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Full Length Research Paper

A new method for moving object detection using variable resolution bionic compound eyes

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The compound eyes of insect are highly optimized for the task of visual acquisition of relevant information from the environment, such as moving object detection. These have attracted the attention of many researchers in recent years. The advantages of compound eyes are illustrated in this paper in relation to other approaches in moving object detection. The paper describes the imaging mechanism for the compound eyes, and we also describe the process of multi-resolution imaging. An image filter with variable resolution is discussed and we propose a new method for moving object detection using variable resolution double-level contours. Firstly, there is the contour detection which occurs in the lowest resolution images. When this is complete, texture gradient computation is performed which carries out contour segmentation in the high resolution image acquired by the single eye. Finally, a Geodesic Active Contour model for texture boundary detection is applied from which the moving target is recognized. The results in this paper show that this method has good potential as a solution for moving object detection problems.

Key words: Moving object detection, bionic compound eyes, variable resolution, double-level contours.

INTRODUCTION

Moving object detection has always been a significant research topic in temporal image analysis and continues to be at present. Using a common camera with single lens imaging couple with the constraint of the photographable screen and the expression of plane image, one has to transform the actual spatial information from three-dimension to two-dimension. At the same time, we need excellent image handling ability to protect high frequency details of the image. When performing moving object detection on a computer, we have to transform the two-dimensional information to three-dimensional characteristics to ensure the reappearance of the actual object. This “3-2-3” dimensional conversion has a large amount of calculation, poor real-time performance and bad precision. All of these factors combine to hinder the development of moving object detection software. In light of this, many researchers begin to turn their attention to a new method for image acquisition. In Hong et al. (2010), the authors use infrared image technology while Yang detect objects using synthetic aperture radar (SAR) images generated by a multi-satellite radar system (Hong et al., 2010; Yang et al., 2009). These new image acquisition approaches bring with them the need to develop new and efficient methods for processing the imagery.

While these forms of image acquisition are important in this paper, we describe the use of the variable resolution bionic compound eyes for this task. Some insects such as dragonflies and honeybees have compound eyes and they provide motivation for this work (Geurten et al., 2007). Insect compound eyes have some very unique advantages that can be applied to the problem of moving object detection. The resolution of compound eyes is far lower than that of human eyes. However the low-resolution image corresponds well to the limited processing power of insect brain. Compound eyes with small size, light weight and large viewing field, are very sensitive to moving objects. The compound eyes can detect fast moving objects with little outline information even when the object is in a wide area. They can detect moving objects quickly with little outline information from a

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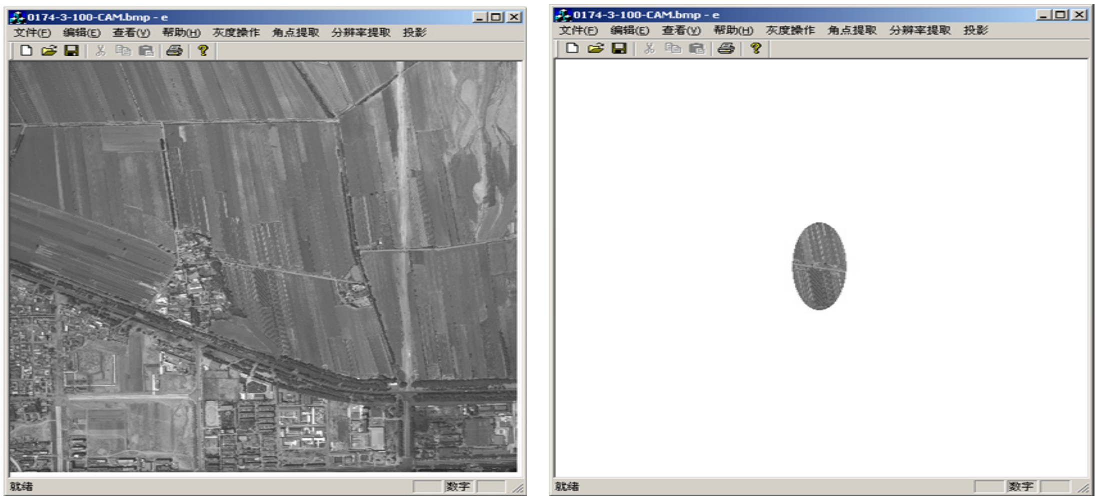


Figure 1. Screenshot of ommatidium imaging on a remotely sensed image from an unmanned aerial vehicle.

wide-area. Contour detection and variable resolution are probably the two most important characteristics of compound eyes. This paper follows from the research work that was described in a paper delivered at the 18th International Conference on Geoinformatics (Sun et al., 2010). This paper extends this work. Here we have analyzed the mechanisms by which insects detect moving objects using variable resolution compound eyes. Based on this analysis we propose a new method for moving object detection using this mechanism.

IMAGING MECHANISM OF OMMATIDIUM

The compound eyes of insects, mantis, shrimp and millipedes composed of units called ommatidia (Dan and Almut, 2007). The advantage of compound eyes relies on its internal structure (Ki-Hun et al., 2006). Compound eyes comprised of thousands or even ten of thousands of small eyes and each ommatidium have its own imaging system. Several authors show that there are two independent channels in compound eyes: one is called as “large field system” and the other is called “small field system”. The large field system detects global motion and small one detects moving targets accurately (Schiff et al., 1985). The advantages of compound eyes lie in their variable resolution imaging and contour detection.

Based on the structure of compound eyes, we have illustrated that the projection from actual objects to a single ommatidium is conic projection. We have developed a moving object detection software program that is connected to bionic compound eyes. As an example, we show a real remotely sensed image from our unmanned aerial vehicle. The image has been acquired in China and is shown as a projected scene in Figure 1. Also, it obtains the elliptical image shown in the bottom of Figure 1. In order to get better ommatidium image, we can properly select the ellipse region.

COMPOUND EYES MULTI-RESOLUTION IMAGING

The small eyes belonging to compound eyes are not evenly distributed (Figure 2). They are concentrated in certain regions and then scattered in other regions (Michael, 1997). These small eyes with low resolution in sparse areas can detect changes in motion, while only requiring a small amount of data. Small eyes with high resolution in dense areas can accurately identify objects. This is often referred to as the acute zone (Qiao et al., 2001). Although, compound eyes have large fields that are viewable, the acute zone lies in just a small part of it. So, in most cases the target does not directly appear in the area of the acute zone. When the other part of compound eyes find the signal of a moving object, the insect will quickly adjust the positioning of the acute zone to the goal object and then subsequently detect it.

According to ommatidium structure, different area detects different information. Re-sampling with an oval projection of a single ommatidium allows us to obtain the information within this oval region, because important information lies in the center of the oval region. However, the elliptical image center extraction is very well suited to the task of extraction of important information.

The elliptical region in plane scene is actually relatively small and it is generally only a few or a dozen pixels in size. Gravity is a more effective method to extract important information in elliptical image center. Gravity has less effect on smaller insects. During the process of gravity positioning image noise has a great influence on positional accuracy. Therefore we use the Gaussian-weighted center of gravity to improve the de-noising ability

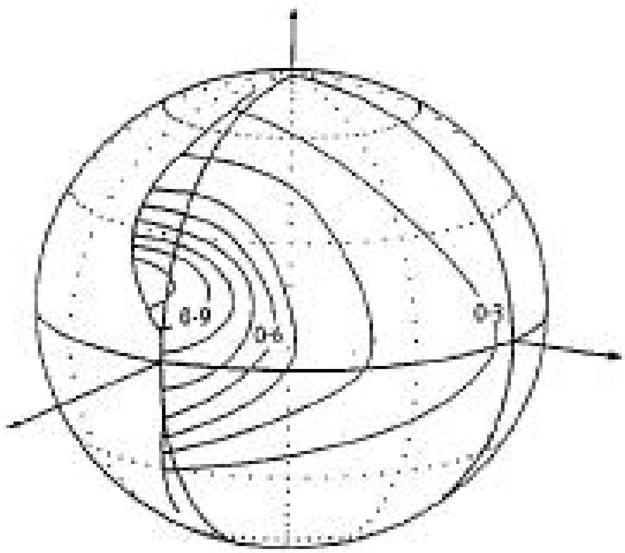


Figure 2. The uneven distribution of small eyes in a compound eye.

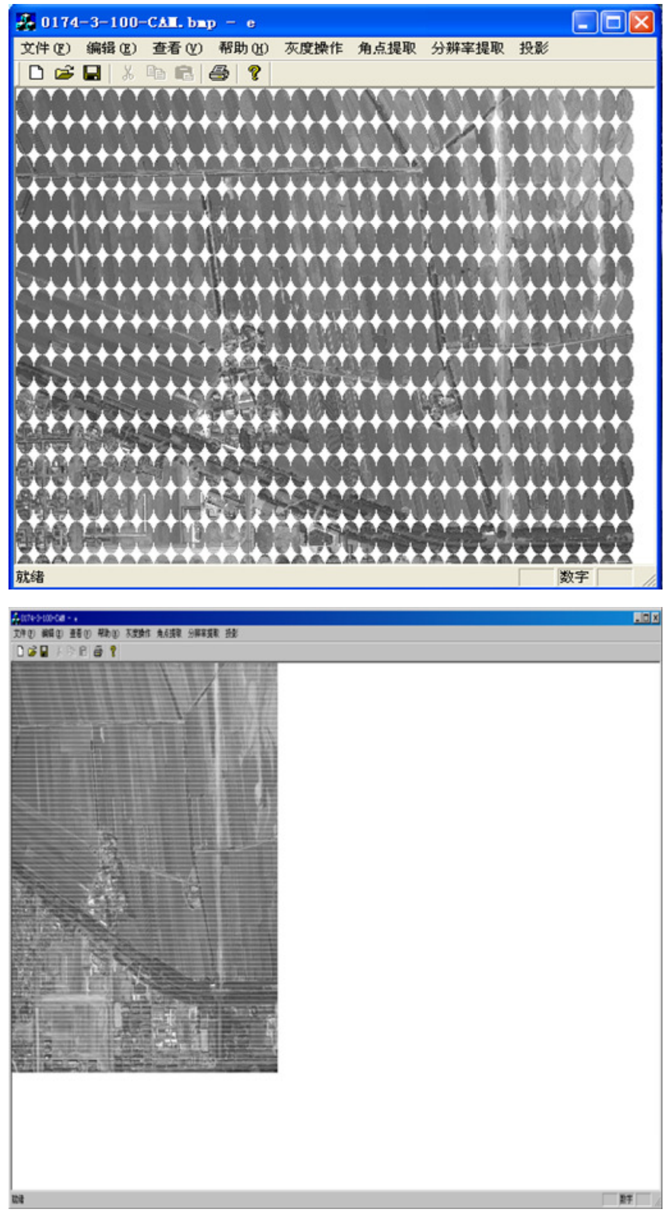


Figure 3. Multi-small eyes projected imaging.

(Van Assen et al., 2002). The equations are shown as follows:

$$x_0 = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} I(x,y)x}{\sum_{x=1}^{m}\sum_{y=1}^{n} I(x,y)}, \quad y_0 = \frac{\sum_{x=1}^{m}\sum_{y=1}^{n} I(x,y)y}{\sum_{x=1}^{m}\sum_{y=1}^{n} I(x,y)}$$

(1)

$$I(x,y) = \sum_{i=-\frac{k}{2}}^{\frac{k}{2}} \sum_{j=-\frac{k}{2}}^{\frac{k}{2}} F(x+i, y+j) g(i,j) \qquad (2)$$

During the gravity position, we calculate the image gray scale value after the Gaussian filter process, where $F(x,y)$ represents the gray value of output image, $g(x,y)$ are the Gaussian coefficients and $I(x,y)$ present image data after Gaussian random processing. According to the different sizes of the oval compound eyes image, we can get different resolution images in return. Figure 3 illustrates the process of compound eyes projected imaging, and shows the variable-resolution image obtained by re-sampling.

IMAGE FILTER WITH BIONIC COMPOUND EYES

According to the different distribution density of insect compound eyes, we use different types of filters to process the images. In scale space analysis, because the Gaussian function can accurately reflect the characteristics of the original image information, we filter image with different Gaussian filters to extract effective information (Bogdanova et al., 2007).

In compound eyes sensitive area, we use a smaller mask to process images with Gaussian filters, even without filtering in the region in order to save image details. In the relatively dense region, we process images with a larger Gaussian filter to save the edge information and omit details. The mask with Gaussian filter has several types, such as 3×3, 5×5 and 7×7.

Firstly, we use a matrix, with the same size of mask matrix, to construct a Gaussian-weighted vector (shown as Equation 3). Secondly we find a matrix region that includes the current pixel and neighborhood pixels. In the last step, we convolute the Gaussian-weighted vector and current pixel acquired from the density library of compound eyes to get gray value for the output image.

$$A = \sum_{i=1}^{n} \partial_i A_i \tag{3}$$

∂ is filter weighted coefficient and its value is 0 to 1. Based on a multi-resolution method, we can divide a large image into several sections. In different sections, we can process the section with different mathematics model based on our requirements. For complicated backgrounds, we may use several filters to emphasize their details and omit useless information. This method can improve image processing speed and facilitate further analysis of the image.

Due to the influence of camera characteristics and the environment, there will always be noise in the image when we capture objects. Successfully, removing noise is required in order to perform further object detection in the image. We then filter several compound eyes projection images with the Gaussian function, and extract effective information from these images. This approach can reduce detection of data and remove noise effectively. Based on the compound eyes of insects in the sampled images we can obtain a small view field image by sampling from the Gaussian pyramid method. After the analysis of these small images, we obtain the moving target contours in the image.

DESCRIPTION OF THE DETECTION ALGORITHM WITH VARIABLE RESOLUTION

At present, there are few study reports about bionic compound eyes moving object detection. In earlier work Sun et al. (2010) described the imaging mechanisms and models required for the detection of moving objects using bionic compound eyes. Qiao et al. (2001) are motivated by a simplified geometrical model of biological compound eye and have developed a new data processing technique, that is, direction quantization representation (DQR) for convex sets (Qiao et al., 2001). Gao (2009) proposed a method using bionic compound eyes in detecting moving target. Based on this method from Gao we improve and perfect it, and then proposed a new algorithm of moving object detection using variable resolution double-level contours. The algorithm belongs to one class of temporal-spatial algorithms that firstly detect objects and then split them.

Level 1: Contour detection

First of all, low-resolution a remotely sensed image is processed. We detected image edges with Canny method and extract the contours of the object (Ghosal, and Mehrota, 1994). We then calculate the minimum area matrix [m1:m2, n1:n2] that includes the contour.

Level 2: Contour segmentation with GAC texture gradient model

After this, the high-resolution remotely sensed image, with the same surface features, is processed. We operate on the image with the geodesic active contour (GAC) texture gradient model (Bo et al., 2010). We initially set the contour in the range of [m1:m2, n1:n2] and the contour gradually reduces to detect the moving target. The contour is set and is based on the formula in Equation 4.

$$E = \iint g\delta(u)|\nabla u| dxdy + c\iint [1 - H(u)] g dxdy \tag{4}$$

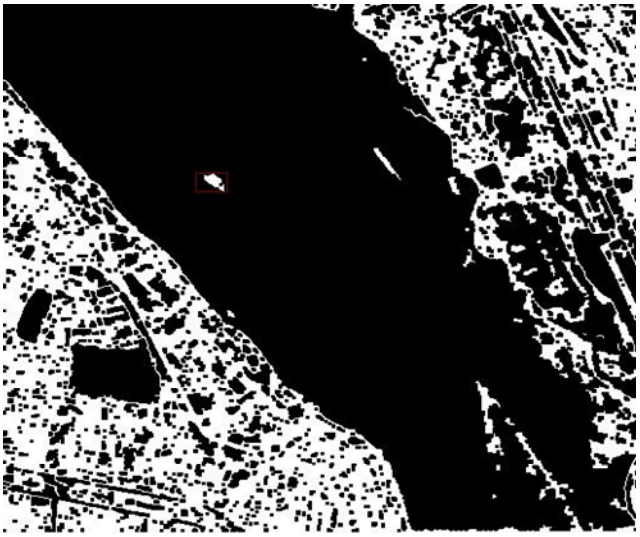
where E stands for a closed curve that minimizes the energy function. The GAC gradient flow model based on texture gradient is proposed and is shown in Equation 5.

$$\frac{\partial u}{\partial t} = \mu\left[\Delta u - div\left(\frac{\nabla u}{|\nabla u|}\right)\right] + \delta(u)\left[div\left(g(MTG)\frac{\nabla u}{|\nabla u|}\right) + cg\right] \tag{5}$$

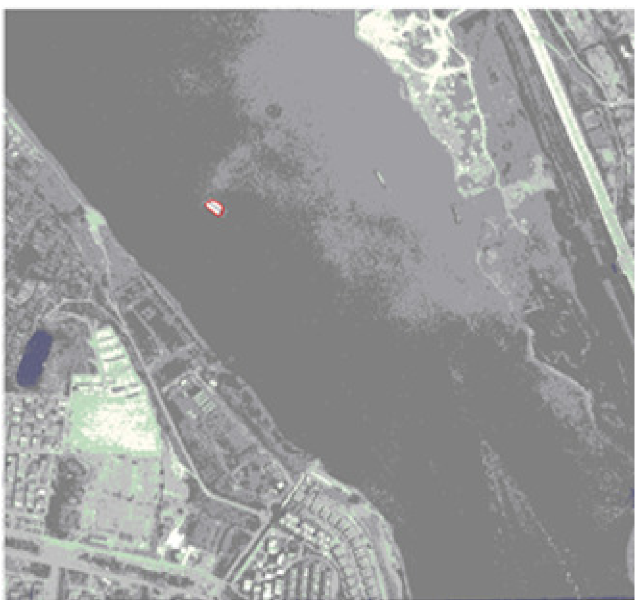
when the energy function achieves the minimum value, the corresponding curve is the split boundary. The parameter g is an arbitrary non-negative monotonically decreasing function. MTG stand for gradient of texture. $L(C)$ is the arc length closed curve, $\delta(x)$ can be expressed as the derivative of $H(x)$ and μ , c are constant.

RESULTS

The result of the application of our algorithmic approach is shown in Figure 4. The image is acquired by a real unmanned aerial vehicle (UAV) and is a photograph of a ship in the river. We first process the low-resolution images to extract the profile and to calculate the minimum area shown as a red rectangle in Figure 4a. Then, we set initial contour rectangle in Figure 4b and use GAC model to detect the object. It is clear in Figure 4b that the red contour stops at the edge of the ship. Finally, we detect the ship in the river channel. In the initial stages of extracting moving objects, only lower resolution images will satisfy our requirements. Since low-resolution images have small amounts of data, the running speed shows a significant improvement. The algorithm firstly, uses low-resolution images to obtain the profile. The algorithm then proceeds to process the high-resolution images. This allows the algorithm to compute the smaller area to accurately extract the target. We feel that this approach is very effective in improving the



a. contour extraction with low resolution image



b. accurate detection with high resolution image

Figure 4. Result of variable resolution detection algorithm.

detection efficiency of moving target detection.

Conclusion

In this paper, we proposed a new method for moving object detection using variable resolution double-level contours. Variable resolution and contour detection are the two main characteristics that insects with compound eyes display when detecting moving objects. The use of low resolution images proceeded by high resolution images provides advantages in terms of improved computational efficiency and data handling. The inspiration from the insect compound eye means that it is a strict requirement that the data storage and processing requirements are not excessive. We described our algorithmic implementation of this approach for the processing of remotely sensed images from an unmanned aerial vehicle. We feel that the detection results are very promising. In future work we shall investigate the application of this approach to other types of moving targets: cars, humans, etc. This will also involve the exploration of the potential real-world applications of this work.

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