5-11-2011

Classification of Marine Vessels in a Littoral Environment Using a Novel Training Database

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A Thesis Submitted to the Graduate Studies Office

in Partial Fulfillment of the Requirements for the Degree of

Master of Science

in

Mechanical Engineering

May 11, 2011

Embry-Riddle Aeronautical University

Daytona Beach, FL

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by

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This thesis was prepared under the direction of the candidate's thesis committee chairman, Dr. Charles Reinholtz, Department of Mechanical Engineering, and has been approved by the members of his thesis committee. It was submitted to the Mechanical Engineering Department and was accepted in partial fulfillment of the requirements for the degree of Master of Science in Mechanical Engineering.

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ACKNOWLEDGEMENTS

Completing this research would have been impossible without certain key people.

I'd like to thank Dr. Charles Reinholtz, my thesis advisor and committee chairman for igniting the fire inside of me that I needed to perform this research. Without his guidance and knowledge, I never would have become so interested in this field. He inspires his students to always do their best and to take a true interest in whatever they do. Thank you, Dr. Reinholtz, for showing me the way.

Secondly, thanks go out to Dr. Sathya Gangadharan without who this research would not have been complete. Dr. Gangadharan never fails to take time out of his busy schedule to help a student and will literally force you to perform the best possible work you can. The students always love him for it in the end. Thank you Dr. Gangadharan.

Finally, I'd like to thank my family, my mom and dad, never hesitant with helpful advice and always willing to lend a hand. My mom, for her excellent grasp of both literature and grammar without whose help this work would seem a poor reflection at best. My dad, for his technical advice and constant reminder to always do my best no matter what it takes to get the job done. Thank you both for believing in me and providing all the help and support I could ever ask for. Without you, this work would not have even begun. Thank you for getting me to where I am and making me who I am today.

ABSTRACT

Author: Robert Andrew Lister

Title: Classification of Marine Vessels in a Littoral Environment Using a Novel Training Database

Institution: Embry-Riddle Aeronautical University

Degree: Masters of Science in Mechanical Engineering

Year: 2011

Research into object classification has led to the creation of hundreds of databases for use as training sets in object classification algorithms. Datasets made up of thousands of cars, people, boats, faces and everyday objects exist for general classification techniques. However, no commercially available database exists for use with detailed classification and categorization of marine vessels commonly found in littoral environments. This research seeks to fill this void and is the combination of a multi-stage research endeavor designed to provide the missing marine vessel ontology. The first of the two stages performed to date introduces a novel training database called the Lister Littoral Database 900 (LLD-900) made up of over 900 high-quality images. These images consist of high-resolution color photos of marine vessels in working, active conditions taken directly from the field and edited for best possible use. Segmentation masks of each boat have been developed to separate the image into foreground and background sections. Segmentation masks that include boat wakes as part of the foreground section are the final image type included. These are included to allow for wake affordance detection algorithms rely on the small changes found in

wakes made by different moving vessels. Each of these three types of images are split into their respective general classification folders, which consist of a differing number of boat categories dependent on the research stage.

In the first stage of research, the initial database is tested using a simple, readily available classification algorithm known as the Nearest Neighbor Classifier. The accuracy of the database as a training set is tested and recorded and potential improvements are documented. The second stage incorporates these identified improvements and reconfigures the database before retesting the modifications using the same Nearest Neighbor Classifier along with two new methods known as the K-Nearest Neighbor Classifier and the Min-Mean Distance Classifier. These additional algorithms are also readily available and offer basic classification testing using different classification techniques. Improvements in accuracy are calculated and recorded. Finally, further improvements for a possible third iteration are discussed.

The goal of this research is to establish the basis for a training database to be used with classification algorithms to increase the security of ports, harbors, shipping channels and bays. The purpose of the database is to train existing and newly created algorithms to properly identify and classify all boats found in littoral areas so that anomalous behavior detection techniques can be applied to determine when a threat is present. This research represents the completion of the initial steps in accomplishing this goal delivering a novel framework for use with littoral area marine vessel classification. The completed work is divided and presented in two separate papers written specifically for submission to and publication at appropriate conferences. When fully integrated with computer vision techniques, the database methodology and ideas presented in this thesis research will help to provide a vital new level of security in the littoral areas around the world.

INTRODUCTION

This work presents a novel framework for a marine vessel ontology for use with classification techniques in a littoral environment. The resulting database consists of over 900 high-quality color images, segmentation masks and segmentation masks with boat wakes representing 79 different marine vessels. For each vessel, multiple viewing angles were captured ranging from about 0° (looking at the stern) through 180° (looking at the bow) at intervals of about 15° allowing for vessel detection over a broad angular range. This should improve the successful identification rate. Because the boat images were captured in real working environments that prohibit controllability, the actual viewing angles have a discrepancy of up to about ±10°. Therefore, images labeled as 90° could actually be as low as 80° or as high as 100°. A compass heading of 0° is taken from the stern of the boat with 90° representing a straight-on side view. Images labeled as "front" represent pictures taken of the bow while those labeled "back" represent the aft of the boat.

The 900 images making up the database are composed of 400 high-resolution, high quality color images cropped and edited to show only the boat and surrounding features. This permits flexibility for future classification methods to determine which features and affordances to use when training the algorithm. An additional 400 black and white segmentation masks are included, one for each color image, to allow for use with simple binary classifiers or application of future algorithms that rely solely on such a classification technique. By using segmentation masks, classification algorithms are able to perform much faster with less computational load on the CPU. Finally, the inclusion of 100 segmentation masks with boat wakes allows identification when specific vessel wakes are present. These images were captured and analyzed when the vessel of interest was moving at wake-creation speeds and is included to allow algorithms that might distinguish the nuances of different wakes to make full use of segmentation masks. The underlying algorithms that do so and the associated methods behind them are beyond the scope of this research paper.

Each image is categorized by a human operator into one of 11 different categories for the first stage and one of eight different categories for the second. The categories are based on common boat types found in the littoral environment around the Halifax River in Daytona Beach, Florida and the Indian River in New Smyrna, Florida. Because this is a framework, not all types of boats are currently incorporated into the database and therefore, expansion of the database is expected. The methodology and techniques required for successful development of the database are explained in this thesis. This should allow for the addition of future categories.

Applications

Currently, most littoral area security is performed manually by human observers presenting an opportunity for improvement through the use of autonomous detection and classification surveillance techniques. The common problems of boredom, fatigue and human error contribute to the current inadequacies in security and surveillance in ports and harbors. Repetitive tasks such as surveillance and categorization are particularly well suited to semi-autonomous techniques that can automatically identify and classify ships entering and leaving congested shipping areas. Implementation of this technology can enhance security for ships operating in littoral environments. This database is the first step toward creating such a semi-autonomous surveillance system as it will allow for the training of algorithms that can perform the classification functions. Furthermore, after an initial baseline system is created, additional autonomous behavior detection algorithms can be applied to enhance security further. This capability has extensive potential applications in both military and merchant environments. Military ships can carry an on-board system to employ in foreign or domestic harbors. Detected potential threats can be evaluated and stopped, if necessary, before they become a significant security issue. Lives can be spared and trade can be protected through implementation of such systems. The first step in achieving this outcome is to successfully classify existing types of vessels so that the proper behavioral algorithms can be applied. The research discussed in this thesis develops the first stage of a useful classification system by providing a useable training database to the security and surveillance world.

Thesis Format

This thesis is presented in a relatively new, “paper” format. Rather than publishing conference or journal papers and then recompiling the same material in the format of a typical thesis, the papers are included directly as appendices. In the case of this thesis, two papers have been written and included as Appendix 1 and 2.

APPENDIX A: PAPER 1

Classification of Marine Vessels in a Littoral Environment Using the LLD-900

This paper was written and submitted to:

OCEANS '11 MTS/IEEE KONA

Hilton Waikoloa Village, Kona, Hawai'i
September 19-22, 2011

Classification of Marine Vessels in a Littoral Environment Using the LLD-900

Robert Andrew Lister **Charles Reinholtz**

Abstract

Research on object classification has resulted in hundreds of databases for object classification. None, however, exist for detailed classification of marine vessels in a littoral environment. This work presents a novel database framework based on seventy nine marine vessels with the goal of providing a complete marine ontology. The research begins with a newly developed database containing over 900 high-resolution images, segmentation masks and masks with boat wakes. The database is then tested using a nearest neighbor classifier to determine its initial strengths and weaknesses. The ultimate goal of such a database is that when used with advanced classification algorithms and combined with sophisticated computer vision processes, it will enable a new, higher level of persistent security in ports and harbor areas. It is a first step toward creating a universal marine ontology for littoral areas.

Keywords:

Object Classification; Image; Marine Vessel; Ontology; Littoral; Nearest Neighbor Classifier; Segmentation Mask

1. Introduction

Shortcomings currently exist in the security and surveillance capabilities of littoral areas. Most ports and harbors lack a consistent method to preempt attacks by marine vessels because the force tasked with this type of surveillance is human [1] and the coverage is limited. Automated methods for classifying vessels and recognizing anomalous behavior do not yet exist, in part because the basic research has not been completed. Today, regular security functions are performed by a person who watches and physically records the boats that travel in and out of an area, surveying traffic by eye. Because the work is done by humans, common problems that accompany repetitive tasks are present. Development of a semi-autonomous surveillance system that alerts a human operator when human interaction may be needed, could significantly improve security. Computer vision processes trained with a high-quality database will help achieve this goal and will improve the safety of littoral areas. The development of such a database allowing for the successful identification of different ship types is the first step in making such a system.

Object recognition and classification methods have advanced exponentially along with the general growth of computer vision tools. From the inception of computer vision [2], through the complex algorithms available in the classification field today, this development is evident through the numerous studies, tests and theories published. Results of these studies show that the algorithms used to obtain the highest identification rates are only as strong as their training set. Today, computer vision algorithms can easily recognize cars, people, and even apples in controlled conditions. This is in large part due to the wealth of databases that are used as high-quality training sets which are available on the market [3, 4, 5, 6, 7, 8, 9, 10, 11]. Some of the more extensive and comprehensive databases began small and simple before growing in size and complexity. Examples of such databases include the original Caltech 101 [12] and the PASCAL collection [13]. Other databases started huge and varied and grew even bigger during evolution, such as the LabelMe database [14]. All of these databases are useful in solving identification problems in their particular task domain. However, no database currently exists representing the variety of marine vessels common in littoral environments. The LabelMe database does includes more than a thousand images of ships, and other databases also offer multiple types of boats for use with classification. However, all of the images in these databases are labeled as simply "boat" category. This works well for distinguishing between boat and non-boat objects, but it will not work to provide the more detailed classification necessary for improved security in ports, harbors and other coastal waterways. Routine traffic in these areas includes many different types of vessels that may be present at any given time. Adequate autonomous surveillance requires a database for the identification of each of these different ship types. This provides motivation for the database developed in the present study.

The database described in this paper is entitled the Lister Littoral Database (LLD-900). It is intended to be used for marine security and surveillance in congested shipping areas including bays, ports and harbors. The ultimate goal is to use the final iteration of this database as the training set in advanced classification algorithms. These classification algorithms can be combined with object-detection algorithms and existing computer vision techniques to create a system that will automatically identify and track marine vessels. Anomalous behavior detection methods will later be included in the system so that maritime traffic can be passively scanned. If a vessel displays behavior which triggers a response during surveillance, a human operator will be alerted. The operator can then determine if further action is necessary. The U.S. Navy and other contractors are currently working to build anomalous behavior detection systems [15, 16, 17, 18], but they face the problem of obtaining both normal and anomalous behavior training sets for use with their algorithms. The LLD-900 is the first attempt to provide a high quality marine vessel training set to the computer vision community.

The purpose of the LLD-900 is to lay the foundation for the use, expansion and continuation of a larger database for future testing. The current database consists of 900 high-resolution images and segmentation masks, categorized into nine main vessel types. Two of these categories are further subdivided to give a total classification choice of 11 different options. Ten of these categories are tested while the remaining category is withheld until more images can be added. The LLD-900 is a combination of three types of images. The first image type is represented by high-resolution color images of boats in their working, active environments. The second consists of segmentation masks showing just boat and background while the third type contains segmentation masks separated into boat, background and wake. The current trial of the database uses the segmentation masks to train a Nearest Neighbor classification method. The database is then tested using the leave-one-out testing technique. These methods were chosen for speed and simplicity in the overall demonstration of the database's potential. The LLD-900 represents the framework for a complete marine vessel ontology; it is the first step in obtaining a training set for use in the littoral environment. In its final form, the database can help protect people and property.

Section 2 provides additional detail and explains the problem of object classification the LLD-900 helps to solve. Section 3 introduces and describes the database in detail, and it discusses the situations where it will be most useful. Sections 4 and 5 describe testing performed on the first iteration of the database and the results obtained. Section 6 discusses future plans and changes that will be required as the LLD-900 database evolves.

2. Object Classification

Computer vision was first studied in the 1980's [2] and quickly became an important field of study. Today, the field encompasses object recognition, classification, tracking, visual analysis, processing techniques and many other areas. The main focus of this paper deals with classification. It is important to understand the difference between object recognition and object classification. Object recognition deals with recognizing an object of interest (OOI) in an image that has been seen previously. The main point of recognition is that the object has been seen before and is not new. The object can be viewed from a different angle, under different lighting or in a different environment but it cannot be a new object. The task of the recognition algorithm is to locate this known object in the image. In comparison, object classification deals with classifying an OOI that may or may not have been seen before. The object classification algorithm is tasked with assigning a correct categorization label to the OOI regardless of whether that object is part of the initial training set. Previously unseen and unknown objects must be classified along with known objects, making classification much harder than recognition. While the two areas are similar important differences exist. Object classification systems must be insensitive to in-class variances of the object characteristics. These include shape, color and size [19]. A green apple must be classified the same as a red apple if the category trained is generic apple. The classification depends strongly on features of the image. Significant research has been conducted towards allowing software to perform this function effectively [20, 21, 22, 23].

Tests and experiments in human cognitive psychology can be thought of as precursors to machine object classification. A broader term, categorization, is used to describe the human phenomenon performed when people perceive everyday objects. Humans are able to easily categorize objects at different levels cascading down until a single object is recognized as different from another [24, 25]. To explain this, all humans realize that horses, dogs and cats are all represented by a super category of mammal. The category dog can be subdivided further into Labrador, Doberman and more. The category of Labrador can be separated into Yellow Lab, Black Lab, Chocolate Lab and Labrador Retriever. This division can keep being applied until one instance of a particular dog is recognized as different from a second dog. However, there also exists a basic level of categorization in which members of the same category exhibit similar shapes. This is the same level where a single mental image conveys the idea of the entire category and where tested human subjects are able to identify the category the fastest. This basic level is also the first understood by children and is often used in picture books to teach young children about their surrounding environment. An example of these categories would be boat, dog or tree. There are numerous databases for object classification that separate objects into basic categories [3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14]. The focus of this paper is detailed classification of boats, where the category of boat is split into multiple classes.

Object classification identifies unknown images by comparing significant features in the unknown object to features in images of a trained class [26]. A feature is defined as, "a function of one or more measurements, computed so that it quantifies some significant characteristic of the object"[27]. Methods to determine what information is useful and useable as a feature are termed feature extractors. Good feature determination is important to the overall quality of the software. If strong features can be extracted, good comparisons can be made. A feature is considered strong if that feature has a large variance between objects of different categories but very little variance in objects of the same category. The features used are assigned a numeric value determined by building a training set and measuring given values. The two stages of classification are training and classifying. During the training phase, the software is taught what samples go in what class. The value of each feature is determined, and an average value for the entire trained class is assigned. When an unknown sample is then measured, it can be grouped to one of the trained classes depending on how close the feature values match. This is the reason that a good training set is vital to any object classification technique and any process which makes use of such algorithms.

It is important to realize that object category labels are simply a learned representation and do not have any physical meaning in the real world [24]. This means that it is possible for one person to see one category in a different way from another person. For example, what one person calls a mouse, another may refer to as a rodent, rat or any number of other names. However, many of the basic category levels recognized by humans are the same or similar enough to all people, that comparison can be made and certain labels can be given. This means that with care, certain category labels can be useful for object identification. The database developed in this study attempts to separate given boat images into classes commonly recognized by humans for use in object classification software. The next section introduces this database and describes some of its characteristics.

3. The Database

The database presented in this paper has been influenced by many existing databases. This includes the first iteration of the ETH database called the ETH-80 [3], the Caltech 101 Database [9] and the LabelMe database [14]. The major difference between these existing databases and the new one is the content and frame layout of categories. The new database contains nine categories of the super-category "boat". Two of these categories are divided further, into subcategories, giving a total of eleven separate categorical options. The purpose of this work is to create a novel database useful to port and harbor security where the boats must be divided into separate types for identification.

For this database, each category contains images of three to twenty different boats. Each boat has images taken from multiple viewing angles. There is also a separate subfolder for every category that holds one view of a single boat when multiple angles were not available. The database has been collected in a real world working environment. This should allow tested algorithms to experience some of the same problems they face in the field. The desired goal is to have the same angle views for each of the separate boat images. The boat images in this database were collected from shore with no control of the passing boats. Images were captured and sorted into approximate viewing angle based on the judgment of the author. For this reason the view angles are not as exact as for some existing databases where the OOI is highly controllable. However, sorting algorithms used on this database should exhibit results similar to those obtained in the field, making the database useful for testing and training. If algorithms do not work with the images in this database, they will probably not be successful in a real world environment.

The database contains images of 79 separate boats with an additional 11 multi-boat folders. This yields 400 high-resolution color images of boats in a littoral environment. The pictures were taken with a 12.1 Megapixel Canon COOLPIX S8100 digital camera using different zoom factors depending on the location of the interest vessel. The images were taken from a variety of viewing angles and in varying light and weather conditions. Viewing angle are approximately 0° , 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135°, 150°, and 180°. 0° is taken from the stern of the boat with 90° representing a straight on side view. The front and back correspond to the bow and stern of the boat respectively. The images have an error of about ±10° as determined by the author due to the uncontrolled subjects and environment of the captured data. This means that while some views may be labeled at 90°, the actual viewing angle could be as high as 100°. All images are separated into their respected final categories labeled as: Barge, Cargo, Cruise, Jet Ski, Monohull Motorboat, Pontoon Motorboat, Canoe, Dinghy, Sail Boat, Tug and Yachts and Luxury. The Canoe category is the 11th category that is left out of testing due to limits imposed by the small amount of images contained under the label. It will be added back into testing when more images are added in the category. This is typical of what can be seen in an everyday harbor/port environment. Segmentation masks for each boat have been developed and are included to allow for use with different classification algorithms whose training depends specifically on such data representation. These segmentation masks are split into black background and white foreground to make them easily identifiable to humans as well as making the threshold value the same throughout all testing images. Furthermore, 136 segmentation masks with wakes were developed showing typical wakes the imaged boat makes at wake-creation speeds. This is included for classifiers that rely on combinations of local features or novel algorithms that may be designed using wakes as a feature for classification. The masks with wakes are divided into three colors for ease of viewing and for the requirements of specific training methods. The masks were each created using Adobe Photoshop and the lasso tool found within. Each color image was imported into the software and then, through use of the lasso tool, the edges were carefully traced out and separated into different layers depending on the subject. The underlying method is a user controlled edge detection method. The boat and wake are both considered foreground layers while the rest of the scene is converted to background. The foreground layer is turned white for boats and red for wake while the background layer is turned black. Figure 1 shows a sample of the high-quality images that make up the database with Figure 2 showing an example of the segmentation masks and segmentation masks with wakes.

The new database allows for a wide variety of classification and recognition algorithm to be tested. . Segmentation models can be used with just the segmentation masks. Segmentation and local feature identifiers can be used with the segmentation-with-wake masks. Further research is necessary to determine the true differences in the wakes that different boats make, but these determinations are beyond the scope of this paper. The masks are included to support testing methods that may be discovered or added in the future. The high-quality color images allow for real world performance tests. The database can be adapted to algorithms that requires different features than those tested here, because the baseline color photo is included, which enables user-defined features to be determined. This provides the user with flexibility to use the database as the training set in other classification algorithms and to test any new methods as they are developed.

The ultimate goal of the database is to provide overall improvement in surveillance methods that will lead to better littoral security. It is important to note that scale has not been included in the initial iteration of this work. The results section discusses how it could be of additional benefit. Scale will be added in later revisions. This will allow the new classification methods that rely on scale-space to be tested. Section 4 discusses the method used to test the database.

4. Test Method

The easiest and most robust algorithm available to test the effectiveness of a recognized classification algorithm for multi-class object recognition is a binary particle classifier known as the Nearest Neighbor Method. This method has been applied using the leave-one-out testing approach to determine the accuracy of the database. The results will show minimum obtainable accuracy, because there are many state-of-the art and novel algorithms available that are likely to achieve better results. The purpose of this test is to show that the database can be used with all such algorithms.

The first step in classification is to determine a set of features to be used in comparison between the training set and the unidentified set. This set of features is known as a feature vector and this vector represents a numerical measure of effectiveness. An example of a feature vector would be {Heywood Circularity, Elongation Factor} [26]. In this example, the closer the shape of a sample is to a circle, the closer its Heywood circularity factor is to 1. The more elongated the shape, the higher its Elongation Factor. A feature tested using these features returning a vector result of {1, 100} would be classified as both circular and long. In general classification, these values would be computed for a single unknown object and then compared to corresponding values in a pre-trained set. Classification would then be assigned based on which group the values of the test image most closely match. For this database, the feature vector used is a scale-invariant, rotation-invariant and reflection-invariant shape descriptor. Because of this simple shape determined classifier, segmentation masks are used as the training dataset. The feature vector is made up from eight separate features representing: circularity, degree of elongation, convexity, detailed convexity, hole locator, detailed hole discrimination, spread, and slenderness. Each of these is available in the Nearest Neighbor classifier offered in the LabVIEW Vision Module.

Figure 1: Sample image thumbnails from database

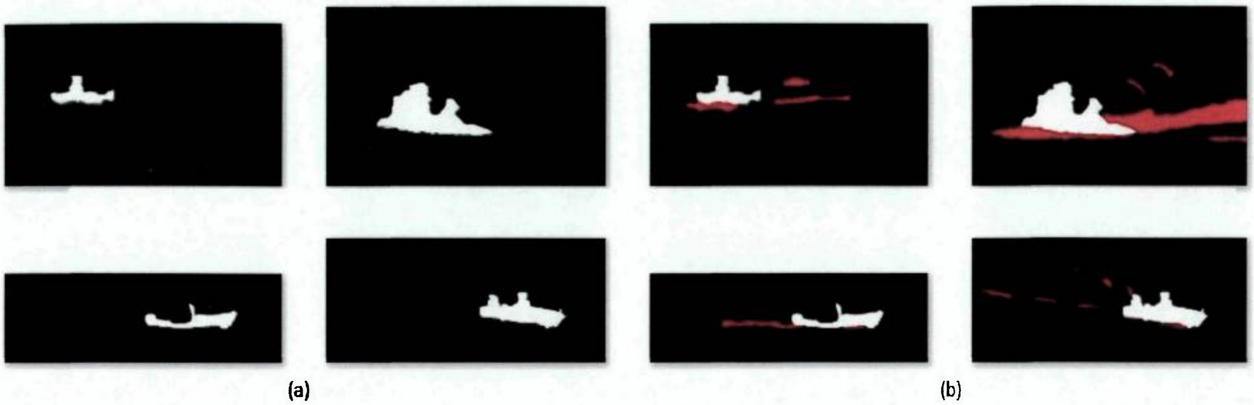

Figure 2: Sample segmentation masks (a), Sample segmentation masks with wakes (b)

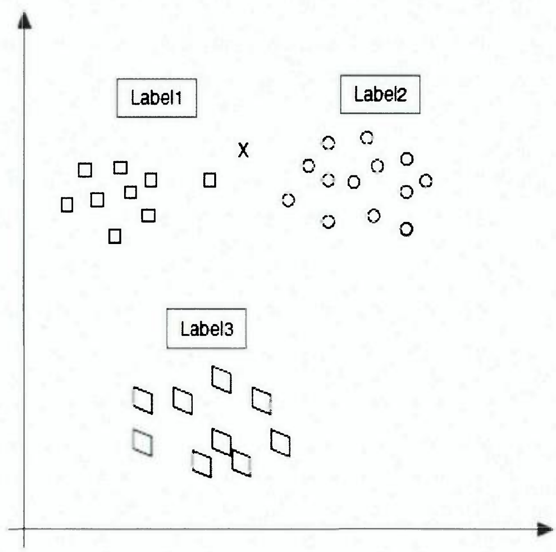

Figure 3: Visualization of Nearest Neighbor Classifier

The first step in using the classifier is to threshold portions of the image that are not needed. In this case the background is thrown out and only the bright portion representing the boat in the segmentation mask is used. The leave-one-out test method is used and is accomplished by training all but one boat set and then running the classifier on the remaining boat. The Nearest Neighbor Classifier works by determining the distance to each of the feature vectors described above. Figure 3 helps to visualize this. In the figure, the different classes are graphed and the X represents the unknown sample's feature vector. Because the X is closest to a "label 1" feature vector, the result would be that sample X is labeled Label 1. The sum distance metric is used to determine the distance and is described in Equation 1. Equation 2 and 3 describe the calculations performed using the Nearest Neighbor classification algorithm. For these equations, X_i and Y_i represent the feature vectors of known classes, X is feature vector of unknown class and C_j is defined as the distance to closest sample that is used to represent the class.

$$d(X,Y) = \sum_{i=1}^{n} |X_i - Y_i| \qquad (1)$$

$$d(X,C_j) = \min d(X,X_i^j) \qquad (2)$$

$$X \in Class\ C_j, if\ d(X,C_j) = \min d(X,C_j) \qquad (3)$$

There are two other distance metrics that can be used, namely, Euclidean and Maximum distance. Euclidean is the standard distance measurement working with closest physical distance and Max distance is the maximum amount of space in block form from vector to vector. The results from the classifier are discussed in the next section.

5. Results

In this section the method described above is applied to the database and the results are presented in Table 1. The results are listed by category for a total of ten classes of boats. While the absolute correct classification score was lower than desired, it is important to remember that this is the first iteration of a novel framework and that with improvement to the database, significant improvements in the results are expected.

In the results, if the algorithm returned at least one correct classification in the tested boat images it was considered successful under the table heading % Single Image. This helps establish a baseline for when the classifier is completely wrong and shows the classification categories that need the most improvement. Under the table heading % Actual Correct, the results for when the classifier is completely correct are recorded. This column represents a true test of the strength of the classifier. Under the table heading % Theoretical with Scale, the percentage is shown as if a scale function were added to the classification database and algorithm. The success rate for this heading is determined based on the next nearest class whenever an image is categorized incorrectly. If the next nearest class according to the algorithm is the correct class and the only difference in misclassification is the difference in size of the two images, the classification is considered correct. An example is that some of the Jet Ski and Cruise Ships were confused with each other but could easily be identified as separate, distinct classes if the classifier included scale information. The column was included to show the possible accuracy of future iterations of the database and to show the importance of adding scale.

The Largest Confusion column is included to show the areas where the classifier became the most confused with another category. This data is included to show where the database needs adjusting and to show how the database is reacting to the classifier. It is important to have this kind of data, since it allows the end user to successfully determine where adjustments are needed.

Category	% Single Image	% Actual Correct	% Theoretical with Scale	Largest Confusion
Barge	57.1	26.3	68.4	Pontoon and Monohull
Cargo	76.9	40.5	81.1	Tug and Monohull
Cruise	0.0	0.0	80.0	Cargo and Monohull
Jet Ski	50.0	9.1	100.0	Tug
Monohull	93.5	51.2	80.8	Pontoon
Pontoon	60.0	19.0	42.9	Monohull
Dinghy	66.7	28.6	100.0	Monohull
Sailboat	90.9	64.7	73.5	Monohull
Tug	90.0	62.1	100.0	Cargo
Yacht and Luxury	86.7	44.4	75.9	Monohull
Overall Results		**44.0**	**76.7**	**Monohull**

Table 1: Classification Results for Nearest Neighbor Testing

The database performed well for the first iteration with an overall correct classification of 44.0%. This is expected to improve significantly with the next iteration of the. By adding scale, the classifier could reach a theoretical level of 76.7% success rate, bringing it on par with many classification systems in use today. The most confused vessel was the Monohull Motorboat. By choosing better feature values to distinguish this category from the others, large improvement can be found. This is due to the size of the Monohull Motorboat category. A small improvement here will have a larger overall effect on the classifier's accuracy. The Sailboat category gave the highest single correct classification rate with over 60% without scale and 73.5% with the addition of scale. The most misidentified categories were the Cruise ship and Jet Ski's which were constantly confused with different sized ships giving a classification rate of 0 and 9.1 %, respectively. By adjusting for scale, a theoretical rate of 80 to 100% rate can be achieved. The Dinghy, Jet Ski, and Cruise ship categories should show the largest improvement with the addition of scale. Section 6 discusses changes that can be made in the future and the next steps for the database.

6. Conclusion

The classification results demonstrate the potential of the new database for use in object classification algorithms. The overall identification accuracy was disappointing, but the work provides hope for significant improvement with refinement. Future versions of the database will incorporate scale to help bring the classification rate up significantly without the need for other changes. However, work is underway to reorganize the database and reassess misclassified boats. The next version of the database will have different categories, different organizations, and different classification options. Future tests will also compare multiple classification algorithms with different clustering methods and distance metrics.

The goal for this work is to evolve the database into a useable training database for use with multiple classification techniques to provide better security in ports and harbor areas.

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APPENDIX B: PAPER 2

Using the LLD-900-2 for Marine Vessel Classification in Littoral Environments

This paper is written for intended submission to:

CVPR 2012

25th IEEE Conference on

Computer Vision and Pattern Recognition

Professional conference on the date of:

October 17, 2011

Using the LLD-900-2 for Marine Vessel Classification in Littoral Environments

Robert Andrew Lister **Charles Reinholtz**

Abstract

The LLD-900-2 research database represents the second iteration of a littoral marine vessel ontology previously referred to as the Lister Littoral Database (LLD-900). The database includes over 900 high-resolution color images, segmentation masks of boats and segmentation masks of boats with wakes. The Nearest Neighbor, K-Nearest Neighbor and Min Mean Distance Classifiers are tested with the new database and the results are presented. The new database has produced a 14.5% increase in classification success rate and a theoretical accuracy of up to 93.1%. The LLD-900-2 is the second step in creating a universal marine vessel ontology for use in the littoral environment.

Keywords:

Object Classification; Image; Marine Vessel; Ontology; Littoral; Nearest Neighbor Classifier; K-Nearest Neighbor; Min-Mean Distance Classifier Segmentation Mask

1. Introduction

This paper represents the continuation of work presented in previous research [1] to develop and further refine a framework for a marine ontology useful for vessel classification in a littoral environment. Strong security and surveillance of ports and harbors are vital to the safety and economy of entities worldwide. Inadequacies in existing alert systems can result in severe consequences to life and property. When terrorists and other extremists circumvent current technology and successfully carry out attacks on military and merchant vessels, the inadequacies become evident. The bombing of the USS Cole and the resulting loss of life is one example where a novel security method could have prevented a horrible outcome. Notably, merchant ships present in ports and harbors worldwide are even more vulnerable to attacks. Currently, ongoing research into anomalous behavior detection and prevention through use of autonomous systems is being conducted by the US Navy [2]. However, in order to successfully identify threats and determine when a vessel is behaving anonymously, normal behavior must first be established. Since different boats behave with different sets of standards, the boats must be properly classified in order to apply the correct behavioral detection algorithms. Currently, no database exists that can be used to properly train the classification algorithms useful for littoral environment classification. The development of the LLD-900 research project details the first steps towards remedying this situation.

The LLD-900 was the first iteration of a framework design for a database useful in littoral area vessel classification [1]. This initial database helped to pinpoint specific areas that needed improvement and refinement. The second iteration, referred to as the LLD-900-2, attempts to remedy concerns identified in the earlier research and provides more focused results. For example, the initial database contained 11 total separate ship classification categories. However, within some of these categories, some features strongly overlap. This led to problems with the classifiers successfully identifying the correct category to which a ship belongs. To help correct this misidentification, the LLD-900-2 reduces the total category number to eight but keeps the original image count at 900 high-resolution images. Boats that were initially misclassified 100% of the time are reevaluated and classifications are redirected based on changes in the parameters that define the new categories. Finally, three separate and readily available classification algorithms are tested with the database to compare and contrast the algorithms under the revised catagories.

The goal of the revised database remains the augmentation of marine security and surveillance in the congested shipping areas of bays, ports and harbors. The goal is to use the final iteration of this training set to successfully train and test advanced classification algorithms. These methods will be combined with object recognition algorithms and other state-of-the-art vision techniques to automatically identify and log each boat that enters an area. The boats behavior can then be monitored and recorded. In the future, anomalous behavior detection methods will be combined with the database so that shipping traffic can be passively scanned. If a vessel displays anomalous behavior, a response can be triggered and a human operator can be alerted. The user can then determine if further action is warranted. As previously stated, this database is a framework and the LLD-900-2 represents the second step in obtaining the ideal training set. In its final form, the database will be used to help solve security problems and will contribute to the increased protection of people and property in littoral environments worldwide.

Section 2 of this paper details the classification methods used while testing the database. Section 3 discusses revisions made from the previous version to the LLD-900-2 database, and section 4 describes the new test methods applied. Section 5 reviews the results and discusses improvements while section 6 details anticipated future research with refinements and further improvements projected for the next iteration.

2. Classification Methods

The wide variety of classification algorithms available today have provided a broad basis for numerous research papers that detail available classification methods. This research area has grown into an enormous field of study and includes case-based collective classification methods [3], appearance based methods [4], contour based methods [4, 5, 6], moment based classifiers [7, 8], local image feature classifiers [9, 10], global image feature classifiers [11, 12, 13], support vector machine classifiers [14, 15, 16], motion and appearance based methods [18], marginalized graph kernel classifiers [10, 18], and the color histogram comparison method [19]. The LLD-

900-2 database allows for testing of any of these methods to determine the strength of the classifier. For this experiment, the Nearest Neighbor, the K-Nearest Neighbor, and the Min-Mean Distance Classifiers are tested. Each of these methods is an example of a binary classification shape detector in which segmentation masks can be used. These methods were chosen for their simplicity and speed in overall demonstration of the database's potential, and they allow for direct comparison with results obtained in the LLD-900 research database[1].

The first step in object classification is to determine a set of features to be used in comparison of a training set and an unidentified image. This complete set of feature values is known as a feature vector. It represents a numerical vector of values to be compared. An example of a feature vector would be {Heywood Circularity, Elongation Factor} used in bolt classification [20]. In this example, the closer the shape is to a circle, the closer its Heywood circularity factor is to 1. The more elongated the shape, the higher its Elongation Factor. Something tested using this feature vector that returned a result of {1, 100} would be classified as circular and long. In general, these feature values would be computed for a single unknown object and then compared to the corresponding computations of a pre-trained set. For the algorithms used in this database test, the feature vectors stay the same for each method. The feature vector is a scale-invariant, rotation-invariant and reflection invariant shape descriptor. The feature vectors for the tests are comprised of eight separate features as follows: circularity, degree of elongation, convexity, detailed convexity, hole locator, detailed hole discrimination, spread, and slenderness. The values for these features are readily determined by each of the classifiers offered in the LabVIEW Vision Module.

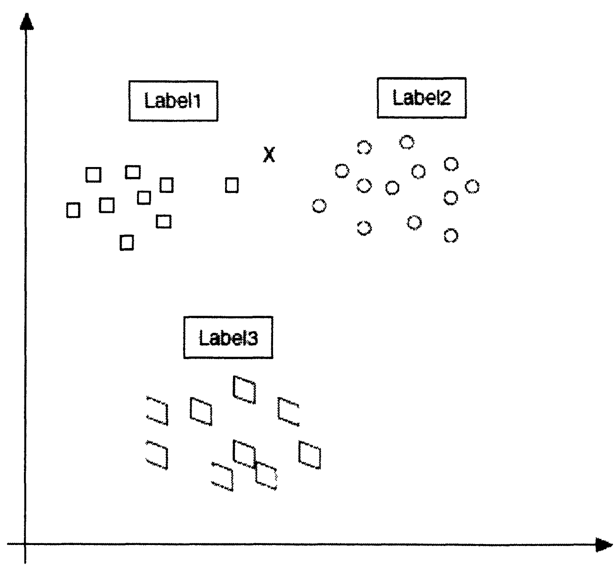


Figure 1: Visualization of Nearest Neighbor Classifier

The Nearest Neighbor Classifier works by determining the distance to each feature vector as represented in Figure 1. In the diagram, the different classes are graphed and the X represents the unknown sample's calculated feature vector. Because the X is closest to a label 1 feature vector, the result is sample X labeled as Label 1.

The K-Nearest Neighbor classifier is similar to the Nearest Neighbor Classifier and requires the same preprocessing techniques. The distance is still the determining factor in classification, but the classifier instead takes the *k* nearest samples and applies a voting mechanism. The class having the majority of the votes is designated as the new class label. In Figure 1, if $k = 3$, the result would be an X labeled as Label 2. While Label 1 has the nearest sample, Label 2 has the next two closest samples and therefore would be selected using the K-Nearest Neighbor classifier. For testing of the LLD-900-2 database, the number of samples representing *k* is four. This is because of the limits imposed by the category with the fewest samples. The dinghy category has only seven trained images separated into three folders containing three different instances of a dinghy. The largest boat folder contains three distinct viewing angles of one dinghy while the remaining two folders each contain two separate viewing angles of other dinghy crafts. When testing this boat with the leave-one-out method, it can only be compared to four other trained dinghy images. This limits the value of *k* to a maximum of four. K-Nearest Neighbor classification is ideal when there is noise in the training set or when the samples are spread out and do not cluster tightly around a center point. The method returns more accurate results, but as with all methods, it depends on the available training set and the situation in which the classifier is used.

The Nearest Neighbor and K-Nearest Neighbor classifiers both rely on the same equations to function. In addition, they both use a sum distance metric when determining the distance as described by Equation 1. Equation 2 describes the method which the algorithm works. A value is assigned to $d(X,C_J)$ based on the min distance between the feature vectors of the known and unknown images. Equation 3 shows how the class is determined by comparing the value assigned to the unknown image to those of known images and whatever the closest image is, that label is applied as the unknown image's category. The only difference is that the K-Nearest Neighbor classifier performs the measurements *k* times. For these equations, X_ι and Y_ι represent the feature vectors of known classes. X is feature vector of unknown class and C_J is defined as the distance to the closest sample used to represent the class.

$$d(X,Y) = \sum_{\iota=1}^{n} |X_\iota - Y_\iota| \qquad (1)$$

$$d(X,C_J) = \min d(X,X_\iota^J) \qquad (2)$$

$$X \in Class\ C_J, if\ d(X,C_J) = \min d(X,C_J) \qquad (3)$$

Two other distance metrics can be used, and these are known as Euclidean and Maximum distance. Euclidean is the standard distance measurement working with closest physical distance and Max distance is the maximum amount of space using the sides of the triangle instead of the hypotenuse as a comparison for distance from vector to vector.

The Min-Mean-Distance classifier works in a similar way to the Nearest Neighbor and uses the same distance metric. However, instead of the nearest sample, the distance to the center of the nearest class is measured. Every sample trained forms into its distinct class and the classes cluster around a central point. Using Equation 4, $\{X_1^j, X_2^j, \dots, X_{n_j}^j\}$ represent n_j feature vectors making up a class C_j. Each feature vector is classified with the label of class j selected to represent the class. The center of the class is defined as M_j and the class is determined using Equation 5.

$$M_j = \frac{1}{n_j} \sum_{i=1}^{n_j} X_i^j \qquad (4)$$

$$X \in Class\ C_j, if\ d(X, M_j) = \min_i d(X, M_i) \qquad (5)$$

The Min-Mean Distance classifier is ideal when the sample sets have little to no feature pattern variability. It is useful when the feature vectors of each class are tightly clustered around the center and can help eliminate errors caused by training set noise.

The following section introduces the LLD-900-2 in detail and discusses the changes made from the first to the second iteration and the progression of improvement in database advancement.

3. Database

The LLD-900-2 is the second iteration of the LLD-900 database research project to develop a novel framework of a marine ontology. The database has been changed to better reflect real-world environments and the type of boats found in littoral areas. The major changes include a reduction in number of categories from 11 to nine classified as Barge, Dinghy, Jet Ski, Large Vessel, Motorboat, Sailboat, Tug, Canoe, and Yacht and Luxury. The Canoe category is currently left out during testing as there are not enough available canoe images to properly test against. The category is left in for expansion in the future. Two new categories, Large Vessel and Motorboat, are introduced while the Monohull Motorboat, Pontoon Motorboat, Cruise Ship, and Tanker Ship categories are removed. The Large Vessel category is a combination of the earlier Cruise Ships and Tanker Ships while the Motorboat is a combination of the Pontoon and Monohull vessels. Furthermore, certain boats have been reclassified to better utilize the descriptors of the determining class.

The new database still consists of the original 400 high-resolution color images with segmentation masks and segmentation masks with ship wakes, making for a total of 900 high quality images. While some vessels have been removed from the database, others have been added in separate folders within each category to allow for better testing of the classification algorithms. The images were taken from a variety of viewing angles and in varying light and weather conditions. Viewing angle are approximately 0° , 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135°, 150°, and 180°. 0° is taken from the stern of the boat with 90° representing a straight on side view. The front and back correspond to the bow and stern of the boat respectively. The images have an error of about ±10° as determined by the author due to the uncontrolled subjects and environment of the captured data. This means that while some views may be labeled at 90°, the actual viewing angle could be as high as 100° or as low as 80°.

The changes made to the new database were influenced by the testing of the LLD-900. The test results for the initial database showed that Cruise Ships and Container Ships were similar and would remain so even after the addition of scale. Because the ships are of the same scale, they will behave in a similar manner when moving through littoral areas. It seems reasonable to classify these in a single category. The same applies to Monohull and Pontoon Motorboats. Additionally, boats that were strongly misclassified in the first round of testing were reevaluated and reclassified. The standards that led to the initial incorrect categorization of the boats were changed to better define the differences between categories. These include size, awning presence, lower decks and optional sail rigging. This led to a better definition of the category boundaries and an overall improvement of classifier accuracy.

Figure 2 shows a sample of the LLD-900-2 database while figure 3 shows a segmentation mask and segmentation mask with wake. The alterations made in the LLD-900-2 have led to the creation of a database with clearer boundaries, cleaner training sets and an overall increase in identification accuracy. The following section details the methods used to determine the new accuracy.

4. Test Method

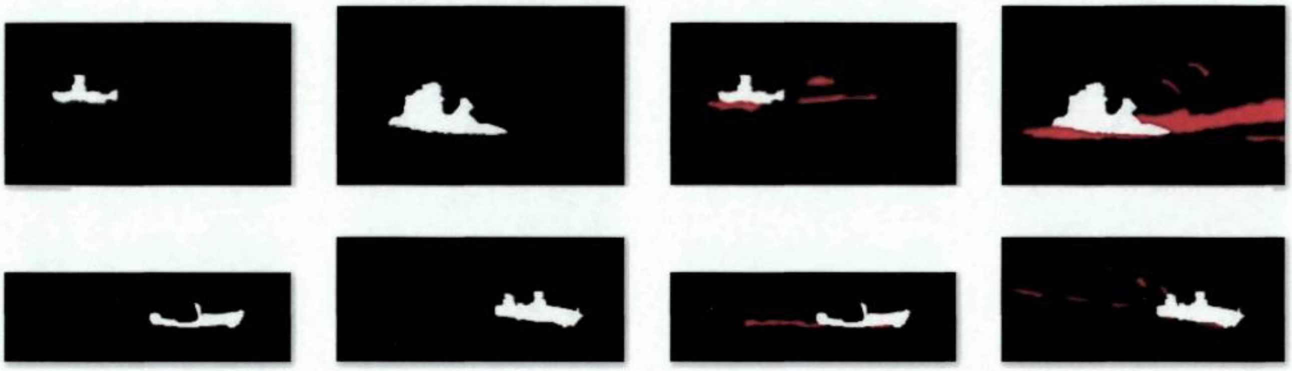
The LLD-900-2 database's accuracy is tested using simple algorithms. These are the binary particle classifiers known as Nearest Neighbor, K-Nearest Neighbor, and Min-Mean Distance. These methods were chosen along with the leave-one-out testing method because of the simplicity, availability and robustness of the algorithms and because they are easy to implement. The results show a minimum in obtainable accuracy because improved identification rates are possible through the use of newer classification algorithms. The purpose of the tests here are to show the improvement and overall usability of the second iteration of this database.

The leave-one-out test method consists of training all but one boat in a training phase. The testing phase then uses the remaining single boat and its multiple views as a test set. To determine the accuracy of the classifier, a properly classified boat is considered a success while a misclassified boat results in a failure. The test environment mimics real world environments with the training set taken directly from the field. The results obtained in the experiment should closely represent those obtained in the final working environment.

The inclusion of the Nearest Neighbor classification method allows for direct comparison between the LLD-900 and the LLD-900-2. This helps to show the overall improvement of the database and identifies the factors that act as the largest contributors towards this improvement. Segmentation masks are reused as the training set because the test algorithms are of binary classification. This means a quicker, easier testing of the database.

The following section presents and summarizes the results and compares them to those obtained in the first iteration of database testing. It is important to note is that the database results show marked improvement in all areas.

Figure 2: Sample Image Thumbnails from LLD-900-2



(a) (b)

Figure 3: Sample Segmentation Masks (a), Sample Segmentation Masks with Wakes (b)

5. Results

This section reports the results of the tests performed on the LLD-900-2 database and summarizes them in Tables 1-3. The tables are ordered by method and the results are listed by type of category. Figures 4-6 show the improvement gained by each method in comparison to the results obtained from the LLD-900 database tests [1]. These results reflect the improvements made in developing the LLD-900-2.

The results are determined as follows. If the algorithm returned at least one correct classification out of all of the viewing angles for a single boat, it was considered successful under the heading % Single Image. This helps establish a baseline for when the classifier is completely wrong and shows the categories that need the most refinement to improve the classification accuracy. Under the % Actual Correct column, the results record when the classifier is completely correct. This column represents a true test of the strength of the classifier. In the % Theoretical with Scale column, the percentage is shown as if a scale function were added to the classification database and algorithm. The success rate is determined based on the next nearest class whenever an image is categorized incorrectly. If the next closest class is the correct class and the misclassification is due only to the difference in the size of the two images, the classification is considered correct. An example is the Jet Ski and Tug categories, which are confused with each other but could easily be identified as separate types of vessels if the classifier is modified to be size dependant. This column is included to show the improvement in accuracy expected of future iterations of the database when scale is added as determined by the author's experience with the classification software. As previously mentioned, the addition of scale is beyond the scope of this paper. The Largest Confusion column is included to show the category that the classifier most confused. This data is included to show where the database needs adjusting and to show how the classifier is reacting to the database. This kind of identification data is important because it allows the end user to determine where the database reports confusion and makes the most mistakes.

Category	% Single Image	% Actual Correct	% Theoretical with Scale	Largest Confusion
Barge	100.0	47.4	94.7	Motorboat
Dinghy	66.7	**28.6**	100.0	Barge and Motorboat
Jet Ski	100.0	**36.4**	100.0	Tug
Large Vessel	81.3	**44.7**	91.5	Tug and Motorboat
Motorboat	100.0	**68.7**	91.9	Large Vessel and Yacht
Sail boat	91.0	**67.6**	76.5	Motorboat
Tug	90.0	**62.1**	100.0	Large Vessel
Yacht and Luxury	100.0	50.0	87.0	Motorboat
Overall Results		**57.5**	**90.8**	**Motorboat**

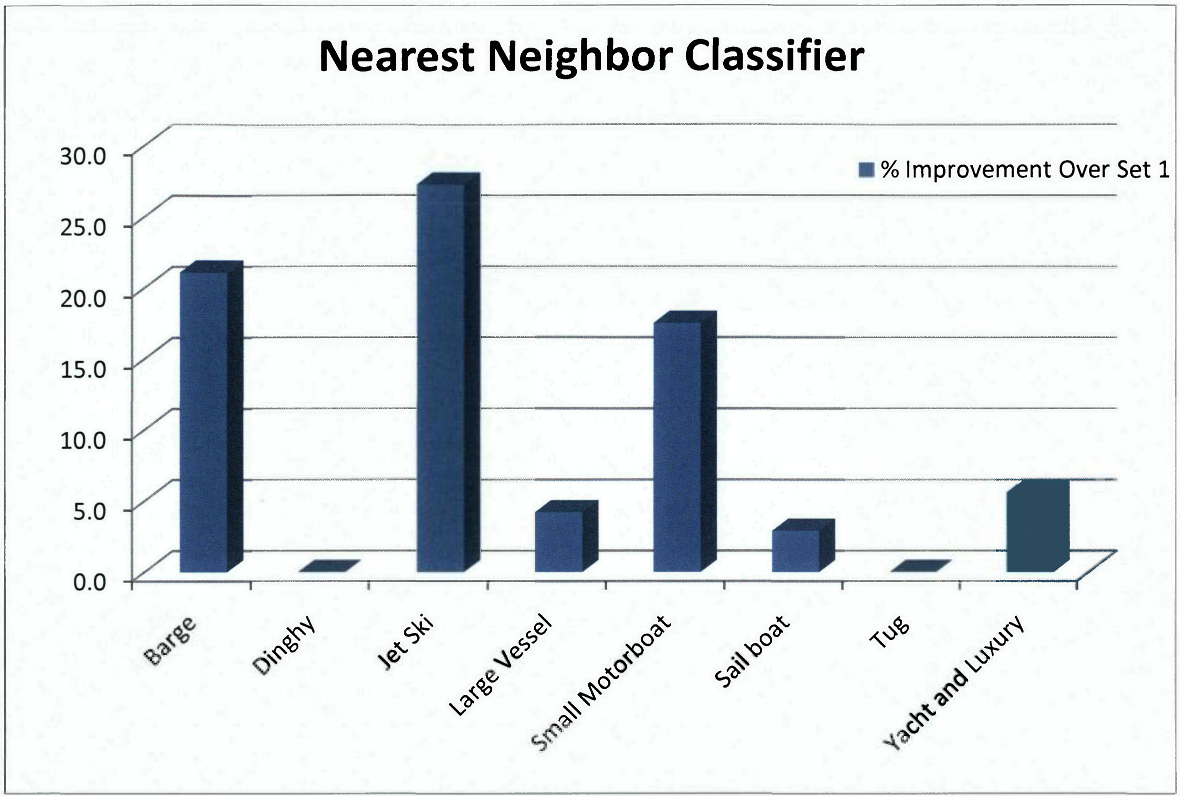
Table 1: Nearest Neighbor Classification Results

Category	% Single Image	% Actual Correct	% Theoretical with Scale	Largest Confusion
Barge	57.1	**26.3**	89.5	Motorboat
Dinghy	66.7	**28.6**	100.0	Barge and Motorboat
Jet Ski	100.0	**36.4**	100.0	Tug
Large Vessel	81.3	**48.9**	91.5	Tug
Motorboat	100.0	**68.7**	93.9	Large Vessel and Yacht
Sail boat	91.0	**64.7**	85.3	Motorboat
Tug	100.0	**72.4**	96.6	Large Vessel
Yacht and Luxury	100.0	55.8	95.3	Motorboat
Overall Results		**58.5**	**93.1**	**Motorboat**

Table 2: K-Nearest Neighbor Classification Results (k = 4)

Category	% Single Image	% Actual Correct	% Theoretical with Scale	Largest Confusion
Barge	85.7	47.4	100.0	Motorboat
Dinghy	100.0	85.7	100.0	Barge and Motorboat
Jet Ski	100.0	63.7	100.0	Tug
Large Vessel	68.8	23.4	76.6	Tug
Motorboat	13.3	**4.0**	88.9	Large Vessel and Yacht
Sail boat	81.8	58.8	88.2	Motorboat
Tug	80.0	72.4	100.0	Large Vessel
Yacht and Luxury	69.2	45.7	69.6	Motorboat
Overall Results		**33.9**	**86.3**	**Motorboat**

Table 3: Min-Mean Distance Classifier



Figure

Figure 4: Nearest Neighbor Classification Improvement

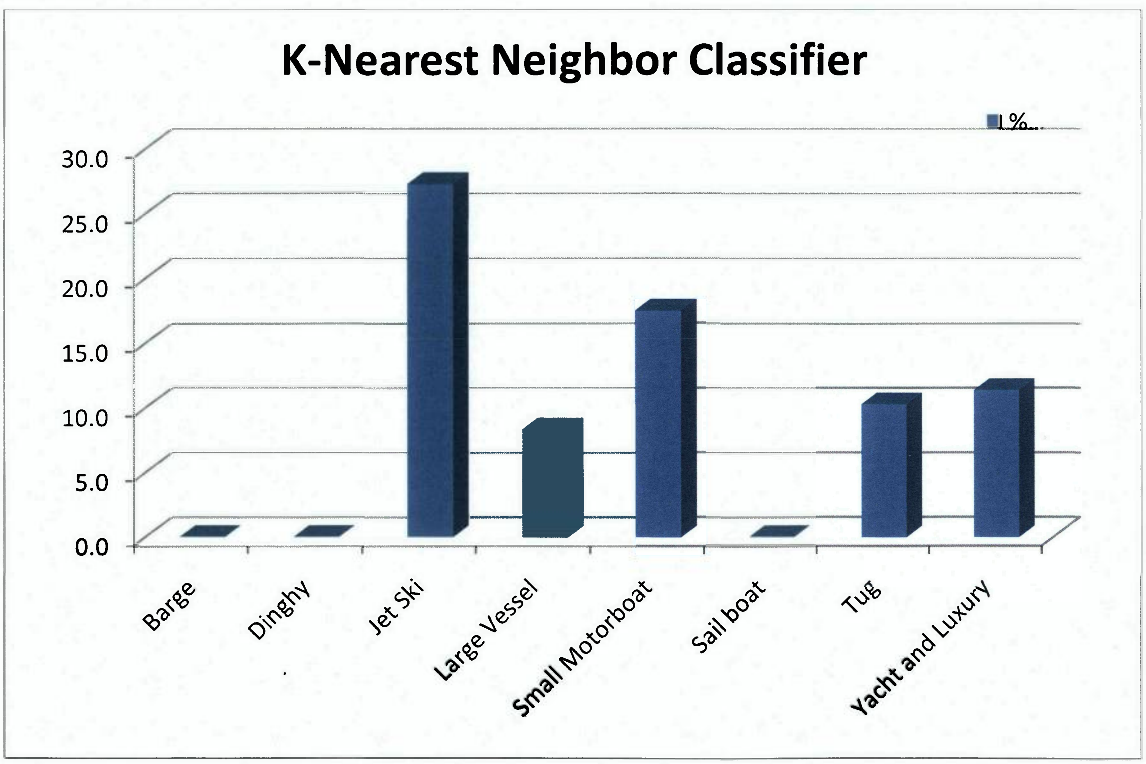


Figure 5: K-Nearest Neighbor Classification Improvement (k = 4)

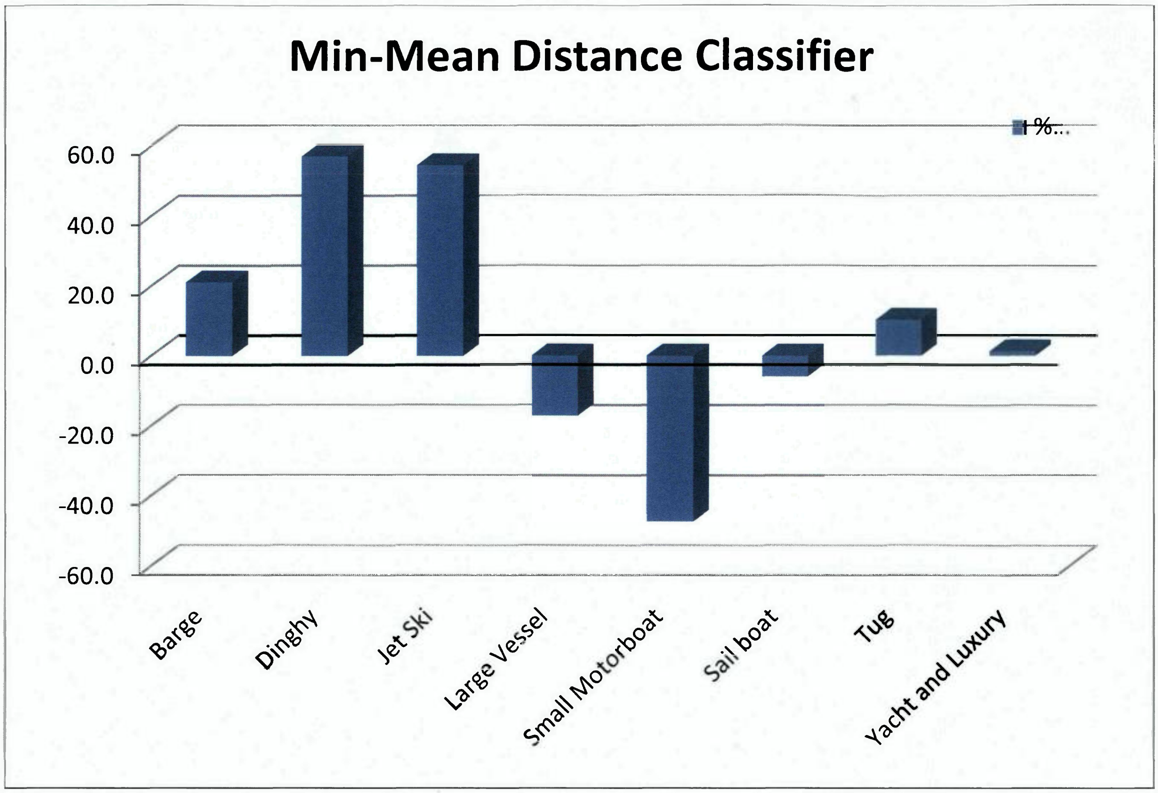


Figure 6: Min-Mean Distance Classification Improvement

The LLD-900-2 shows marked improvement over the LLD-900 with the highest overall classification rate of 58.5% achieved with the K-Nearest Neighbor Classifier. This is a significant improvement from the previous high of 44.0 % achieved by the Nearest Neighbor Classifier tested with the LLD-900. By adding a scale space to the database, a success rate of 93.1% is expected through use of the K-Nearest Neighbor method. The Nearest Neighbor Classifier improved by 13.5% in overall accuracy to a high of 57.5% correct identification. The Min-Mean Distance algorithm fared the worst losing 10.1% accuracy with the overall success rate dropping to 33.9%. While this method performed admirably in most sections, the Motorboat and Large Vessel categories proved detrimental to its overall effectiveness. The cause for the reduction in accuracy is the expansive Motorboat class, where many trained samples are scattered loosely around the class center. While this effect proves beneficial to the Nearest Neighbor and K-Nearest Neighbor classifiers, the sample set confused the Min Mean Distance method into thinking most Motorboats were actually Yachts or Large Vessels. This happens because the center of the Yacht and Large Vessel categories are much closer to most of the motorboat images. The tests show that the Min Mean Distance Classifier is not an ideal choice for littoral maritime classification systems at this time.

The K-Nearest Neighbor Classifier showed the most improvement in the Jet Ski category with an improvement of nearly 30%. This was followed by the Small Motorboat increase of 17.5%. This category had the single largest impact on overall accuracy because of the size of the sample base. Other improvements were found in the Tug, Large Vessel, and Yacht and Luxury classes. No improvements were found in the Barge, Dinghy or Sailboat categories. The Nearest Neighbor Classifier showed marked improvement in the Barge category with over 20% increase in accuracy. The Jet Ski remained the most improved category while no change was found in the Tug or Dinghy categories. The Min-Mean Distance Classifier failed in the Large Vessel, Small Motorboat and Sailboat categories with the Motorboat contributing most of the loss. With a decrease of nearly 50% in classification accuracy of the Motorboat category, the Min-Mean Distance Classifier established itself as a poor choice for use in littoral areas where many motorboats are present. However, the classifier did show remarkable improvement in the Barge, Dinghy and Jet Ski categories, overshadowing the improvements made using the other methods. These categories proved ideal for the Min Mean Distance Classifier because there is little difference between the individual trained samples. All of the images in these categories cluster tightly around the center of their classes.

The final section discusses future changes envisioned in database advancement and the next steps towards reaching the final goal of obtaining a viable littoral area marine vessel ontology.

6. Conclusion

The classification results show a significant improvement in overall accuracy of the LLD-900-2 as a training set. While the accuracy is still lower than ideal for a marketable field system, theoretical projections using an addition of scale indicate that the classification rate can be high enough to be extremely useful in the surveillance and security industries. The next step will be to add this scale space and incorporate it into the algorithms used with the database. Future tests should compare the newer algorithms that exist today and make use of different feature vectors and affordances. These improvements should continue to improve accuracy as the database develops.

The goal for this project is to evolve the current database into a useable training dataset for use with multiple classification techniques to improve security in the littoral environment. The second database revision shows encouraging progress towards reaching this goal.

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