BIOSYSTEMS ENGINEERING 169 (2018) 139–148

Available online at www.sciencedirect.com

ScienceDirect

journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Research on insect pest image detection and recognition based on bio-inspired methods

Limiao Deng [a,b], Yanjiang Wang [a,*], Zhongzhi Han [b], Renshi Yu [b]

[a] College of Information and Control Engineering, China University of Petroleum, Qingdao 266580, China
[b] College of Science and Information, Qingdao Agricultural University, Qingdao 266109, China

ARTICLE INFO

Article history:
Received 29 March 2017
Received in revised form
22 January 2018
Accepted 14 February 2018

Keywords:
Pest recognition
Invariant features
HMAX model
Saliency map
Bio-inspired

Insect pest recognition and detection are vital for food security, a stable agricultural economy and quality of life. To realise rapid detection and recognition of insect pests, methods inspired by human visual system were proposed in this paper. Inspired by human visual attention, Saliency Using Natural statistics model (SUN) was used to generate saliency maps and detect region of interest (ROI) in a pest image. To extract the invariant features for representing the pest appearance, we extended the bio-inspired Hierarchical Model and X (HMAX) model in the following ways. Scale Invariant Feature Transform (SIFT) was integrated into the HMAX model to increase the invariance to rotational changes. Meanwhile, Non-negative Sparse Coding (NNSC) is used to simulate the simple cell responses. Moreover, invariant texture features were extracted based on Local Configuration Pattern (LCP) algorithm. Finally, the extracted features were fed to Support Vector Machines (SVM) for recognition. Experimental results demonstrated that the proposed method had an advantage over the compared methods: HMAX, Sparse Coding and Natural Input Memory with Bayesian Likelihood Estimation (NIMBLE), and was comparable to the Deep Convolutional Network. The proposed method has achieved a good result with a recognition rate of 85.5% and could effectively recognise insect pest under complex environments. The proposed method has provided a new approach for insect pest detection and recognition.

1. Introduction

The occurrence of insect pests can have significant negative effects on the quality and quantity of agricultural products. If the pests are not detected in time, there will be an increase in food insecurity (Faithpraise & Chatwin, 2013). Pests are usually detected manually by agriculture experts. This task requires continuous monitoring of the crops, and is subjective, labour intensive, and expensive for large farms (Al Hiary, Bani Ahmad, Reyalat, Braik, & ALRahamneh, 2011). The rapid development of image processing technology has provided a new way for pest recognition, which can not only greatly improve the recognition efficiency, but also solve problems such as lack of agriculture experts and poor objectivity (Hu, Song, Zhang, Xie, & Li, 2014).

In recent years, lots of researches have been made on pest detection and recognition based on image processing technology. Gassoumi, Prasad, and Ellington (2000) used a neural

* Corresponding author.
E-mail address: yjwang@upc.edu.cn (Y. Wang).
https://doi.org/10.1016/j.biosystemseng.2018.02.008
1537-5110/

Nomenclature

Abbreviations

ICA	Independent Component Analysis
LBP	Local Binary Pattern
LCP	Local Configuration Pattern
MiC	Microscopic configuration
NNSC	Non-negative Sparse Coding
PCA	Principal Component Analysis
ROI	Region of Interest
SIFT	Scale Invariant Feature Transform
SUN	Saliency Using Natural statistics
SVM	Support Vector Machines

Variable symbols

B	Blue channel of a colour image
C	Regularisation parameter of sparse coding
D	Number of C1 image patches
f	ICA feature vector
G	Green channel of a colour image
M	Number of C1 image patches
N	Number of image templates
R	Red channel of a colour image
s	Scale parameter of generated Gaussian distribution
T	Set of image templates
X	Set of C1 image patches
x	Horizontal ordinate of a pixel
y	Vertical coordinate of a pixel
α	Regularisation parameter of sparse coding
Γ	Gamma function
γ	Spatial aspect ratio of Gabor filter
θ	Orientation of Gabor filter
λ	Wavelength of Gabor filter
σ	Standard deviation of Gabor filter
ϕ	Shape parameter of generated Gaussian distribution

network-based approach for insect classification in cotton ecosystems, and achieved an accuracy of 90%. Li, Xia, and Lee (2009) proposed a new pest detection method based on stereo vision to get the location information of the pest. Faithpraise and Chatwin (2013) proposed an automatic method for pest detection and recognition using k-means clustering algorithm and correspondence filters. Boissard, Martin, and Moisan (2008) presented a cognitive vision system to detect white flies in greenhouse crops, and demonstrated that automatic processing was reliable. Dey, Bhoumik, and Dey (2016) presented an automated approach for detecting white fly pests from leaf images and used the k-means clustering method to segment pests from infected leaves. Roldan-Serrato, Baydyk, Kussul, Escalante-Estrada, and Rodriguez (2015) developed a recognition system based on a special neural network – the random subspace classifier – for the Colorado potato beetle and obtained a recognition rate of 85%. Wen, Wu, Hu, and Pan (2015) proposed the IpSDAE architecture to build a deep neural network for moth identification and achieved a good identification accuracy of 96.9%. Cheng, Zhang, Chen, Wu, and Yue (2017) proposed a pest identification method using deep residual learning and achieved an accuracy of 98.67% for 10 classes.

Despite great achievements on pest recognition in recent years, most researches were not performed in outdoor field environment, and were carried in highly controlled lab environments instead of using real-world scenes. However, in actual field conditions, complex environment, different viewpoints and poses impose great challenge for pest detection and recognition. Though some research involved automatic detection in natural environments, most concerned only one species or had high time complexity. Detecting pests rapidly and accurately and extracting features that are invariant to viewpoint, scale and lighting conditions is crucial for the recognition of crop pests.

Humans can recognise objects rapidly, no matter how complex the conditions are. This outstanding ability is supported by the visual system. Inspired by the research findings of cognitive neuroscience, some computational models have been proposed in recent years to model the human visual system. A well-known model, Hierarchical Model and X (HMAX) (Serre, Wolf, Bileschi, Riesenhuber, & Poggio, 2007) showed outstanding performance in object recognition tasks. Although HMAX shows good invariance to position and scale, it is sensitive to rotation. So this paper extended the HMAX by integrating Scale Invariant Feature Transform (SIFT) (Lowe, 2004) and Non-negative Sparse Coding (NNSC) into it, which was denoted as SIFT-HMAX model. First, the Saliency Using Natural statistics (SUN) model (Zhang, Tong, Marks, Shan, & Cottrell, 2008) was used to detect the pest and extract region of interests (ROIs). Then the SIFT-HMAX model and Local Configuration Pattern (LCP) algorithm were used to extract the invariant features. Finally, the extracted features were standardised and fed to a Support Vector Machine to perform recognition.

2. Materials and methods

2.1. Materials

We investigated a collection of ten categories of insect pests (mainly affecting tea plants), which are: *Locusta migratoria*, *Parasa lepida*, *Euproctis pseudoconspersa* Strand, *Empoasca flavescens*, *Spodoptera exigua*, *Chrysochus chinensis*, larva of *Laspeyresia pomonella*, larva of *S. exigua*, *Acrida cinerea*, and *L. pomonella*. Some of the sample images are presented in Fig. 1. Each category contained about 40–70 sample images as detailed in Table 1. Among these samples, some were collected from online resources (see Appendix), such as Insert Images, IPM images, Dave's Garden and so on. The others were taken outdoors using a digital Single Lens Reflex (SLR) camera, which have been uploaded to Mendeley Data, and the links are provided in the Appendix. The sample images show great variation in scale, position, viewpoint, lighting conditions and backgrounds.

2.2. Methods

The complete flowchart of our method is illustrated in Fig. 2. First SUN model was used to create the saliency map and