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Automatic classification for field crop insects via multiple-task sparse representation and multiple-kernel learning ☆

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ABSTRACT

Classification of insect species of field crops such as corn, soybeans, wheat, and canola is more difficult than the generic object classification because of high appearance similarity among insect species. To improve the classification accuracy, we develop an insect recognition system using advanced multiple-task sparse representation and multiple-kernel learning (MKL) techniques. As different features of insect images contribute differently to the classification of insect species, the multiple-task sparse representation technique can combine multiple features of insect species to enhance the recognition performance. Instead of using hand-crafted descriptors, our idea of sparse-coding histograms is adopted to represent insect images so that raw features (e.g., color, shape, and texture) can be well quantified. Furthermore, the MKL method is proposed to fuse multiple features effectively. The proposed learning model can be optimized efficiently by jointly optimizing the kernel weights. Experimental results on 24 common pest species of field crops show that our proposed method performs well on the classification of insect species, and outperforms the state-of-the-art methods of the generic insect categorization.

1. Introduction

There are over a million species of insects in the world. Manual categorization and identification of these species is time-consuming and requires expert knowledge of field crops. Traditionally, insect categorization has mainly relied on manual identification by expert entomologists. However, for laymen without a thorough understanding of the terminology of insect taxonomy and morphological characteristics, it is hard to discriminate insect categories at the species level. Therefore, effective identification of insects is a key issue that needs to be well addressed. Computer vision techniques play a crucial role in many research fields such as entomological science (Weeks et al., 1999), environmental science (Larios et al., 2008), and agricultural engineering (Zhao et al., 2012). In this case, computer vision methods could be a feasible way of solving the problem of automated insect categorization and identification. Although many insect categorization approaches have been proposed and have shown to be successful under various scenarios, insect identification is challenging because the variability of colors, textures, and shapes within a single species is very large relative to the variability between species.

There is a rich literature on image or insect appearance modeling (Larios et al., 2008; Luis et al., 2011; Yaakob and Jain, 2012). See an example in Fig. 1. Color histogram is perhaps the simplest way to represent object appearance in the classification of insect species. However, it misses the spatial information of object appearance, making the method sensitive to noise as well as appearance variations in insect categorization. It is widely understood that instead of using a single feature from insect species, combining complementary features such as color, shape, and texture information should be more effective to discriminate among various insect species. An issue is that the performance of feature-based fusion methods, which depend mainly on simple feature extraction and fusion, may deteriorate after the reduction of data dimensionality. In this paper, we propose a robust insect-categorization model that confronts the aforementioned difficulties. The novel idea is to use a sparse-coding technique, which creates global feature descriptors for insects, in combination with a multiple-kernel learning (MKL) technique. The work flow of our method can be decomposed into two stages. The first stage focuses on image or insect object representation. At this stage, global color, texture, and shape features of insect images are extracted using the sparse coding technique. The second stage, which deals

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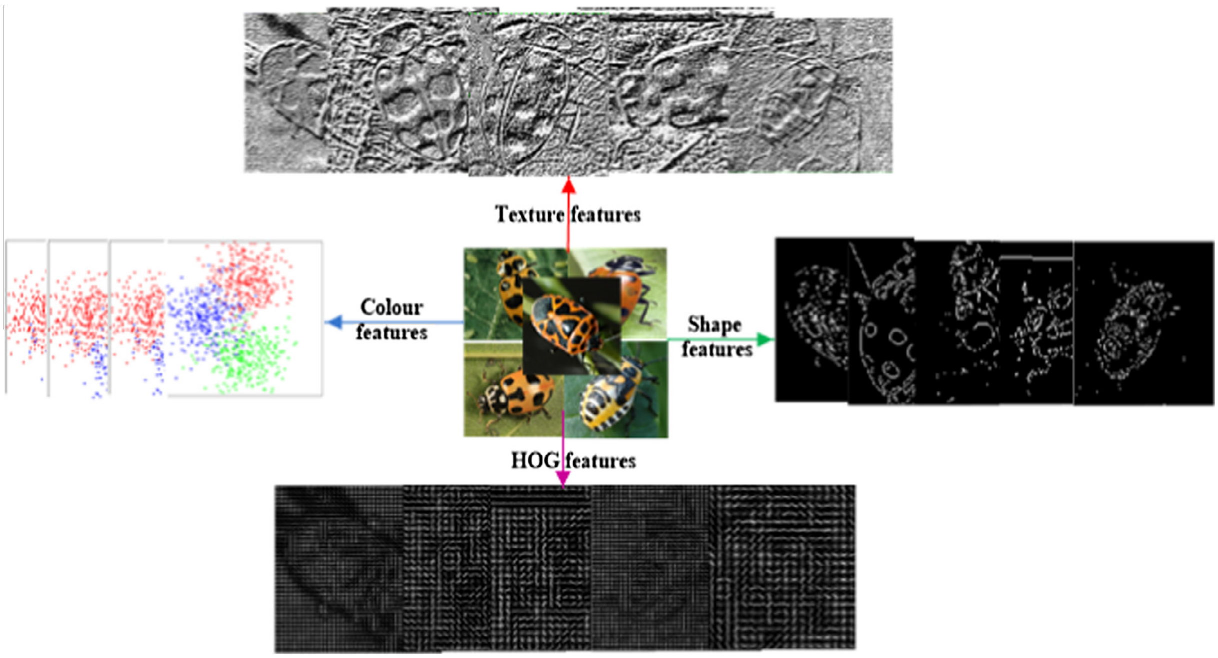

Fig. 1. Visual representations of insect appearance with color, texture, shape, and histogram of oriented gradients (HOG) features.

with effective fusion of multiple insect-categorization features, constructs a kernel-level fusion classifier using all the features.

A novel multiple-task sparse representation of insect objects is proposed by this work (Fig. 2), motivated by the considerable progresses made recently in the research area of sparse representation and coding. For the object representation, multiple over-complete dictionaries with multiple feature modalities of labeled insect images is learned first. Then, multiple modalities of local features are extracted from an insect image, and then the local image patches of the insect object are represented by their sparse codes with the corresponding training dictionary. Despite the fact that insect appearance is modeled using local patches, the global structure information is necessary for accurate insect identification. Finally, insect appearance is represented by concatenating the sparse-coding histograms of all the image patches.

At the second stage, a kernel-level fusion approach with MKL is exploited to classify insects (Fig. 3). In many real classification systems for insect species, a single type of feature is too weak to represent an insect because many features are common to different classes with similar colors or shapes, which leads to ambiguousness in insect classification. To ensure greater discriminative ability, the MKL approach is adopted to combine multiple features via the sparse-coding histograms. Given a set of positive and negative insect samples, multiple modalities of local features are extracted, and then, local image patches of the samples are represented by their sparse codes using the corresponding training dictionary. Finally, an MKL classifier is constructed by learning the sparse-coding histograms of the negative and positive samples for insect categorization and recognition. Compared with existing algorithms for automatic classification of insect species, our technical novelties are as follows:

- the highly discriminative and robust insect object representation with sparse-coding histograms, and
- the combination of multiple complementary features with MKL, where MKL is a tool that represents each image by the use of multiple sets of features in object recognition.

2. Related works

Automated insect identification has been intensively studied over the past two decades, including computer vision-based systems for the classification of insect species (Weeks et al., 1999; O'Neill, 2000; Steinhage et al., 2001; Arbuckle et al., 2001; Wen and Guyer, 2012; Yaakob and Jain, 2012). Weeks et al. (1999) established the digital automated identification system (DAISY) to classify wasp insect images using principal component analysis. To improve classification accuracy, O'Neill (2000) applied DAISY to recognize insect images by analyzing their wing patterns and shapes. Steinhage et al. (2001) developed the automated bee identification system (ABIS) using linear discriminate analysis (LDA) technique. Instead of using LDA, Arbuckle et al. (2001) proposed an improved ABIS system using support vector machine (SVM) and kernel discriminate analysis based on geometric features of wings (such as length, angle, and area). Moreover, many literature works have focused on constructing object appearance models, a key part of object classification. Generally, based on their appearance models, most object feature descriptors can be categorized as either global features or local features. Russell et al. (2005) adopted global features (including color, texture, and geometry) to classify insect images and obtained good results using high-quality images. However, because the features are very sensitive to rotation, scale, translation, and viewpoint changes, this classification method did not work well on objects with large intra-species variation or high inter-species similarity. To address these issues, Wen et al. (2009a) developed a local feature-based insect identification scheme to account for variations in insect appearance. Furthermore, Wen and Guyer (2012) devised an image-based automated insect identification and classification method using three models: an invariant local feature model, a global feature model, and a hierarchical combination model. Luis et al. (2011) extended the LOSS algorithm (Solis-Sánchez et al., 2009) for analyzing the geometrical characteristics of insects to improve insect classification. Wang et al. (2012) adopted artificial neural