Sensors & Transducers, Vol. 183, Issue 12, December 2014, pp. 172-176

Sensors & Transducers

http://www.sensorsportal.com

Remote Sensing Dynamic Monitoring of Biological Invasive Species Based on Adaptive PCNN and Improved C-V Model

[1] PENG Gang, [1*] JIA Zhen-Hong, [1] QIN Xi-Zhong, [2] YANG Jie, [3] Nikola Kasabov

[1] College of Information Science and Engineering, Xinjiang University, Urumqi 830046, China
[2] Institute of Image Processing and Pattern Recognition Shanghai Jiao Tong University, Shanghai 200400, China
[3] Knowledge Engineering and Discovery Research Institute, Auckland University of Technology, Auckland 1020, New Zealand
[1] Tel.: 13659936702
E-mail: 397589141@qq.com, jzhh@xju.edu.cn

Received: 27 October 2014 /Accepted: 28 November 2014 /Published: 31 December 2014

Abstract: Biological species invasion problem bring serious damage to the ecosystem, and have become one of the six major enviromental problems that affect the future economic development, also have become one of the hot topic in domestic and foreign scholars. Remote sensing technology has been successfully used in the investigation of coastal zone resources, dynamic monitoring of the resources and environment, and other fields. It will cite a new remote sensing image change detection algorithm based on adaptive pulse coupled neural network (PCNN) and improved C-V model, for remote sensing dynamic monitoring of biological species invasion. The experimental results show that the algorithm is effective in the test results of biological species invasions. *Copyright © 2014 IFSA Publishing, S. L.*

Keywords: Biological species invasion, Adaptive pulse coupled neural network, Improved C-V model, Remote sensing dynamic monitoring.

1. Introductions

Biological species invasion problem as an important component of global change is considered to be one of the most difficult environmental problems in the current. Once the alien species invasion success, such as the successful invasion of Spartina alterniflora Loisel, tend to reduce the invaded region's biodiversity, change the original structure and function of the local ecosystem, eventually led to the degradation of ecosystem, and loss of ecosystem functions and services, bring the global environmental problems, economic development, and even the human body health immeasurable losses. Therefore, in order to effectively detect and management, reasonable development and utilization of alien species invasion, turn bane into a boon, need for invasion species population spatial distribution and dynamic change in real-time monitoring [1-3].

At present, the remote sensing image change detection technology has become the key technologies of new generation intelligent earth observation satellite, has been successfully used in urban planning and layout, land cover/use monitoring, military surveillance, disaster assessment, etc. The technology to a certain extent, makes up for the big interval of time and space of traditional monitoring methods, laborious and difficult to have overall and common sense and the defects of high cost and difficult [4-6]. In order to better dynamic monitoring of biological invasions, more effectively reduce the harm brought by biological invasion, this article will cite a new remote sensing image change detection method with the combination of adaptive pulse coupled neural network image fusion algorithm and the improved C-V model segmentation algorithm on biological invasions dynamic monitoring problem, ultimately achieve the desired monitoring purposes. The experimental results show that the algorithm is effective in the test results of biological invasions.

2. The Dangers of Alien Species Invasion and Cause Problems

According to statistics, at present our country found that at least 188 species of invasive plants, 81 species of invasive animals, 19 species invading microbes; released by the world conservation union the world's 100 kinds of the most dangerous invasive species, found 50 species in our country, causing serious damage to the agriculture, forestry, water conservancy, animal husbandry [7, 8].

Estuarine wetlands and coastal tidal flats wetlands is the highest per unit area ecosystem service value ecosystem types, but it is also a type of environment which is very easy to be invaded by alien species. Spartina alterniflora Loisel is native to the Atlantic coast and the Gulf of Mexico, because of intentionally or unintentionally into, has now become one of the most successful invasion plants of the coastal salt marsh ecosystem. Invasive species cause a series of problems, such as, directly reduce the number of species, indirectly reduce the number of species depends on the local species to survive; change local ecosystem and landscape, reduce the ability of control and resistance on fire and pests, lower the capability of soil conservation and nutrition to improve, reduce the ability of moisture to maintain and water quality to improve, ultimately reduce biodiversity protective capability [9].

According to the above analysis, in order to better dynamic monitoring of biological invasions, more effectively reduce the harm brought by biological invasion, it is necessary to adopt the new remote sensing image change detection method combining adaptive pulse coupled neural network image fusion algorithm with improved C-V model segmentation algorithm.

3. Theoretical Models and Algorithm

3.1. Theoretical Model

This paper cites an unsupervised change detection algorithm in remote sensing images based on adaptive pulse coupled neural network (PCNN) and improved Chan-Vese model.

The new algorithm flow chart is shown in Fig. 1. Firstly, the adaptive PCNN algorithm fuses the results of the subtraction method [10] and the ratio method [10] to obtain complementary information [11]; then, the image segmentation algorithm based on improved C-V model separates the change regions from the merged difference image [12]. This method can overcome the shortage of the threshold method which is difficult to get accurate result when the difference between changed area and unchanged area is inconspicuous.

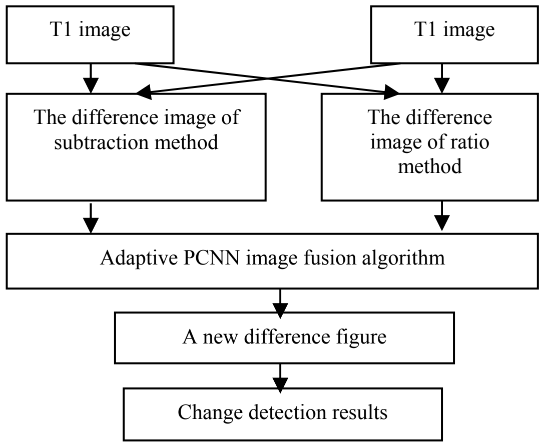


Fig. 1. Algorithm flow chart.

As shown in Fig. 1, this paper proposes an unsupervised change detection algorithm consists of three main steps: 1) use the subtraction method and the ratio method for difference image; 2) adopt adaptive PCNN image fusion algorithm to construct a new difference figure; 3) improved C-V model separates the change regions from the merged difference image.

3.2. Implementation Algorithm

According to the above theory model, the algorithm implementation steps are as follows:

Step 1: Read the two remote sensing images not at the same time phase needed for processing, using the subtraction method and the ratio method to gain the corresponding difference image of subtraction method A and difference image of ratio method B [10].

$$A = \left| I_2 - I_1 \right|, \tag{1}$$

$$B = I_2 / I_1, \tag{2}$$

Step 2: Normalize the two difference images A and B, respectively denote as A' and B'. Order A' as the feedback input to each neuron of the first neural network PCNN1 and the second neural network PCNN2; Order B' as the feedback input to each neuron of the third neural network PCNN3 and the fourth neural network PCNN4;

Step 3: Calculate the EOL of each pixel in both A' and B', and respectively order as the connection strength value of corresponding neurons in the neural network PCNN1 and PCNN3; calculate the SD of each pixel in both A' and B', and respectively order as the connection strength value of corresponding neurons in the neural network PCNN2 and PCNN4; Order $L_{ij}(0)=U_{ij}(0)=T_{ij}(0)=Y_{ij}(0)$, $\theta_{ij}(0)=1$;

The EOL and SD of the pixel point (x,y) defined as [11]:

$$EOL=\sum_{(u,v)\in\omega}(f_{uu}+f_{vv})^2, \tag{3}$$

$$SD=\sqrt{\frac{1}{l^2}\sum_{(u,v)\in\omega}\left[f(u,v)-f^{\bullet}\right]}, \tag{4}$$

Among them

$$\begin{aligned}f_{uu}+f_{vv}&=-f(u-1,v-1)-4f(u-1,v)-f(u-1,v+1)\\&-4f(u,v-1)+20f(u,v)-4f(u,v+1)-f(u+1.v-1),\\&-4f(u+1,v)-f(u+1,v+1)\end{aligned} \tag{5}$$

where $f(u,v)$ is the pixel values of point (u,v); ω is a $l\times l$ window with (x,y) as the center of the window; l is an odd number; generally choose 3 or 5; $f^{\bullet}$ is the average of all the pixel in the window. Weighted function is defined as [11]:

$$f^{\circ}=\omega_1 f_1+\omega_2 f_2, \tag{6}$$

where f° is the new ignition map of the image; f_1 and f_2 respectively are the corresponding ignition map of EOL and SD; $\omega_1+\omega_2=1$, $\omega_i>0(i=1,2)$, in this paper, taking $\omega_1=\omega_2=0.5$.

Step 4: Set $O_i\ (i=1,2,3,4)$ as the output of the neural network $PCNNi$, by Eq. (5) to get the corresponding new ignition map O_A and O_B of A and B, $O_A=\omega_1 O_1+\omega_2 O_2$, $O_B=\omega_1 O_3+\omega_2 O_4$;

Step5: use the rules show in Eq. (7) to select the fusion coefficient, gain the merged difference figure $F(i,j)$.

$$\begin{cases}F(i,j)=A(i,j),\text{if} & O_A(i,j)>O_B(i,j)\\ F(i,j)=B(i,j),\text{if} & O_A(i,j)\le O_B(i,j)\end{cases}, \tag{1}$$

Step 6: Normalize the image $F(i,j)$ and filter it by a 3 * 3 median filter to erase the noise; Do morphological close operation to erase the small holes and then fill the larger holes in the image, convert it to binary image;

Step 7: Label all the four connected regions of the image, then do morphological dilate operator to link the broken edge and extract the first k biggest connected regions (maximum pixels); apply the canny operator on the extracted regions to get the initial curve ϕ_1 and ϕ_2.

Step 8: Compute c00, c01, c10, c11 by Eq. (8). c_{ij} as the mean vector of each phase or class, can be as follows:

$$\begin{cases}c_{11}=\dfrac{\int_\Omega u_0(x,y)H(\phi_1)H(\phi_2)dxdy}{\int_\Omega H(\phi_1)H(\phi_2)dxdy}\\ c_{12}=\dfrac{\int_\Omega u_0(x,y)H(\phi_1)(1-H(\phi_2))dxdy}{\int_\Omega H(\phi_1)(1-H(\phi_2))dxdy}\\ c_{01}=\dfrac{\int_\Omega u_0(x,y)(1-H(\phi_1))H(\phi_2)dxdy}{\int_\Omega(1-H(\phi_1))H(\phi_2)dxdy}\\ c_{00}=\dfrac{\int_\Omega u_0(x,y)(1-H(\phi_1))(1-H(\phi_2))dxdy}{\int_\Omega(1-H(\phi_1))(1-H(\phi_2))dxdy}\end{cases}, \tag{1}$$

Adding gradient information to the traditional model, to accelerate the edge orientation, to eliminate the interference of small area. In Eq. (8), u_0 will be changed into:

$$u_0=a_1u_0+a_2g, \tag{9}$$

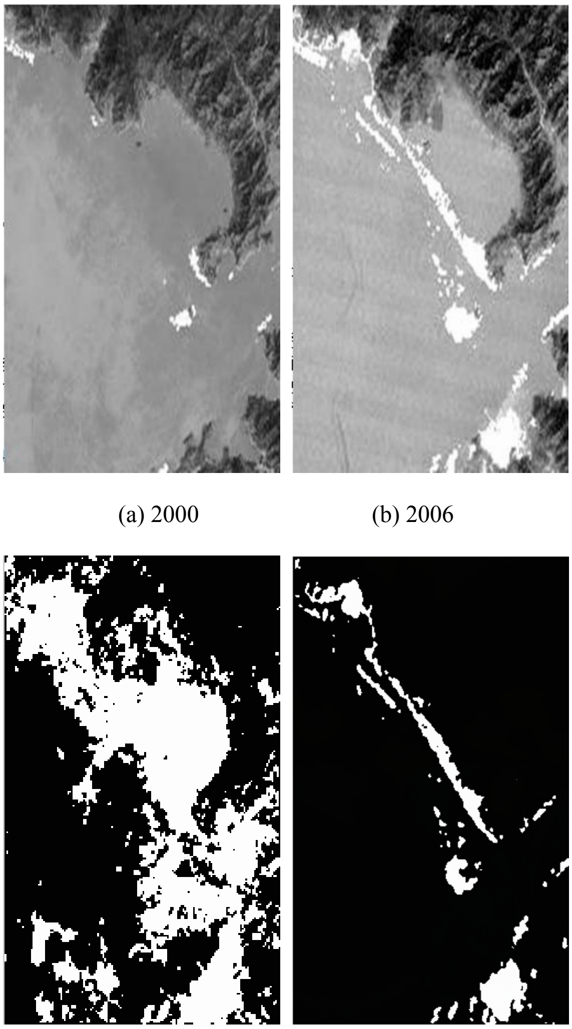
Step 9: Solve the partial differential equation in φ using central difference.

Step 10: Repeat the process in steps 8 and 9 until the terminating criteria are met, then output the final segmentation result, also the change detection results.

4. Experiments and results

In order to test the performance of the new method in the dynamic monitoring of biological invasions, choose the distribution information of Spartina alterniflora Loisel in LuoHai bay area from different periods of satellite image data as the experimental data [13]. Fig. 2 (a) is the remote sensing information of Spartina alterniflora Loisel in LuoHai bay area in 2000, Fig. 2 (b) is the remote sensing information of Spartina alterniflora Loisel in Luo Hai bay area in 2006. Black in Fig. 2 (a) and Fig. 2 (b) is the land; gray is waters and tidal flats; white is Spartina alterniflora Loisel.

In order to better illustrate the performance of the new method, comparing with the NSCT-FCM method [14].



(a) 2000 (b) 2006

(c)NSCT-FCM (d) new method

Fig. 2. The remote sensing information of Spartina alterniflora Loisel in LuoHai bay area.

From Fig. 2 can be qualitatively known: NSCT-FCM method almost no way to accurately detect the change information of Spartina alterniflora Loisel, this article cited the new algorithm in dynamic monitoring of biological invasions have certain breakthrough. From Table 1, the run time of new method is faster than NSCT-FCM method.

Table 1. Run time of the two methods.

Methods	Run Time(s)
NSCT-FCM	34. 6335
New method	20. 3452

As you can see, this method is basically accurately detect the change information of Spartina alterniflora Loisel. Compared with traditional monitoring methods, this method can not only save manpower and material resources, also can more quickly and accurately provide information about the spread information of the invasive species, provide a scientific basis for better protect the ecological environment and biodiversity [15].

5. Conclusions

Research results show that the use of advanced remote sensing image change detection technique, can more effectively to do real-time testing and research on the spatial distribution and dynamic change of invasive species, more effectively reduce the harm brought by biological invasion. The referenced new method in this paper makes full use of the adaptive PCNN image fusion algorithm to realize the complementary information of difference image, and image segmentation algorithm based on improved C-V model overcomes the deficiency of threshold value method, thus achieves better change detection results. But due to the lack of comprehensive knowledge of invasive species at the present, the basis is relatively weak, so the study on invasive species control techniques and measures to prevent is less. So keep learning the comprehensive knowledge of invasive species, also strengthen the research on invasive species of remote sensing dynamic monitoring.

Acknowledgements

The research work was supported by the ministry of education to promote cooperation with the large areas of scientific research and high-level personnel training project No. 20101595.

References

[1]. Zhang Ying, Lu Jianbo, Progress on monitoring of two invasive Species Smooth Cordgrass (Spartina alterniflora) and Water Hyacinth (Eichhornia crassipes) by remote sensing, *Bulletin of Science and Technology*, Vol. 26, Issue 1, 2010, pp. 130-135.

[2]. Janie C. Civille, Stuart D. Smith, Extracting complex data from estuarine imagery: Spartina alterniflora in Willapa Bay, WA, in *Proceeding of the Ecological Society of America Annual Meeting Abstracts*, 2002, pp. 87-99.

[3]. Xi Cai, Guang Han, Jinkuan Wang, Image fusion method based on directional contrast-inspired unit-linking pulse coupled neural networks in contourlet domain, *Journal of Computers*, Vol. 8, Issue 6, 2013, pp. 1544-1551.

[4]. Hai Fang, Quan Zhou, Kaijia Li, Robust watermarking scheme for multispectral images using discrete wavelet transform and Tucker decomposition, *Journal of Computers*, Vol. 8, Issue 11, 2013, pp. 2844-2850.

[5]. C. Idawo, G. Laneve, Hyperspectral analysis of multispectral ETM+data: SMA using spectral field measurements in mapping of emergent macrophytes,

in *Proceedings of the Geoscience and Remote Sensing Symposium*, Vol. 1, Issue 3, 2004, pp. 246-249.

[6]. Liu Chunxing, Wen Junbao, Luo Youqing, The history and revelation of the alien species invasion, *Journal of Dialectics of Nature*, Vol. 32, No. 189, 2010, pp. 42-47.

[7]. Xu Haigen, Qiang Sheng, Han Zhengmin, et al, The distribution and introduction pathway of alien invasive species in China, *Biodiversity Science*, Vol. 25, Issue 6, 2006, pp. 626-638.

[8]. M. Williamson, A. Filter, The varying success of invaders, *Ecology*, Vol. 77, Issue 5, 1996, pp. 1661-1666.

[9]. Fan Xiuqin, Zhang Xiongshuai, Shu Jingchang, Invasion by alien species in China, control methods and new directions of research, *Hebei Journal of Forestry and Orchard Reseach*, Vol. 26, Issue 2, 2011, pp. 195-198.

[10]. Xu Xiaoqin, Shen Jiajie, Wu Youfeng, et al, Aviation remote sensing image change detection, *Geospatial Information*, Vol. 9, Issue 2, 2011, pp. 67-68.

[11]. Li Meili, Li Yanjun, Wang Hongmei, et al, A new image fusion algorithm based on adaptive PCNN, *Journal of Optoelectronics Laser*, Vol. 21, Issue 5, 2010, pp. 779-782.

[12]. Yi Xin, Jia Zhenhong, Qin Xizhong, et al, A kind of image segmentation based on multiphase level set, *Laser Journal*, Vol. 34, Issue 6, 2013, pp. 37-39.

[13]. Pan Weihua, Chen Gujin, Li Lichun, et al, Remote sensing dynamic monitoring of Spartina alterniflora Loisel in LuoHai bay area, *Chinese Agricultural Science Bulletin*, Vol. 25, Issue 13, 2009, pp. 216-219.

[14]. Li Qingsong, Qin Xizhong, Jia Zhenhong, et al, An unsupervised change detection of SAR images based on NSCT and FCM clustering, *Laser Journal*, Vol. 34, Issue 4, 2013, pp. 21-22.

[15]. R. D. Macleod, A quantitative comparison of change detection algorithms for monitoring eelgrass from remotely sensed data, *PE&RS*, Vol. 64, Issue 3, 1998, pp. 207-216.