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Research Article

An Ant Cuticle Texture Classification Algorithm for Ecological Anaylsis

Noah Gardner[1], **John Paul Hellenbrand**[2], **and Chih-Cheng Hung**[1*]

[1] College of Computing and Software Engineering, Kennesaw State University, 1000 Chastain Road, Kennesaw, GA 30144, USA; email

[2] College of Science and Mathematics, Kennesaw State University, 1000 Chastain Road, Kennesaw, GA 30144, USA; email

* **Correspondence:** chung1@kennesaw.edu

Academic Editor: First-name Last-name

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. The process of classifying a texture into a set of categories and relies on three different approaches: feature-based, model-based, or structural [6]. In this paper, we focus on a *model-based approach* which attempt 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. Methods

2.1. Sculpture Identification Protocol

2.2. 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

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

Table 2. Dataset Class Distribution

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

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.

3. Experimental Results

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