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Detection and Discrimination for Shadow of High Resolution Satellite Images by Spatial Filter

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Abstract
This paper presents a new and effective procedure to extract shadow regions of high- resolution color images. The method applies this process on modulation the equations of the band space a component of the *C1-C2-C3* which represent RGB color, to discrimination the region of shadow, by using the detection equations in two ways, the first by applying Laplace filter, the second by using a Kernel Laplace filter, as well as make comparing the two results for these ways with each other's. The proposed method has been successfully tested on many images Google Earth Ikonos and Quickbird images acquired under different lighting conditions and covering both urban, roads. Experimental results show that this algorithm which is simple and effective too increase the precision rate of shadow detection, can be colored the result, and also reduces the error rate of detecting non- shadows as shadows. In this technical didn't need to morphological filters.

Keywords: Remote Sensing Image, Shadow Detection, *C*3 Component, Laplace filter.

كشف وتمييز الظل لصور الاقمار الصناعيه العالية الدقة بواسطة المرشح المكاني

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الخلاصة
في هذا البحث نقدم اجراء جديد وفعال لانتزاع مناطق الظل لصور درجة الوضوح العاليه الدقه ، تطبق هذه النظريه بأجراء عمليه تحوير لمعادلات مركبات الفضاء اللوني للفرق الثلاثه *c1 c2 c3* لتمييز منطقه الظل بأستعمال معادلات الكشف في طريقتين الاولى بتطبيق مرشحات لابلاس ولب لابلاس المطورين بعد ذلك تتم مقارنه بين نتائج الطريقتين مع بعضهما البعض . الطريقه المقترحه اختبرت بنجاح على العديد من صور Google Earth , Ikonos and Quickbird لهما نفس شروط الاضاءه وكلاهما تغطي مناطق حضريه وطرق. وقد اظهرت النتائج التجريبيه بأن هذه الخوارزميه التي هي بسيطه وفعاله تزيد نسبة الدقه لكشف الظل ، ويمكن تلوين النتجه ، وكذلك تخفض نسبه كشف مناطق غير الظل كظل. في هذه التقنيه لم تكن بحاجه لمرشحات مورفولوجية .هذه ميزات العمل الغير مألوف .

Introduction

Shadow detection has become a hot issue in the field of remote sensing image processing, and the algorithms for the shadow detection can be divided into two categories: One is based on the model and the other shadow nature. The first category requires a prior knowledge of the environment conditions. The shadow areas are calculated according to the geometric feature in the image, the height of the suns angle, the remote sensor and other relevant parameters, the shadow nature mainly includes spectrum and geometry. The method based on the shadow spectrum is widely used. In recent years, the

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characteristic of the color invariability of the remote sensing image in some color space has attracted widespread attention [1, 2].

Shadow detection algorithms using the feature of the *C1C2C3* color space are only suitable for simple scenes and the *C3* component without processing makes the results unsatisfactory, for high - resolution images, the algorithm based on *C*1-*C*2 -*C*3 color space to distinguish the black areas and shadow areas have been presented on paper.

The way of shadow detection_in the paper has made using the color invariance characteristics and regional expansion [3]. The Shadow detection method based on principal component analysis has been proposed in the paper the ratio of the C3 component of the first principal component is used, in this work the features with high brightness are easily detected as shadows. A shadow detection algorithm is proposed in this paper, which normalizes the C3 component to apply the developed Laplace operators to detect edges precisely with less noise. First is to get the C3 component and normalize it. Then the shadow edges are detected by the kernel filter, depending on physical fact, that the itself shadow didn't have any color (DN=0), the color of shadows is zero grayscale (black) on images, employ the develop Laplace and kernel Laplace filter in this work, in this our method didn't need to make morphological processing. The results show that the algorithm improves the efficiency of the shadow detection on the whole. Its new approach, the program in Matlab it's easier didn't need any auxiliary data (height of the sun angle, the remote sensor and other relevant parameters), this is the advantage of the method.

Methodology

Shadow Detection Techniques for High-Resolution Satellite Imagery, high-resolution, satellite-based imaging sensors (Quickbird and Ikonos) provide one band of panchromatic data and four bands of multispectral data at a quarter of the resolution of the panchromatic data. The choice of which bands to use for shadow detection (panchromatic, multispectral, or a combination of both) depends on the type of the detection algorithm employed. Spatial detection will obviously require higher spatial resolution, whereas spectral detection (such as classification) will require greater spectral resolution. Proposer algorithms for separating shadow pixels from non-shadow pixels are classier, segmentation, thresholding and geometric modeling. Each of these procedures is described in more detail below. The *C*1*C*2*C*3 color space is a scale model between the three *RGB* components in *RGB*-space, the three color components of which clearly vary with the surface reflection and the sensor. The model is defined as follows [4]:

$$\mathbf{C1=arctan\ (R/max\ (R,G))} \quad (1)$$

$$\mathbf{C2 = arctan\ (G/max(G,B))} \quad (2)$$

$$\mathbf{C3= arctan\ (B/max\ (R,G))} \quad (3)$$

C1C2C3-space, the best nonlinear transformation model for shadow detection, is barely sensitive to reflect light. Moreover, the brightness of the R and G color component is lower, but The B color component is larger than the non-shadow areas under the same reflection condition, so the *C*3 component is suitable for the shadow detection. Figure -1 (a, b, c) shows a remote sensing image and its *C1C2C3* components. Shown, the *C*3 component can clearly distinguish the shadow regions and the non-shadow regions. Both the noise of *C*3 component and the edge of the shadow regions are high-frequency signals, so the edge may be blurry while removing the noise. The *C3* component has a concentrating character of pixel values and a small difference of gray values, which lead to unobvious image contrast, and it is difficult to distinguish surface features from the shadows and make the detected shadow edges blurred. For these shortcomings, the *C*3 component is normalized to the 8-bit gray scale distributed in [0, 255] here, which makes the gray value uniform and enhances the contrast of the remote sensing image the equation is as equations (1, 2, 3).

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$$dst(x,y) = \left[\frac{(src(x,y) - \min(src)) \times (255 - 0)}{\max(src) - \min(src)}\right] \quad (4)$$

Where $src(x, y)$ the gray value of the pixel position (x, y) of the original image, $dst(x, y)$ the gray scale value in pixel position (x, y) after normalization, and min(src), max(src) denote the minimum and maximum gray value in the original image respectively.

2.1 Laplace operator Adaptation

Laplace operator is a second differential edge detection operator. The maximum value of the first derivative in the gray image corresponds to the zero value of the second derivative in the x-axis. The edge detection with Laplace operator is to estimate the output of the Laplace operator and to find its zero value. For an image $F(x, y)$, the Laplace operator in two dimensions is defined as[6]:

$$\nabla^2 f(x,y) = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \quad (5)$$

$$\frac{\partial^2 f}{\partial x^2} = \frac{\partial f_x}{\partial x} = \frac{\partial\,(f(x+1,y) - f(x,y))}{\partial x} = f(x+1,y) - 2f(x,y) + f(x-1,y) \quad (6)$$

$$\frac{\partial^2 f}{\partial y^2} = \frac{\partial f_y}{\partial y} = \frac{\partial\,(f(x,y+1) - f(x,y))}{\partial y} = f(x,y{+}1) - 2f(x,y) + f(x,y-1) \quad (7)$$

The Laplace operator is particularly good at finding the fine detail in an image. Any feature with a sharp discontinuity will be enhanced by a Laplace operator. Application of this operator is to restore fine detail to an image which has been smoothed to remove noise; it's implemented as a convolution between an image and a kernel. The kernel Convolve function is used to perform the convolution. The Laplace kernel can be constructed in various ways, the new algorithm developed these operators to perform the edge detection between the shadow and non shadow objects in high resolution image the Laplace operator adaptation, will be called the first operator while the kernel Laplace operator adaptation, will be called second operator . On images, the kernel is centered on each pixel in turn, and the pixel value is replaced by the sum of the kernel multiplied by the image values. In the particular kernel we are using here, we are counting the contributions of the diagonal pixels as well as the orthogonal pixels in the filter operation. This is not always necessary or desirable, although it works well here [6].

A Laplace filter can be used to compute the second derivatives of an image, which measure the rate at which the first derivative's change. This helps to determine if a change in adjacent pixel values is an edge or a continuous progression for more information on edge detection).Kernels of Laplace filters usually contain negative values in a cross pattern (similar to a plus sign), which is centered within the array. The corners are either zero or positive values. The center value can be either negative or positive. The following array is an example of a 3 by 3 kernels for a Laplace filter:

1- [-1 -1 -1; -1 8 -1;-1 -1 -1]
2- 1/3*[-1 -1 -1; -1 8 -1;-1 -1 -1]
3- 1/8*[-1 -1 -1; -1 8 -1;-1 -1 -1]

The following array is an example of a 3 by 3 for a Laplace filter:

1- [1 1 1; 1 -8 1; 1 1 1]
2- 1/3*[1 1 1; 1 -8 1; 1 1 1].
3- 1/8*[1 1 1; 1 -8 1; 1 1 1]

This new technique depends on the subtractive equations CMY color takes from 1, 2, 3

CC1=1- arctan (R/max (G, B)) **(8)**
CC2=1- arctan (G/max (R, B)) **(9)**
CC3=1- arctan (B/max (R, G) **(10)**

In this study the maximum (G, B) =1, maximum (R, B) =1 maximum *(*R, G) =1, Therefore the equations are becoming:

CC1=1-R **(11)**
CC2=1-G **(12)**
CC3=1-B **(13)**

In additive color =Red + Green + Blue=1, requites this in equations 11, 12, 13, get the following:

CC1 = R+ G + B - R= G+B = Cyan color
CC2 = R+G +B - G=R+B=Magenta color
CC3 = R +G+ B - B=R+G=Yellow color **(14)**

New Algorithm design

Algorithm and Experimental Result

Step 1. Load the remote sensing image Figure-1a, find the R-G-B grayscale images.
Step 2. Apply the modulation Eq. 8-9-10 to find the *CC1-CC2-CC*3 image see Figure -1(b-c-d).
Step 3. Normalize the *CC*3 component image in step 2 with Eq. (4), obtain an image in Figure -1 (e).
Steps 4. Apply the first operator, on normalized image to make edge detection for shadow Figure-1 (f), and apply automatic threshold to get the result in Figure -2 (a).
Step 5. Inverse the threshold to get the result in Figure -2 (b)
Step 6. coloring the result of step 5 by RGB color. To get the Figures-3 (B-C-D)

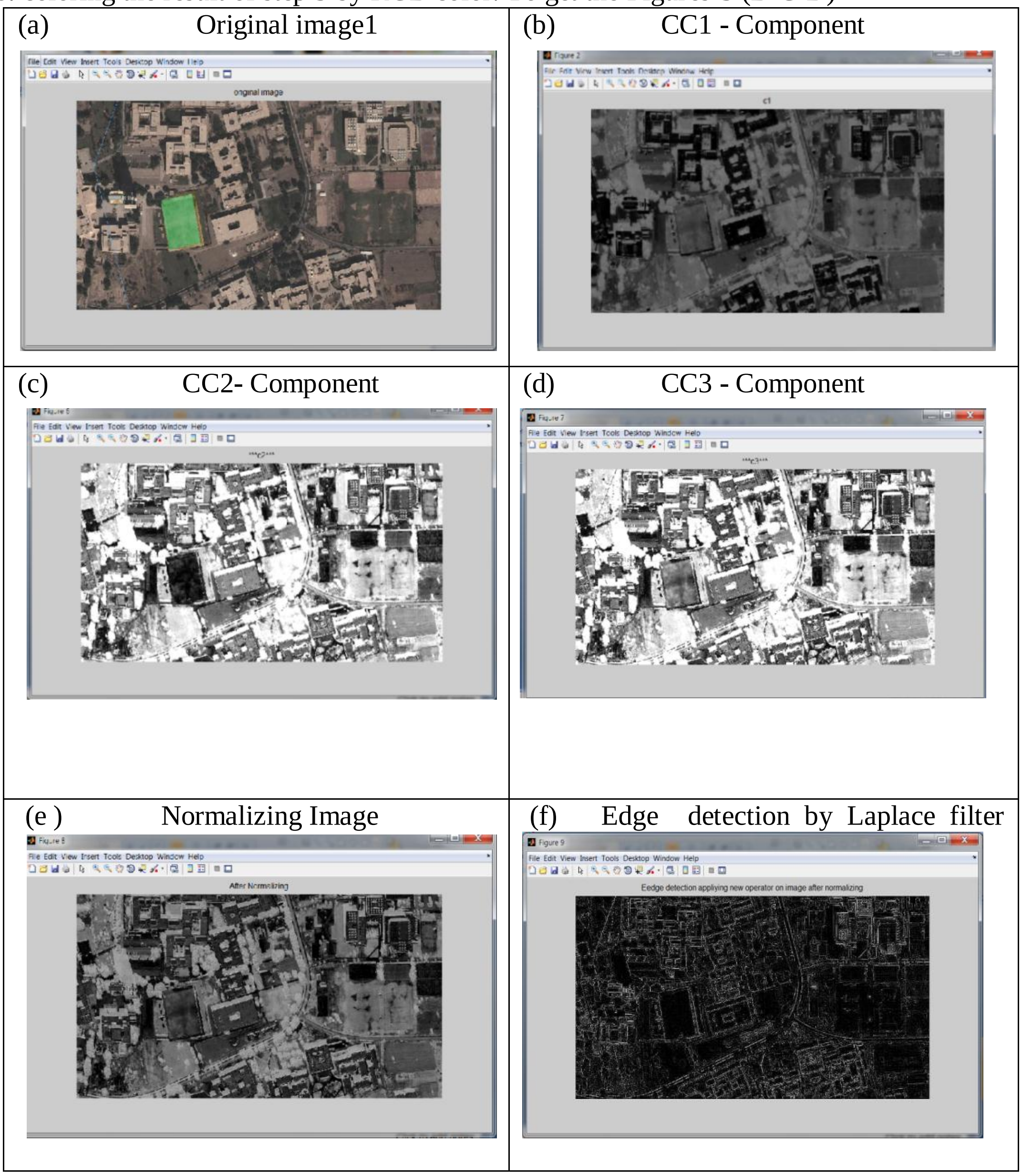

Figure 1- Illustrates the (a) original image (b) CC1- (c) CC2-(d) CC3 (e) the normalizing image (f) Edge detection by Laplace filter.

A B

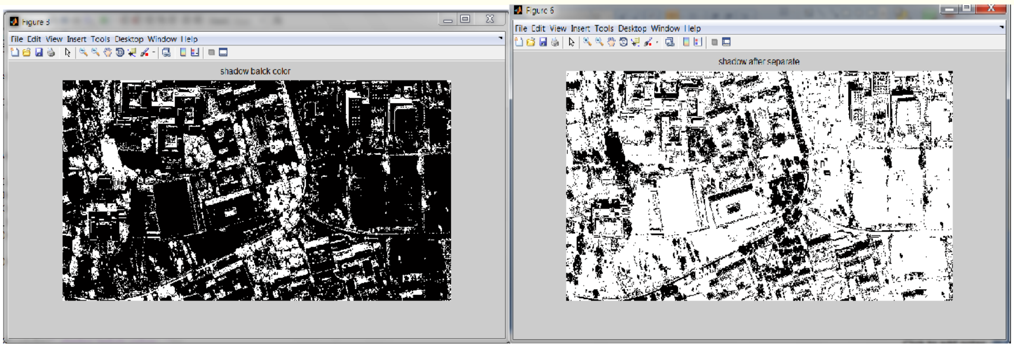

Figure 2- (A) shadow segmentation by Laplace filter, the shadow is white with black background, (B) Inverse the threshold makes the shadow is black with white background

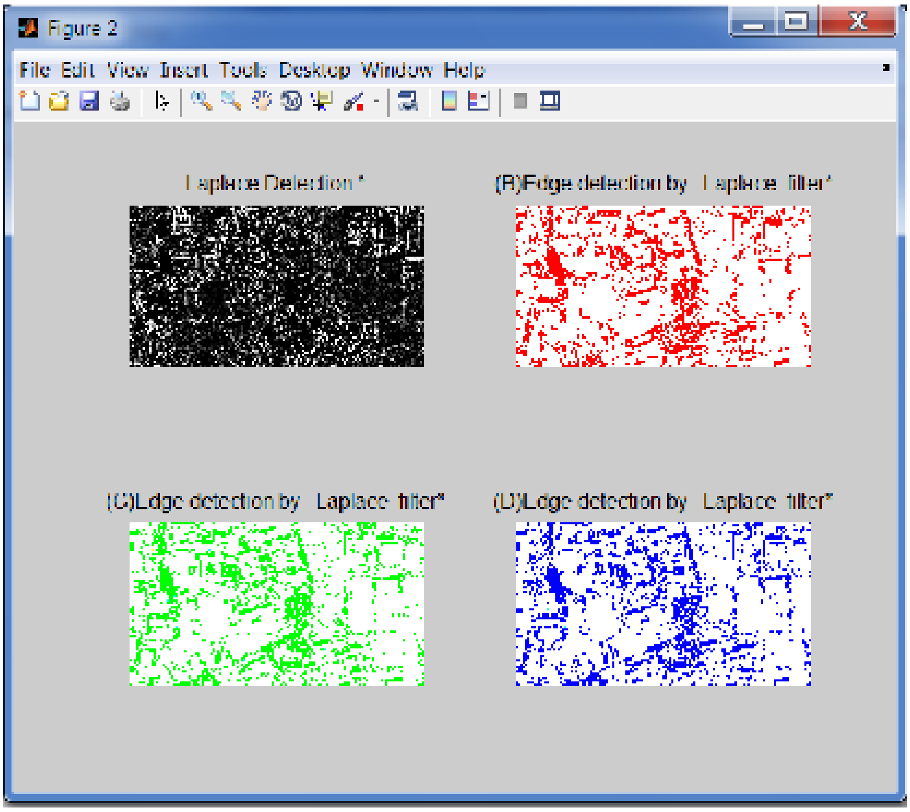

Figure 3- A- Shadow detection by first operator for image 1
B-Shadow segmentation by Red band
C-Shadow segmentation by Green band
D-Shadow segmentation by Blue band

Now apply the same upper steps, by using the 3x3 mask Kernel Laplace filter to get the result in Figure-4.

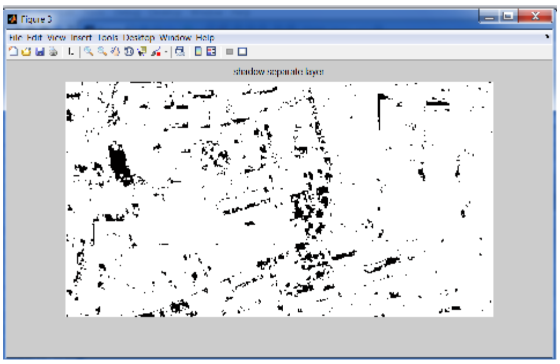

Figure 4- Segmentation shadow by Kernel filter, the shadow is black with white background

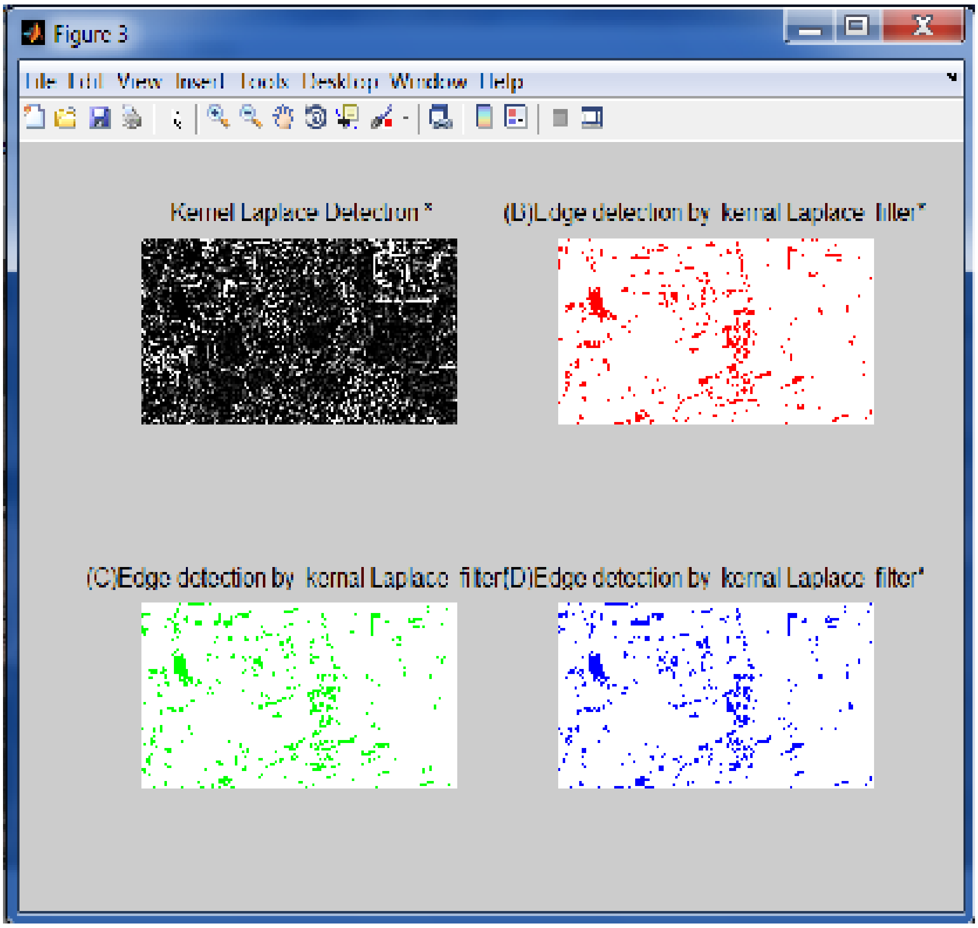

Figure 5 - A- shadow detection by second operator for image
B-Shadow segmentation by Red band
C- Shadow segmentation by Green band
D- Shadow segmentation by Blue band

Conclusion

A new shadow detection algorithm is proposed here, which takes use of the normalization of the *CC3* component and the propose Laplace, kernel Laplace operator . Experimental results show that the algorithm detects the shadow regions more accurately and efficiently, and reduces the error rate of detecting the non-shadows as shadows. Furthermore the method can better eliminate the confusing shadows, thus improving the overall efficiency of the shadow detection the detection by threshold has presented the good result of shadowing in high-resolution satellite imagery and methods to detect and discrimination all types of shadows. It was found that simplest algorithms providing the best chances for separating shadow from non-shadow regions in the imagery In this technique see, when employ the Laplace mask give the all edges for all bodies with shadow,while when employ the Kernel mask get on the shadow separating from edge bodies, moreover see, the results like the result when use morphology functions, that is because the Kernel contains negative values, make the image is smooth and remove the redundant pixels.

References:

1. Yan Chen, Kaimin Sun, Zongjian Lin. **2011**. Measures of Information in Remote SensingImagery. *Journal of Computational Information Systems*, 7(5), pp: 1648-1654.
2. Paul M. Dare. **2005**. Shadow analysis in high-resolution satellite imagery of urban areas. *Photogrammetric Engineering and Remote Sensing*, 71(2), pp: 169-177.
3. Y. Li, P. Gong, T. Sasagawa. **2005.** Integrated shadow removal based on photogrammetry and image analysis. *International Journal of Remote Sensing*, 26(18), pp: 3911-3929.
4. Elena Salvador, Andrea Cavallaro, Touradj Ebrahimii. **2001**. *Shadow identification and Classification using invariant color models*. In IEEE International Conference on Acoustics, Speech and Signal Processing, 3, pp: 1545-1548.

5. Jianguo JIANG, Yuan TIAN, Mifeng WANG, Yingchun ZHENG.**2013**.*Journal of Computational Information Systems* 9(10), pp:3783–3790.
6. Qirong ZHANG, Zhongshi H.E. **2010.** The Two-dimensional Bidirectional Inverse Laplacian Margin Maximum Criterion for Face Recognition. *Journal of Computational Information Systems*, 6(4), pp: 1101-1109.