated. To accomplish that, this paper exploits Mean squared error. The average of the squares of the errors is measured. Errors simply represent the pixel deviation between input and output image (i.e., Errors = Differences).

$$MSE = IEF = \frac{(\text{Shadow less image} - \text{shadow image})2}{\text{Original image size}} \qquad (4)$$

This IEF tells the percentage of reconstructed pixels from the given original image. For the verification processes, this IEF test is implemented on two different images as given in figs. 7(a) and 8(a).

TABLE I

COMPARISON OF IEF VALUES OF IMAGES AFTER RECONSTRUTION

Approaches	**Methodology for Detection**	**IEF value in %**	
		Image 7(a)	***Image 8(a)***
Existing system	Morphological filtering	358.0222	95.3585
Our proposed system	Image Imposing	399.6038	141.2608

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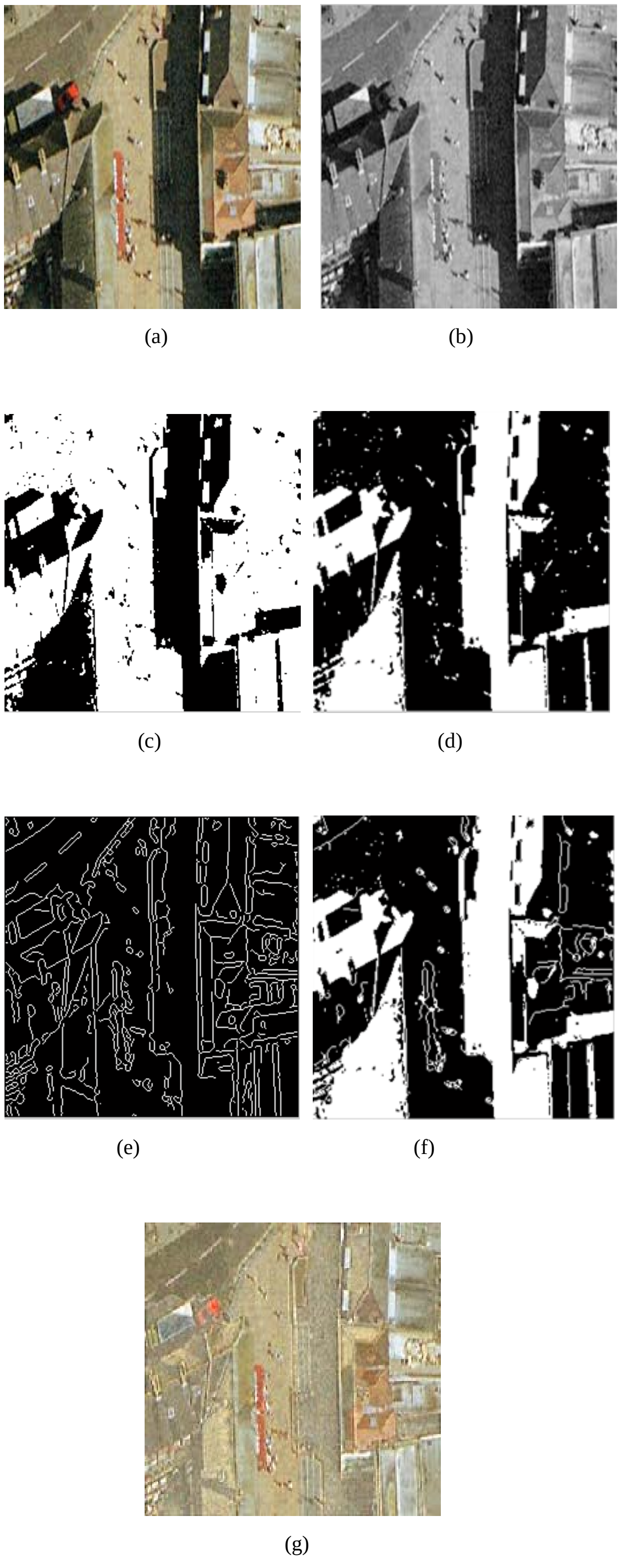

Fig.5. Final Restoration results for the first MS satellite image. (a) Original MS image of a sub-urban area.(b) Grayscale version. (c) Binary Mask. (d) Complement image for the binary mask. (e) Canny Edge detected image. (f) Super-imposition of edge detected image and complemented image. (g) Recovered image of the proposed system.

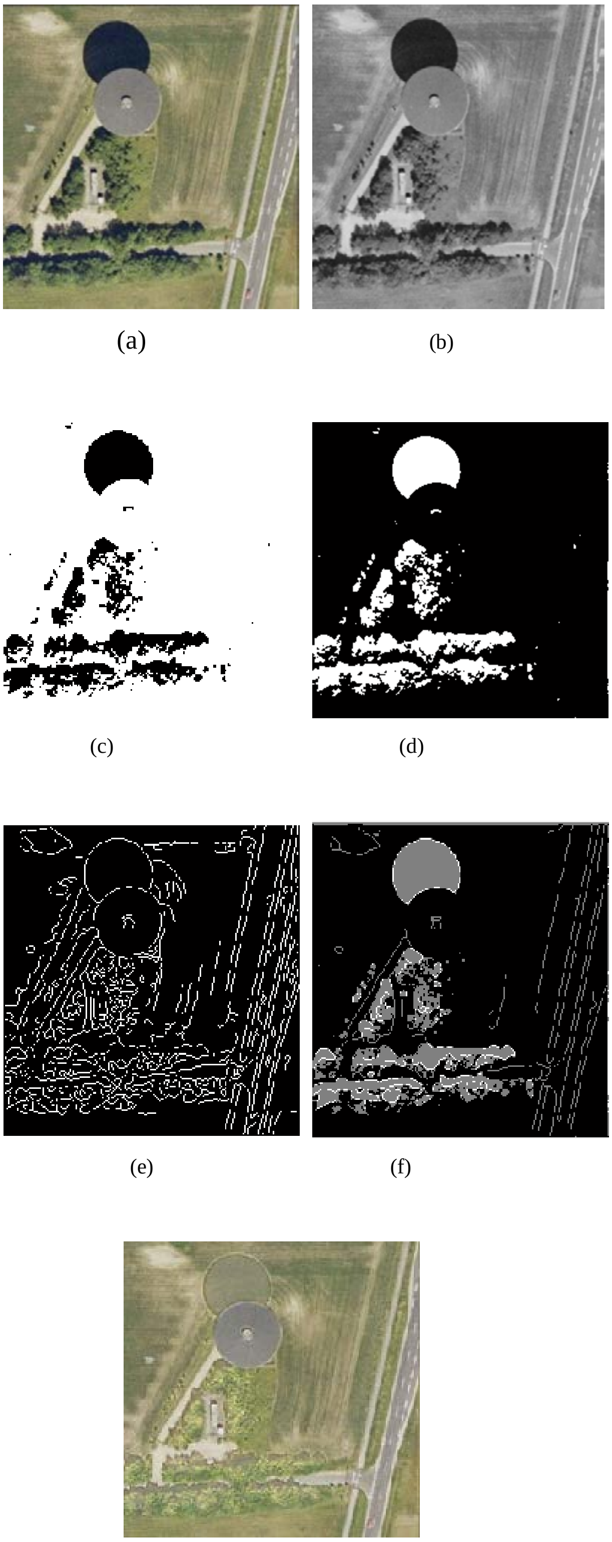

Fig.6. Final Restoration results for an MS satellite image. (a) Original MS image of a road-side area.(b) Grayscale version. (c) Binary Mask. (d) Complement image for the binary mask. (e) Canny Edge detected image. (f) Super-imposition of edge detected image and complemented image. (g) Recovered image of the proposed system

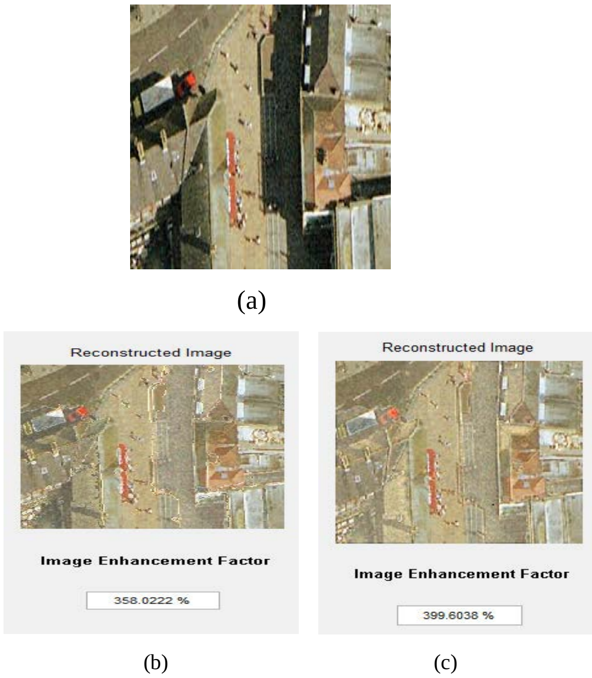

Fig.7. Comparison results for an MS satellite image after the evaluation test. (a)Final reconstructed image with its IEF value, processed via an existing method which uses Morphological filtering for shadow detection. (b) Final reconstructed image with its IEF value, processed via the proposed method which uses Image imposing technique for shadow detection.

Fig.8. Comparison results for an MS satellite image after the evaluation test. (a)Final reconstructed image with its IEF value, processed via an existing method which uses Morphological filtering for shadow detection. (b) Final reconstructed image with its IEF value, processed via the proposed method which uses Image imposing technique for shadow detection

The first image is returned with an IEF value of 399.6038%. The second image is returned with an IEF value of 141.2608%. This conveys that the first image will have a pixel count (quantity of pixels) which is 3.99 times greater than its original image's pixel count. For the second image, number of pixels in the original image (fig. 8(a)) are multiplied with the value 1.412. The same test is executed on the output images of a different methodology which includes morphological filtering for shadow detection and this existing method is also supplied with a same aforementioned images as in figs. 7(a) and 8(a).From the figs. 7(b) and 7(c), it is clearly noticeable that the existing method produces 3.58 times greater no. of pixels while our proposed method produces approximately four times greater no. of pixels in the reconstruction process. As shown in figs. 8(b) and 8(c) the existing method gives 95% of enhancement while our proposed method presents with 141% of enhancement. From the results and their corresponding enhancement factor values, it exhibits that the proposed methodology produces shadow less images with better performance compared to the existing approaches.

V. CONCLUSION

The goal of this paper is to prescribe a novel methodology for accomplishing the problem of Reconstruction in order to mitigate the shadow effects present in the satellite image of interest. Not only the shadow regions are recognized but also categorized using the supervising algorithm SVM. Boundary and Edge detections are properly achieved by the composition of Canny Edge Detector and Image Imposing technique. To recover the dark shadow pixels, a novel pixel restoration algorithm is recommended. This stage carries off a training phase which has the Example-based learning method as a substructure and a conclusion phase based on Bayesian Belief Propagation algorithm. Training phase is completed by exploiting the properties of the pixels and correlating the shadow and nonshadow regions with MRF. From the information derived in the training, a decision is made by concluding the uncertainty by means of Probability theory. With the experimental results and visual inspection, it manifests that the prescribed methodology returns an accurate and proper shadow recognition and better pixel restorations. This investigation has an advantage of solving the problem as a whole. Still further refinements and improvisations are necessitated and lead to the future work. The required betterments are listed as follows.1.A strong ground truth investigation should be carried out.2.Shadow itself needs to be classified.

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