Available online at www.sciencedirect.com
ScienceDirect
journal homepage: www.elsevier.com/locate/issn/15375110

Research Paper

Pose estimation-dependent identification method for field moth images using deep learning architecture

Chenglu Wen [a], Daoxi Wu [a], Huosheng Hu [b], Wei Pan [a,*]

[a] Cognitive Science Department, Xiamen University, Xiamen 361005, China
[b] School of Computer Science & Electronic Engineering, University of Essex, Colchester CO4 3SQ, United Kingdom

ARTICLE INFO

Article history:
Received 24 October 2014
Received in revised form
10 January 2015
Accepted 1 June 2015
Published online 19 June 2015

Keywords:
Automated identification
Deep learning
Feature extraction
Field moth
Image segmentation

ABSTRACT

Due to the varieties of moth poses and cluttered background, traditional methods for automated identification of on-trap moths suffer problems of incomplete feature extraction and misidentification. A novel pose estimation-dependent automated identification method using deep learning architecture is proposed in this paper for on-trap field moth sample images. To deal with cluttered background and uneven illumination, two-level automated moth segmentation was created for separating moth sample images from each trap image. Moth pose was then estimated in terms of either top view or side view. Suitable combinations of texture, colour, shape and local features were extracted for further moth description. Finally, the improved pyramidal stacked de-noising auto-encoder (IpSDAE) architecture was proposed to build a deep neural network for moth identification. The experimental results on 762 field moth samples by 10-fold cross-validation achieved a good identification accuracy of 96.9%, and indicated that the deployment of the proposed pose estimation process is effective for automated moth identification.

1. Introduction

Integrated pest management (IPM) is an effective way for pest control, which is based on the presence of pest in the field rather than regular sprays. For example, moth pest control and monitoring work in the field are implemented by calculating the number of pests on traps, which are placed around the orchard by growers or IPM consultants. The pest control strategies are then developed based on the number of pests on the traps, population and distribution. Regular checking of traps involves a great number of traps spread out around the orchard, which is very time-consuming. The identification of the species of moth requires biological knowledge, and the spraying strategy needs to be developed quickly as some pests are emerging in a very short term. Automated insect identification and classification can improve the identification efficiency and

* Corresponding author.
E-mail addresses: clwen@xmu.edu.cn (C. Wen), 278034343@qq.com (D. Wu), hhu@essex.ac.uk (H. Hu), wpan@xmu.edu.cn (W. Pan).
http://dx.doi.org/10.1016/j.biosystemseng.2015.06.002

Nomenclature

Abbreviations

IpSDAE	Improved Pyramidal Stacked De-Noising Auto-Encoder
IPM	Integrated Pest Management
SSIM	Structural Similarity Index Similarity
GLCM	Gray Level Co-occurrence Matrix
HSV	Hue Saturation Value
LCH	Luminance Chroma Hue
RGB	Red Green Blue
AE	Auto-encoder
DAE	Denoising Auto-encoder
SDAE	Stacked Denoising Auto-encoder
pSDAE	Pyramidal Stacked Denoising Auto-encoder
BP	Back Propagation
SVM	Support Vector Machine
LRC	Logistic Regression Classifier
BayesNet	Bayes Network
RF	Random Forest
RBF	Radial Basis Function

Symbols

L	Left part of an insect image
R	Right part of an insect image
$l(L,R)$	The luminance component of Hessian matrix of SSIM index
$c(L,R)$	The contrast component of Hessian matrix of SSIM index
$s(L,R)$	The structure component of Hessian matrix of SSIM index
C_1	Stabilising parameter in $l(L,R)$
C_2	Stabilising parameter in $c(L,R)$
C_3	Stabilising parameter in $s(L,R)$
μ_L	Mean intensity of L
μ_R	Mean intensity of R
σ_L	Standard deviation L
σ_R	Standard deviation R
σ_{LR}	Covariance of L and R
k_1	Stabilising parameter in C_1
k_2	Stabilising parameter in C_2
$h(x,y)$	The mean squared error of the i's iteration epoch of IpSDAE
$h'(i)$	The difference between the i's and $(i-1)$'s mean squared error of IpSDAE
$h'(i)$	The difference between $h'(i)$ and $h'(i-1)$ of IpSDAE
S_LR	Scaling factor of IpSDAE
D_LR	Fine-tuning factor of IpSDAE

accuracy, and many relevant studies have been published (Gaston, & O'Neill, 2004; Platnick, Huff, Do, & Russell, 2007; Wang, Lin, Ji, & Liang, 2012; Weeks, O'Neill, Gaston, & Gauld, 1999; Wen, Guyer, & Li, 2009).

Recently, more results related to automated insect identification and classification using different feature combination and identification models have been released (Guarnieri, Maini, Molari, & Rondelli, 2011; Kang, Jeon, & Lee, 2012; Wang, Ji, Liang, & Yuan, 2012; Wen & Guyer, 2012; Yaakob & Jain, 2012). There are some automated species identification systems available for commercial or academic deployment, for example the commercial DAISY software (http://www.tumblingdice.co.uk/daisy) and the SPIDA system (http://research.amnh.org/iz/spida/) are able to generically classify species. The ABIS (Arbuckle, Schroeder, & Wittmann, 2001) and DrawWing systems (http://drawwing.org/) are able to identify the species with membranous wings. Most of these methods and systems work well when the insects' images are acquired with good poses, clean background and under uniform lighting situations. However, they do not function well when the images of field insects have higher complexity, such as varied insect pose and cluttered background. Further studies are needed to deal with the identification task of field sample images.

Our previous study found that the insect pose changes before the insect completely lies down on the trap (Wen & Guyer, 2012). Using wind tunnel experiments, we also studied the time-dependent pose change of insects on traps. The automated moth identification on trap suffers the problem of incomplete feature extraction and misidentification since the insect images with side view poses have insufficient features to be obtained. Moreover, intra-species variances bring difficulties for moth identification, for example the same species at different life stages and different sexes. These inter-species similarity and intra-species variances make the identification of the moth difficult. To solve these problems, it is necessary to develop the stable and robust feature extraction and description method according to the moth pose, and the better learning model for identification.

Deep learning architecture consists of multiple levels of non-linear operations and is an effective way to represent high-level abstractions. Automatically learning features at multiple levels of abstraction allows a deep learning system to learn complex functions mapping the input to the output directly from data, without depending completely on feature extracted (Bengio, 2009). Over the last few years, a large amount of research on visual recognition has focused on learning low-level and mid-level features using unsupervised learning, supervised learning, or a combination of both (Lee, Grosse, Ranganath, & Ng, 2009; Hinton, Osindero, & The, 2006; Krizheysky, Sutskever, & Hinton, 2012; Cireşan, Meier, Masci, Gambardella, & Schmidhuber, 2011; Turaga et al., 2010). The ability to learn multiple levels of good feature representations in a hierarchical structure helps to construct sophisticated recognition systems (Kavukcuoglu et al., 2010).

This study aims to develop a pose estimation-dependent method to identify the field moth species using a deep learning architecture, to ultimately solve the pose variety problem in automated identification of field moth pests. The