A Shackle Process for Shadow Detection

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ABSTRACT
The presence of shadows in images can represent a serious obstacle for their full exploitation. Shadows are a decrease in the amount of light that reaches a surface. They are a local change in the amount of light rejected by a surface towards the observer. Coping with shadows is a crucial challenge in object detection, scene understanding, recognition and tracking applications. In the proposed technique, detection of shadow region is performed by using morphological operations. Borders are identified by finding the difference between dilation and erosion processes. The classification process is implemented by means of the KNN (K-Nearest Neighbourhood) classifier. Colour segmentation is performed to compare with the results of the border image created. The comparison results of the colour segmented and border image are considered in terms of classification. Thus, using the proposed technique the classification of shadows and non-shadows is better than the segmentation technique.

General Terms
Geoscience and remote sensing, Thresholding, Morphological operations, KNN classifier and colour segmentation, LORENZI et al.

Keywords
KNN, ROI, img, class, dataset, segmentation

1. INTRODUCTION

1.1 Shadows
The shadow detection is an important issue in machine vision systems for many purposes. Shadows in an image may reveal information about the object's shape, orientation and even about the light source. A typical utilization might be given as detecting a building's height from its shadow. Another example to beneficial usage of shadow information is on post event photographs of earthquake damaged scenes.

A shadow occurs when an object partially or totally occludes direct light from a source of illumination. A shadow is a region where direct light from a source cannot reach across the object due to obstructions. This obstruction is caused by the object itself. Shadows could also be defined as the parts of the scene that is not directly illuminated by a light source due to an obstructing object or objects. The shadow occupies the space behind the opaque object with light in front of it. The sun causes many objects to have shadows at certain times of the day.

When the source is at certain heights, the lengths of shadows change. This means that the size and position of the shadow varies according to the following factors (a) distance of the object from the source and (b) direction of incident light. The shadows produced by an object depend on both the object's shape and the position of the light sources by which it is illuminated. If the position of the light sources remains fixed and the shape of the objects change, then the shadows change as well.

Shadows are regions occluded from the light source and come in two types as explained below: Self shadows are formed on the very surface which is occluding the light whereas cast shadows are formed on remote surfaces. The cast shadow is usually further divided into 2 parts, umbra and penumbra. The umbra represents the shadow region where the primary light source is completely obscured; whereas the penumbra is the region around the edge of a shadow where the light source is only partially obscured. For extended light sources, penumbras surround the cast shadows. Finally, attached shadows sometimes include inter-reflections that result from light rays bouncing back from surrounding surfaces.The various regions are shown in fig 1.1

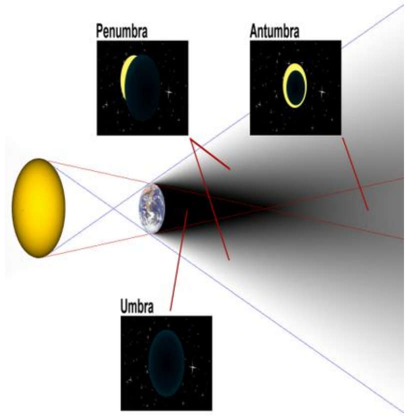

Fig 1.1: A detailed view of Umbra and Penumbra regions

1.2 TWO TYPES OF SHADOWS
Cast shadows are related to two distinct surfaces, the surface of the casting object and the surface on which the shadow is cast. As such, cast shadows are potentially informative about the shapes of either of the surfaces and about the spatial layout of the scene. Cast shadows are caused when a caster comes between a light source and a surface or screen. The information content in these types of shadows can therefore be used to provide knowledge about any or all of these three elements. As a very elementary example, assuming that the light does not move very fast and that the screen is at horizontal, conclusions about the size, motion and shape of casting objects by looking at their shadows conclusions can be drawn.

Self shadows are produced when an object shadows on itself. Self-shadow usually have a higher brightness than cast shadows since they receive more secondary lighting from surrounding illuminated objects. Usually, self shadows are vague and gradually change intensity and have no clear boundaries. The formation of shadows is shown in fig 1.2.

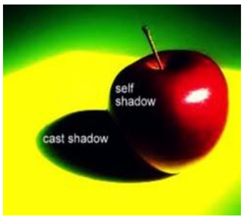

Figure 1.2: Image of self shadow on an object

Self shadows do not have exact or precise border information. Hence cast shadows are used more for analysis when shadow information is considered.

1.3 SHADOW ANALYSIS AND DEFECTS

Shadows appear as surface features in images, when they are caused by the interaction between light and objects. This may lead to problems in understanding the image, object segmentation, tracking, recognition, etc. The presence of shadows in very high resolution images can represent a serious obstacle for their full exploitation. As a consequence, shadows can impact negatively in the exploitation of VHR(Very High Resolution) images, influencing detailed mapping, leading to erroneous classification or interpretation (e.g. biophysical parameters such as vegetation, water, or soil indexes), due to the partial or total loss of information in the image.

Although it is feasible to exploit shadow characteristics to recognize building position and to estimate their height and other useful parameters, usually, shadows are viewed as undesired information that strongly affects images. Shadows may cause a high risk to present false colour tones, to distort the shape of objects, to merge, or to lose objects. Shadows represent an important problem for both the users and sellers of remote sensing images. An aerial image covered by shadows is shown in fig 1.3.

Fig 1.3: Aerial image with areas covered by shadows

If this occurs during satellite imaging or aerial image analysis it can result in loss of the precise information. In order to overcome this aspect, shadow detection and removal is performed hence producing better images for analysis.

2. LITERATURE SURVEY

The detection and removal of shadows have been simulated using various methods. A survey of these methods and their drawbacks are discussed in this section.In some applications, especially traffic analysis and inspection system, the subsistence of shadows may cause stern nuisance while segmenting and tracking objects. Shadows can cause object unification as a consequence of this, shadow detection is applied to situate the shadow regions and discriminate shadows from foreground objects[13]. Algorithms dealing with shadows were classified in two-layer taxonomy. Deterministic approaches use an on/off decision process, whereas statistical approaches use probabilistic functions to describe the class membership [8]. It relies on models of the scene that they inevitably become too complex and time-consuming. A method which is an example of the statistical nonparametric approach and denoted it with symbol SNP has been proposed [6]. These approaches exploit colour information and used a trained classifier to distinguish between object and shadows. A statistical parametric loom which is also called SP approach has been proposed. It utilizes both spatial and local features, which enhanced the detection performance by daunting spatial constraints [10]. A method has been proposed in which DNM1 and DNM2 are legislatures of deterministic non-model based method respectively. DNM1 was based on a conjecture that shadows in image do not change the hue of surfaces [4].

A physical model based method to detect moving shadows in video has been proposed [12]. A multistage approach where each stage of the algorithm removes moving object pixels with knowledge of physical models was used. Experimental results demonstrated that their approach was robust to widely different background surface, foreground materials and illumination conditions. A method has proposed to detect and classify shadows for still images. Shadow identification and classification using invariant colour models to classify cast and self shadows was introduced [15], [16].

3. PROPOSED METHOD

A methodology for extracting shadows from high resolution panchromatic satellite images has been developed. The algorithm separates shadows from non-shadows and it involves the various steps as shown in fig 3.1.

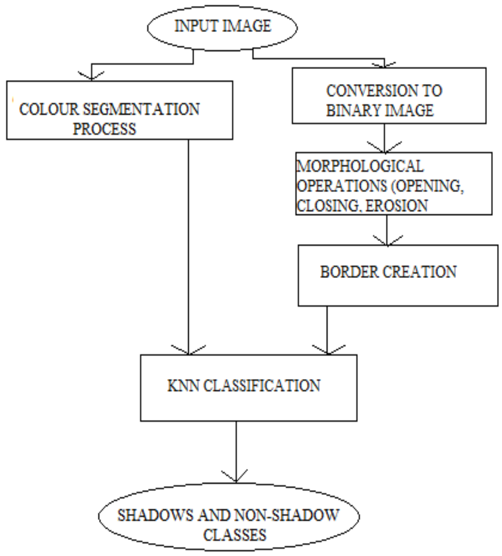

Fig 3.1: Flowchart of the proposed method

Thresholding is the first step in the processing and is followed by post-processing operations such as morphological opening, closing, erosion and dilation. The segmentation of the input image is also performed for comparison. The border is created using the difference between dilation and erosion. This border image is given as the input to the KNN classifier. Similarly the segmented image is also given to the classifier and the results are compared. Each of the processing steps of the proposed algorithm is described in detail in the next section.

3.1 Thresholding

Thresholding is an ideal method of shadow detection in high resolution satellite images due to the spectral content of the images. However, the difficulty with thresholding lies in selecting the most appropriate threshold level.

3.2 Morphological operators

Morphological operations are used to understand the structure or form of an image. This usually means identifying objects or boundaries within an image. Morphological operations affect the form, structure or shape of an object. They are used in pre or post processing (filtering, thinning, and pruning) or for getting a representation or description of the shape of objects/regions (boundaries, skeletons convex hulls).The two principal morphological operations are dilation and erosion. Dilation allows objects to expand, thus potentially filling in small holes and connecting disjoint objects. Erosion shrinks objects by etching away (eroding) their boundaries. These operations can be customized for an application by the proper selection of the structuring element, which determines exactly how the objects will be dilated or eroded.

3.2.1 Dilation

The dilation process is performed by laying the structuring element B on the image A and sliding it across the image in a manner similar to convolution. The difference is in the operation performed.

The structuring element can have any shape. Typical shapes are presented below in fig 3.2.

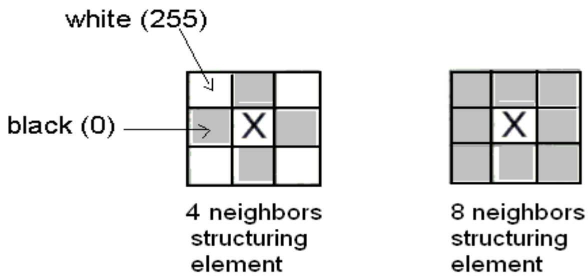

Fig 3.2: Typical shapes of the structuring elements

An example is shown in Fig 3.3. With a dilation operation, all the 'black' pixels in the original image will be retained, any boundaries will be expanded, and small holes will be filled.

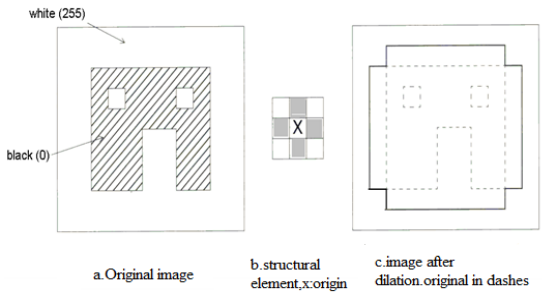

Fig 3. 3: Illustration of the dilation process

3.2.2 Erosion

The erosion process is similar to dilation, but here the pixels are converted to 'white', not 'black'. Slide the structuring element across the image to do erosion process.

An example of erosion process is shown in fig 3.4.

Because the structuring element is 3 pixels wide, the 2-pixel-wide right leg of the image 3 object was eroded away, but the 3-pixel-wide left leg retained some of its centre pixels.

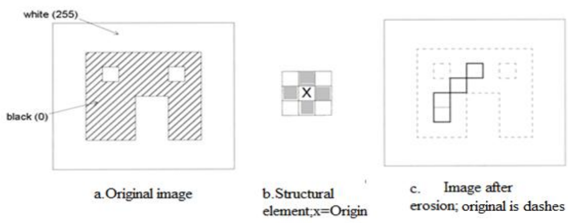

Fig3.4: Illustration of the erosion process

3.3 Opening and closing

Opening and closing are two important operators from mathematical morphology. They are both derived from the fundamental operations of erosion and dilation. Like those operators opening and closing are normally applied to binary images, although there are also gray level versions. The basic effect of an opening is fairly like erosion in that it tends to remove some of the foreground (bright) pixels from the edges of regions of foreground pixels. However it is less destructive than erosion in general. Closing is similar in some ways to dilation in that it tends to enlarge the boundaries of foreground (bright) regions in an image (and shrink background colour holes in such regions)

Opening consists of an erosion followed by a dilation and can be used to eliminate all pixels in regions that are too small to contain the structuring element. The structuring element is often called a probe, because it is probing the image looking for small objects to filter out of the image. Fig 3.5 illustrates the opening process.

Notation: A◦B = (AΘB) ⊕ B

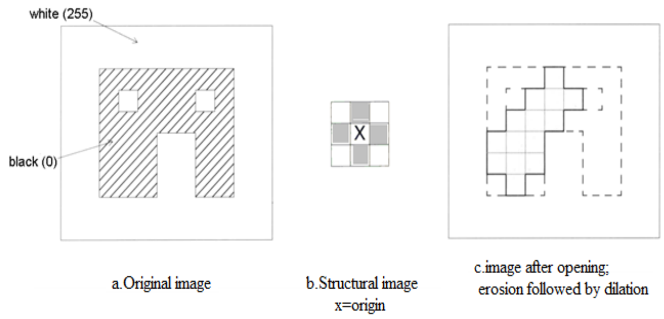

Fig 3. 5: Illustration of the opening process

Closing consists of a dilation followed by erosion and can be used to fill in holes and small gaps In Fig.3. 6 the closing operation has the effect of filling in holes and closing gaps.

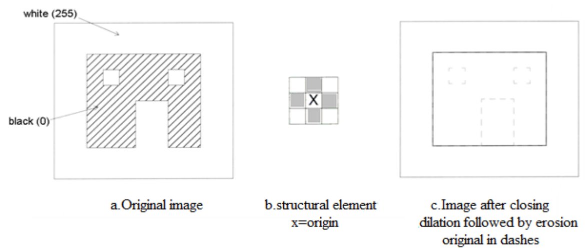

Fig 3.6: Illustration of the closing process

Comparing the left and right images from Fig 3.10, the order of operation is identified. Closing and opening will generate different results even though both consist of erosion and dilation. (Notation: A●B = (A⊕ B) Θ B)

3.4 Border creation

The outline image of a binary object can be computed using dilation followed by a subtraction (or XOR operation). The difference between opening and closing is considered as the border information.

3.5 Colour Segmentation

Colour segmentation is another method that is applied to the existing methods. By using this method, segmentation process is applied to the border image. The segmented output is then directly given as the input to the classifier.

3.6 Classification Process

The process of classification is used in order to define the spectral relationship between the shadow and non-shadow versions of the same object (class) and, thus, to perform customized reconstruction of shadow areas.There are various methods to perform this classification process. The nearest neighbour algorithm has been used.

3.6.1 K Nearest Neighbour Algorithm

The nearest neighbour algorithm is also known as KNN. This is a method for classifying objects based on closest training examples in the feature space. The KNN algorithm is simulated as follows: an object is classified by a majority vote of its neighbours, with the object being assigned to the class most common amongst its KNN (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of its nearest neighbour. The KNN algorithm is sensitive to the local structure of the data. This is represented by means of a diagrammatic representation. Fig 3.7 represents the process by which classification is done by an example of the KNN either to the first class of blue squares or to the second class of red triangles. If k = 3 (solid line circle) it is assigned to the second class because there are 2 triangles and only 1 square inside the inner circle.

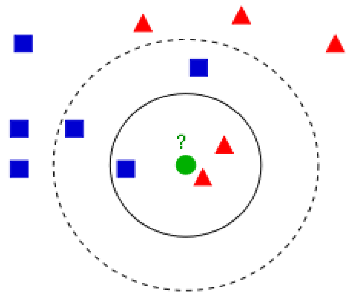

Fig 3.7: Example of KNN classification

If k = 5 (dashed line circle) it is assigned to the first class (3 squares vs. 2 triangles inside the outer circle).In the classification phase, k is a user-defined constant, and an unlabeled vector (a query or test point) is classified by assigning the label which is most frequent among the *k* training samples nearest to that query point.

A training example is an ordered pair (x, y) where x is an instance and y is a label. A test example is an instance x with unknown label. The goal is to predict labels for test examples. The training table is shown in fig 3.8.

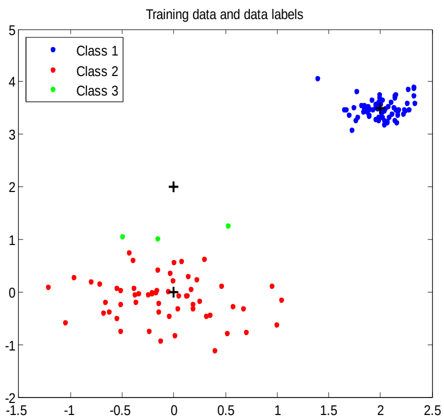

Fig 3.8: Training data and data labels

The results of the classifier after the process, shows a shadow and a non-shadow region as represented in fig 3.9.

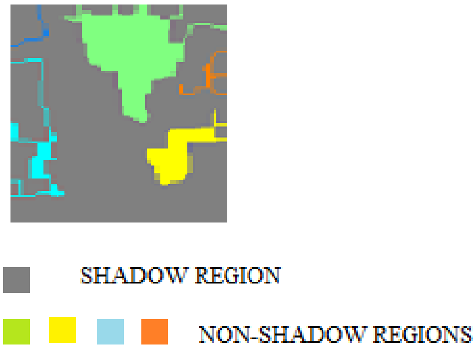

Fig 3.9: Classification result of an image

3.6.2 Advantage of KNN Classification

A major advantage of the KNN method is that it can be used to predict labels of any type. Suppose that training and test examples belong to some set X, while labels belong to some set Y.

4. RESULTS AND DISCUSSION

Simulation is done using MATLAB software. The results obtained after the simulation are presented in this section.

4.1 Simulation of border image

The simulation result for an input image is shown step by step. After the border is created the image is fed into the KNN classifier in order to discriminate between the shadow and non shadow regions. A similar classification process is carried out by using colour segmented image of the border image.

STEPS	Image 1	Image 2
1.Input image		
2.Binary classified image		
3.Morphological opening image		

4.Morphological closing		
5.Dilated image		
6.Eroded image		
7.Difference between eroded and dilated image		

8.border image		

Table 1: Simulation of border images

Testing has been done for many database images and the performance is tested in terms of the classification of shadows and the detection rate. The proposed technique gives higher detection rate of shadows when compared to the segmentation technique**.**

4.2 Colour Segmentation

Colour image segmentation is useful in many applications. . Colours in the image are coarsely quantized without significantly degrading the colour quality. The purpose is to extract a few representing colours that can be used to differentiate neighbouring regions in the image.

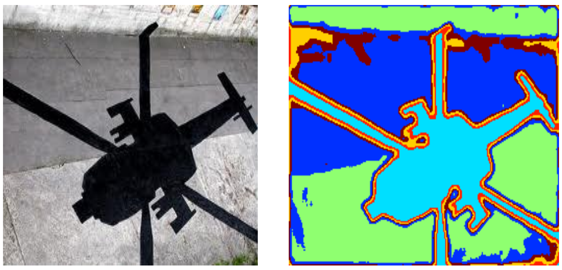

Fig 4.2: Colour based segmentation (a)input, (b)segmented image

5. CONCLUSION

The role of cast shadows for the perception of surface shape and spatial layout is crucial. Cast shadows are those shadows that are projected on a remote surface. It is found that even though shadows were potentially informative about surface shape, cast shadows served very weakly in this function. On the other hand, cast shadows clearly provide very salient cues for the relative dispositions of objects in space, particularly when an object and its cast shadow are moving. This raises some unique and difficult conceptual issues for perception. The issues revolve around three problems: segmenting and labeling cast shadows in scenes, linking cast shadows with the objects which cast them and interpreting spatial relations fromthe changing displacement between an object and its shadow in an image. By using K-NN algorithm, the shadow class has been simulated. This classification process is also done by means of filtering methods by the use of Canny, Sobel and Prewitt filters. The results have been compared to identify the most effective shadowed and non-shadowed classified images. The classification results that produce best results are used for reconstruction of shadow regions.

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LIST OF SYMBOLS

$\circ$ Morphological Opening
$\bullet$ Morphological Closing
$\oplus$ Dilation
Θ Erosion