To the Graduate Council:
I am submitting herewith a dissertation written by David Lon Page entitled “Part Decomposition of 3D Surfaces”. I have examined the final paper copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Electrical Engineering.

Mongi A. Abidi, Major Professor

We have read this dissertation and recommend its acceptance:

Accepted for the Council:

Vice Chancellor and Dean of Graduate Studies
Part Decomposition of 3D Surfaces

A Dissertation
Presented for the
Doctor of Philosophy
Degree
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David Lon Page
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Dedication

This dissertation is dedicated to my father, Bob Page, who tragically died too young but gave me so much, and to my mother Shirley Page, who has supported and encouraged me to persevere through life’s challenges.
Acknowledgments

First and foremost, I am deeply indebted to my family, especially my mother, Shirley Page, and my brother, Dan Page. Where I am today is in no small part due to their love and support. I also owe a special thanks to my Uncle Momo, Lon Boyd, who has always encouraged me to “get that education.”

I additionally would like to thank my advisor, Dr. Mongi Abidi. His willingness to support my work and his guidance throughout my studies has allowed me to develop my skills as a researcher within a supportive team environment. I thank him for that opportunity. Also, I would like to thank, Dr. Paul Crilly. His advice and counsel over the years have been of equal importance. To Dr. Andreas Koschan, I say thank you as well for the many technical—and sometimes not-so technical—discussions with regard to this research and life in general. I would further like to thank the other members of my committee: Dr. Daniel B. Koch, Dr. Conrad Plaut, and Dr. Hairong Qi. I greatly appreciate their time and input to this dissertation.

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Finally, I must express my appreciation to the many friends outside of my studies who have helped to relieve the sometimes stressful solitude of graduate school. In particular, Clint and Andrew have earned a special place in Heaven for putting up with me as a roommate. Your friendships through both good times and hard times have been a source of strength. To Molly and Marci, I can not say thank you enough for the many wonderful adventures as we followed the Vols from Pasadena to Timbuktu. I am profoundly grateful for your friendships as well. I also wish to thank the Ultimate Frisbee folks whose comaraderie each Wednesday evening has been invaluable. Last but not least, I would like to thank Lisa whose encouragement in the final days of this work have truly inspired me and have opened my eyes to the world beyond graduate school.
Abstract

This dissertation describes a general algorithm that automatically decomposes real-world scenes and objects into visual parts. The input to the algorithm is a 3D triangle mesh that approximates the surfaces of a scene or object. This geometric mesh completely specifies the shape of interest. The output of the algorithm is a set of boundary contours that dissect the mesh into parts where these parts agree with human perception.

In this algorithm, shape alone defines the location of a boundary contour for a part. The algorithm leverages a human vision theory known as the minima rule that states that human visual perception tends to decompose shapes into parts along lines of negative curvature minima. Specifically, the minima rule governs the location of part boundaries, and as a result the algorithm is known as the Minima Rule Algorithm. Previous computer vision methods have attempted to implement this rule but have used pseudo measures of surface curvature. Thus, these prior methods are not true implementations of the rule.

The Minima Rule Algorithm is a three step process that consists of curvature estimation, mesh segmentation, and quality evaluation. These steps have led to three novel algorithms known as Normal Vector Voting, Fast Marching Watersheds, and Part Saliency Metric, respectively. For each algorithm, this dissertation presents both the supporting theory and experimental results. The results demonstrate the effectiveness of the algorithm using both synthetic and real data and include comparisons with previous methods from the research literature. Finally, the dissertation concludes with a summary of the contributions to the state of the art.
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Chapter 1

Introduction

Let us begin with a brief exercise. Take a few minutes and glance around the room. Note objects in the room, perhaps items on your desk. Can you distinguish specific objects? Can you visually separate them from their background? For instance can you isolate the coffee mug on your desk from the clutter of books and papers? The answer is—of course—yes, you can and you do so with ease.

This seemingly simple task—deceptively simple—actually requires the coordination of millions of receptors within your eyes and billions of neurons in your brain. Photons of light bounce throughout the room and into your eyes striking each retina. Then rods and cones in the retina translate this light into neural signals and transmit them along the optic nerve. The optic nerve splashes this avalanche of input across neurons at the back of the brain—the visual cortex.

These neurons fire sending ripples, like stones tossed into a pond, out to other areas of the brain and energize millions of neural networks. More neurons now fire igniting their own networks and again sparking new ripples. The mind orchestrates this rippling activity into a coherent thought that elevates to the conscious plane. The little voice in your mind replies, “There’s my mug!” The graceful elegance of this complex process is truly a marvelous wonder—a wonder that allows you to isolate and identify the mug on your desk. Yes, all that for a mug.

Now, imagine that you are a computer vision engineer. How can you get a computer to do the same thing—separate the mug from the clutter of books and papers? How can you get a computer to decompose, or segment, a complex scene into simpler parts? In a very focused context, an answer to this question is the research goal of this dissertation. In particular, we have developed a novel part decomposition, or part segmentation, algorithm for surfaces. For input, instead of neural signals from a human eye, we will use triangle meshes generated from laser range scanners. For processing, instead of the neural networks of your mind, we will use segmentation algorithms implemented in a computer. Hopefully, our proposed algorithms mimic your visual perception, at least to a certain extent.

As a simple example of part decomposition, again think of the mug on your desk. Suppose the mug is similar to the one in Fig. 1.1(a) and that we can somehow generate a computer model of the mug as shown in Fig. 1.1(b). If your perception is like most viewers, then you decompose the mug into three or four different smaller parts. Most viewers would agree that the mug consists of a bowl-shaped cup, a handle protruding from the cup, and a base at the cup bottom. The color labels in Fig. 1.1(c) illustrate this segmentation. You have mentally decomposed the mug into three simpler parts. By extension, when we view
more complex scenes such as the clutter on a desk top, we also decompose the scene into simpler parts. This example illustrates the objective of our research. In fact, our algorithm generated the segmentation shown.

This dissertation presents the details of our part decomposition algorithm. The remainder of this first chapter outlines the applications for our algorithm in Sec. 1.1 and the motivation for this research in Sec. 1.2. In Sec. 1.3, we then present the minima rule, which is the human vision theory that serves as the foundation of our research. To implement the minima rule, we briefly review the state of the art in Sec. 1.4. Next, we emphasize the contributions of this dissertation in Sec. 1.5, and we conclude with a block diagram of our system and the document organization in Sec. 1.6.

1.1 Applications

Segmentation, whose roots date back to the dawn of digital image processing, is an age-old problem in computer vision. As Marr [Marr, 1982] has stated, the goal of segmentation is to partition a data set into groups that are more meaningful. The difficulty is that this partitioning is not well posed and the term “meaningful” is highly subjective. Consequently, useful solutions are often ad hoc in origin. Marr points out that segmentation is a vague all-encompassing notion that typically digresses into a philosophical debate. In the context of image processing, he further argues that most images are too complex and often do not contain enough information for segmentation to succeed. Despite Marr’s objections, segmentation has become a fundamental and ubiquitous topic in computer vision and in image processing, specifically [Gonzalez and Woods, 1993]. The lesson to be learned from Marr however is that useful segmentation requires a precise formulation—or better yet, a formulation with strong philosophical support—of the segmentation goals. Such a formulation requires specific knowledge of the application at hand. To this end, we identify our application domain in the following paragraphs and in so doing assert our motivation for research. Additionally, as we will see, we are not interested in the traditional image segmentation problem but in the more general surface segmentation problem where we approximate a surface with a triangle mesh representation.

What is our application and why does it require segmentation? Our two applications are scene modeling and reverse engineering.
Scene modeling is the process of constructing a 3D computer model of a real-world scene where such models are useful in flight or driving simulators, architectural walk-throughs, and other virtual reality applications [Burdea and Coiffet, 1994]. Research examples include urban landscapes [Frueh and Zakhor, 2001, Frueh and Zakhor, 2002], indoor environments [Yu et al., 2001], architectural structures [Faber and Fisher, 2002], industrial facilities [Johnson et al., 1995, Hebert et al., 1995], and precious art statues [Bernardini et al., 1999, Levoy et al., 2000]. To illustrate, imagine a military simulator where a tank commander is training for a mission in an urban environment such as Mogadishu, Somalia. We could populate this simulation with cartoon-like models of buildings and roadways designed by a computer artist. To achieve convincing realism, an artist would methodically build-up the simulation from basic shapes such as boxes and cylinders. On the other hand, we could use the scene modeling techniques in [Frueh and Zakhor, 2001, Frueh and Zakhor, 2002] to rapidly model the streets of a specific city by driving through that city. Instead of an artist recreating a city-scape, we reconstruct it using a scene modeling system mounted on the roof of a van. As another example, imagine an art student in Knoxville who wishes to study the chisel patterns on Michelangelo’s statues in Italy. Although she could travel to Europe, statue modeling such as [Levoy et al., 2000] offers a much more convenient alternative. She could simply download a 3D model of Michelangelo’s David and use a virtual reality viewer to study the sculpture without ever leaving Knoxville. Creating computer models of buildings, rooms, and statues is the goal of scene modeling.

With reverse engineering instead of visually pleasing models, the objective is accurate as-built models of existing objects. Although reverse engineering is actually a broad field that encompasses many concepts, our specific definition is the ability to create a computer-aided design (CAD) model of a real-world part [Bernardini et al., 1999, Motavalli et al., 1998]. By contrast, forward engineering is to create a real-world part from a CAD model. The automation of forward engineering, or computer-aided manufacturing (CAM), has significantly impacted recent technologies in system design. CAM has also introduced rapid prototyping into the design loop and facilitated changes on demand after the deployment of a design [Yan and Gu, 1996]. The automation of reverse engineering, or computer-aided reverse engineering (CARE), promises to impact the design process in a similar fashion. CARE allows electronic dissemination of as-built parts for comparison of original designs with manufactured results. Additionally, CARE allows construction of CAD models of existing parts when such models no longer exist as when parts are out of production [Thompson et al., 1999]. A military example of the potential for CARE is the Mobile Parts Hospital initiative within the U. S. Army Tank-automotive and Armament Command. The vision for the parts hospital is an emergency manufacturing unit for frontline deployment. Although the hospital should ideally have access to a CAD database, CAD models for a part may not necessarily be available such as for vehicles that have undocumented field modifications. A CARE scanner, however, allows even an untrained—in terms of engineering practices—soldier to create high quality CAD models. Additionally, a CARE scanner is a valuable tool for documenting part failures and thus creating an electronic history of the life cycle for a part.

### 1.2 Motivation

Although scene modeling and reverse engineering may seem dissimilar, they in fact share the common thread of *surface reconstruction*. Methods of surface reconstruction include [Hoppe
Figure 1.2: Scene modeling of an industrial scene. (a) The original scene with a barrel, cone, and blocks. (b) A point cloud derived from measurements of the scene. (c) A mesh reconstructed from the point cloud data. Notice that the mesh models the entire scene as a single connected surface—a blanket model.

et al., 1992, Hoppe et al., 1994, Edelsbrunner and Mücke, 1994, Delingette, 1994, Curless and Levoy, 1996, Whitaker, 1996, Curless, 1997, Pulli et al., 1997, Amenta et al., 1998, Mencl and Müller, 1998, Bernardini et al., 1999, Gopi et al., 2000]. Surface reconstruction is a two step process where by we first acquire the geometry of a scene or an object and then reconstruct its topology. The geometry acquisition is a digitization process whereby a sensor such as a coordinate measuring machine, a touch probe, a stereo pair, or perhaps a range scanner measures the location of points on the surfaces in a scene or on an object. Then, topology reconstruction finds the interconnection of these points. We refer to the collection of points as a point cloud and their interconnection as a surface mesh, or simply a mesh. Consider Figs. 1.2 and 1.3 that show examples of the process.

Notice that the meshes in Figs. 1.2(c) and 1.3(c) are single contiguous surfaces. The meshes represent each connected object, that is to say objects that are physically touching each other, as one ubiquitous surface. By way of analogy, we describe this representation as a blanket model where Fig. 1.4 shows a simple illustration. Recalling our visual exercise, grab a blanket from your bedroom and lay it over your desk. The blanket will take the form of the desk, the books, the papers, and the mug.* Now, suppose we can apply an epoxy to the blanket so that it hardens and thereby creates our blanket model. We can pick up the stiffened blanket and carry it with us. We can show it to other people. The problem is that if someone is only interested in the mug we have to give them the whole blanket. We really do not know which section of the blanket might contain the mug. Would it not be better if we could segment the blanket into smaller blankets—ones that are more manageable and more meaningful? We need a mesh segmentation algorithm. We need to decompose the blanket into smaller meaningful parts.

*In the case of a mug, our blanket analogy does breakdown, somewhat. Consider that the blanket cannot change genus, without tearing it, to conform to the topology of the mug handle. So, we must tear the blanket and stitch it appropriately to truly model the mug. This point may seem minor but a reconstruction algorithm that accurately recovers topology is crucial and is an active area of research.
Figure 1.3: Reverse engineering example of a manufactured component. (a) Rendering of reconstructed part. (b) A point cloud derived from measurements of the part. (c) Underlying triangular mesh showing the blanket model.

Figure 1.4: Reconstruction of a scene from multiple range images. These illustrations depict the blanket model analogy.
1.3 The Minima Rule

The term meaningful has cropped up again, echoing back to Marr. Although we know our applications are scene modeling and reverse engineering, we still need to identify what type of segmentation we expect. We need to counter Marr’s objections and identify a theory to govern our segmentation. For scene modeling, we expect a segmentation that benefits real-time visualization of the scenes. We need to chop up the blanket so that the pieces are amenable to visualization. For reverse engineering, we expect a segmentation that leads to a more compact description of the object and that possibly facilitates the most grandiose of all computer vision tasks—the illusive task of object recognition. We look to the world of cognitive psychology for help. Researchers in human perception have identified a theory, known as the minima rule [Homan and Richards, 1984], that provides a precise formulation for segmentation. This rule defines meaningful in terms of human visual perception. If we segment our blanket mesh using a theory of human perception, the subsequent submeshes should naturally meet our needs for both applications. This point will become clear later. The marriage of the minima rule to scene modeling and reverse engineering is the primary impetus for our research. Is this marriage out in left field, or is it an important research pursuit? In the next section, we look at the state of the art in mesh segmentation to address this concern and to highlight the hole that our research fills.

1.4 State of the Art

Although image segmentation is a well known and thoroughly researched topic in computer vision, mesh segmentation has only recently become of interest where Mangan and Whitaker [Mangan and Whitaker, 1999] are perhaps the first to coin the term itself. In this section, we identify the current research on this topic and highlight a few shortcomings.

From a review of the literature, we have identified five papers that represent the state of the art. The first three are Vincent and Soille [Vincent and Soille, 1991], Wu and Levine [Wu and Levine, 1997] and Mangan and Whitaker [Mangan and Whitaker, 1999], whose methods directly address the mesh segmentation problem. The other two are Tang and Medioni [Tang and Medioni, 1999] and Taubin [Taubin, 1995], whose methods address curvature estimation. As we will see, curvature estimation is an essential component of the mesh segmentation algorithm that we propose.

Wu and Levine [Wu and Levine, 1997] are perhaps the first to directly attack the mesh segmentation problem as we have posed it. Their method uses electrical charge distribution equations to simulate the charge density on a mesh, and they identify segmentation boundaries as regions with the lowest charge density. This physics-based approach may seem unusual but their results are quite nice for certain data sets. The strength of their algorithm is its robustness to measurement noise. The drawbacks however are that the method does not scale well to large data sets and that simulated charge distribution has limitations as a definition for segmentation. Wu and Levine suggest that their approach follows the minima rule—just as we propose to do—but in practice charge distribution does not directly relate to the rule. Additionally, the search algorithm they have implemented has certain limitations as well. Their algorithm tends to become trapped in local minima.

Mangan and Whitaker [Mangan and Whitaker, 1999] offer a different approach. The major contribution of their work is that they implement the well-known watershed algorithm from image processing on a mesh data structure. They reformulate the watershed
algorithm from morphological image operations to gradient-following mesh operations. The capabilities of the watershed algorithm is a tremendous strength of their algorithm. The basis for their segmentation is the local curvature on the mesh. In particular, contours of high curvature bound areas of low curvature. They argue with heuristics that these boundaries offer a meaningful segmentation, but Marr’s warnings about meaningful come to mind. From our literature review, we argue that high curvature boundaries indeed do not form a meaningful segmentation—at least for our applications—and we suggest that this approach is one drawback to their implementation.

Further, we suggest two other drawbacks. The first is the curvature estimation that governs their segmentation. The estimate they use is not robust to noise and in most cases leads to significant over segmentation. Also, since their method estimates Gaussian curvature, it is not useful for the minima rule, which requires estimation of the principal curvatures. The second drawback is their implementation of the watershed algorithm. Although Mangan and Whitaker demonstrate nice results, they have implemented a “bobsledding” version of watersheds where one initiates a segmentation with random seed points and follows the gradients from the seeds to watershed basins. This formulation is susceptible to local plateaus and thus requires post processing to handle over segmentation. As a result, Mangan and Whitaker implement an \textit{ad hoc} solution to account for over segmentation, based on the depth of each watershed region.

Although Vincent and Soille [Vincent and Soille, 1991] propose a segmentation algorithm for 2D images, they generalize their algorithm to the arbitrary connectivity of a graph, such as a mesh. This algorithm does not appear in the review of Mangan and Whitaker, but it does propose a fast implementation of watersheds where one initiates a segmentation with random seed points and follows the gradients from the seeds to watershed basins. This formulation is susceptible to local plateaus and as such has implementation advantages over Mangan and Whitaker. The downside to their algorithm is that it requires a pre-sorting of the mesh vertices according to water heights. As we will see, this pre-sorting is not suitable for our application of the minima rule.

Finally, since we are interested in the minima rule, curvature is important to our proposal as well. Unfortunately, as noted above, both curvature segmentation methods above [Wu and Levine, 1997, Mangan and Whitaker, 1999] have drawbacks with regard to their curvature estimations. Subsequently, we look to the literature for better methods. Tang and Medioni [Tang and Medioni, 1999] and Taubin [Taubin, 1995] represent the state of the art. Tang and Medioni offer a robust algorithm that estimates the sign of Gaussian curvature and the principal directions for noisy point clouds while Taubin presents an algorithm that estimates both principal directions and principal curvatures for triangle meshes. The drawback of Tang and Medioni is that they do not estimate principal curvatures while the drawback for Taubin is that he does not handle surface noise.

1.5 Contributions

The algorithms that we have developed extend the above state of the art. Wu and Levine present a robust curvature estimation method with a simple segmentation algorithm while Mangan and Whitaker present a robust segmentation algorithm with a simple curvature estimation method. We have developed an algorithm that has both traits—a robust curvature estimation method and a robust segmentation algorithm—and we ground our algorithm in the theory of the minima rule.
In particular, we have developed a Minima Rule Decomposition Algorithm, or more simply the Minima Rule Algorithm, that overcomes many of the drawbacks with Wu and Levine and Mangan and Whitaker. The heart of this segmentation is two new algorithms known as Normal Vector Voting and Fast Marching Watersheds. Normal Vector Voting is a curvature estimation algorithm, and the Fast Marching Watersheds is a new implementation of the watershed algorithm for surface meshes. Finally, we have developed a Part Saliency Metric that handles any over-segmentation problems that may arise. To emphasize, this dissertation yields four contributions to the state of the art as follows listed in Table 1.1.

<table>
<thead>
<tr>
<th>Contribution</th>
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<tbody>
<tr>
<td>1 Minima Rule Algorithm</td>
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<tr>
<td>2 Normal Vector Voting</td>
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<tr>
<td>3 Fast Marching Watersheds</td>
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<tr>
<td>4 Part Saliency Metric</td>
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Table 1.1: List of contributions in this dissertation. This table is actually a contrived example for illustration.

Part Decomposition: Minima Rule Algorithm The most significant contribution is the development of a computer vision algorithm that follows the human vision theory of the minima rule. To date, no computer vision algorithm implements the minima rule for 3D surfaces. As we have noted, Wu and Levine [Wu and Levine, 1997] do attempt an implementation, but their approach is not true to the minima rule theory since they do not use a proper curvature estimate. The algorithm that we present in this dissertation represents the first computer vision implementation of the minima rule for mesh segmentation.

Curvature Estimation: Normal Vector Voting The second major contribution is the development of a robust curvature estimation algorithm known as Normal Vector Voting [Page et al., 2001, Page et al., 2003]. Although Tang and Medioni [Tang and Medioni, 1999] and Taubin [Taubin, 1995] offer important contributions, we have developed an algorithm that bridges the gap between these two algorithms. Our algorithm robustly estimates both principal directions and principal curvatures at the vertices of a triangle mesh, despite measurement error in creating the mesh.

Mesh Segmentation: Fast Marching Watersheds The third contribution is the development of a mesh segmentation algorithm inspired by the popular watershed algorithm for image segmentation. We call our algorithm Fast Marching Watersheds. Although Mangan and Whitaker [Mangan and Whitaker, 1999] have demonstrated the feasibility of adapting image processing watersheds to surface meshes, their algorithm is a “bobsledding” approach that leads to significant over segmentation and requires handling of certain special cases. Similar to Vincent and Soille [Vincent and Soille, 1991], Fast Marching Watersheds avoids these problems by employing a “hill climbing” approach. Unlike Vincent and Soille, our algorithm does not require the pre-sorting step and thus does not require random access to each of the vertices in a triangle mesh. This difference is important to our application of
the minima rule since we make local decisions about “water heights” and not global ones, as we explain in later sections.

Shape Measure: Part Saliency Metric The final contribution is a new Part Saliency Metric, derived from a human vision theory [Hoffman and Singh, 1997]. After we decompose a scene or object into a set of parts, we create a Part Adjacency Graph to define the relative relationship of each part. Our proposed metric assigns a value to the visual salience, or importance, of each part and to the salience of connections between parts. This metric enables filtering of oversegmentations that might occur where we merge the least visually salient parts with other more salient ones.

1.6 Document Organization

The remainder of this dissertation documents the details of our algorithms and the above contributions. Chapter 2 presents a survey of the literature for each contribution and also justifies our choice of the minima rule. Then, we overview the complete algorithm for part decomposition in Chapter 3. The results from this dissertation research are in Chapter 4. These experimental results demonstrate the robust capabilities of our algorithms and their successful application to a wide variety of objects and scenes. Finally, we conclude in Chapter 5.
Chapter 2

Literature Review

Blah blah blah.
Chapter 3

Part Decomposition Theory

Blah blah blah. The normal vector voting equation is as follows:

\[ N_i = N + 2 \cos \theta_i \frac{v_{c_i}}{\|v_{c_i}\|} . \tag{3.1} \]

The vector \( N_i \) in (3.1) represents the normal vector for triangle \( f_i \).
Chapter 4

Experimental Results

Blah blah blah.
Chapter 5

Conclusions

Blah blah blah.

“A JOURNEY OF A THOUSAND MILES BEGINS WITH A SINGLE STEP.”
—Confucius
Bibliography
Bibliography


Appendix
Appendix

Blah blah blah.
Vita

David Lon Page was born in Kingsport, Tennessee, on September 12, 1969, the son of Bobby Mellville Page and Shirley Jean Boyd Page. After graduating in 1987 from Sullivan South High School, Sullivan County, Tennessee, he attended Tennessee Technological University in Cookeville where he received both a Bachelor of Science degree, magna cum laude, in 1993 and a Master of Science degree in 1995 from the Electrical Engineering department. During his undergraduate studies, he worked for two years at the Oak Ridge National Laboratory in Oak Ridge, Tennessee, as a cooperative education student and for one summer at the U. S. Space Camp in Huntsville, Alabama, as a team leader. In the fall of 1995, David entered the workforce as an electronics engineer with the Naval Surface Warfare Center in Dahlgren, Virginia. In 1997, he again returned to the academic world as a doctoral student at The University of Tennessee in Electrical Engineering. During the summer of 1998, he joined the Imaging, Robotics, and Intelligent Systems Laboratory as a graduate research assistant where he completed his Doctor of Philosophy degree in 2003. In the future, David hopes to pursue a professional career in flag football.