A COMPARATIVE ANALYSIS OF TEXTURE ANALYSIS METHODS ON ANT HEAD IMAGES

A Thesis Presented to

The Faculty of the Computer Science Department

by

Noah Gardner

In Partial Fulfillment

of Requirements for the Degree

Master of Science in Computer Science

Kennesaw State University

May 2022

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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.

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To my family

Never fail to have this attitude of mind, go forward without hurry, learn the essence of things through frequent experiences, taking advantage of every occasion. Fight against all kinds of people and be aware of their mind. Follow a road that is a thousand leagues long one step at a time. Be without haste and be convinced that all these practices are the duty of a bushi. Be victorious today over what you were yesterday; tomorrow be victorious over your clumsiness and then also over your skill.

Miyamoto Musashi [1]

[1] Miyamoto Musashi, The Book of Five Rings

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1 CHAPTER 1: INTRODUCTION

1.1 Introduction

Insects comprise over half of the world's animal biodiversity [1]. Insects are vital to many ecosystem functions, including nutrient recycling, plant propagation, and maintenance of plant and animal communities [2], [3]. As technology advances, systems which can automatically analyze insect-based information are growing in demand by biologists [4]. For example, automatic insect identification systems can be applied to conserve natural ecosystems, to prevent commercial loss, and to support the study of insect-related diseases [5]–[7].

Due to the extensive number of insect species, manual exploration of insect-based information is difficult and often requires specialized expertise. Therefore, automated entomology is gaining attraction by both biologists and computer scientists and is expected to be a major contribution to the future of insect-based research [8]. One of the most commonly used data types for insect analysis is image data. To develop an image-based system for insect analysis, we can take advantage of existing work in general image processing and texture analysis methods.

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 [9]. 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 [10].

Ants are highly diverse, fill many ecological niches, and thus are a major topic of interest [11]. In this work, we explore automated entomology specifically for ants in order to support ant-based ecological research. Although there is some work regarding grouping ants into categories of similar exoskeleton texture (*cuticle*), automated categorization has yet to become an active area of research. In general, the goal of automated insect classification methods is species indentification - *i.e.* the identification of species from a set of observations. Due to the large number of different ant species, large scale ant species indentification with standard classification methods is not feasible. Therefore, we must simplify the problem by either other classifying a certain subset of ant species or by applying categories to the entire set of ant species.

In many texture analysis methods, the general goal is to automatically categorize an object into a set of objects with similar texture-based features. The approach of texture analysis to categorize similarly texture-based objects corresponds well to the demands of ant identification. Texture analysis has shown promising results in related fields, such as plant identification [12]. With modern texture analysis methods, the categorization of ants can be automated and the results can be used to study the influence of cuticle texture on ant ecology.

1.2 Research Question

The overarching question that we wish to address by beginning this research is: *how does the texture of ant cuticle affect the ant ecology*? However, to even begin contemplating this question requires a substantial amount of preliminiary research. One point that is necessary to begin this research is to propose a method of group ants by texture. Additionally, due to the sheer number of ant species, an automated effort is necessary to group similar ant species. Therefore, we start our endeavor with a more straightforward research question: *are texture analysis methods able to group similar ant species*? By the end of this research, we will answer this question by demonstrating a variety of texture analysis methods and comparing their results on a custom dataset.

1.3 Proposed Approach

In order to group similar ant species, we require mostly uniform images that depict the texture of the ant cuticle. We source our raw images from AntWeb [13], a database of ant head images. An example image is shown in Figure 1. 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, may show

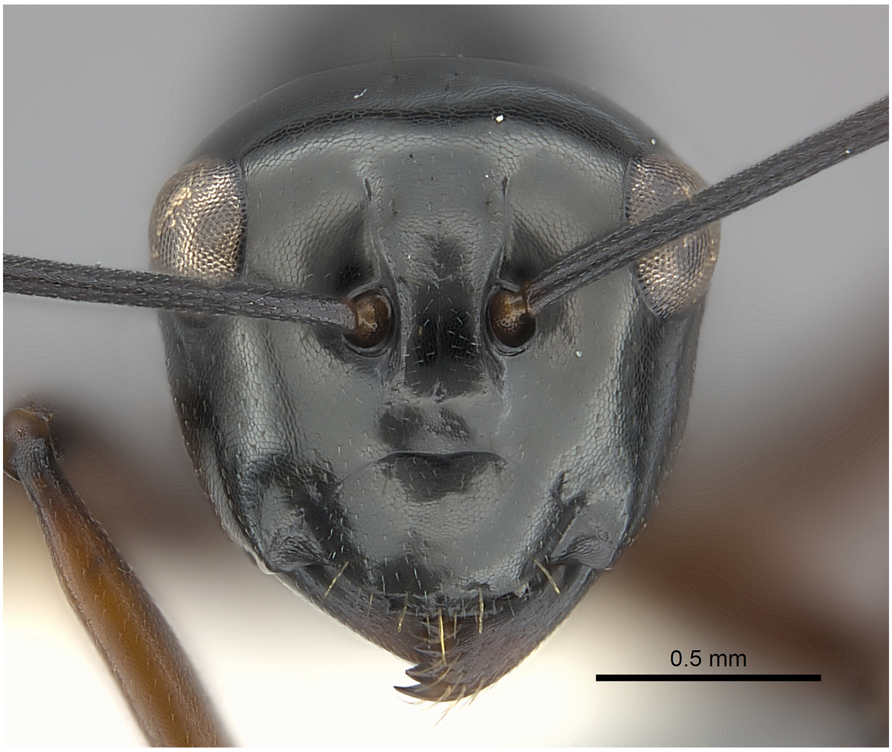


Figure 1: An example ant head image from AntWeb of species *Polyrhachis abbreviata*. CASENT0217419 by Estella Ortega, from AntWeb, is licensed under CC BY 4.0.

the ant head in a different orientation, or may have a drastically different resolution from the average image. With some data preprocessing methods, these ant head images are suitable for traditional methods of image classification. Therefore, we will apply several image classification and texture analysis methods to a custom dataset of ant head images and compare the results using standard evaluation metrics.

1.4 Research Impact

The primary contribution of this research is the development of a unique dataset for ant cuticle texture classification. Additionally, we compare the results of state-of-the-art deep learning and texture analysis methods on our proposed dataset. The secondary contribution is the analysis of the results of these methods and data analysis.

2 CHAPTER 2: LITERATURE REVIEW

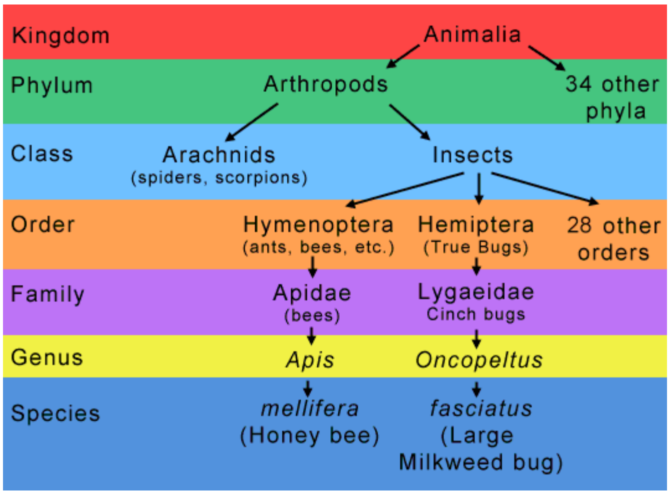


Figure 2: Taxonomy chart showing taxonomy of the honey bee and large milkweed bug. Taxonomy chart by Adam Dolezal, Page Baluch, from Ask a Biologist, is licensed under CC BY 4.0.

2.1 Insect Classification

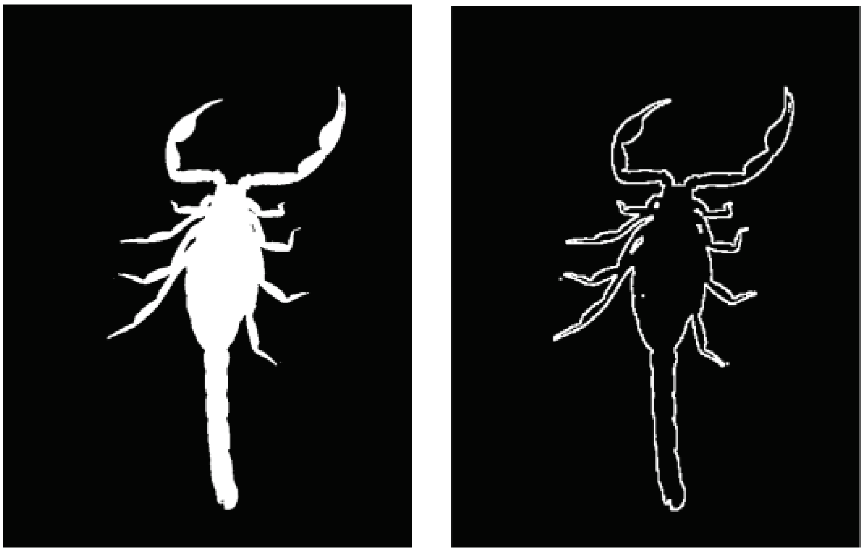
In this section, we provide an overview of some insect classification methods. Proposed insect classification methods seek to classify insects at different hierarchical levels, such as species, genus, family, and order. Additionally, some methods may classify insects at a combination of different hierarchical levels. An example taxonomy chart with some insect taxonomy is shown in Figure 2. Insect classification methods can be applied to a variety of fields. In agriculture, insect classification methods can be used to identify the presence of pest insects in crops, which can inform crop managers in their choice of pesticides and help prevent crop loss [14], [15].

Feng *et al.* apply an automated system to classify moth images based on

Figure 3: An example image of a set of moth wings for moth species indentification, from Feng *et al.* [16].

semantic related visual attributes, which are defined as a pattern on the moth wings [16]. Feng *et al.* use a custom texture descriptor based on the combination of Grey Level Co-occurence Matrtix and *Scale-Invariant Feature Transform* (SIFT) features [17], [18]. The method proposed by Feng *et al.* is used to classify 50 different moth species across 8 families and is based on standard texture analysis features [16]. A set of example moth wing images is shown in Figure 3. The results from Feng *et al.* suggest that traditional feature extraction techniques for the semantic visual attributes of the moth wings are sufficient for training a classifier to classify an image between 10 randomly selected moth species [16].

Urteaga-Reyesvera *et al.* use machine learning methods in order to classify images between two different scorpion species: *Centruroides limpidus* and *Centruroides noxius* [19]. After applying background distinction based on dynamic color threshold, Urteaga-Reyesvera *et al.* apply feature extraction to extract features from the separated scorpion image such as aspect ratio, rectangularity, and compactness [19]. Urteaga-Reyesvera *et al.* apply three different classification models to classify the image as one of the species:



(a) Area image. (b) Contour image.

Figure 4: An example image of a scorpion for a scorpion species classifier with the background removed, from Urteaga-Reyesvera *et al.* [19].

Artificial Neural Network, Regression Tree, and Random Forest classifiers [19]. An example image of a scorpion with the background removed is shared in Figure 4. The results from Urteaga-Reyesvera *et al.* show that after background removal, characteristics from the entire body of the scorpion can be used to create a binary classifier that can classify the image as one of the two species. Therefore, we may consider an experiment on the presence of the background from the ant head image in order to improve classification accuracy. However, the features extracted from [19] do not make use of any deep learning methods and are not compatible with our texture-based dataset.

Figure 5: An example image of three distinct ant species from ImageNet, from Glick *et al.* [20].

Lim *et al.* apply a CNN-based algorithm for insect classification [21]. Lim *et al.* classify a subset of insect species and families based on the classes available in the ImageNet dataset [22]. ImageNet is a widely used dataset of images labeled by experts with millions of images and thousands of categories [22]. In the ImageNet dataset, there are some categories that specify the class of the insect on a species level, *e.g. monarch butterfly* and *ringlet butterfly* as well as some categories that specify the class of the insect on a family level, *e.g. ant*, *fly*, and *bee* [23]. Lim *et al.* use a modified AlexNet architecture and experiment with different numbers of kernels and their effect the performance of the model [21]. Glick *et al.* employ a similar approach by classifying 277 insect classes from ImageNet using a hierarchical CNN [20]. The results from Lim *et al.* and Glick *et al.* suggest that a CNN is capable of differentiating between different hierarchical classes of insects. In our research, we are interested in the classification of ant images of a hierarchical level between species and family.

2.2 Automated Ant Indentification

In this section, we explore some machine learning methods applied directly to automated ant systems. We define automated ant systems as methods which process information about ants in a computer environment. Many automated ant systems have the purpose of tracking individual ants and their movements. An example of ant tracking software is shown in Figure 6. Systems that can track multiple individuals in a colony are applied to support research that investigates social group behaviors of ants [24]–[26].

Sosiak *et al.* use morphometric traits as features to analyze the relationship between the traits and the ecology of the ant [11]. Sosiak *et al.* apply a supervised Random Forest algorithm to classify ants based on their ecology [11]. The research carried out by Sosiak *et al.* is similar to the end goal of this research - by creating a system that categorizes ants based on their cuticle texture, we hope to support a framework that can be used to analyze the ecological niche of ants in future work.

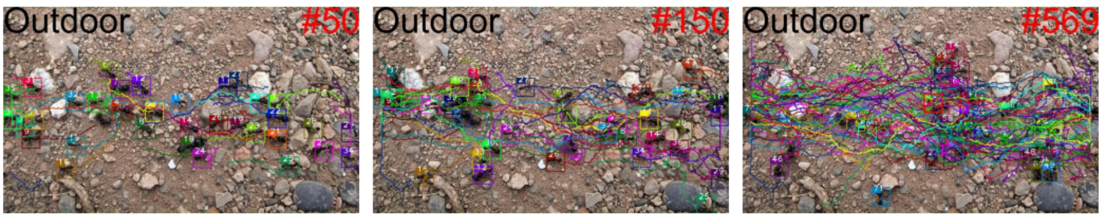


Figure 6: An example output of an individual ant track from a group of outdoor ants, from Cao *et al.* [27].

Cao *et al.* apply ResNet to automatically extract deep features from individual ants for offline learning [27]. Cao *et al.* modify the parameters of the softmax classifier to obtain a cosine similarity metrix classifier to automatically track 10 individual ants in a group [27]. Cao *et al.* use a dataset of 50 images for training and test their model on a much larger dataset of 24000 images [27]. The results from Cao *et al.* suggest that ResNet is able to differentiate between individual ants.

Gal *et al.* also propose a framework for tracking inidividual insects by taking advantage of color tagging. Gal *et al.* show examples of their software tracking individual ants from a group that are identified with different colors of paint applied to the ants [28]. The method from Gal *et al.* should generalize to any type of insect and have relaxed requirements for image quality due to the constraint of applying color tags [28]. However, the images of the group of ants used for multi object tracking is not similar to our dataset of ant head images, other than the fact that both datasets were collected in a laboratory setting.

3 CHAPTER 3: METHODOLOGY

3.1 Dataset

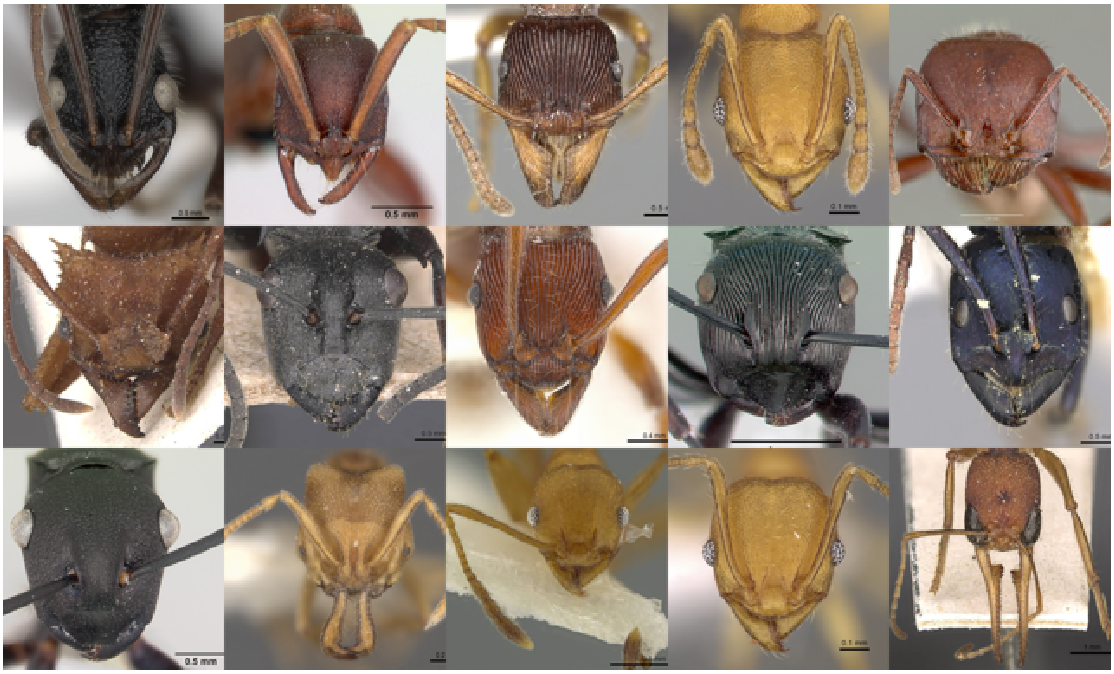


Figure 7: Examples of rough cuticle texture ant images in the dataset after center cropping, sourced from AntWeb [13].

In this section, we describe the creation of the custom dataset used in this research. In our dataset, we classify ant head images from AntWeb [13] into two categories: *rough* and *smooth*. Some randomly selected images from each category are shown in Figures 7 and 8.

3.1.1 Sculpture Identification Protocol

To begin, a master spreadsheet was created with the 2,499 different ant species to be identified for the primary dataset. A team of three assistants were in charge

Figure 8: Examples of smooth cuticle texture ant images in the dataset after center cropping, sourced from AntWeb [13].

of the manual identification process. The team was trained to identify cuticle sculpturing through a process which consisted of one 45-minute introductory lesson explaining the project and texture categories and then given a training set of photos to identify from the genus *Polyrhachis*, whose members display among the highest diversity of cuticle patterns all categories. The sculpture identification protocol describes the two primary categories: *rough* and *smooth*.

Initially, the sculpture identification protocol had 8 subcategories of cuticle texture, including dimpled, ridged, and differing levels of smooth texture. However, for simplicity, we work only with the two main categories. The training set identifications were reviewed together as a group. Once training was complete, assistants were assigned the same genera of ants to identify independently each week. A weekly meeting was held to discuss identifications and assign new ones. These identifications were collected in the master spreadsheet and the identifications were assigned to individual ant species on a majority basis.

3.1.2 Data Collection

To collect the images, the assistants followed the taxonomy information available in the master spreadsheet to the appropriate AntWeb page. In many cases, there are multiple ant head images of the same species, and occasionally there are multiple image resolution available from a single image. To simplify the data collection process, the assistants were instructed to download the first ant head image of the species being identified in the highest resolution possible. Each image was named with an identifier that corresponds with the row number in the master spreadsheet. The same ant head images that were downloaded in the data collection phase were the same ones used in the sculpture identification protocol. Ant species which did not have any images of the head were excluded from the dataset. Additionally, ant species which only had a head image of a queen ant were excluded from the dataset.

3.1.3 Data Preprocessing

3.2 Models

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4.1 Environment

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5.1 Conclusion

5.2 Future Work

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