Applied Computing and Intelligence

http://www.aimsciences.org/journal/aimsaci

Applied Intelligence and Computing
1(1): 1–30
DOI: to appear
Received: June 2022
Accepted: July 2022
Published: October 2022

Research Article

An Ant Cuticle Texture Classification Algorithm for Ecological Anaylsis

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Abstract: There is a large variety of ant species, and most species are diverse in terms of size, shape, behaviors, and especially skin (cuticle) textures. However, the significance of ant cuticle texture is not widely researched. This research employs modern machine learning methods such as texture analysis and classification with CNN and clustering to automatically group similar ant species to allow for the study of influences cuticle texture on ant ecology.

Keywords: Texture Analysis, Image Processing, Clustering, Machine Learning, Myrmecology, Ecology

1. Introduction

Insects compose half of biodiversity and rank among the most dominant organisms in terrestrial ecosystems [1]. A key factor for the ecological success of insects is their exoskeleton, also known as cuticle. The cuticle protects insects from predation, provides structural support, prevents desiccation, and serves as a canvas for advertising visual and chemical signals [2]. Research has heavily focused on the macrostructures and internal chemical components that make the exoskeleton functional and more recent work is being done to understand the functional aspects of external cuticle micro sculpturing [3–5].

Texture is an important feature in many applications, such as image processing, pattern recognition, and computer vision. Analysis of textures can be broken into three main categories: texture classification, texture segmentation, and texture synthesis [6]. The process of classifying a texture into a set of categories and relies on three different approaches. In this paper, we focus on a *model-based approach* which attempts to extract parameters to reveal common patterns and use those parameters to automatically distinguish between different textures [7].

Although there is some work regarding grouping ants into categories of similar cuticle, automated classification has yet to become an active area of research. Due to the large number of different ant species, the classification of ants into categories of similar texture is difficult to accomplish manually. Texture analysis has shown promising results in related fields, such as plant identification [8]. With modern texture analysis methods, the classifications of ants can be automated and the results can be used to study the influence of cuticle texture on ant ecology.

We examine ants (*Formicidae*) as they display an extreme diversity of cuticle micro sculpturing across all subfamilies. Sculpturing ranges from parallel longitudinal ridges to deep oval impressions to erratic protuberances. The sculpturing has arisen convergently and independently throughout ant's evolutionary history, which suggests some inherent function. Cuticle sculpturing on ants may help increase strength and rigidness, resist abrasion, increase internal and external surface area, resist microbial growth, and rear beneficial anti-biotic producing bacteria [9–11]. These specific functions may be associated with certain sculpturing types and the purpose of classification is to group similar textures based on proposed function.

2. Related Work

3. Proposed Approach

4. Methods

4.1. Sculpture Identification Protocol

4.2. Dataset

In order to classify the cuticle, we used ant head images sourced from AntWeb [12]. In general, the ant head images are centered in the image, facing the front, and share a similar posture. However, some images may not be centered, show the ant head in a different orientation, or may have a drastically different resolution from the average image. Fortunately, each can have several scales available such that the images' scales can be roughly similar.

Table 1. Dataset Subclass Distribution

Label	Samples (n)	Samples (%)
Rough Dimpled	173	0.07
Rough Netted	503	0.21
Rough Ridged	317	0.13
Rough Tuberous	41	0.02
Smooth Gritty	16	0.01
Smooth	1393	0.57
Total	2443	1.0

Table 2. Dataset Class Distribution

Label	Samples (n)	Samples (%)
Rough	1034	0.42
Smooth	1409	0.58
Total	2443	1.0

Images were collected and classified by undergraduate students according to the sculpturing identification protocol. Overall, there are a total of 2443 images in the dataset. The class distribution with all considered subclasses is shown in Table 1, and the class distribution with overall distribution is shown in Table 2. The relatively small number of images in the dataset paired with the uneven class distribution makes it difficult to perform a meaningful classification. However, the goal of this project is to develop a classification algorithm that can be used to help classify over 200,000 ant images. Therefore, it is desirable to use a few representative images from each class to train the algorithm. Additionally, data augmentation and other methods are performed to increase the number of training images to create a more robust classification algorithm.

4.3. Subimage Dataset

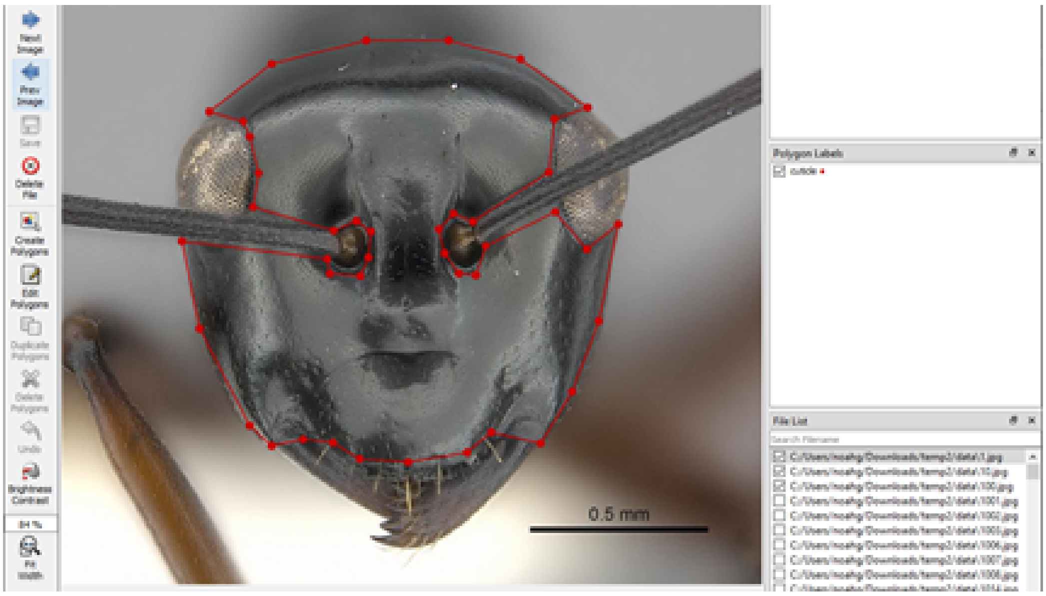

Figure 1. Hand segmented ant head image to separate head cuticle from other sections of the image. CASENT0217419 by Estella Ortega, from AntWeb, is licensed under CC BY 4.0

When using the Sculpture Identification Protocol, the class of the overall image is based only on the texture of the head, not the eyes, antenna, or any other exposed cuticle. We use image segmentation to analyze the texture by splitting the ant head image into a set of regions: *cuticle* and *background*. A benefit of this approach allows us to pull patches or subimages of various sizes from the region to increase the number of samples available for training and at the same time, reduce the number of features to simplify the classification algorithm. With a given subimage size to extract from the segmented image, we label each subimage extracted based on the class of the input image. Overall, there are 73 images that were hand segmented in this manner and the class distribution for various sizes of subimages are shown in Table 3.

Table 3. Subimage Dataset Class Distribution

Label	(8, 8)	(16, 16)	(24, 24)	(32, 32)
Rough	101584	23655	9790	5108
Smooth	104981	24356	10022	5177
Total	206565	48011	19812	10285

5. Experimental Results

In the first experiment, we investigate the ability of a basic CNN to classify cuticle texture into the two main categories: *rough* and *smooth*. The goal of this experiment is to determine if more intricate data preprocessing or a more powerful model is necessary to classify the texture of the ant. Images were resized to different sizes for CNN input and different samples per class were also tested.The dataset used is shown in Table 2, and the results are shown in Table 4.

Table 4. Binary Classification of Full Size Images

Size	Samples (per class)	Accuracy (avg)	Loss (avg)
(64, 64)	250	70.83%	0.705
(64, 64)	500	74.9%	0.763
(64, 64)	750	76.72%	0.712
(128, 128)	250	71.93%	0.977
(128, 128)	500	74.39%	1.133
(128, 128)	750	75.7%	1.137
(256, 256)	250	71.0%	1.353
(256, 256)	500	73.31%	1.532
(256, 256)	750	74.96%	1.504
(512, 512)	250	68.16%	1.790
(512, 512)	500	71.25%	1.625
(512, 512)	750	71.74%	1.852

Acknowledgments

We would like to thank the constructive feedback provided by the reviewers.

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