An Automatic Image Recognition System for Winter Road Surface Condition Monitoring

by

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I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Municipalities and contractors in Canada and other parts of the world rely on road surface condition information during and after a snow storm to optimize maintenance operations and planning. With an ever increasing demand for safer and more sustainable road network there is an ever increasing demand for more reliable, accurate and up-to-date road surface condition information while working with the limited available resources. Such high dependence on road condition information is driving more and more attention towards analyzing the reliability of current technology as well as developing new and more innovative methods for monitoring road surface condition. This research provides an overview of the various road condition monitoring technologies in use today. A new machine vision based mobile road surface condition monitoring system is proposed which has the potential to produce high spatial and temporal coverage. The proposed approach uses multiple models calibrated according to local pavement color and environmental conditions potentially providing better accuracy compared to a single model for all conditions. Once fully developed, this system could potentially provide intermediate data between the more reliable fixed monitoring stations, enabling the authorities with a wider coverage without a heavy extra cost. The up to date information could be used to better plan maintenance strategies and thus minimizing salt use and maintenance costs.

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To my Abu and Ami.

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Chapter 1

Introduction

With increasing economic growth and hence traffic loads, authorities are under more and more pressure to maintain the safety and mobility of highways which play a key role in economic development. It is estimated that the U.S alone spends an approximate $2.3 billion on road snow and ice control [1] where as Canada spends more than $1 billion in winter maintenance of roads [2]. To ensure safer driving conditions on highways during winter, municipalities and government agencies in North America and Europe are constantly exploring new technologies in road condition sensing and monitoring that can provide reliable and up-to-date information about road condition status [3].

Up-to-date and reliable information about road surface conditions can help highway agencies in better utilizing the available resources as efficiently as possible. Having up to date information can result in more streamlined maintenance operations that focus on specific highway sections instead of broader patrol routes where the entire route may not need the same level of maintenance. As a result, labor, material and equipment usage can be optimized while maintaining a standard level of safety along the entire road network. With awareness about environmental concerns regarding salt usage, precise road surface condition information can lead to more efficient usage of salt, which otherwise would not be possible.

Reliable and up to date road surface condition can also be used to warn drivers about potential hazardous locations where the presence of ice may pose a threat to passenger safety. Delivering this information to authorities and users in a timely manner can significantly reduce the loss and damage caused due to dangerous road surface condition during winter. MTO (Ministry of Transportation Ontario) and other agencies use bare pavement reporting as one of their primary sources of road surface condition information. Bare pavement reporting usually involves dedicated patrolmen who patrol the highways several times a day to manually observe road surface condition. Based on these observations, the authorities plan maintenance operations and also gauge the performance of maintenance contractors in removing snow off the roads during and after a particular snow event.

As a first step towards a more technologically advanced road condition reporting system, several states in North America and many countries in Europe have invested heavily in RWIS (Road Weather Information System). With advancements in sensing, data processing and telecommunication, the RWIS has evolved to become a complex yet costly solution for remote sensing and transmission of real time road surface condition monitoring. Today, the province of Ontario alone has deployed more than 200 RWIS stations. With RWIS being an important tool in winter maintenance planning and deployment, the number of RWIS deployments is expected to increase in coming years. Coming sections will discuss the advantages and limitations of RWIS and many other monitoring technologies in detail.

1.1 Spatial and Temporal Variation in Road Condition

Road surface condition changes in time as well as space during winter snow events. To elaborate, it is important to know how the condition of a particular point changes as time passes and similarly it is important to know how the road condition changes in space (over a stretch of road or within a defined area) at a particular instant in time. Both these requirements can be met using two fundamentally different measuring techniques. These techniques include fixed sensors, which are primarily used to monitor conditions over a point as time passes, and mobile sensors that measure conditions over a large road network in a given time.

Most road condition monitoring technologies today rely on fixed sensors such as the RWIS that are installed at a point on the road; this point is assumed to be representative of the surrounding area (e.g. radius of 100 Kilometers or more). An inappropriately placed sensor can thus largely limit the use of gathered data due to its lack of similarity with the surroundings. Hence considerable work has been done in optimizing the location of RWIS stations to get the data that is best representative of the surroundings and also capable of detecting hazardous conditions effectively [4]. However, due to the nature of the measurand, point data can often be misleading and unrepresentative of the surroundings and thus limiting the usefulness of data obtained by fixed type sensors. The following figure depicts road temperature and friction data for a 2km stretch of pavement recorded around the location of a fixed type sensor. The high variation in collected data clearly shows misrepresentation of surrounding data by a fixed point measurement due to high spatial variation in road surface conditions.

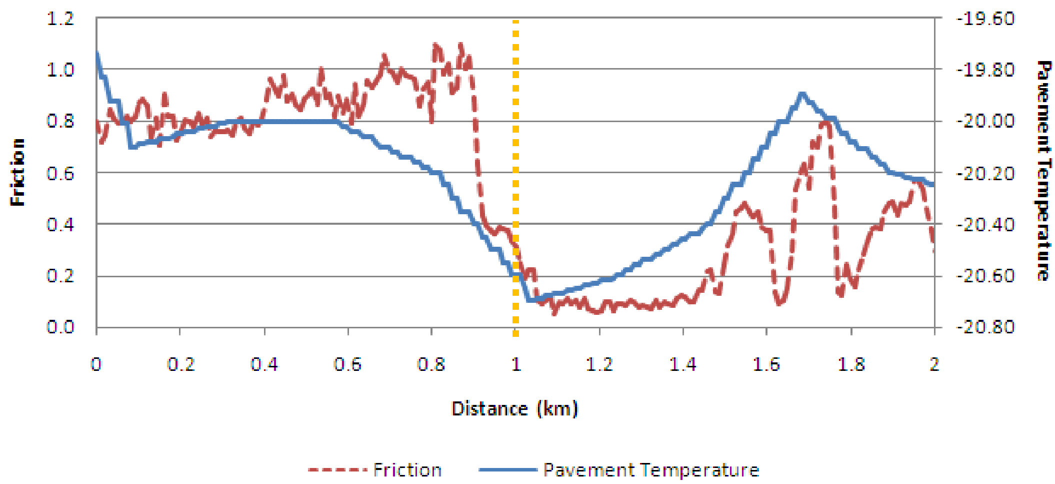


Figure 1.1: Spacial Variation of Road Surface Condition

With precipitation, traffic and maintenance activities directly affecting pavement surface conditions, it is often important to have up-to-date road condition data over full spacial extension. As a stationary point is often not a good representative of the surroundings. Mobile sensing stations are usually deployed to cover a large area over a defined time interval. However, rapid changes in road conditions over a particular point cannot be monitored by mobile systems.

This point is elaborated by the Figure 1.1, depicting road condition information as seen by a stationary sensor over a twelve hour period. From Figure 1.1, it is clear that information from a mobile sensor can be deceptive in rapidly changing environments where previously recorded values may no longer hold as the sensor moves along in space.

1.2 Problem Definition

Road surface contaminants can adversely affect the safety and mobility of travelers during and immediately after the occurrence of a snow event. This not only causes loss of life, property and time for those directly affected but also adversely affects the economy of the region in general. While under-maintained roads pose an economic threat to the region, over-maintenance is extremely costly and excess salt usage can harm the environment incurring further indirect costs. In order to efficiently plan road maintenance operations, gauge performance of maintenance contractors and inform general public about hazardous road conditions, authorities have deployed a variety of road condition sensing and monitoring systems. These range from stationary RWIS stations and webcams installed at predetermined locations to dedicated personnel periodically patrolling the roads to observe road surface status and potential hazardous conditions that need immediate attention.

Despite the efforts to improve the collection and coverage of pavement condition data, there is a large void between information that is available and what is needed to optimize the road maintenance process for better safety and mobility while reducing salt usage and overall costs. The void between available and needed data can be covered by creating hybrid systems that combine existing technologies to obtain data that is rich in temporal and spatial dimensions. Moreover, there is need to deploy new sensing technologies that are being used for other applications but still have not been used in the domain of winter road maintenance.

1.3 Research Goals and Objectives

The objective of this research is to analyze the different existing road condition monitoring technologies in use, followed by an overview of other technologies that could potentially be used to monitor road surface conditions. The goal is to understand the winter maintenance process, its data requirements and evaluate the various road monitoring technologies available. The final objective of this research is to implement a prototype of an automated winter road condition monitoring system to explore the possibilities of road surface classification through machine vision and the possibility of publicly deploying such systems for use by authorities and general public. The specific objectives are as follows:

- Conduct a literature review of the different road condition monitoring technologies to better understand their principle of operation along with their strengths and weaknesses.
- Conduct a literature review of vehicular sensor networks and newly evolving mobile monitoring solutions and how they can be used with respect to Intelligent Transportation Systems and road condition monitoring.
- Conduct machine vision based analysis of pavement images with the development of a Support Vector Machine based model for Road classification.
- Develop and test a prototype that can be used for automatic road condition information collection.

Chapter 2

Literature Review

There are a variety of technologies and methods that have been in use for monitoring road surface conditions to help aid in winter operations. This chapter reviews the available and upcoming technologies that are/can be used to aid winter maintenance operations.

2.1 Road surface condition indicators

Before analyzing the various road monitoring technologies that exist, it is important to first define the various measurands that are being used to represent the road surface condition. Table 2.1 shows the different measurands that have a direct or indirect correlation with the road surface condition and are usually monitored in order to infer road surface condition.

2.2 Road Condition Monitoring Technologies

In this section we summarize the major winter road condition monitoring technologies in use today. While summarizing, the technologies have been divided into mobile and stationary sensing as both modes serve a different purpose in terms of spatial and temporal coverage with each having its own advantages and disadvantages.

2.2.1 Stationary Monitoring Technologies

Stationary monitoring technologies refer to monitoring systems that remain fixed at a particular location during their period of operation. The constraint of being fixed is usually due to the physical nature of the sensors that have to be embedded in the pavement and thus

Table 2.1: Road Surface Condition Indicators

Measurand	Method	Usage
Pavement Friction	Friction wheels Acceleration/deceleration based devices Estimation using non intrusive spectral sensors (RWIS)	Road friction provides a good estimate of the road's level of safety at a point in time.
Temperature	IR Thermometers & thermal imaging Embedded Puck Sensors (RWIS)	Pavement temperature can be used to infer the status of contaminants and can be helpful in predicting ice formation
Contaminant	Puck type salanity sensors (RWIS) Hand held salanity meters Vehicle based salanity sensing systems.	Contaminant concentration levels help determining the amount of salt present on the road and hence optimize future salting operations.
Contaminant type	Visual observation, Video Cameras, Spectral Sensors	Road coverage information is used to plan ploughing operations and evaluate the effectiveness of maintenance contractors as well as maintenance strategies

cannot be moved or due to technology limitation that does not allow proper functioning while the system is mobile.

RWIS (Road Weather Information Systems)

RWIS are the most commonly used systems deployed by transportation departments for road surface condition information and monitoring. The RWIS can be summarized as a set of sensors connected to a data collection and transmission system installed along the roadside, typically used for environmental and pavement data collection. Starting in the 1960s several European countries developed sensing systems to assist maintenance personnel in decision making for snow and ice control operations. RWIS began to gain popularity in North America during the 1990s and have evolved to be one of the most reliable sources of road and weather information for winter road maintenance. Due to its large numbers and extensive use, there have been numerous studies done on the effectiveness of using RWIS information[5][6] [7] Discuss the benefits and cost savings incurred due to RWIS usage and the need for more RWIS sites to achieve complete coverage of the geographical region of interest. Most RWIS are an aggregation of a set of permanently fixed sensors connected to an on-site communication and processing unit (CPU). The CPU allows for simultaneous data collection from multiple sensors installed on site. The collected data can then be stored, validated and communicated to a central location via telephone lines or cellular links where available. In terms of sensor connectivity, the RWIS offer a wide variety of communication protocols and standards enabling a large variety of sensors from different manufacturers to be connected. Following is a description of the various types of sensors that are commonly used with RWIS:

Air and pavement temperature sensors are an important part of an RWIS station. Available in different types from different manufacturers, these sensors can either be embedded in the pavement (for road temperature) or more sophisticated IR based sensors can also be installed on a pole alongside the roadway for contact free pavement temperature. Due to their cost, not all RWIS stations were equipped with these sensors, however they are becoming a standard feature on many new stations being deployed nowadays [8].

Puck or Contact type Pavement sensors are a breed of purpose designed pavement sensors and are often used with RWIS stations offering a wide range of sensing capabilities. Most common sensors offer pavement temperature as measured at the point where the puck is installed. Puck sensors have the inherent advantage of being present at the site along with the measurand and can hence detect changes in with less sophisticated equipment when compared to spectral sensors.

Puck sensors can be divided into two major types, namely passive and active sensors. While passive type sensors sense the change in conditions without interfering with the environment, active type sensors have the capability of heating and cooling parts of the sensor surface to detect presence of snow or ice (converts to water when heated) or possibility of frost formation (water converts to thin layer of ice upon cooling). Special conductivity sensors can also measure the type of contaminant which is often used to detect the amount of salt or de-icing agents present on the road surface. However, none of these sensors have achieved a level of reliability at which they can be used for planning and deployment of maintenance operations [9].

Previous studies indicate that pavement sensors offer a high installation and operating cost whereas the benefits gained from these sensors to aid winter road maintenance are not yet fully quantifiable [3]. The puck sensors require lane closures during installation and have to be removed before heavy maintenance of the road surface. Moreover, incorrect readings can result in incorrect maintenance deployment decisions leading to high financial losses [9].

Contact free Pavement Sensors are another branch of pavement sensors that have been developed to overcome the practicality and reliability issues posed by puck type pavement sensors. Common examples are spectral and IR based pavement sensors. At glance, a spectral sensor resembles a video camera installed on a pole along the road side instead of being installed on the pavement. Relying on infra-red and microwave radiations emitting from the road surface, spectral sensors can provide surface condition classification in dry, wet, snowy, icy and slushy categories.

A detailed study on the performance of different spectral sensors in is presented in [3][10]. Experimental results show high accuracy while detecting presence of snow/ice and water while poor accuracy for detecting presence of slush. Promising experimental results along with ease of installation and easy portability give these sensors a sharp edge over the usual puck type sensors. Spectral pavement sensors can be easily connected to the RWIS for data logging or transmission and can also operate in stand-alone mode with the capability of relaying live road data to a server via telephone or cellular links. Due to these benefits, actual field test for these devices are being encouraged [3]; however long term reliability and accuracy in the field is yet to be proven.

As the RWIS consists of a generic CPU capable of communicating to a variety of different devices, a large number of non RWIS specific sensors such as visibility, traffic etc can be connected for data logging, validation and communication purposes.

Video Surveillance

With increasing Internet availability and affordable high resolution video cameras, road condition on highways is now being monitored via CCTV feeds from cameras installed at priority locations. Despite their simplicity, CCTV video feeds can provide an overview of snow and slush coverage on highways. This information can be used by maintenance staff as well as the general public high level road coverage information in real time. Once such camera network is the COMPASS system that provides live image feeds from various locations on highways around the GTA. While initially installed for traffic monitoring, COMPASS[11] images are now being used for high level road coverage information used for research.

2.2.2 Stationary Monitoring: Advantages and Challenges

RWIS have evolved to be a reliable source of road and weather information for planning maintenance operations. RWIS can be used to improve the Level Of Service, material and labor cost savings, improve maintenance quality and improvement in environmental impacts [12]. However a RWIS is a fixed type of sensing system and can only measure variation of condition at a given location making the location of RWIS and the position of sensors highly critical. RWIS and other stationary type sensors are intended to be installed at locations such that the data from the sensor best represents conditions prevalent in that area. This may not include extreme conditions like ice formation that may only occur in small patches and patches and thus do not represent the general road conditions in that area. However while this target is being met, it is in contradiction with one of the main purposes of road condition monitoring which is to detect icy roads and other extreme conditions that can pose a high threat to safety and mobility of a road. The stationary nature of even the most well placed sensors also make it impossible to cover for lateral variation in the road surface conditions like center covered and track bare roads making the information misleading in many ways. A detailed analysis on sensor installation and positioning in discussed in [6]

2.2.3 Mobile Road Condition Monitoring

Mobile road condition monitoring technologies refer to systems that sense road conditions while moving along the highway. They differ from stationary systems in coverage, cost, reliability and the kind of variable monitored. This section summarizes the different mobile monitoring technologies and methods in use today.

Manual Bare Pavement Reporting

The practice of patrolling highways by trained patrolmen for observing changes in road surface conditions is referred to as bare pavement reporting. Even today, bare pavement reports are used as a major aid in planning winter maintenance operations and evaluating the performance of maintenance contractors.

The bare pavement reporting procedure involves patrolmen performing frequent runs around a defined highway to observe improving/deteriorating road conditions. The observations are then logged onto a bare pavement reporting form. At the end of the trip, the logged information is entered into a computer system for archiving and easy access to decision makers. A complete guide to the bare pavement reporting process can be found in [13].

Bare pavement reports are generally subjective and not repeatable; this is due to various human factors that can bias the decision of the observer. Moreover, it offers only limited coverage as it can be difficult for patrolmen to move during storm and high traffic situations. In terms of cost, manual bare pavement reporting is considered to be a cost intensive as it involves dedicated patrol personnel, vehicle and fuel costs.

Road Friction

Friction can be defined as the resistance encountered by an object while moving over another object and the magnitude of the resistive force is known as the frictional force. The friction coefficient is the ratio of the normal and resistive forces acting at a point [14]. Road Friction is an intuitive road condition indicator that can be used to aid winter maintenance decision making and performance evaluation and over the years a number of different techniques have been developed to measure friction. Unlike the RWIS sensors, friction is an actual measurement of the forces between the road surface and the wheel and can be determined by the following methods:

- **Friction Trailer**
  The friction trailer is one of the most commonly used friction measurement devices

today. Initially developed to measure friction for airport runways during winter condition, the friction trailers are now used in Europe and North America for road grip level estimation for benchmarking and research purposes.

Most friction trailers consist of a tire (or multiple tires in some models) connected to special force measuring sensors and an interface box inside the vehicle for control and display. Unlike the RWIS, friction trailers measure friction while moving along a road as they are towed by another vehicle. Some of the different friction measurement techniques used are: locked wheel, fixed slip, variable slip and side force devices. An in depth analysis of different friction trailers can be found in [15].

Studies show that friction trailers show good repeatability and reliability almost independent of vehicle speed and the technology is mature enough to be used for road friction measurement during winters[16]. The newer friction trailers promise to work well on bends and sharp turns where previous models failed. Most friction trailers can provide accurate friction values at a continuous rate with a frequency of up to multiple readings per second. Manufacturers offer multiple options for data logging and transmission. Friction readings can be monitored using the in-vehicle display or directly stored on a laptop computer using an RS 232 connection. Friction trailers can also be interfaces with AVL systems for automatic GPS tagged data logging.

While the method of measurement may be different, all friction trailers require a dedicated vehicle and driver for operation. For this reason friction measurement using friction trailers not only require a high initial investment but also a high running cost in terms of labor, vehicle and fuel costs. Thus it is difficult to deploy a large number of friction trailers for everyday road monitoring, making friction trailers less popular amongst maintenance contractors. Moreover, as the friction readings are measured along the wheel-track in a particular lane or wheel-track, they offer very limited lateral coverage and the collected data does not represent road conditions along the lateral surface of the different lanes. This factor could be significant in case of different traffic levels on different lanes or in situations where the there is high lateral variation in road conditions due to maintenance operations or other factors.

- **Acceleration Based Friction Estimation**
  The road grip can also be estimated using the deceleration patterns of a vehicle to which sudden breaks are applied while driving. A new range of accelerometer equipped in-vehicle devices are now available. Once calibrated using a reference road grip value (from a friction trailer), these devices can estimate the road grip level based on the deceleration patterns of a vehicle. Unlike the friction trailers, these devices do not require costly modifications to the vehicle, however, these devices require the driver to apply sudden breaks so that the deceleration patterns can be analyzed.

Even though the deceleration based devices offer a low cost alternative to the friction trailer, their repeatability and reliability are yet to be proven. Moreover these devices provide average friction readings sampled at short intervals instead of continuous values.The requirement for sudden breaking and acceleration can make them difficult to operate in many cases with high levels of traffic.

Mobile Surface Temperature Measurement and Thermal Mapping

Maintenance personnel regard pavement temperature as essential information to better determine the correct chemical application rates for winter maintenance. Non-contact infrared sensors have been widely used in the vehicle-mounted pavement temperature measuring devices to quantify the radiation emitted by the surface of the road and thus measure of surface temperature. IR-based surface temperature thermometers are usually made of an IR-sensor, a processor and a display. The sensor assembly can be mounted on the exterior of the vehicle according to the manufacturer's specifications. The control unit can be mounted on the inside and supports small a display screen for direct temperature readings or can also be used to connect to a laptop, AVL or data logging device. The study in [17] indicates that the IR based mobile temperature sensor has reached a high enough level of repeatability and reliability to be used in commercial applications.

Road surface temperature measured by mobile devices is often used for thermal mapping. Thermal mapping is a process of quantifying the variation in road surface temperatures along a route or network. It has been used on roads and runways in Europe, USA, Canada and Japan to ensure that roads remain free of ice and snow. The process involves repeated collection of road surface temperature over long stretches of road under different weather conditions. The data is collected using vehicles equipped with IR surface temperature sensors and special data logging equipment. The work in [18] validates the data collected by a thermal mapping system in Nevada USA against RWIS sensor data and it is shown that thermal mapping is an easy and economic way to display changes in road temperature variations.

In practical scenarios, thermal mapping is achieved using a fleet of IR pavement sensor mounted vehicles that follow an assigned route to collect data. This process requires dedicated equipment and labor and as road conditions change frequently, keeping the thermal maps up to date for a large highway network may not be possible.

2.2.4 Mobile Monitoring: Advantages and Challenges

Vehicle based road condition monitoring technologies have evolved to become one of the key tools used by winter maintenance agencies to optimize winter maintenance operation in order to deliver the right amount of material and resources to the right location and the right time.

Unlike the RWIS and other stationary technologies, vehicle based systems have the advantage of covering a large area with a single set of equipment. Another key advantage for vehicle based monitoring is the possibility of measuring friction which directly related to the road surface condition and thus safety of a given road.

However, due to their mobile nature, vehicle based systems have an inherent disadvantage of low temporal resolution. As vehicles move along a route, the road condition of sections left behind keeps changing. Hence data collected from moving vehicles under rapidly changing conditions could lead to incorrect maintenance decisions, financial losses, low safety and poor level of service.

2.3 Vehicular Sensors and Environmental Monitoring

In order to acquire data with high spatial and temporal density, vehicular sensor networks are being proposed as platforms for automated non-specialized vehicle based data collection systems that sense, log and transmit acquired data. This section discusses some of the relevant vehicular sensor networks that have been proposed for road and environmental data collection.

2.3.1 Automated Pothole Detection

The work in [19] discusses an automated pothole detection system that has been successfully deployed and tested on the streets of Boston MA. The high level architecture consists of an onboard mobile computing platform that is used for all data collection, processing and transmission. Potholes are detected based on readings from a three axis accelerometer attached to the body of the vehicle, a GPS to determine the speed of the vehicle and location of the pothole and a wifi/GPRS modem to transmit collected data to a central server upon network availability.

The system uses handpicked loosely labeled data for model training. This involves a complex feature extraction algorithm which is beyond the scope of our work. Once trained, the prototype is deployed onto multiple taxis around the greater Boston area and proved to detect potholes with an accuracy of greater than 95%. This high accuracy was achieved by fusing data from multiple sensors to reduce the number of false positives.

This attempt is one of the first fully deployed and tested mobile end-to-end system to detect road anomalies. While pothole detection and determining winter road condition have little in common, the attempt shows the potential of using mobile sensor nodes as a cost effective and reliable method to automatically collect environmental data. Technological barriers in the form of network availability, processing power and precision sensing are no longer a hurdle in exploring new avenues for vehicular sensor networks as probes for environmental data collection.

2.3.2 Automated Urban Monitoring

With growing research interest in urban monitoring, there have been several attempts to develop generic sensor platforms capable of interfacing with a variety of sensors, storing and transmitting information over available networks. The work in [20] develops a two tier mobile sensing platform for the purpose of post-facto crime scene investigation. In rapid overview, the system consists of a generic sensor interface layer for easy communication with a variety of sensors. Irrespective of the communication mode and type of data collected, the sensor interface layer communicates with the connected sensors to ensure robust data collection. The collected data is transferred to the data harvesting layer that ensures storage and transmission of stored data to patrol vehicles over an ad-hoc network. The system proves the feasibility of vehicular sensor networks for the purpose of decentralized data collection and storage. When equipped with the right type of sensors, such systems could be used to monitor chemical attacks and other pollution indicators along with real-time traffic information in the form of images and vehicle speed data.

2.4 Application of Machine Vision in Pavement Analysis

2.4.1 Automated Crack Detection and Repair

Many studies have applied machine vision to detection and sealing of cracks on pavements. The need to precisely detect and fill pavement cracks has lead to the development of a new research field focusing on machine vision based analysis of road images. This section describes some of the relevant work in the field of machine vision assisted crack detection. The work in [21] exploits the difference in intensity of cracks and smooth pavement to detect the presence of cracks. A set of empirically obtained threshold values are used to pre process the image in order to remove the noise that could otherwise be falsely detected as cracks.

The work in [22] develops an algorithm to precisely detect pavement cracks for automated repair. The algorithm relies on an initial set of points that marking the crack on an image. Unlike [21] the entire crack is then actively tracked by detecting the difference in intensity levels between the crack and the pavement (pavement is assumed to be of a lighter color than the crack). Even though crack detection is a fundamentally different problem than detection of snow, it highlights the use of different gray levels as an important source of information to discriminate between different physical features in an image.

The work in [23] develops a localized thresholding technique to enhance the appearance of cracks on pavements. The Hough transform is then used to detect the presence of cracks that have already been enhanced due to thresholding. While the above mentioned works rely on a pre determined process for crack detection, the wok in [24] develops a machine learning approach to determine the thresholding parameters needed to enhance the presence of cracks for any given image. An artificial neural network is trained using the mean, standard deviation and desired threshold value or a set of training images. Once trained, the neural network model is then used to predict best possible threshold values for a given set of test images. As the predicted threshold values will e specific to very test image, better edge will be achieved in comparison to a pre-determined set of threshold values discussed in [21].

2.4.2 Detection of Lane and Pavement Boundaries

Automated analysis of the road often requires the detection of pavement boundaries in order to restrict the bulk of processing only to the area of interest and to reduce noise that may be induced by the surroundings. Lane detection is also an important part in the design of driver assistance systems and other intelligent vehicle applications. The work in [25] develops a circular shape model to detect road boundaries in images obtained from a high resolution millimeter-wave radar. Most highways in the Unites States follow a design scheme where pavement boundaries are laid ad concentric circles when sheen in short segments. The highway design and image properties of millimeter-wave radar make it possible to achieve high detection rates under most driving conditions. The work in [26] proposes fusion of vision and radar images for detection of lane and pavement boundaries. Similar to work in [25], [26] also uses a gradient based global template model for detection of lane boundaries.

2.4.3 Detection of shadows

Shadows are a common problem in implementing many vision based solutions in outdoor environments. For road and pavement image analysis, shadows from trees, other vehicles and road signs are a common source of noise which may cause many algorithms to perform poorly. The work in [27] proposes novel shadow detection algorithm. Shadows are detected by enhancing the contrast difference between shadow and asphalt road by using a set of fuzzy decision rules. Edge detection methods are applied to detect edges between asphalt and pavement. Detection of vehicles The work in [28] uses an R G B color comparison approach to detect shadows cast by other vehicles on the roadway. Empirical constants are used to distinguish if a pixel belongs to a shadow or to the actual pavement. The width of the shadow is then used to determine if it is from a vehicle or another source.

2.5 Application of Machine Vision Winter Road Surface Classification

We find many examples of automated road surface condition monitoring where new and innovative methods of monitoring have been applied. While many of these attempts infer road surface condition using vehicle dynamics and acceleration/deceleration patterns, we also find attempts where a computer vision based approach has been applied to classify road surface conditions. This section describes work that is most related to our research of developing a computer vision and machine learning based road condition monitoring system.

2.5.1 Stationary Camera Based System

The work in [29] developed a road surface condition classifier prototype that classifies road images into one of the set classes. The following provide detail about the data collection, feature extraction, training, testing and results of the prototype. Data collection. Road images were extracted three times a day (08:00, 12:00 and 16:00) from a fixed location with the final data set consisting of 2000 unique images. The images were taken from the identical camera which happened to be a high end movie camera from which frames were extracted using an image grabber card. Then each image was manually classified as being one of the following categories.

1. Dry
2. Wet
3. Snow
4. Tracks
5. Ice

Feature Extraction

A total of three distinct features were extracted from the available images. Even though the detail of the feature extraction algorithm is not provided, the report mentions the features being based on pixel intensity, gradients and location of the brightest 10% pixels in the image.

Training, Results and Comments

A subset of the collected images with close to equal images from all classes was used to train an Artificial Neural Network. The detail of model training and testing is not provided. The results show a maximum of 90 % accuracy for detection of ice, where as detection for other road conditions was relatively low.

2.5.2 Color Based Road Segmentation

The study in [30] presents a comparison of two methods for color based road segmentation. The first was implemented using a neural network, while the second approach is based on SVM.

Data Collection

A large number of training images were collected using a camera mounted on an all terrain mobility device. The images were manually classified into the following road conditions:

1. Snow
2. Dirt or gravel surfaces
3. Asphalt or paved

The duration of data collection, variability in illumination conditions and the quality of images are all important factors in image based road surface classification, but these factors have not been discussed in the study.

Feature Extraction and Model Training

The images were divided into blocks of 31 x 31 pixels and RGB histograms were created. Experimentation was done with grouping the training images by road condition and generating a separate model for each group. In another set of experiments, the image coordinates of each point we added as an additional feature in the models. For the first model, an Artificial Neural Network based classification was done. Out of the acquired images 75% were used to train the network with 20 hidden units in one layer and weights were updated using conjugate gradient back-propagation, with the 'tansig' activation function. With the training portion of each set, we used a cross-validation method to help improve accuracy. Four nets were trained, each using a different 75% of the training set, and estimated the network's accuracy over the remaining 25%. The network with the best accuracy was kept. For the second model, the use of Support vector Machines (SVMs) was made. To train the SVMs a radial basis function with gamma term 10 was used.

Chapter 3

Background

This chapter provides a basic overview of some of the concepts that may be required to understand the work presented in the following chapters. Topics covered in this section are mainly focused on Machine Vision and Support Vector Machines as a classification algorithm.

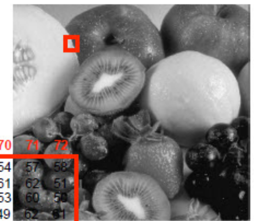
3.1 Machine Vision

This section provides a basic introduction to some of the machine vision methods and terminology that has been used in following chapters.

3.1.1 Digital Image

A grayscale image is a method of image representation where each pixel (dot) is represented as a shade of gray. The degree of brightness depends upon the number representing that pixel. Figure 3.1 elaborates this concept.

The RGB color model is an additive color model in which red, green, and blue light are added together in various ways to reproduce a broad array of colors. The name of the model comes from the initials of the three additive primary colors, red, green, and blue. Each layer is represented as a two dimensional matrix with n rows and n columns and the final image consists of three layers or matrices called R, G and B layers, each of size (m x n).



y \ x =	58	59	60	61	62	63	64	65	66	67	68	69	70	71	72
y = 41	210	209	204	202	197	247	143	71	64	80	84	54	54	57	58
42	206	196	203	197	195	210	207	56	63	58	53	53	61	62	51
43	201	207	192	201	198	213	156	69	65	57	55	52	53	60	50
44	216	206	211	193	202	207	208	57	69	60	55	77	49	62	61
45	221	206	211	194	196	197	220	56	63	60	55	46	97	58	106
46	209	214	224	199	194	193	204	173	64	60	59	51	62	56	48
47	204	212	213	208	191	190	191	214	60	62	66	76	51	49	55
48	214	215	215	207	208	180	172	188	69	72	55	49	56	52	56
49	209	205	214	205	204	196	187	196	86	62	66	87	57	60	48
50	208	209	205	203	202	186	174	185	149	71	63	55	55	45	56
51	207	210	211	199	217	194	183	177	209	90	62	64	52	93	52
52	208	205	209	209	197	194	183	187	187	239	58	68	61	51	56
53	204	206	203	209	195	203	188	185	183	221	75	61	58	60	60
54	200	203	199	236	188	197	183	190	183	196	122	63	58	64	66
55	205	210	202	203	199	197	196	181	173	186	105	62	57	64	63

Figure 3.1: Digital Representation of an Image

3.1.2 Convolution

Convolution is a mathematical operation that is commonly used in image processing for smoothing, differentiating and other tasks. In simple terms, convolution can be seen as sweeping a kernel matrix and performing convolution calculations after every step. This process can be seen in figure 3.2 where an image I and kernel H are convolved.

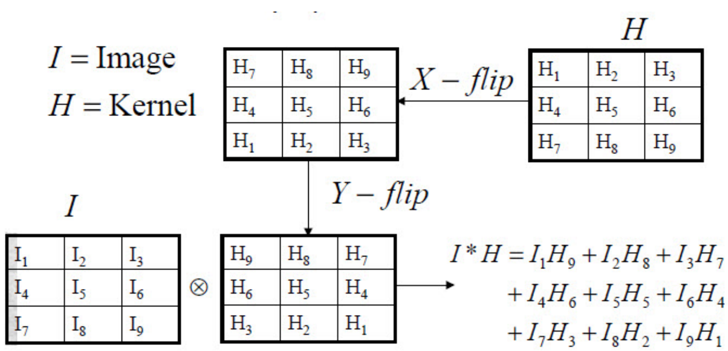


Figure 3.2: Basic Convolution

3.1.3 Image Gradient

An image gradient is a directional change in the intensity or color in an image. Image gradients may be used to extract information from images. Each pixel of a gradient image measures the change in intensity of that same point in the original image, in a given direction. To get the full range of direction, gradient images in the x and y directions are computed. Figure 3.3 shows an image and its gradient.

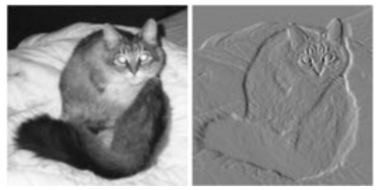


Figure 3.3: Visualization of Gradient

3.1.4 Edge detection

Special kernels (also known as masks) can be convolved to enhance the presence of edges in an image. Edges refer to points of high change in image intensity; they may occur in any direction, however in our work, we mostly focus on vertical edges. Figure 3.4 illustrates how convolution of vertical edge enhancement mask can highlight edges in an image. We see that as the mask passes over an edge, the convolution sum is much higher than sections with minimal or no intensity change.

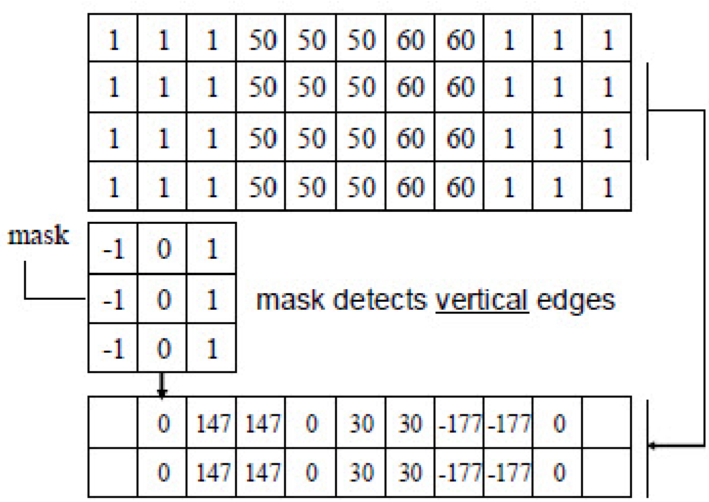


Figure 3.4: Edge Enhancement

3.1.5 Image Smoothing

Another application of convolution is smoothing. Just like edge enhancement masks, there are a variety of masks that can have the effect of smoothing an image. These masks are known as averaging or smoothing masks. Smoothing masks work by replacing the value at a pixel by the average value of pixels in its close vicinity. The weight given to neighboring pixels depends on the type of average filters used.

3.1.6 Image Histograms

An image histogram is a type of histogram that acts as a graphical representation of the tonal distribution in a digital image. It plots the number of pixels for each tonal value. By looking at the histogram for a specific image a viewer will be able to judge the entire tonal distribution at a glance.

The horizontal axis of the graph represents the tonal variations, while the vertical axis represents the number of pixels in that particular tone. The left side of the horizontal axis represents the black and dark areas, the middle represents medium grey and the right hand side represents light and pure white areas. The vertical axis represents the size of the area that is captured in each one of these zones.

Thus, the histogram for a very bright image with few dark areas and/or shadows will have most of its data points on the right side and center of the graph. Conversely, the histogram for a very dark image will have the majority of its data points on the left side and center of the graph. In the field of Computer Vision, image histograms can be useful tools for summarizing the content of an image based on occurrence of shades. For non discrete data, the horizontal axis of the histogram is usually dscretized into bins. All data points belonging to a certain range are collected into the bin representing that range.

3.1.7 Histogram Concatenation

Concatenation can be defined as combining two or more arrays of same or difference sized into a single array. Consider two arrays A and B. If A =1,2,3 and B=4,5,6, the concatenation of A and B will result in the array 1,2,3,4,5,6. In our work, multiple histograms are concatenated to form single arrays which are then used to describe a particular feature of a particular image. Figure 3.5 shows two separate image histograms and Figure 3.6 shows the result of concatination.

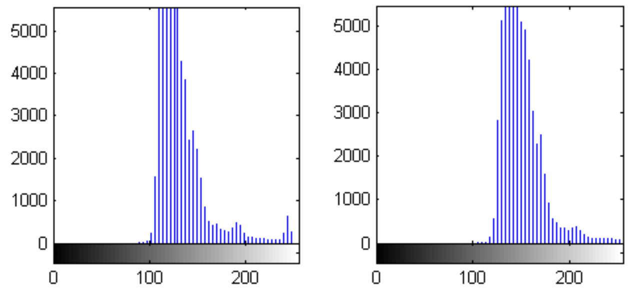


Figure 3.5: Two Separate Histograms

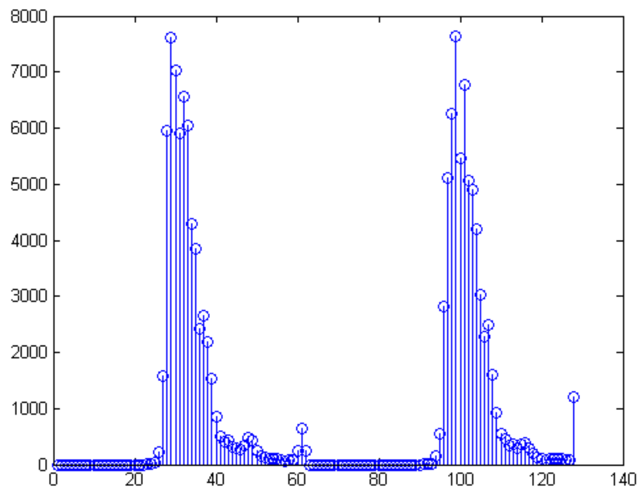


Figure 3.6: Concatinated Histograms

3.2 Support Vector Machines

Support vector machines (SVMs) are a set of related supervised learning methods that analyze data and recognize patterns and are used for classification and regression analysis. A Support Vector Machine (SVM) performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories.

The task of choosing the most suitable representation is known as feature selection. A set of features that describes one class is called a feature vector. So the goal of SVM modeling is to find the optimal hyperplane that separates clusters of feature vectors in such a way that cases with one category of the target variable are on one side of the plane and cases with the other category are on the other size of the plane.

Assume that a set of data contains variables from two different classes. If we plot the data points for the variables from the two classes using the value of one predictor on the X axis and the other on the Y axis we might end up with an image such as shown in Figure 3.7[31] One category of the target variable is represented by rectangles while the other category is represented by ovals [31].

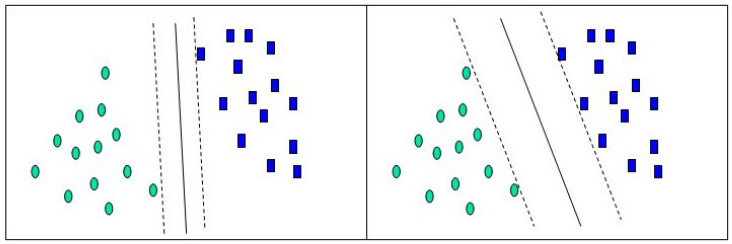


Figure 3.7: SVM Classification

However Figure 3.7 is an idealized example, the cases with one category are in the lower left corner and the cases with the other category are in the upper right corner; the cases are completely separated. The SVM analysis attempts to find a 1-dimensional hyperplane (i.e. a line) that separates the cases based on their target categories. There are an infinite number of possible lines; two candidate lines are shown above. The question is which line is better, and how do we define the optimal line. The dashed lines drawn parallel to the separating line mark the distance between the dividing line and the closest vectors to the line. The distance between the dashed lines is called the margin. The vectors (points) that constrain the width of the margin are the support vectors as shown in Figure 3.8[31]. An SVM analysis finds the line (or, in general, hyperplane) that is oriented so that the margin between the support vectors is maximized. In figure 3.8, the line in the right panel is superior to the line in the left panel[31].

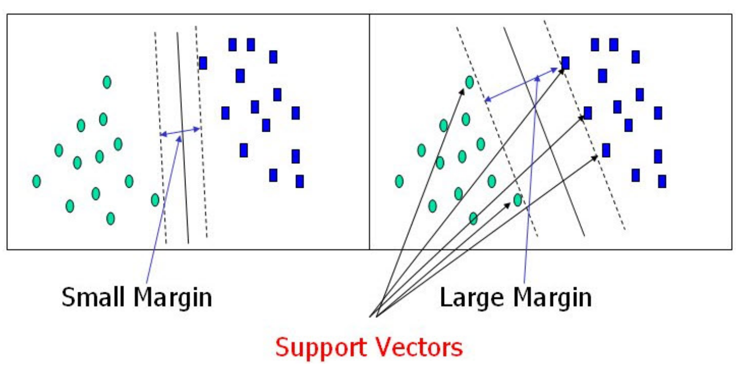


Figure 3.8: SVM Classification: Margins and Support Vectors

While the data illustrated in Figure 3.8 is good for conceptual understanding, in many cases the data is not separable by a linear dividing line. As shown in 3.9[31] the dividing line required in this case is non linear. Hence a kernel function is needed to transform the data so that the dividing line can be linear, as shown in Figure 3.9[31]

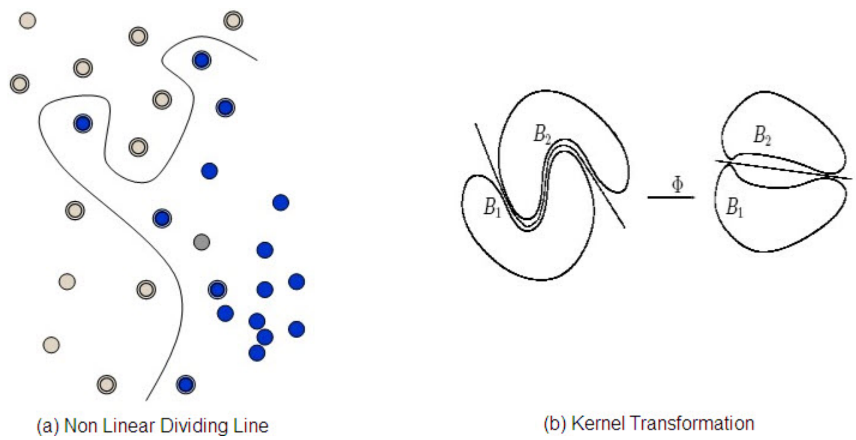


Figure 3.9: SVM Classification: Use of Kernel Functions

Chapter 4

Road Condition Classification Using Machine Vision

The previous chapters evaluated the various road condition monitoring solutions in use today. It was concluded that in order to effectively keep track of changing road surface conditions over a wide network of roads, there is a need for an inexpensive monitoring solution that can be deployed in large numbers.

As discussed in Chapter 2, vehicular sensor networks (VSNs) have proven to be a reliable and cost effective method for automatic environmental data collection. Some examples of systems that have successfully proven to use vehicles as non-dedicated probes for automated data collection have also been discussed.

Chapter 2 also discusses some related work with respect to the use of machine vision for road surface classification. All the relevant work was presented and many of their weaknesses were identified. The objective of this thesis is to explore the possibility of using dedicated hardware that can be installed on no-dedicated vehicles with the purpose of road condition monitoring and its effectiveness in replacing many of the existing solutions including manual bare pavement reporting.

Before going out to build a dedicated data collection prototype that collects road images for classification, we first develop a set of classification algorithms on already available data. This is done to better evaluate the potential of machine vision in solving our problem and to also find out the various data requirements from the dedicated data collection hardware to be built.

Due to a large number of applications, image recognition has been a subject of intensive research over the past decades [32]. While there is limited work on monitoring of winter road surface condition using machine vision, there has been a tremendous increase in applications where machine vision is used for a variety of sensing and recognition purposes.

Everyday examples include face detection which is present in most point-and-shoot digital cameras and more complex application can be seen as machine vision based system is the ASIMO robot [33] that uses machine vision to learn and recognize previously unseen objects.

The extensive use of machine vision in everyday devices is further propelled by the availability of affordable high quality imaging hardware that has made it possible to capture images and video to a quality that was previously un-thought of. Motivated by the tremendous growth and the inherent advantage of contact free sensing, we decided to explore machine vision as a possible solution to winter road condition monitoring.

In This chapter we first describe the challenges related to machine vision based classification that need to be addressed in order to infer road surface condition, this is followed by a detailed description of our methodology for achieving image classification.

4.1 Winter Road Surface Condition Classification

Most computer vision tasks often seem deceptively simple to solve, this is primarily because the human vision system is by far the most developed system in the human body. Backed by tremendous processing power, large memory, precise sensing ability and training of a life time, the human vision system does an outstanding job of seamlessly steering us in our everyday lives. This section describes the various challenges that in our understanding need to be addressed to be able to automatically infer winter road surface condition.

4.1.1 Classification of Road Surface Condition

As discussed in Chapter 1, road surface condition has a large variation and is hence difficult to classify using a simple measure of scheme. Many of these classes are often indistinguishable even by the trained human eye.

In order to tackle this problem with a machine vision based approach, we start with a simplified classification method in the following main categories:

- Bare Road (dry or wet)
- Snow Covered
- Center Covered Tracks Bare

While conditions like ice, freezing rain, packed snow and lose snow also exist, they have been merged into the above classes for two reasons. Firstly, we are mostly interested in knowing the overall cover instead of the exact contaminant type. Secondly, many of the categories are often indistinguishable by the naked eye and require other means in order to be detected.

Feature Extraction

In order to infer the condition of the road using machine vision, our second challenge is to identify critical discriminating features that can be used to discriminate one road condition from the other. Literature provides a large set of features that have previously been used to discriminate between different scenes and objects. Our methodology and uniqueness of approach is discussed in later sections of this chapter.

Illumination

Variation in light levels is one of the major concerns in machine vision based recognition of outdoor scenes, which is the third challenge. Different light angle and intensities from uncontrolled sources like the sun can dramatically change the image features. While this may not be of concern in cases where images are obtained from radar (e.g. work discussed in [25]) but may be a primary concern when in case of optical images. As a result, the recognition and classification algorithm must have a mechanism to compensate for different light levels. There is large amount of literature covering a variety of methods that can be used to compensate for different levels of light for outdoor machine vision applications. For instance, the work in [34] proposes a model for variation in color due to changes in ambient light. As all images for this research come from an outdoor scene with a large variance in ambient light and a number of uncontrolled light sources as the sun, making the classification algorithm light invariant will be a major challenge.

Ambient Noise Compensation

Outdoor images are particularly noisy signals. In our case, road images will be poised with noise in the form of other vehicles, cracks and road markings, image blur due to speed are a source of noise which may cause classification problems. For better reliability, these sources of noise will have to be identified and effective solutions will have to be proposed.

Model Training

In most cases, identifying good features is not enough to achieve a high classification rate. The features need to be used to train a model that can then be used to classify unseen images based on the images that the model has previously *seen*. It is important to understand the distribution of data and make possible transformations before the data can be used to train a model. Moreover, training data needs to be carefully picked so that it represents a large set of all possible images that the model will be used to classify. For different features, different models will have to be trained and then a combination of a selected set of models will have to be used for final classification.

4.2 Methodology

This section describes the step by step process that has been followed to achieve image classification for winter road surface condition monitoring. The overall methodology is illustrated in Figure 4.1 and each step is explained in the following sections.

4.2.1 Data Preparation

Data preparation is the first step towards feature extraction and image classification. All data used for this project is assumed to be standard jpg color images. In the data preparation step, we manually divide each set of data (a set is defined as images from a particular highway on a particular day) into snow covered, bare and center-covered categories and placed into respective folders. As we use a binary classifier for our work, training and testing data sets are created based on the type of model being used. For instance, when a bare pavement detection model is being trained, the positive set will contain images where the pavement is bare, and the negative set will contain images that are not bare (including snow covered and center covered track bare). All images are assumed to be color images in jpg format and manually labeled (put into respective folder) before the start of the feature extraction process.

4.2.2 Image Reading

This is the first step in image classification. All images are read and processed by the system one after the other. The images are read into a [n x n x 3](Chapter 3) matrix and stored in the memory.

4.2.3 Image Cropping

Image cropping refers to the extraction of defined parts of the image that will be used for the feature extraction and classification process. As seen in Figure 4.2, a large part of

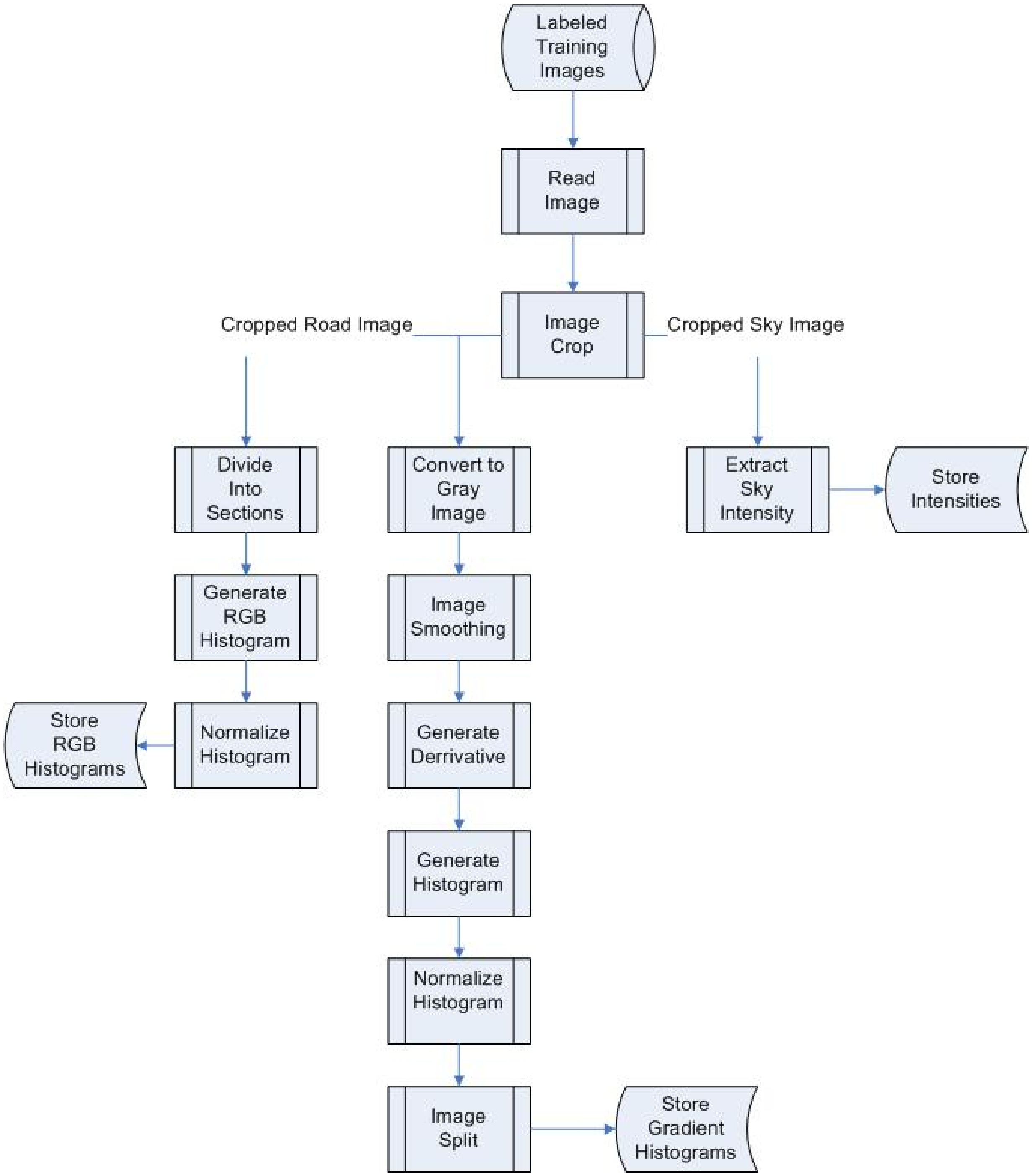


Figure 4.1: Data Preperation for Model Training

Figure 4.2: Image Cropping

the image contains little or no information about the road surface. This information may induce noise hence negatively affect the classification results. In order to constrain our algorithm to an image that is most representative of the road, the road section from each image is automatically cropped for further analysis. As discussed earlier, the sky color of an image is of particular importance to us, this is also cropped and stored for further processing.

4.2.4 Image Segmentation

Each image is divided into smaller squares for further processing by the feature extraction algorithms. Dividing the image into smaller sections plays a crucial role in the classification rate of the model. This can be explained by considering each of the smaller boxes as a representative of a bare or snow covered road. When an unknown image is tested for classification, the training features (small squares in our case) are matches with testing Figure 4.3. If an entire test image was to be matched to a set of training images as a whole, the probability of finding a match will be low. This is because each image can be different from the other in terms of vehicle position, shade of pavement color and other anomalies.

On the other hand, if small squares from the test image are matched to a large set of small squares obtained from within the training set the classification algorithm will be able to mix and match a number of squares from the entire set of training images to see if each square in the test image matches to a square in the training set.

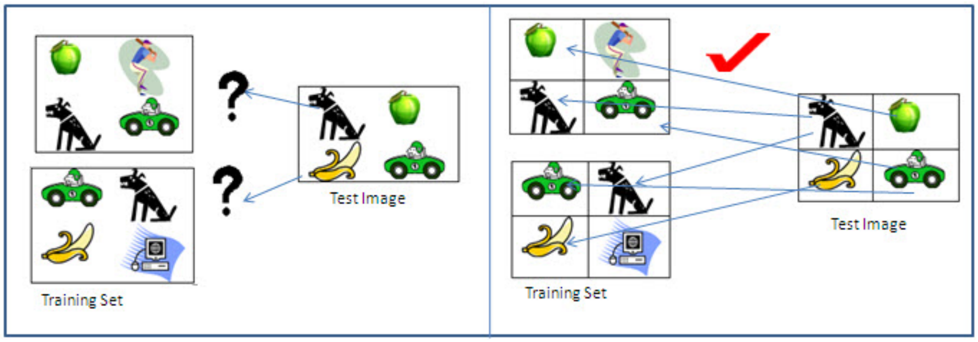


Figure 4.3: Image Segmentation

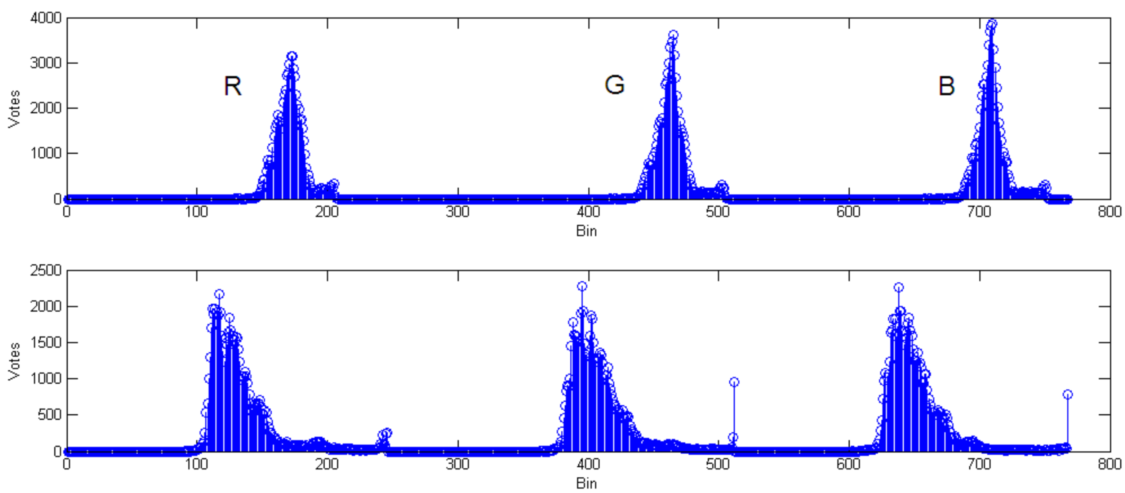


Figure 4.4: RGB Histograms for Bare and Covered Roads

4.2.5 RGB Histogram Generation

To discriminate snow covered pavement from bare and partially covered, we use color information as our primary cue. As the presence of snow largely brightens the image, the scene is dominated by bright pixels as compared to a large number of dark pixels over a dark pavement section. This difference can be seen in Figure 4.4 .

As the color information of an image lies in the RGB layers, we divide the image into smaller squares and generate RGB histograms for each of the squares. These histograms represent key information about the color distribution in an image and will be used as key features in classifying bare and snow covered roads. Figure 4.6 demonstrates the histogram generation procedure.

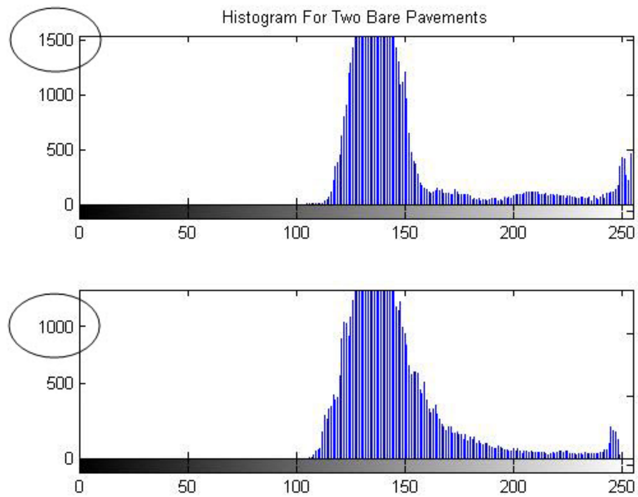


Figure 4.5: Red Layer Histograms for Bare Pavements Before Normalization (B and G layers show similar results)

4.2.6 Histogram Normalization

Histogram normalization plays an important role in the classification efficiency of the model. As discussed in earlier sections, color based classification relies on dominance of dark or white pavement colors to infer snow covered surfaces from bare pavements. While the models are being trained to identify the region in the color spectrum (bright or dark) that dominates in an image, image histograms also carry extra information about the number of pixels that belong to the region. As seen in Figure 4.5 the two histograms from different bare pavement show peaks at nearly the same brightness of color but have different peaks on the y axis. This difference can cause the model to misclassify the images.

Once histograms are normalized (see **??**for code), height differences similar to those shown will reduce misclassification.

4.2.7 Histogram Storage

Once histograms for all small squares have been normalized, the need to be combined and stored as a single feature. This single feature vector is then used to train SVM based model for classification of bare and snow covered pavements. The final form of the histograms can be seen in Figure 4.7.

4.2.8 Extraction of Sky Intensity

While preparing data for training the snow and bare pavement classification model, we also collect luminance data for the entire training set. This is to keep track of the average brightness of scenes that have been used to train the model. In order to extract brightness information from the given images, a pre defined sky section for each image is cropped. We use a thin sky section for brightness estimation as the sky has the minimum probability of finding unpredictable anomalies like vehicles, cracks, trees and vegetation. Luminance is extracted by converting each RGB image into its HSV (Hue Saturation Value) equivalent. In HSV model of color representation, the V (Value) component is said to represent the luminance of an image. For each sky image in the training set, the luminance value is extracted and stored in a luminance vector. Once all training images have been read, the average luminance value is calculated by taking the arithmetic mean of the luminance vector (see Figure 4.8). Following sections illustrate how the luminance is used to adjust the luminance of the test images.

4.2.9 RGB to Gray-Scale Conversion

Color information is not necessary to see tracks (center covered bare road) on an image; we convert the color images into a grayscale format before proceeding to the next step of feature extraction for detection of tracks. This is done using in-built functions from the MATLAB image processing toolbox.

4.2.10 Image Smoothing and Gradients

Image smoothing is the process of dampening sharp color and brightness changes in an image. This is normally done by replacing the color value at a pixel by the average of a group of neighboring pixels in its close vicinity. Doing so dampens any sudden changes in the color of the image. As track detection relies on gradient, image smoothing can help remove any anomalies in an image that may cause false gradients. The effect of image smoothing can be seen in figure 4.9

Gradients are a measure of change; to detect the presence of tracks, we detect sudden changes in image contrast as queues for the presence of tracks. Figure 4.10 illustrates the use of gradients as features for detection of tracks. It can be seen that there is high gradient at points where there is larger color change as compared to sections with smaller color change. We see that presence of road tracks can easily be detected in the gradient image, however noise from other sources also causes intensity changes similar to tracks and thus needs to be filtered.

In order to detect tracks on pavement, a problem specific algorithm has been developed that highlights image intensity changes that only occur with the presence of tracks while suppressing intensity changes due to other anomalies.

4.2.11 Noise Suppression and Track Enhancing Algorithm

In this section, we describe the noise suppression and track enhancing algorithms for the purpose of detecting center covered track bare situations in a scene. We first smooth image noise to suppress false gradient alarms that may be caused due to rough road texture, pixel blur and presence of other contaminants. Hence we required a mask that was biased towards enhancing intensity changes due to the edge between pavement and snow but at the same time successfully suppressing noise that could be a cause of potential false alarms after image derivatives have been applied.

Finding an appropriate smoothing filter for road noise suppression was found to be an iterative process and a variety of different smoothing algorithms had to be tried before developing the one that yielded the required results. A Gaussian filter mask based on the Gaussian function was developed. The graphical form of the mask can be seen in Figure 4.12 . The mask is based on a 9x9 filter with pixel values displaced as shown. The mask serves the purpose of being rotation invariant and hence unbiased towards noise in any particular direction. Moreover, the pixel weight distribution works well to suppress small changes in intensity caused by noise and less affect large changes due to tracks. Image smoothing was implemented using simple 2D convolution of the developed smoothing function with the image. The result of smoothing from the tuned Gaussian smoothing filter can be seen in Figure 4.11

$$H[m,n] = f \otimes I = \sum_{k,l} f[k,l] I[m-k, n-l] \tag{4.1}$$

To highlight tracks on a smooth image, an intensity gradient approach was used. A partial derivative of image intensity was calculated (intensity derivative).

$$\nabla I = \frac{dI}{dx}\hat{x} + \frac{dI}{dy}\hat{y} + \frac{dI}{dz}\hat{z} = I_x\hat{x} + I_y\hat{y} + I_z\hat{z} \tag{4.2}$$

To highlight the change in intensity the magnitude of intensity gradient (grad mag) is calculated.

$$\|\nabla I\| = (I_x^2 + I_y^2 + I_z^2)^{\frac{1}{2}} = \nabla I \cdot \hat{n} \tag{4.3}$$

To enhance vertical edges, a gradient mask shown in equation (4.4) was used. The scaling parameter k has been introduced to scale the mask to best detect vertical edges, the tuning process of this mask is explain in the following Section r̃eftuning . The mask is designed to only highlight vertical edges and maximum weight is given to adjacent pixels parallel to the direction of convolution and thus enhancing vertical edges.

The effect of the mask can be seen in Figure 4.14. It can be see seen that the tracks are highlighted and the test of the noise in the image is suppressed. The effectiveness of this method can be compared to standard image gradients in figure 4.10. Comparing figure 4.14 it can be seen that the algorithm works effectively in suppressing edges due to noise where as highlighting edges due to tracks.

We extract a feature vector from tracks based on gradient histograms. The discriminating strength of this approach can be seen in 4.15 there is an order of magnitude difference between the gradient values obtained from the two images. The final form of gradient histograms as feature vectors can be seen in Figure 4.16.

4.3 Summary

In this section, we developed a set of feature extraction algorithms specific for winter road condition classification. While highlighting the feature of interest and suppressing ambient noise required a variety of machine vision based techniques, the end feature vectors have been condensed into concatenated histograms representing a feature of interest in the image (Figure 4.7 and 4.6). This has been done to reduce the size of the feature and improve computation time. Moreover, histograms are a common preference for representing image features and work well with Support Vector Machines.

```
For Each Image In Dataset
    Read Image
    RGB Feature=Vector of size 1xN
    Split Image into 40 x 40 pxel squares
    For Each Square
        R-hist=  Histogram for Red Layer
        Normalize R-hist
        G-hist=  Histogram for Green Layer
        Normalize G-hist
        B-hist=  Histogram for Blue Layer
        Normalize B-hist
        Concatinate R-hist, G-hist and B-hist to RGB Feature
        (after every iteration, RGB Feature three more
        histograms concatinated to it)
    End
End
At the end of the loop, RGB Feature will be a 1xN array of
concatinated RGB historgams
```

Figure 4.6: Histogram Generation

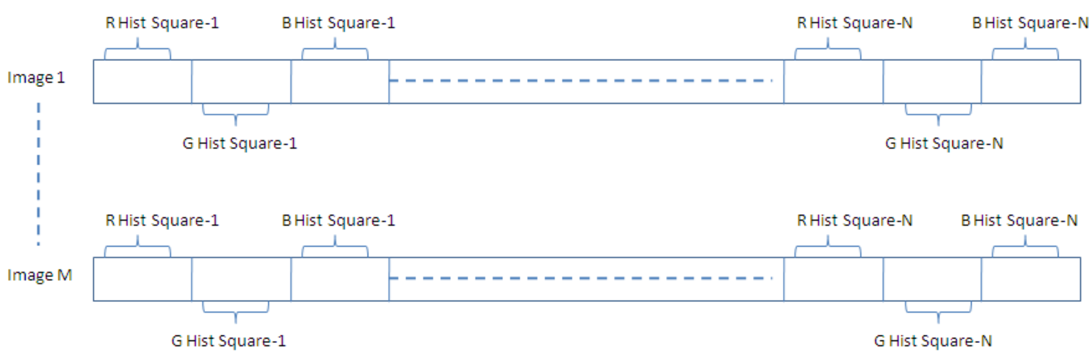


Figure 4.7: Histogram Storage

```
Value=0
For Each Image In Dataset
    Convert image to HSV form
    value=value+ V (value) component of Image
End
At the end of the loop, Value will be a sum of all V comopnents of image
average Value = Value/total number of images
```

Figure 4.8: Average Brightness of Image Data

Figure 4.9: Image Smoothing

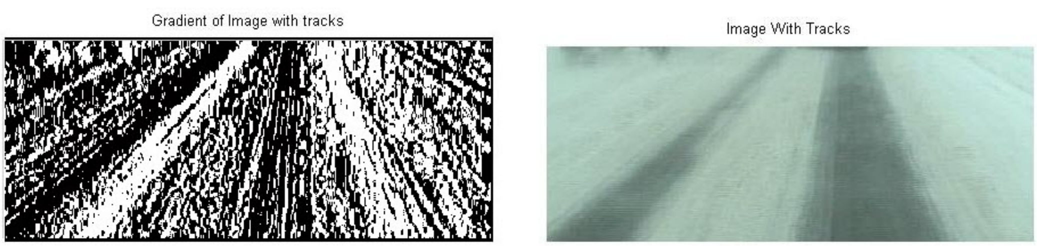


Figure 4.10: Gradients

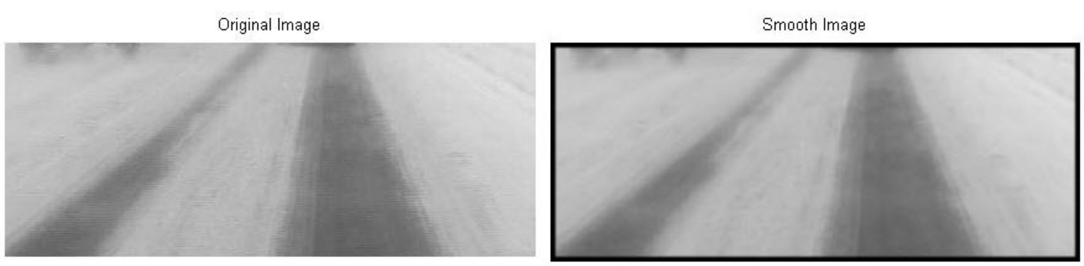


Figure 4.11: Image Smoothing

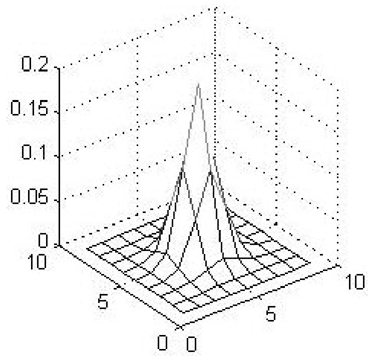
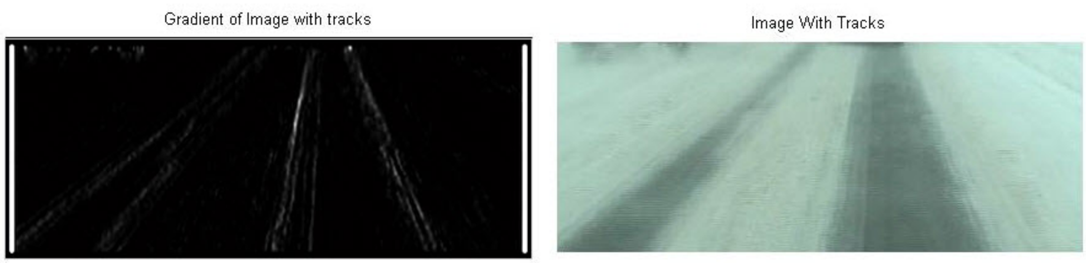


Figure 4.12: Gaussian Mask

$$x = k \begin{bmatrix} -0.5 & 0 & 0.5 \\ -1 & 0 & 1 \\ -0.5 & 0 & 0.5 \end{bmatrix} \tag{4.4}$$

Figure 4.13: Modified Sobel Mask for Vertical Edge Detection



(a) Gradient of Road with Tracks

(b) Gradient of Bare Road

Figure 4.14: Gradients of Tracks and Bare Roads

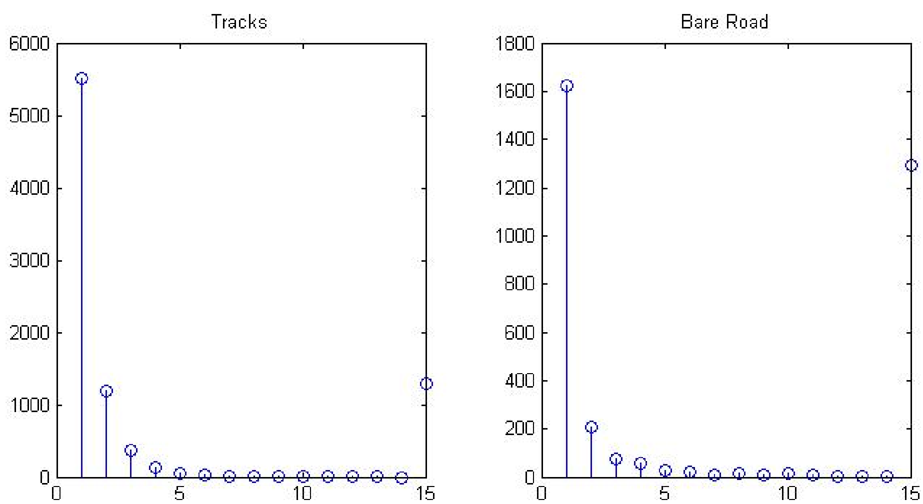


Figure 4.15: Gradient Histograms for Bare and Center Covered Track Bare Roads

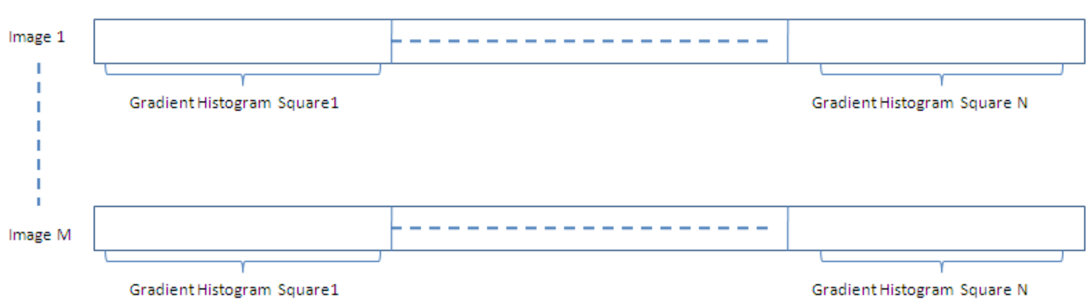


Figure 4.16: Gradient Histograms as Feature Vectors

Chapter 5

Model Calibration and Results

This chapter outlines the model calibration process and summarizes model classification results for different training and testing sets. During the discussion, we also show the effectiveness of some novel image feature extraction and model training techniques specific to the problem of winter road condition classification.

5.1 SVM Based Binary Classification

In order to classify images based on extracted features, an SVM (Support Vector Machine) based classification system is used. An introduction to SVM is provided in Section 3.2. As discussed in [13], road surface conditions cannot be easily classified into distinct classes. There are often situations where even the trained eye can also misclassify road conditions due to its complex nature. Moreover, the idea of multiple classes existing together further complicates the boundaries which separate one class from the other. Hence decomposing a K-class classification problem into a number of binary classification problems allows a scheme to model binary class boundaries with much greater flexibility at a lower computational time [35]. This approach suits particularly well to our application as a large number of intermediate classes exist and defining boundaries between each class is not always possible. Moreover, in our application, the presence or absence of a particular class is of more importance than an exact prediction of the intermidiate class to which an image may belong. For instance, if bare pavement is to be detected, all images representing bare pavement could be combined into one set of data while images from all other classes that are not bare could be combined into another set. The binary classifier will then be able to differentiate bare pavement from all other types. Similarly, when detecting the presence of tracks, the binary classifier can be trained with a positive set of images that contain tracks only and a negative set that contains images from all other road conditions that do not contain tracks. The negative set in this case would automatically combine all classes that do dot show tracks into a single class and thus make classification more robust.

5.1.1 SVM Training and Testing

For this work, we use LIBSVM, an SVM implementation for MATLAB [36]. Training of an SVM requires an equal number of labeled training data from both classes. It is also required that the data should be normalized and all training data should be of identical dimensions (see Figure 5.2). For training purposes, extracted features from images are combined into a two dimensional matrix where each row of the matrix consists of features from a single image. Figure 4.7 and 4.16 show the format of gradient and RGB feature vectors. The output of the training process is a model that defines the hyperplane dividing the two sets of data in a multi-dimensional plane.

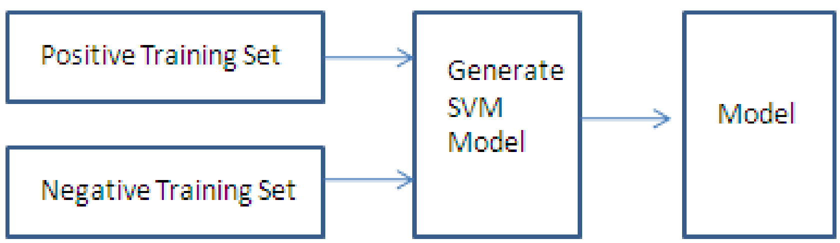


Figure 5.1: SVM Training

Similarly, to test the model, a matrix of feature vectors is generated from a set of testing data. The SVM model is then used to classify the testing data. The result of this process is a set of labels labeling each of the data in the testing set.

5.2 Training and Testing Data

For our experiment, we required images of road surface taken from a camera mounted on a vehicle. As the final system is intended to automatically acquire road images for classification, it was preferred to work with images that had been acquired automatically, without any human intervention.

Amongst the available data sources were traffic surveillance cameras deployed by MTO (Ministry of Transportation Ontario). The available video was low quality and taken from

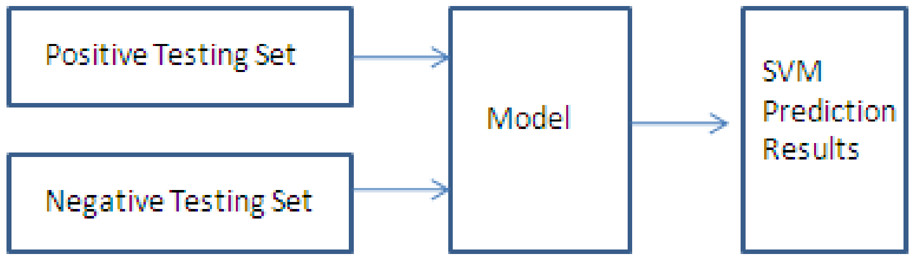


Figure 5.2: SVM Testing

locations far from the actual road surface. As a result, the images did not well mimic data that would be collected by an automatic camera mounted within a vehicle. Moreover, the stationary camera would not be a good representative of spatial changes in road surface condition

Another source of data that could be used for this research was in the form of surveillance videos recorded by patrol vehicles monitoring road surface condition during and after an event. The detailed procedure of bare pavement reporting has been discussed in [13]. The videos covered a variety of different road conditions under variable lighting and other environmental factors. Moreover, as the video was recorded from within a moving vehicle with minimal human intervention it well mimicked the images that would be expected from the developed prototype. A total of more than a thousand frames were manually extracted from the available videos (see Section 5.2).

5.3 Classification of Bare Pavement

As discussed in Section 4.2.5, RGB histograms are key features for discriminating bare pavement from snow covered pavement. This section describes the feature vector creation process and how each of the parameters have been adjusted to improve accuracy of classification.

5.3.1 Segment Size Optimization

Segment size is one of the first variables that needed consideration before RGB features could be extracted. As shown in figure 3.4 the image is broken down into smaller segments before histograms are generated. A number of different segment sizes were tried to evaluate the effect of segment size on classification. A total of four experiments were conducted with the following segment sizes (in pixels): 5x5, 10x10, 20x20, 40x40, and 80x80. In each of the experiments, an SVM model was trained with data extracted using one of the above segment sizes. The model was then tested with a predefined testing set.

It was found that segment sizes had little effect on classification results, however, smaller segments resulted in much larger feature vectors and hence computation time was significantly longer. On the other hand very large segments were computationally fast but had less accuracy. The reason for this difference is unknown and it is suspected that the difference may only be due to the nature of testing and training data set. For this reason, a 40x40 segment size has been used.

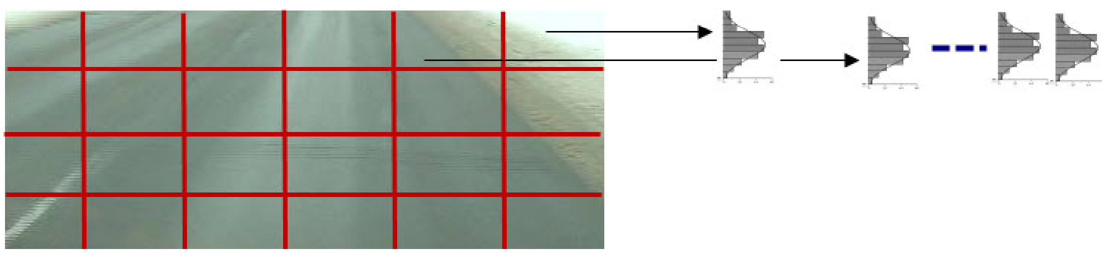


Figure 5.3: Division Into Smaller Segments

5.3.2 Histogram Bin size

Histogram bin size plays an important role in determining the effectiveness of histograms as classifiers. It can be seen in Figure 5.4, there is a maximum of 20% difference in the histograms for bare and snow covered pavement. If the bin divisions were to be too small, there is a risk of the difference being combined into a single bin. If this were to happen, histograms from covered and bare pavement would contain bulk of the data in the same bin and hence classification would become impossible. After analyzing a number of bin combinations for different snow covered and bare images, it was seen that 32 bin histograms best discriminated bare pavement and covered roads. The discrimination strength of 16 bin histograms fell under conditions where a light colored bare pavement was compared to a dull snow covered road. Hence, 32 bin RGB histograms have been used in this experiment.

5.3.3 Histogram Normalization

There are a variety of approaches that can be used to normalize RGB histograms before training the SVM model. To test the best normalization approach for our problem, each of the following approached were tried:

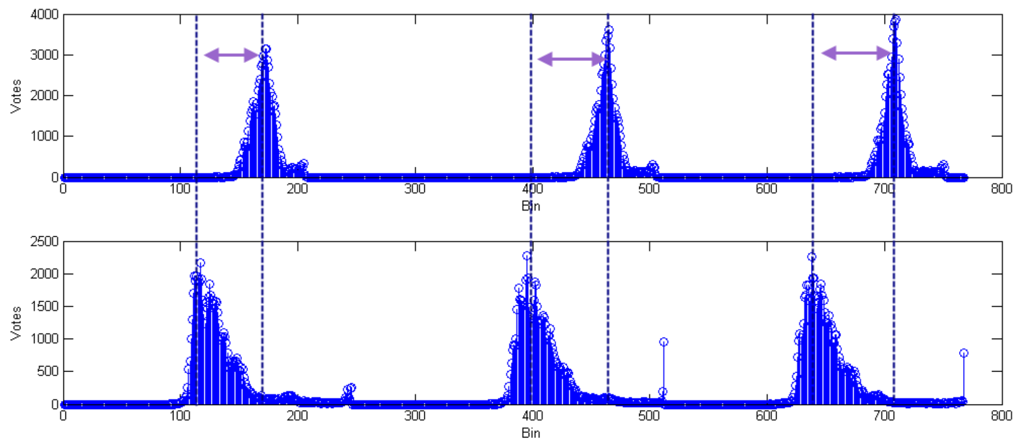


Figure 5.4: Color Difference Between Bare and Covered Pavement

1. Individually normalize histograms for each segment before concatenating them into a single feature.

2. Normalize the complete feature vector after all histograms for a single image have been concatenated.

3. Normalize all histograms together once the entire set of feature vectors is ready for SVM training or testing.

Our analysis shows that the best approach is to normalize each histogram before concatenation (defined in Section 3.1.7) into a feature vector. This can be explained by comparing the RGB histograms of a typical covered and bare image (see figure 5.4). It is seen that bare pavement and snow covered scenes are not discriminated based on the number of values per histogram bin but rather based on the relative position of actual bins to which the bulk of the values belong. It is also seen that the largest number of values in any bin may differ from image to image. Hence if data from different images is normalized together, there is a risk of significantly shrinking the height of some of the histograms. Even though the relative position of the bins with the bulk of the values is preserved, the relative height differences may cause misclassification. Therefore the best normalization method would be to normalize each image on its own. This would preserve the relative position of bins containing bulk of the values without significantly shrinking some of the histograms.

5.3.4 Luminance Adjustment

Average luminance for training Images is calculated using the Equation 5.1 where T is the total number of Images each of size (M, N) pixels.

$$L = \frac{\sum_{k=1}^{T} \sum_{k=1}^{N} \sum_{k=1}^{M} (Vk)}{T} \tag{5.1}$$

For each testing image, luminance V is found using the equation (5.2)

$$V = \sum_{k=1}^{N} \sum_{k=1}^{M} (Vk) \tag{5.2}$$

The value at each pixel in testing image is then multiplied by the adjustment factor K to scale the luminance of the testing image according to the training set (equation 5.3)

$$k = \frac{V}{L} \tag{5.3}$$

The brightness scaled image is then used as a test image to test the prediction accuracy of the model.

5.3.5 Results for Bare Pavement Classification

After finalizing the parameters mentioned in Sections 5.3.1, 5.3.2, 5.3.3, the final RGB feature vector is created. The size and construction of the vector can be seen in Figure 5.5. Various tests were performed to test the bare pavement classification model. The following section presents the purpose of model, test data and results of the SVM model. All feature vectors are generated using RGB histograms described in Section 5.3. The term *Classifier* refers to the SVM model that is trained and tested using the datasets described in the experiment.

```
Size of cropped image (pixels) = 160x400x3
Number of segments = 4x10x3=120
Size of histogram= 32 bins
Total length of feature vector = 32x120= 3840
Size of feature vector = [3840 x 1]
```

Figure 5.5: Final RGB Feature Description

Test 1:

Test Purpose: Test and train model with data from similar light conditions.

Positive Training Set: 92 images of bare or almost bare road taken from highway 417 under medium ambient light.

Negative Training Set: 92 images of snow covered or almost snow covered roads taken from highway 417 under medium ambient light.

Positive Testing Set: 45 images of bare or almost bare road taken from highway 417 under medium ambient light (brighter than training set)

Negative Testing Set: 45 images of covered or almost covered road taken from highway 417 under medium ambient light (brighter than training set)

Results without illumination adjustment: the classifier performed poorly, 65 out of the 90 images were classified correctly.

Results with illumination adjustment: The classifier performed well, 84 out of the 90 images were classified correctly.

Comments: Results show that even slight differences in ambient light can adversely affect classification rate.The illumination adjustment works well for small changes in ambient light between testing and training images.

Test 2:

Test Purpose: Test and train model with data with different pavement color.

Positive Training Set:92 images of bare or almost bare road taken from highway 416 (light pavement color) under medium ambient light.

Negative Training Set:92 images of snow covered or almost snow covered roads taken from highway 417(dark pavement color) under medium ambient light.

Positive Testing Set: : 45 images of bare or almost bare road taken from highway 417 and 416 under medium ambient light.

Negative Testing Set: 45 images of covered or almost covered road taken from highway 417 and 416 under medium ambient light.

Results without illumination adjustment: the classifier performed poorly 57 out of the 90 images were classified correctly.

Results with illumination adjustment: performed poorly 65 out of the 90 images were classified correctly.

Comments: Results show that changes in pavement color can adversely affect classification results. While illumination adjustment works well in scaling test images according to training set, their effect is limited when testing and training data comes from different pavement color areas.

Test 3:

Test Purpose: Test and train model with mixed images from bright and low ambient light.

Positive Training Set:100 images of bare or almost bare road taken from highway 417 under medium and bright ambient light.

Negative Training Set:100 images of snow covered or almost snow covered roads taken from highway 417 under medium and bright ambient light.

Positive Testing Set: : 50 images of bare or almost bare road taken from highway 417 under medium and bright ambient light.

Negative Testing Set: 45 images of covered or almost covered road taken from highway 417 under medium and bright ambient light.

Results without illumination adjustment: the classifier performed poorly, 55 out of the 95 images were classified correctly.

Results with illumination adjustment: The classifier performed poorly, 61 out of the 95 images were classified correctly. .

Comments: Results show that a model under different ambient light conditions performs poorly. From this we infer that different models trained for different light conditions may work better than generic models trained for a broad range of light conditions.

5.4 Classification of Center Covered Track Bare Roads

As discussed earlier, gradient lines are key features for discriminating center covered track bare pavement from snow covered from snow covered or bare. This section describes the feature vector creation process and the various techniques that were used to enhance classification results.

5.4.1 Image Smoothing

Each gray scale image was first smoothed to remove noise and edges due to road anomalies. As explained earlier, finding right filter parameters was an iterative process and it took

$$x = k \begin{bmatrix} -0.5 & 0 & 0.5 \\ -1 & 0 & 1 \\ -0.5 & 0 & 0.5 \end{bmatrix} \tag{5.4}$$

Figure 5.6: Modified Sobel Mask for Vertical Edge Enhancement

several attempts to tune a mask that servers the purpose. A variety of linear, Laplacian and Gaussian mask configurations were tried. It was found that linear and Laplacian masks had better smoothing capability, but convolving these masks with the image often smoothed out edges due to tracks and hence a [9x9] Gaussian mask with a sigma value of 0.9 was used.

5.4.2 Edge Detection

As discussed in Section 4.2.11 a modified Sobel mask of the form 5.6 is used for edge enhancement. In order to tune the mask to best highlight edges as those produces by tracks of bare road and snow, a large range of values for the constant k were tried on a large set of images under different light conditions. Through an iterative process, it was found that a k value of 1/40 highlighted track edges best. A value too small resulted in suppression of actual snow tracks and a value much greater resulted in detection of edges due to pixel blur and other sources of noise.

5.4.3 Feature Vector Generation

Due to perspective depth in the image, the vertical edges do not remain vertical over the entire scene and instead moved closer to each other as the distance from camera increased. For this reason, the image was divided into two sections and two separate feature vectors were extracted 5.8. The algorithm for extracting gradient feature vector from an image is explained in 5.7.

Results from single and double SVM methods were compared. In the two SVM approach, the pavement was considered to have tracks if one or both models predicted tracks. It was seen that two models at different depths would result in better feature matching and hence higher classification results. Moreover, images with tracks present in depth but not close to the camera were often misclassified by the single SVM based classifier. However, many of these images could be correctly classified by the double SVM classifier.

```
    Feature vector=[]
    Convert image to gray scale
    Apply Gaussian smoothing
    Apply Sobel Mask
    For each segment in image
        Generate 16 bin gradient histogram
        Concatinate gradient histogram to Feature vector.
    End

At the end of the loop, Feature vector will consist of
concatinated histograms from all segments of the image.
The final size of the vector will be number of segments x size of each histogram
16 x 10 x 4 = 640 x1.
```

Figure 5.7: Gradient Feature Extraction

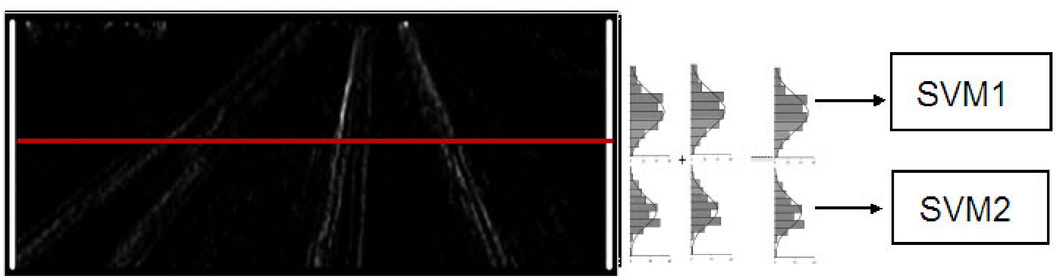


Figure 5.8: Seperate Models for Different Depth Levels

5.4.4 Histogram Normalization

Unlike RGB histograms, relative height of gradient histograms contains key information that is necessary for classification (Figure 4.15). The height of a gradient histogram indicates the number of points on the image with significant change in contrast (gradient). This means the while bare or fully covered roads will have a small number of gradient hits; a center covered track bare road will have will have a greater number of hits due to the edges between the wheel track and snow. Hence, the normalization criterion for gradient histograms is opposite to that of RGB histograms. In order to preserve relative height differences between different images, the entire set for feature vectors was normalized together before being used for SVM training figure 5.9

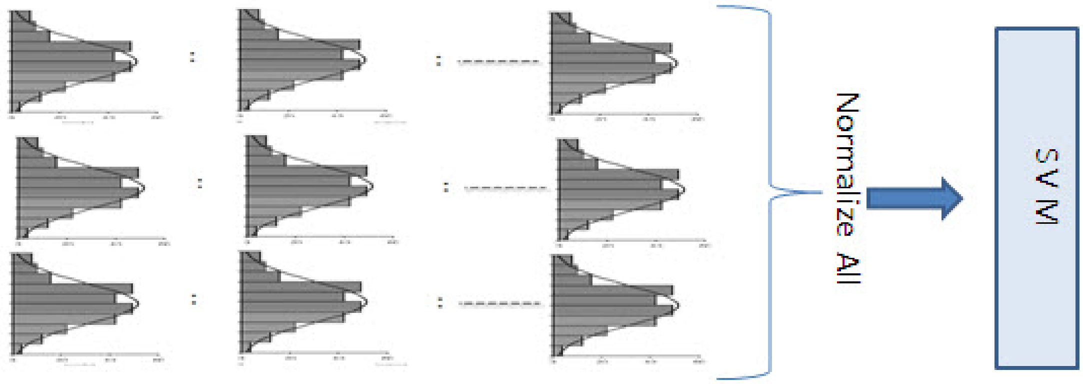


Figure 5.9: Histogram Normalization After All Histograms Have Been Generated

5.5 Results for Center Covered Track Bare Classification

After finalizing the parameters mentioned in Sections 5.4.2, 5.4.1, the final gradient feature vector is created. The size and construction of the vector can be seen in Figure 5.7. Various tests were performed to test classification model. The following section presents the purpose of test, test data and results of the SVM model. All feature vectors are generated using gradient histograms. The term *Classifier* refers to the SVM model that is trained and tested using the datasets described in the experiment.

Test 1:

Test Purpose: Test and train model with data from similar light conditions.

Positive Training Set: images of center covered track bare roads with varying track widths.

Negative Training Set: 100 images of bare or almost bare, fully snow covered or almost snow covered roads.

Positive Testing Set: 40 images of center covered track bare roads with varying track widths.

Negative Testing Set: 40 images of bare or almost bare, fully snow covered or almost snow covered roads.

Results: performed well, 73 out of the 80 images were correctly classified.

Comments: Results show that a gradient based features work well in highlighting edges arising from snow and bare roads. Some test images that were classified incorrectly had slight tracks due to thin layers of snow. On the other hand, the training set was carefully chosen and did not have any similar training data.

Test 2:

Test Purpose: Test and train model with data with slushy roads.

Positive Training Set:100 images of center covered track bare roads with varying track widths.

Negative Training Set:100 images of bare or almost bare, fully snow covered or almost snow covered or slushy roads.

Positive Testing Set: 45 images of center covered track bare roads with varying track widths.

Negative Testing Set: 45 images of bare or almost bare, fully snow covered or almost snow covered or slushy roads.

Results:classifier performed well, 75 out of the 90 images were correctly classified.

Comments: Results show that the gradient values from slushy roads are similar to gradient values from center covered track bare conditions.Missclassified images were mostly slushy roads with wheel tracks that mimicked a track bare and center covered scene.

5.6 Conclusion

We conducted a preliminary analysis to explore the possibility of machine vision based winter road condition monitoring. In our work, we developed feature extraction and modeling algorithms specially designed to work with winter road images. While the system is still not capable of discriminating between different types of road cover, the track and snow detection models can together be used to complement the existing manual bare pavement reporting system [13]. If done so, the system (combined with RWIS info) can be of particular use to monitor the performance of maintenance contractors in terms of bare pavement recovery time. This system can also be used to monitor local phenomena like drifting snow as they are hard to predict and can be a major cause of accidents. Section 5.7 suggests future work that should be done to improve the performance and reliability of the proposed system. The following is a summary of the progress made in modeling and feature extraction processes.

5.6.1 Illumination Invariance

We developed an illumination scaling method to adjust brightness of test images to match the brightness of the training set. Unlike previous work ([29]) we perform illumination scaling on every test image before being fed into the classifier. Results show that our illumination scaling technique has significant impact on the final classification results.

5.6.2 Localized Models

Unlike other related work, we have introduced a localized model training approach. Results show that models trained for specific light conditions and pavement color outperform generic models that are trained for a variety of conditions.

5.7 Future work

Our work is only an initial step towards an automated bare pavement reporting system that can be used to aid monitoring of road surface condition during winter. This section suggests some work that can be done to improve the reliability and accuracy of the model and classification system.

5.7.1 Automated Road Detection

This work currently assumes a fixed camera position and crops a predefined section from the original image. Depending on the type of road, the cropped images often contain sections with sidewalks and other vegetation. This information adds noise the system and decreases the classification accuracy of the system. Automated cropping of surroundings and horizon from the road image can help eliminate this noise and improve reliability. There has been a significant amount of work done in the field of roadway and pavement, one such example is the work done in [37]. While the intent of most of the work is to guide robots and other automated machinery, the concepts can be fruitfully used in cropping horizon and surroundings from the main road image.

5.7.2 Automated Vehicle Detection

This work currently assumes that the cropped image used for training and testing purposes is free of anomalies like other vehicles traveling on the road. Even though the section of the image that is used for detection lies in close vicinity to the data collection vehicle, there is still a chance of finding a vehicle in the image frame that may cause noise in color and gradient features and thus affect the reliability of the system. The work in [28] proposes an automated vehicle detection system to aid collision avoidance for machine driven vehicles. With vehicle detection in place, images with vehicles can automatically be dropped and not considered for analysis.

5.7.3 Automated Shadow Detection

The color and gradient based analysis in our work can be adversely affected by shadows from trees and other sources. From our analysis of the available video and image data, we learn that multi-lane higher class highways are less prone to shadows but rural highways have significant vegetation along the roadside and can cast large shadows onto the road. The work in [27] proposes a shadow detection technique for road scenes.

Chapter 6

Prototype Development

After a basic assessment of machine vision as a possible solution to automatic road surface classification, we move on to develop a data collection prototype to collect primary data for this task. This section describes the development of a data collection system to collect road surface data for image analysis.

6.1 System Requirements

6.1.1 Physical Requirements

- The developed system should be physically robust able to withstand slight shocks and jerks while in operation on a data collection vehicle.
- The system should be physically small enough to reside within the available space.
- The hardware components should be physically accessible for easy upgrades and repairs.

6.1.2 Data Collection and Communication Requirements

The data collection system should meet the following requirements:

- The system should be capable of communication to a variety of sensors at a given time to collect, validate and store sensed data in an organized fashion. Sensors include but are not limited to friction meters, GPS, road temperature sensors and Imaging devices.

- Upon available internet connection, the stored data should be automatically transferred to a central server.
- Data collection frequency and scheduling should adjustable by the user.
- The user should be able to upload human observation the form of text of short survey forms.

6.1.3 Image Quality Requirements

- Minimum image resolution should be 1024 x 768 pixels.
- Motion blur of more than one pixel

6.2 System Design

To simplify our task, we divided the system into five core modules with specific functions. The overall system design can be seen in the Figure 6.1. All modules of the prototype have been developed using Microsoft C# .net technologies. Code snippets for the system can be found in appendix A1.

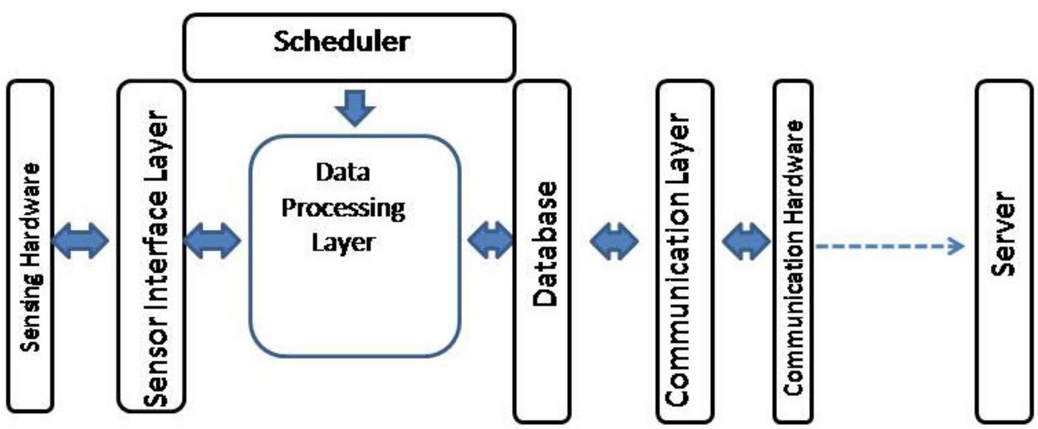


Figure 6.1: System Diagram for Prototype

6.2.1 Sensor Interface Layer

To ensure robust reliable sensor communication, we have developed the Sensor Interface Layer (SIN) which manages communication between the system and the sensors. The SIN is capable of communicating with a variety of different hardware including RS 232, USB and other hardware interfaces. The sensor interface layer can be upgraded with new drivers or APIs to ensure reliable access to data recorded by a variety of sensors. Due to the SIN, the rest of the system can communicate to the sensors in a seamless fashion.

6.2.2 Scheduler and User Interface Layer

In order to precisely control the frequency and nature of data collection an independent scheduling and user communication layer have been developed. The Scheduler and UI layer is responsible for invoking data requests for the DPL to execute. As the Scheduler and UI layer runs an isolated process, changes in data collection frequency can be easily made with a simple scheduler upgrade without having to change any other part of the system. Data Processing Layer (DPL) The DPL is responsible for all the data handling in the system. Upon being invoked by the scheduler, the DPL requests the SIN for appropriate data. Upon receiving the data, the DPL validates the data based on existing data validation rules. The data is then GPS tagged and organized into a record form. Once the data has been validated, it is encoded into a base 64 packet for storage into the database. Base 64 encoding ensures efficient storage and reliable transfer over HTTP.

6.2.3 Database

Implemented using MYSQL, the database is used to temporarily store the acquired data on the systems permanent memory till an internet connection is available.

6.2.4 Communication Layer

Isolated from the rest of the system, the communication layer is responsible for transmitting acquired data to a central server for processing. If explained briefly, the communication layer constantly polls the communication hardware for network connectivity regardless of the mode of communication. This enables the system to send acquired data to the central server from a variety of different connections. Once a connection to the server is made, the system fetches data from the local database and sends it to the main server. With the communication layer and the database combined, we have built a delay tolerant data storage and transmission system that enables the prototype to collect data for long periods of time before internet connectivity is available.

6.3 System Implementation

The system was implemented on an Acer Aspire-One netbook with the following specs

- 1.5 GHz Processor
- 1 GB of system memory
- 8GB solid state hard drive.
- ZTE GSM modem with Rogers data plan
- Microsoft Windows Xp operating system.
- Microsoft .Net Framework Runtime Environment.

A relatively low spec machine was chosen to assess the software load on low power machines. This was to evaluate the processing capability required from the hardware of the final product.

A total for four sensors were connected to the system and are described as follows.

1. Haliday RT3 Friction tester.
2. Point Grey Chameleon 1 Mega Pixel camera.
3. RoadWatch ss Pavement and Air Temperature Sensor
4. Garmin GPS.

Each of the above mentioned devices were connected to the system using USB and Serial links. Once connected, the hardware was configured in the sensor interface layer for seamless communication with the rest of the system. The final deployed system can be seen in figure 6.2

6.4 System Testing and Results

The implemented system is currently being tested at a Burlington and Oakville test site. The test site is currently running a project to evaluate the performance of different bio based winter road treatment liquids. While deployed on patrol vehicle, the developed system is currently being used to collect the following data.

Figure 6.2: Prototype Installed on a Patrol Vehicle

- High resolution road images
- Road friction,
- Temperature
- Location

Since first installed in December 2010, the prototype has collected more than 200 hours of road condition data and will continue to operate until the end of the winter season. All modules have been thoroughly tested, the data collection system is highly reliable and works with minimum human intervention. Once all data is collected, another database of primary road image data will be compiled to fully test the developed algorithms.

Chapter 7

Conclusion

The purpose behind this research was to explore the possibility of developing a machine vision based automated winter road condition monitoring system. In this work, we conducted a preliminary analysis of machine vision and its application to monitoring of winter surface conditions. This was followed by the development of a prototype than can automatically collect road condition information for machine vision based classification.

From this research we conclude that there is immense potential in using machine vision for automated road condition monitoring. Results show that the feature extraction and model training algorithms suggested in this work can largely improve classification accuracy of a machine vision based system in comparison to previous efforts that take a more generic approach.

We developed an automated road condition data collection system (discussed in chapter 6) to explore the practical constraints in developing a low cost automated data collection system. The prototype has been subject to rigorous field testing and has proven to be a reliable data collection system capable of collecting storing and automatically transmitting road condition data.

Overall, the results of this work have been highly motivating and encouraging. Results from algorithm and prototype testing indicate that development of an automated road condition monitoring system is highly practical and warrants further effort to convert the suggested algorithms and hardware design into an actual product.

APPENDICES

Appendix A

A.1 Sample Images

Following are some sample images chosen from the dataset:

Figure A.1: Bare Road

Figure A.2: Bare Road With Tracks-Still classified as bare


Figure A.3: Rough Snow


Figure A.4: Smooth Snow

Figure A.5: Center Covered

Figure A.6: Center Covered With Slush

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