Retinex-Based Visibility Enhancement System for Inclement Weather with Tracking and Distance Estimation Capabilities

Marwan S. Alluhaidan

Western Michigan University, marwan1_2000@yahoo.com

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RETINEX-BASED VISIBILITY ENHANCEMENT SYSTEM FOR INCLEMENT WEATHER WITH TRACKING AND DISTANCE ESTIMATION CAPABILITIES

by

Marwan S. Alluhaidan

A dissertation submitted to the Graduate College in partial fulfillment of the requirements for the degree of Doctor of Philosophy
Electrical and Computer Engineering
Western Michigan University
December 2018

Doctoral Committee:

Ikhlas Abdel-Qader, Ph.D., Chair
Johnson Asumadu, Ph.D.
Osama Abudayyeh, Ph.D.
Azim Houshyar, Ph.D.
ACKNOWLEDGMENTS

All thanks to God for giving me the strength, knowledge, and ability to work towards fulfilling my goals. Without his blessings, this achievement would not have been possible.

I would like to express my deepest appreciation to my supervisor Dr. Ikhlas Abdel-Qader, who has the attitude and the substance of a genius. She continually guides and supports me during all phases of this research. Without her guidance and persistent help, this dissertation would not have been completed. Also, I would like to thank my committee members, Dr. Johnson Asumadu, Dr. Osama Abudayyeh and Dr. Azim Houshyar, for their contribution and support.

In addition, I must express my gratitude to my parents Hila and Saleh, their love and prayers made me always believe in myself and gave me the boost I needed. I dedicate my success to them. My sibling, and all my family, God bless you all.

Marwan S. Alluhaidan
Road conditions affected by weather are well known to have an impact on the number of vehicle accidents and fatalities, due to low- to no-visibility conditions. According to the U.S. Department of Transportation, there are more than 1,259,000 crashes each year. On average, 6,000 people are killed and more than 445,000 people are injured annually due to severe weather conditions. These accidents could be significantly reduced if real-time visibility enhancement systems were made available. However, eliminating the impact of weather conditions on visibility is still lacking and beyond our control. The time has come to develop technology that is capable of improving visibility and creating safe driving conditions. It is the goal of this study to improve visibility and enhance drivers’ safety during severe weather and poor visibility conditions.

When capturing images of inclement weather conditions, the light that reaches the camera is severely scattered by atmospheric obstacles (e.g. fog, rain, and snow), resulting in the degradation of the contrast quality. Depending on the nature of the distortion, or the environment conditions, the system can be custom-designed to enhance the visibility of the captured images and improve safety. Moreover, going through poor visibility can be seriously dangerous, since
drivers may lose perception of distances, objects’ orientations relative to a focal point, and/or the depth of objects.

In this study, Retinex technique was selected as the basis framework for developing a system capable of enhancing visibility for drivers. This technique was used due to its ability to achieve a good dynamic range compression and spectral rendition. These unique features, when properly deployed in a framework, can overcome the loss of background details. An innovative system is proposed through a multistage framework that not only incorporates a modified Retinex technique, but also uses object detection and depth estimation to overcome some of the current algorithms’ and systems’ drawbacks. The performance of the proposed system, along with histogram equalization and the basic Retinex enhancement techniques, are presented. Performance was assessed using Peak Signal to Noise Ratio (PSNR) and Structural SIMilarity (SSIM) parameters. The results show that the proposed system outperforms the comparable methods and indicates the efficacy of the system under a variety of visibility degradations.
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CHAPTER I
INTRODUCTION

Low visibility is considered one of the major reasons for accidents in United States. According to the U.S. Department of Transportation, there are more than 5,748,000 vehicle crashes each year. Approximately 1,259,000 crashes, almost 22% of the accidents, are caused by poor weather conditions such as heavy snow, rain and fog. Over 445,303 people were injured and another 5,897 were killed in these accidents. Based on U.S. National Highway Traffic Safety Administration (NHTSA) data, 17% of the accidents occurred during snowy weather. Without a doubt, poor weather conditions significantly decrease a driver's vision, which too often leads to vehicle accidents. Table 1 shows the statistics of average crashes in the U.S. from 2005 to 2014 caused by poor weather conditions [1].

Table 1. Average Weather Crashes Statistics [1]

<table>
<thead>
<tr>
<th></th>
<th>10-year Average (2005 – 2014)</th>
<th>10-year percentages</th>
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<tr>
<td><strong>Crashes</strong></td>
<td>1,258,978</td>
<td>22%</td>
</tr>
<tr>
<td><strong>Injuries</strong></td>
<td>445,303</td>
<td>19%</td>
</tr>
<tr>
<td><strong>Fatalities</strong></td>
<td>5,897</td>
<td>16%</td>
</tr>
</tbody>
</table>

The impact of bad weather, such as snow and rain, on visibility can make the difference between life and death especially, in a world that depends on satellite imagery and live feeds from surveillance cameras in policing and information gathering [2]. Poor weather conditions can significantly damage the image contrast and colors (see Figure 1). The effects of poor weather increase exponentially with the distance from the camera. As a result, consistently predictable space filtering techniques fail to adequately remove varying and significant weather impacts.
Lately, imaging under poor weather conditions has been under the spotlight and finally attracted interest in the vision and image processing communities. During bad weather conditions, the atmosphere severely scatters the light contacting the camera, and causes declining contrast variations throughout the scene. Indoor environments provide the ideal atmosphere for video capturing due to the formation of artificial illumination. In outdoor environments, the removal of weather effect is crucial in the creation of standard and quality images [3].

Figure 1. Low Visibility During a Snowstorm [5]

Weather scientists have been conducting numerous research studies on computer vision and image processing for the past 60 years and have discovered that both areas share common problems: image visualization, image compression, conducting object recognition from an image, and the development of poor quality image. Image visualization creates a broader range of potential problems in such domains such as medical, military, industrial, and agriculture. Image enhancement is a major idea in the removal of bad weather. It describes the practice of handling an image to improve its quality regardless of low contrast, noise, or a blurred image. The practice aims at making the images suitable for various applications including surveillance and driver assistance systems. The image enhancement system is composed of four parameters: contrast
enhancement, noise removal, sharpening, and inverse filtering. Weather conditions differ depending on the type and size of particles in space as well as the concentration levels shown in Table 2 [4].

Table 2. Weather Conditions and Responsible Particle Types [4]

<table>
<thead>
<tr>
<th>Condition</th>
<th>Particle Type</th>
<th>Radius (μm)</th>
<th>Concentration (cm(^{-3}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air</td>
<td>Molecule</td>
<td>(10^{-4})</td>
<td>(10^{19})</td>
</tr>
<tr>
<td>Haze</td>
<td>Aerosol</td>
<td>(10^{-2} - 1)</td>
<td>(10^3 - 10)</td>
</tr>
<tr>
<td>Fog</td>
<td>Water Droplet</td>
<td>1 - 10</td>
<td>(100 - 10)</td>
</tr>
<tr>
<td>Cloud</td>
<td>Water Droplet</td>
<td>1 - 10</td>
<td>(300 - 10)</td>
</tr>
<tr>
<td>Rain</td>
<td>Water Drop</td>
<td>(10^2 - 10^4)</td>
<td>(10^{-2} - 10^{-5})</td>
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</table>

Poor weather impacts the visibility and the captures images by interfering with every part of the atmosphere light waves. The drops of rain and snowflakes deflect and reflect light waves away and towards the camera, which affects the illumination of the image. If the raindrop and snowflakes come into direct contact with the camera, there is an increase in low visibility because of the contrasting perceptions in the image taken by the wet camera. Perception is affected because water and snow affect the intensity and color of an image and its surrounding regions differently. Altered perception can result in misjudgments on depth, distance, and time, which are important elements in gathering information from an image [6].
1.1 Problem Statement

Poor weather conditions significantly damage the contrast of the image and video and it damages the color. This makes it imperative to eliminate weather effects from the images to improve the reliability of vision systems. Low visibility during poor weather conditions is considered one of the main reasons for vehicle accidents. Storms can diminish visibility to zero at times and thus negatively impacts safety. Approximately, 22% of accidents are caused by low visibility during poor weather conditions. Also, low visibility in poor weather conditions limits the value of images and videos for many human activities. Driving, target tracking, surveillance and autonomous navigation are some of the most common outdoor vision applications that can benefit from an enhancement technique.

1.2 Research Objectives

This work aimed to develop a reliable and real-time low visibility video enhancement that is critical to safety. In this dissertation, the goal is to develop a novel framework to enhance video from extremely low visibility scenes, such as whiteout conditions in snow storms or dust storms, to enhance safety. The proposed framework is based on Retinex algorithm and augment this by object detection and a distance quantification within the view of the driver. The results of this method show a satisfactory performance to enhance visibility and investigate vehicles in front of the driver where the images and video are degraded by severe weather.
1.3 Dissertation Outline

This dissertation is presented in five chapters starting with an introduction in Chapter I. Chapter II presents a literature review of works that aimed to enhance visibility conditions during poor weather conditions with image enhancement techniques. Chapter III describes the proposed method that is based on a modified Retinex. Chapter IV provides the implementation results of the proposed method with a comparative analysis of several weather conditions and technique modifiers. Finally, section V presents the conclusions and future work suggestions for the improvements and potential of custom design the framework to specific weather conditions.
CHAPTER II

PERTINENT LITERATURE

This chapter discusses the proposed methods to remove weather impact from images. There are two main techniques of image enhancement that are normally applied for such purposes: frequency domain-based and spatial domain-based methods. The frequency domain focuses on enhancing the frequency or the intensity in which grey values occur in an image. The frequency domain techniques work by increasing the magnitude of the high frequency components in an image to enhance clarity [7]. On the other hand, the spatial domain method focuses on the total number of pixels that make up an image. Unlike frequency domain techniques, spatial domain methods operate directly on individual pixels within the image. By focusing directly on the pixels, an observer can increase their understanding of the data in the image through manipulation. The image enhancement process in this case involves changing the grey scale pixels in the image to create a clearer image [8]. The following sections present some of the techniques used to remove poor weather effects, detecting and tracking vehicles, and depth estimation.

2.1 Background on Removing Poor Weather Effects

2.1.1 Frame Difference Methods

Huiying and Garg in [9 and 10] proposed a method of detecting and removing rain and snow based on frame difference. In this method of poor weather removal, it is vital to understand the structure of raindrops and snowflakes. One of the vital physical structures of raindrops is size, which generally varies between 0.1 and 3.5mm. When falling and before hitting the ground, raindrops are spherical and are less than 1mm in diameter. Snow is similar to raindrops and conforms to a variety of varying shapes. Single snowflakes commonly have a diameter range
between 0.5 and 3.0 mm. Raindrops and snowflakes fall rapidly and in masses. For this reason, rain and snow cannot cover a single pixel, but a whole area. In the binary image, the area is referred to as the connected region. The photometry of snowflakes and raindrops makes it possible for them to reflect and refract light up to 165° in the atmosphere. These reflections and refractions are a result of the spherical shape assumed by these particles and they are also responsible for increasing the intensity and brightness of rain [9].

The frame difference method, also known as the threshold value of inter frame difference method, is the most employed technique in the detection algorithm of moving objects. Various frame differences are used in the detection of snow and rain; each with an outstanding principle.

a. Two Frame Difference: Applies the use of equation to process the nth frame image, which later subtracts its former frame n-1th.

b. Three Frame Difference: Used in the detection of snow covered pixels. The three-frame differences include: n-1th, nth, and n+1th.

c. Five Frame Difference: Is an improvement of both the two frame difference and three frame difference.

d. Constraint Addition to Frame Difference: Is a three step process that (see Figure 2)

1. Detects whether the communicated area will rain or snow.

2. Directly determines if the direction angle will be non-rain and snow depending on whether it is at 0°.

3. Conducts the statistics of the remaining communication area if the orientation angle is not 0°.
The two, three, and five frame differences are as vital in the removal as they are in the detection of rain and snow from videos. The five-frame difference technique offers a more equitable snow removal technique. Figure 3 shows an example of the frame difference technique. The shortcoming of this method is that it assumes the rain drop and snow are stationary, and the background should not be bright or white [9].

Figure 3. Example of Frame Difference Technique [9]
2.1.2 Saturation and Visibility Features

Saturation and visibility features have been proposed by Pei, Tsai and Lee to remove rain and snow from a single image. To effectively understand the saturation and visibility features method, there are various image features to be explored:

a. Image Feature in Color Space: To eradicate rain and snow, the raindrops and snowflakes must first be detected through enhancing their signals. The signal, which is contained in the color image, can be enhanced through the multiplication of the visibility level and the transpose of the saturation level pixel by pixel. The process helps acquire the first probable rain or snow candidate visibility pixel.

b. Image Feature in Shape: Unlike raindrops, snowflakes are not elliptical or oriented to any specific direction in 2D frequency, raising the need for varying models to process each weather condition.

Figure 4 shows the process of rain removal involves the signal increases of the object contained in the image to improve the accuracy of object detection [11].
Both rain and snow have similar properties when in relation to visibility and saturation. The rain augmentation and detection process involves four vital steps: saturation and visibility merging, high pass filter, orientation filter and threshold. The first step involves the merging of saturation and visibility to help in the detection of the probability of rainfall. In poor weather photographs, separated directal streaks represent rainfall. In these photographs, raindrops convey high frequency signals. A high pass filter must be used to remove the low frequency signal in its candidate image. Under normal circumstances rain falls vertically, and under no circumstance can that fall change from vertical to horizontal no matter how strong the winds might be. A high pass filter must be used to get rid of the horizontal streaks that are not raindrops. At this stage the photograph presents a gray image that has boosted the view of the raindrops. The constant repetition of the process should give better end results each time. This method removes some image detail and also blurs the image [11].

![Flowchart of Rain and Snow Removal as Proposed in [11]](image-url)
2.2.3 Image Decomposition

The image decomposition method has been proposed by several researchers to remove rain and snow from images. For example, Rajderkar and Mohod [12] presented a rain and snow removal from a single image using image decomposition. The image decomposition is mostly carried out through morphological component analysis using the morphological diversity of varying image data features. These features must pass through the process of putrefaction and then each constituent must be linked to articulate a lexicon of atoms. Some of the common morphological component analyses techniques include:

a. MCA-Centered Image Decomposition: The criterion offers a consistency constraint. The general decomposition of images into snow and non-snow components requires the employment of curvatures and wavelets to be used as a lexicon to denote geometric components. The representation of the textual component of the image’s overall distinct cosine alters the fundamental roles that are used as lexicon.

b. Sparse Coding and Dictionary Learning: Sparse coding is a method used to show an illustration for signal with fewer digits of non-zero constants in a lexicon. A coding criterion that capitalizes sporadically is adequate for confined representation. Band pass and algorithms that are employed in the showcasing of meager linear encryptions for regular scenes cultivate a series of restricted, sloping, and band pass amenable fields. Up until the merging point, the ultimate image decomposition is attained through the iterative presentation of MCA procedures and lexicon learning procedures.

The same method works for snow as well. The snowfall image must initially be separated into high and low frequency parts using the smoothing filter. The fundamental information attained will be reserved in the LF portion and the outstanding data will be reserved in the HF portion. The
image decomposition process is later conducted through applying the MCA method on the HF portion to facilitate further disintegration to create snow and non-snow constituents. The HOG method is mainly applied in the decomposition step to facilitate the extraction of feature atoms. However, this method needs long procedure for dictionary learning step. In addition, the output image is a gray scale image that lost all color information [13]. (see Figure 5).

![Diagram of image decomposition process](image-decomposition-diagram.png)

Figure 5. Framework of Rain Removal via Image Decomposition [13]

### 2.1.4 Guided Filter

Xu, Zhao, Liu and Tang [14] proposed a method that removing rain and snow in a single image by using guided filter. The fundamental idea for using the guided filter method involves the employment of transformation in foreground and background images to pinpoint active objects. If the subsequent variance after the deduction is greater than the guaranteed inception, it defines a
pixel to pixel movement target. The amount and bulk of model updates significantly affecting foreground effects. Big changes in the object’s background cannot be easily or rapidly overcome by slow adapting background models, for example a cloud passing above a scene. As a result, there exists a time frame where countless background pixels are classified inaccurately as foreground pixels. The process should be quick to avoid slow update rates that lean towards the creation of ghost masks that trail the real object. Quickly adjustable background models have the capacity to deal with background changes as they occur, but they crush at truncated frame rates. They are highly prone to noise as well as the aperture issue. The output image is blurred and lost most of the image details and edges [14] (see Figure 6).

![Figure 6. Example of Removing Snow Using Guided Filter [14]](image)

2.1.5 Wavelet Multi-Level Decomposition

Zhen and Jihong [15] proposed a new approach to remove rain and snow from multiple degraded images using wavelet multi-level decomposition and wavelet fusion. The wavelet analysis is a poor weather removal method aimed at disintegrating signals into EEG sub-bands with varying tenacities, regularity and directional features. The rain and snow elimination
techniques of various images entail such aspects as the digital image and wavelet analysis as well as the determination of the rain/snow noise layer. Scenes of disintegrated images describe varying frequency from that of rain/snow noise, rain is greater than disintegrated image scenes. The consistency frequency and advantage of the division data is reasonably high and may even be greater than one on rain, but that of background and pigment data of imageries is truncated. Another vital feature of the wavelet analysis is the fusion on multiple continuous degraded images, which identifies that rainy and snowy days represent dynamic and adverse weather, which simplifies the process of the acquisition of multiple continuous varying disintegrated images. However, the results of this approach are not accurate enough [15] (see Figure 7).

![Image](image1.png)  ![Image](image2.png)

(a) Image under snow conditions  (b) Enhanced Image

Figure 7. Example of the Results of Wavelet Multi-Level Decomposition [15]

### 2.1.6 Histogram

Histogram techniques have been applied to remove poor weather from images and video by many researchers [16, 17, 18, 19, 21]. Histogram techniques work by reducing the frequency of the occurrence of different gray levels in an image. There most common techniques of
Histogram are Histogram Equalization, Adaptive Histogram Equalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) [16].

2.1.6.1 Histogram Equalization

In [6], the Histogram Equalization technique is highlighted as focusing on the probability distribution of certain types of data that are useful to the user. The Histogram Equalization technique focuses on the probability of tonal distribution on the gray values of a digital image [6]. It is a representation of the frequency of occurrence of the different gray levels contained in a certain image. The aim of Histogram Equalization is to enhance the appearance of an image by stretching out the contrast of an image to attain an almost even distribution of gray values between the ranges of 0 to 255 [17].

Kaur and Kaur [16] represent the Histogram Equalization technique as one of the best non-linear methods of correcting the contrast within an image using the tonal distribution as represented in a histogram. The method works simply by increasing brightness of a gray-scale image to enhance contrast [16]. Histogram Equalization is unique because it works by remapping the intensity values of individual pixels within the entire image [17]. The method works by dividing an image into overexposed regions and underexposed regions and normalizing the tonal distribution to create a more balanced image by remapping the distribution of pixels in the image [18]. The Histogram Equalization algorithm is expressed as:

\[ Y = f (X (i, j)) \forall X (i, j) \in X \]  

(1)

The method starts by plotting the frequency distribution of the occurrence of grey levels within an image. The distribution of the dynamic range of the pixels should be uniform. The findings of the frequency distribution determine the shape of the histogram and define the quality of the image. A narrow histogram means the image has low quality because there is little contrast
among the pixels in the image. On the other hand, a wider histogram is indicative of a higher quality image because there is more contrast among the components of the image [17].

Once Histogram Equalization has determined the distribution of the pixels in the image, it corrects the image by enhancing contrast in the image by brightening the dark regions of an image to create a more uniform intensity across the entire image [16]. The normalization process of the Histogram Equalization method works by dividing each component of the histogram by the total number of pixels in the image to determine the distribution of pixels on the dynamic range [19]. The total sum of all the components should be 1 in a normalized histogram. If the total of the images is not equal to one, the image is modified further until the sum of the components is equal to 1.

Histogram Equalization is limited since it is not effective in the image enhancement of images with non-uniform illumination in the background. This is because Histogram Equalization works by adding additional pixels to the light producing regions and reducing the number of pixels in the darker areas of the image. The remapping of pixels within the image enhances the image by creating contrast since there is a higher dynamic range between the features of the image [20]. If there is non-uniform illumination the result of the image enhancement process will not be significant between the input and output image. Histogram Equalization is also limited since by adding extra pixels in the background can result in an excessive contrast of the image giving it an unnatural look. In addition, Histogram Equalization is limited to digital images and cannot work on analog images since the method is highly dependent on pixels, which are only present in digital images.
2.1.6.2 Adaptive Histogram Equalization

Histogram Equalization works by normalizing the contrast between pixels by adding or reducing pixels depending on whether the image is underexposed or overexposed. The drawback of Histogram Equalization is that the method cannot be used if there is non-uniform illumination in the background of the image. If there are high peaks in the histogram the sharp remains relatively narrow which is an indication of a low quality image. Since Histogram Equalization is ineffective in pictures with non-uniform illumination, observers can use Adaptive Histogram Equalization to normalize the dynamic range within the image. Adaptive Histogram Equalization works using the principle of multilevel thresholding [18].

Abubakar [21] presents multilevel thresholding as an innovative algorithm that works by segmenting an image into levels using a localized mean and variance of the dynamic range of pixels within each level. The algorithm starts from the most contrasting pixel values on both ends of the histogram based on the probability distribution frequency (pdf) of the gray-scale levels within the image [21]. The algorithm is applied recursively since the success of the image enhancement process depends on the success of the multilevel thresholding process on each block or tile of the image. Once an optimal image is attained at one level, it forms the subrange for the next level and the process is repeated until there can be no more significant improvement on the image. Multi-level thresholding is advantageous because it allows non-uniform size segmentation of the levels depending on the dynamic range of gray scale. The segments are bigger near extreme pixel values and smaller around normalized sections with an almost even dynamic range.

An adaptive Histogram Equalization works by creating localized histograms in varying grayscales. Adaptive Histogram Equalization works by dividing the main histogram into blocks of smaller histograms. The Histogram Equalization mapping for the individual blocks assigns a
central pixel for each block. The central pixel works as a reference point in plotting frequency
distribution of grayscale for each individual histogram. The frequency distribution of grayscale is
calculated and plotted for each localized histogram. This means the focus is not simply on
enhancing the entire image, but also enhancing each feature relative to the other features.
Histogram Equalization solves the problem of overexposure and underexposure by enhancing each
feature instead of the entire image [18].

Methods that enhance the entire image have a limitation since they cannot achieve optimal
brightness across the entire image without overexposing or underexposing certain regions of the
image. The Adaptive Histogram Equalization method is effective since this technique works on
smaller regions in the image rather than the entire image. Once each block is enhanced, the
histogram of each output block matches the recommended histogram specified by the ‘Distribution’
parameter. In most cases the ideal ‘Distribution’ parameter is a flat histogram since it is indicative
of a uniform distribution of gray scale pixels in an image [8].

Adaptive Histogram Equalization is limited since it cannot regain the brightness of the
original input once the normalization process occurs [19]. This means the method cannot be used
alongside with any intensity transformation, which can reverse white and black intensities by
making dark regions of an image darker and lighter regions of an image lighter.

2.1.6.3 Contrast Limited Adaptive Histogram Equalization

Adaptive Histogram Equalization is ideal in overcoming the brightness preservation
problem created by over and underexposure of other image enhancement methods [16]. Adaptive
Histogram Equalization, on the other hand, creates artificial boundaries between the blocks during
the image enhancement process [19]. Adaptive Histogram Equalization also creates more noise in
an image if the block of an image being processed has a relatively small intensity range. The under
or overexposed regions might have more contrast, but the lack of intensity creates more noise in that region of the image. To mitigate the drawback of the Adaptive Histogram Equalization method, a user can employ the Contrast Limited Adaptive Histogram Equalization (CLAHE).

CLAHE works by limiting the slope of the cumulative distribution function (CDF) by limiting the height of the histogram in each block. Limiting the height of the histogram involves clipping the height of the histogram right before the computation of its cumulative distribution function (CDF) slope during the mapping of the image. CLAHE works to reduce the noise in the image created by the local Histogram Equalization. After all the blocks are normalized and enhanced, this method uses a bilinear interpolation process to eliminate the artificial boundaries between blocks. The bilinear interpolation process considers the contrast and intensity in all the pixels within an image, ensures that small features are not washed out by larger features within an image and downplays any overemphasized features in an enhanced image [22].

2.1.7 Retinex Technique Algorithms

E. Land conceived the idea of the Retinex algorithm for image correction in his 1964 paper. The Retinex Algorithm uses the principle of human sight which is controlled by the retina and the cortex [2]. The human eye allows human beings to perceive light through a process of spatial comparison of the different rays of light allowed into the eyes [6]. Color perception of the human eye and correction by the retina and cortex ensures the capturing of a dynamic range of colors. Perception of light by the eye is a complex process that compares the lightness within the three main bands of light waves receptors in the eye. The three bands of light waves correspond to short-wave, medium-wave, or long-wave photoreceptors on the blue, green and red color spectrum [23]. Meaning the human eye perceives images in color constants and allows for near perfect perception. Images, on the other hand, lack of color constancy and perception due to spectral shifts in poor
illumination situation. The difference between viewing in direct observation and viewing images is a loss of details and color in the image, which negatively affects the observer’s experience of the image [24].

Land (1964) showed that the observer’s viewing experience can be enhanced by responding to the changes in the environment such as the color constancy or illumination. Depending on the circumstances, Retinex improves the image by sharpening it, improving the color constancy, and dynamic range compression in the image [25]. Sharpening works to correct any blurring and fuzzy effects on the image introduced at the formation stage. Color constancy involves improving the consistency of an output image by correcting differences in illumination in different regions of the image. Dynamic range compression amplifies quiet sounds and reduces volume on loud sounds within a video. Simply Retinex algorithms work by improving an image’s dynamic range compression and tonal rendition [26]. This method has been developed through many different techniques:

### 2.1.7.1 Single Scale Retinex (SSR)

Single Scale Retinex works by either improving dynamic range compression or tonal rendition. Rahman, Jobson, and Woodell present an analysis of different techniques that apply the Retinex processing algorithm. The review highlights how different Retinex enhancement algorithms are applied in responding to tonal rendition and dynamic range variations. A major issue with the algorithm is that it lacks the capability to improve both simultaneously. The trade-off between dynamic range compression and tonal rendition is governed by the Gaussian distribution. The Gaussian distribution creates a space constant of 80 pixels between the dynamic
range compression and tonal rendition [26]. The SSR algorithm is expressed as:

\[ R_i(x, y) = \log I_i(x, y) - \log[F(x, y) \ast I_i(x, y)] \quad (2) \]

Where \( I_i(x, y) \) is the distribution in the \( i \)th color band of the image, and \( F(x, y) \) is the surround function. On the other hand, the Gaussian surround function is expressed as:

\[ F(x, y) = Ke^{-\left(\frac{x^2+y^2}{\sigma^2}\right)} \quad (3) \]

Where \( \sigma^2 \) is the variance and with \( K \) selected so that:

\[ \iint F(x, y)dx \, dy = 1 \quad (4) \]

The Single Scale Retinex method aims to improve image formation and color in a certain image by enhancing the pixel values. This method is different since it does not focus on the intensity transformation of an image. Intensity transformation works by modifying intensity values in gray-scale images [25]. Intensity transformation allows a user to reverse white and black intensities by making dark regions of an image darker and lighter regions of the image lighter [2]. Intensity transformation can increase the contrast between intensity values in an image, which makes feature within an image more discernable. The Single Scale Retinex method focuses on the dynamic range of the picture to modify the image. The process works by combining the principles of illumination and reflectance to enhance the underexposed and overexposed features within an image. The use of illumination and reflectance in improving the quality of an image enhances the observer’s perception of an image through increased definition, entropy, and a better contrast ratio [19].

The limitation of the Single-Scale Retinex Algorithm is that it does not have the capabilities to simultaneously enhance dynamic range compression and tonal rendition. The output images are characterized by halos and graying [23].
2.1.7.2 Multi Scale Retinex (MSR)

The Multi Scale Retinex (MSR) is better than the SSR in image enhancement since it produces a better balance of dynamic compression and color rendition [20]. The MSR works like most image enhancement methods by lightening the image to increase contrast and dynamic range. The drawback of the MSR is that it results in less color saturation in the output image due to the lightening effect [26]. Meaning, the method is ideal for gray-scale images, and less ideal for colored images. Since the MSR output is simply the weighted sum of several SSR’s with different scales, the MSR algorithm is expressed as:

\[
R_{MSR} = \sum_{n=1}^{N} \omega_n [\log I_i(x, y) - \log[F(x, y) * I_i(x, y)]]
\]

Where \( \omega_n \) is the weight for the nth scale and \( N \) is number of scales.

The limitations of MSR are that it is not ideal for applications that are sensitive to color since it works best for grayscale images. On the other hand, the MSR works by multiple image processing tasks, which are performed simultaneously during the image enhancement process. The interaction of the tasks should be taken into consideration in determining the impact of the image enhancement process on the output. This is because the interaction of the processing method can change features within an image in unpredictable and irreversible ways [25].

2.1.7.3 Multi Scale Retinex with Color Restoration (MSRCR)

Since Retinex algorithms work by basically brightening the image, it is possible to lose the quality of an image by over-enhancing an image. The MSRCR is unique because it is a post-processing step similar to gamma correction that focuses on the entirety of the picture [25]. MSRCR restores details by reducing overall image brightness achieved by other image enhancement methods. An overexposed image lacks enough contrast and color depth to give the
image any perception. This is because an over emphasis on illuminating certain features on an image leads to a loss in intensity and color in the surrounding areas of an image. Without proper intensity it is impossible for the human eye to have perception of an image in terms of the placement of features in the picture. The MSRCR technique restores intensity and color in an image and helps to improve perception of the image [2]. The MSRCR algorithm is expressed by:

\[ R_{MSRCR}(x, y) = C_i(x, y) \, R_{MSR_i}(x, y) \]  \hspace{1cm} (6)

\[ C_i(x, y) = \beta \log[ \alpha \, I_i'(x, y)] \] \hspace{1cm} (7)

\[ I_i'(x, y) = I_i(x, y)/ \sum_{S=1}^{S} I_i(x, y) \] \hspace{1cm} (8)

Where \( \beta \) is gain constant, \( \alpha \) controls the strength of the nonlinearity and \( s \) is the number of spectral channels.

To achieve the required level of color correcting, the image must go through adaptive filtering. The key limitation of the MSRCR is that the image has halo artifacts and regions of graying out even after the application of adaptive filtering [26]. The halo artifacts and graying out are due to regions of low contrast and poor color rendition [23].

### 2.1.8 Halo Artifacts Reduction Method for Variational based Real-time Retinex Image Enhancement

Tsutsui, Yoshikawa, Okuhata and Onoye [27] proposed a method to reduce the halo artifacts and lower the computational costs associated with the Retinex algorithm. This method works by minimizing the cost function, which is depicted as:

\[ F[l] = \int_{\Omega} \left( |\nabla l|^2 + \alpha (s - l)^2 + \beta |\nabla(s - l)|^2 \right) dxdy \] \hspace{1cm} (9)
Where \( \alpha \) and \( \beta \) are parameters, \( s(x,y) \) is input image, \( r(x,y) \) is reflectance image, \( l(x,y) \) is illumination image, \( |\nabla l|^2 \) is spatial smoothness of the illumination image, \( (s-l)^2 \) is closeness between \( l \) and \( s \), and \( |\nabla(s-l)|^2 \) represents spatial smoothness of the reflectance image.

The Halo Artifacts Reduction Method for Variational based Real-time Retinex Image Enhancement method is iterative in nature and works by finding the illumination image which minimizes the function \( F[l] \) through an algorithm executed from the lowest resolution layer to the highest. This algorithm is referred to as the PNSD which stands for Projected Normalized Steepest Descent [27].

In this method they used two approaches, which are the edge adaptive parameter to estimate the illumination and the erosion of the illumination. This method cannot enhance the dark regions near edges, which remains halo affect around those regions.

**2.1.9 Contrast-Enhanced Fusion of Multisensor Images Using Subband-Decomposed Multiscale Retinex**

In [28] Jang, Bae and Ra present contrast-enhanced fusion of multisensor images using the Subband-Decomposed Multiscale Retinex (SDMSR) method. This method refers to the combination and integration of images from more than one source into a single image without introducing artifacts or causing distortions, which may lead to the loss of vital information. The fusion of more than one sensor image occurs at three main levels; namely the pixel, feature, and decision levels. The SDMSR aims to enhance image fusion and contrast enhancement to improve the overall quality of an image or video while maintaining vital information in the image.

The SDMSR algorithm is a combination of two logarithmic functions known as Hybrid Intensity Transfer Function (HITF). HITF works by contrasting the dark and light features of an
image, as well as enhancing the dynamic range of the image or video. The SDMSR Algorithm is represented as:

\[ h_{\log(I(x,y))} = w \cdot I^+(x,y) + (1-w).I^-(x,y) \] (10)

\[ I^+(x,y) = \log(I(x,y) + 1) \] (11)

\[ I^-(x,y) = \log D - \log(D - I(x,y)) \] (12)

Where \( I \) is the input image and \( D \) the dynamic range (256 for 8-bit image) [28].

This method works by fusion two algorithms together to reach both image fusion and contrast enhancement. This method works for some application such as remote sensing, surveillance and medical image diagnosis. However, this approach is not suitable for real time applications [28].

**2.1.10 Fog Removal Using Anisotropic Diffusion**

Single image fog removal using anisotropic diffusion has been proposed by Tripathi and Mukhopadhyay to remove fog and poor weather visibility from an image. Fog and haze are caused by water and dry particles hovering in the atmosphere. These particles are substantial in size ranging from 1–10 mm, which affects the quality of an image since these particles caused by ‘attenuation’ and ‘airlight’. The size of the particles and their saturated distribution in the atmosphere means light from the atmosphere and light reflected from other objects is scattered by the particles. The scattering of light reduces the contrast within the environment the image or video is being recorded in; this is referred to as attenuation. On the other hand, light is scattered towards
the camera, which contributes to the lack of contrast and whiteness of the environment which is referred to as airlight [29].

The whiteness and lack of contrast of an image can only be eliminated by understanding the relative distance of the camera from the image known as the depth map or airlight map. The principle of the depth map posits that since different objects are positioned at different distances from the camera then the algorithm should be used differently on each object. The aim is to provide intra-region smoothing over inter-region smoothing. This is referred to as Anisotropic Diffusion and works by combining the edge detection and diffusion into one single process, which enhances intra-region smoothing [29].

The Anisotropic Diffusion Algorithm is expressed by:

\[ I(x, y) = I_0(x, y)e^{-kd(x,y)} + I_\infty(1 - e^{-kd(x,y)}) \]  

Where the image intensity is \( I_0(x, y) \) in absence of fog, \( k \) is extinction coefficient, \( d \) is the distance from the camera, \( I_\infty \) is global atmospheric constant and \( I \) is image intensity.

This algorithm uses anisotropic diffusion to remove the fog from image and can be used as preprocessing for some other methods such as object detection, tracking and segmentation. However, this method is limited and can only be used in very limited situation.

### 2.1.11 Enhancement of Weather Degraded Video Sequences Using Wavelet Fusion

In [30] John and Wilscy proposed an enhancement of video degraded by poor weather using wavelet fusion. The presence of water or dry particles in the atmosphere affects how light is reflected from the source of light to the object until the light reaches the sensor which might be in the form of a camera or surveillance equipment. In most cases, the net effect of foggy or hazy weather conditions is increased whiteness or lightness in the image, which is referred to as airlight
or atmospheric background radiation. The phenomenon reduces the contrast elements within an image and makes the objects undiscernible and unidentifiable. Conventional filtering methods do not have the ability to enhance weather degraded images. On the other hand, colored images subjected to methods such as histogram equalization lose their color constancy and dynamic compression.

Other models like the Anisotropic Algorithm assume that objects within the same distance from the sensor will have a uniform airlight. Since this is rarely the case, Anisotropic Algorithms are useful in enhancing contrast but are limited in enhancing visibility. Enhancing visibility requires the algorithm to appropriate intensity and color information to the image during the image enhancement process.

Wavelet fusion enhances visibility and contrast while maintaining the color intensity. The image enhancement method comprises of three phases aimed at increasing the quality of the image while reducing the computational cost. In the first phase, the value of the atmospheric background radiation is calculated by augmenting the cost function of the algorithm. In the second phase, intensity data from the YIQ color model is used to estimate the airlight value. The first and second phases are critical in eliminating the whiteness from the image while adding depth. Once the first and second phases are complete, the wavelet fusion algorithm takes over to produce the final image which is has more contrast, color fidelity, and dynamic compression. The Wavelet Fusion Algorithm is:

\[
I_\infty \rho(x) = (E(x) - \lambda)e^{\beta d(x)}
\]  
\[
e^{\beta d(x)} = \frac{1}{1 - \frac{\lambda}{I_\infty^r + I_\infty^g + I_\infty^b}}
\]
Where \((I^r_{\infty} + I^g_{\infty} + I^b_{\infty})\) are the environmental light, \(E\) is the image intensity and \(\lambda\) the optimized cost function.

It is important to note that when estimating the airlight value in the YIQ color model, the value of \(Y\) is assumed to be the optimized cost function denoted by \(\lambda\). This is not necessarily the case since the value of \(\lambda\) is an estimate. To make the value of \(\lambda\) more accurate the estimated value of \(\lambda\) is diffused using the Gaussian blur by calculating the depth information denoted by \(e^{\beta d(x)}\) [30]. This method works good for an application that doesn’t required real time such as surveillance and object detection.

2.1.12 Single Image Dehazing Via Multi-Scale Convolutional Neural Networks

Ren, Liu, Zhang, Pan, Cao, and Yang [31] proposed a single image dehazing method via a multi-scale convolutional neural network. The wavelet fusion algorithm, which is like most non-module methods including the Retinex algorithm, has its own limitations. Non-module methods affect clear regions of the image and lead to loss of color fidelity. This is because most image enhancement methods use algorithms that are statistical and deterministic in nature. These algorithms are no random which means the algorithm will produce the same output when given the same input. The input in this case is the hazy image or video and is applied to a non-module algorithm that yields a transmission map, which is used as input in the iteration [31].

The transmission map extracts textual, chromatic, and contrast features of the image used to enhance the image. However, the assumptions made about non-module algorithms do not hold in all circumstances. For instance, the value of dark channels is not always approximately zero when the objects in the image have the same hue as the atmospheric light. The use of the Multi-Scale Convolutional Neural Network (CNN) is useful in overcoming some of the limitations of non-module methods [31].
CNN aims to improve how transmission maps are formed since they provide the input for the image enhancement algorithm. The CNN Algorithm is non-deterministic and non-statistical in nature. This means the image enhancement process does not depend on statistical (non-random) features from prior transmission map inputs. Instead the algorithm is self-adjusting and correcting depending on the learnable convolutional layers of the transmission map which translates to a more accurate transmission map. The method works by performing a regression on the transmission map using coarse-scale and the fine scale network to dehaze an image or video.

The coarse-scale is used to determine the entire structure of the scene transmission while the fine scale utilizes output from the coarse-scale and local scale to remove spurious pixels. Since the CNN algorithm is non-deterministic it is configured to automatically develop features at various frequencies and scales, which yields a higher quality image [31].

The CNN algorithm is expressed as:

$$J(x) = \frac{I(x) - A}{\max(0.1, t(x))} + A$$  \hspace{1cm} (16)

Where \( t(x) \) is transmission map, \( A \) is the atmospheric light and \( I \) is the hazy image.

\textbf{2.1.13 Single Image Haze Removal Using Dark Channel Prior}

Single image haze removal using the dark channel prior method is proposed by He, Sun, and Tang [32]. This method does not require multiple reference images and uses only one reference image [31]. The advantage of using a single reference image is that it simply depends on using the characteristics and features of a haze-free image that is highly contrasted to correct the distortions caused by haze.
DCP is an algorithm that works in four main steps. The algorithm estimates the atmospheric light, estimates the transmission map, next it refines the transmission map, and finally it reconstructs the image. DCP algorithm assumes that dark pixels in a normal image, other than in the sky, have low intensity in at least one of the colors within the RGB color channel. The dark pixels intensity values are estimated to be about zero for one or more colors within the color channel. In an image that is distorted by foggy or hazy weather conditions, the intensity of the dark pixels, other than those in the sky, is augmented by atmospheric background radiation also known as airlight. It means by determining the value of the airlight, the dark pixels can be used to make an accurate estimate of the haze’s transmission on the image. The algorithm produces a more accurate depth map by fusing the distorted image with a soft matting interpolation method based on the estimate of the airlight value [29].

This method does not work for all images and has limitation since the DCP is a kind of a statistic algorithm. Also, this method can’t remove heavy hazy effect on images and can’t be used for real time systems.

2.1.14 Chromatic Framework for Vision in Bad Weather

Narasimhan and Nayar in [33] proposed a method that reduce bad weather effect by using Chromatic Framework. The Chromatic Framework algorithm assumes different pixels have different scene radiance. The algorithm also assumes the observed color of an image or video during bad weather can be determined by factoring the direct transmission color and the airlight color. This is the color of a scene on a clear day combined with the airlight color caused by haze or fog [33]. It therefore means an effective image enhancement algorithm must use segmentation methods to deal with similar pixels differently from those with different scene radiances [29].
A Chromatic Framework Algorithm is effective in not only removing distortions caused by bad weather, but also can be used to recover lost information normally lost by non-module methods. The algorithm works by optimizing attenuation and airlight atmosphere scattering methods to extract the scene structure in its entirety by depending on a one or two reference images. The algorithm also incorporates the dichromatic atmospheric scattering model that posits the wavelength of reflected light which needs to be taken into consideration in the image enhancement process [33].

2.1.15 Quantification of Retinex in Enhancement of Weather Degraded Images

Joshi and Kamathe [34] describes a system that would enhance the images whose clarity has been affected by adverse weather conditions. The authors understood that poor weather could affect the quality of the outdoor scenes captured under such conditions. In most instances, the colors of the resultant images are significantly altered. Apart from that, it is often common to see discrepancies between the images captured and the real scenes. The circumstances would make it necessary to carry out operations meant to eliminate the effects of the poor weather and to ensure that the images are clear and show every detail as they should. In proposing to use the Retinex for this context, the authors came from the point of seeing it as a solution to restore balance or harmony between the human vision and the machine vision. For their paper, the authors opted to use the MSRCR in the enhancement of the images that had been damaged by the weather to approach direct observation. The limitation of this method is that it will take more time on processing which makes it not suitable for real time processing.
2.1.16 Visibility Enhancement Based Real–Time Retinex for Diverse Environments

Yu, Kim, and Lee [35] proposed a modified structure of the Retinex algorithm which would achieve robust performance in conditions of bad weather and night vision. Previous models using the Retinex algorithm suffered from the problem of the halo effect as well as color distortion. In their proposed solution, the authors would use a combination of a reflectance and a luminance image with some constant factors. The inclusion of the luminance component makes the method that the authors came up with applicable to different environments and grants it the ability to work on foggy as well as night vision images. However, this system works only on foggy images and may not always be 100% accurate.

2.1.17 An Efficient Fog Removal Method Using Retinex and DWT Algorithms

Sowjanya, Rao, and Pushpalatha [36] developed a solution that promised to remove the fog in images captured in foggy weather and make them clearer and easier for recognition. Combining the Retinex algorithm and the wavelet transform algorithm would help enhancement of images whose quality had been adversely affected by fog. The solution would be two-fold. First, the image would be enhanced using the Retinex algorithm. Then, it would be further enhancement by using the wavelet transformation algorithm to obtain high-frequency information from the Retinex image. However, the method takes a considerable amount of time, and that may affect its efficiency.
2.2 Background on Vehicle Detection and Tracking

Car detection and tracking is critical in traffic surveillance. The ability to accurately track vehicles enhances traffic management and improvement of safety. This subject has been of interest to many researchers for years now. On the same line, various methods have been proposed to address the issue of car detection and tracking. The aim is to develop a system that offers efficient, consistent, and reliable vehicle tracking. The system must also meet the user’s needs. There is perhaps no one universal way of doing it, but rather a raft of solutions based on well-known scientific principles. Consequently, this section discusses some of the methods that have been proposed by researchers who have done research on vehicle detection and tracking.

2.2.1 Parallel Optical Flow Method for Vehicle Detection and Tracking

A study carried out by Bhaskar, Yong, and Jung [37] explored the possibility of tracking vehicles throughout their life spans and monitoring them in real time. The aim of the researchers was to devise a system with the capability of counting vehicles automatically and process footage recorded by stationary cameras on places such as road junctions. They needed to make significant improvements to the options that existed at that time by developing a unique algorithm that would recognize and track vehicles. Apart from that, they relied on the Lukas- Kanade algorithm for the Parallel Optical Flow method that would underlie their proposed solution. Under this system, temporal differencing determines the detection of motion [37]. The researchers decided that the final count would be determined by tracking the objects that were detected by the cameras as well as their regions in real time. After testing the system, the authors achieved a 98% track rate on the real video. The significant drawback is the possibility of some vehicles being missed during heavy traffic. Such an occurrence would occur due to the frames having too many images in a defined area or a vehicle not entirely passing within the lenses' capture area.
2.2.2 Vehicle Detection Precision Based on Image Processing

Congsheng and Zhaoyang [38] designed a system meant to improve vehicle detection through improved frame difference and enhanced image contrast. The use of the system that the authors propose should result in improvements in identification speed, reduced computation, higher recognition and robustness. This would all contribute to efficient vehicle recognition. The proposed system addresses challenges at the three key detection stages. During the pre-processing phase, the researchers use digital images which allow for the separation of the vehicle from the rest of the image. Secondly, the system accumulates frame difference to help in clearly recognizing a moving vehicle. Finally, it combines morphological filtering with the technology based on tag area filling to further enhance the image at the post-processing stage.

The system can eliminate the noise in the image better than current alternatives. However, the system faces a significant hurdle about slow-moving vehicles or those that have a body color close to that of the road surface. In that case, the resultant image would show a black hole formed inside the car, and mathematical morphology would not be applicable in removing the noise.

2.2.3 Vehicle Detection and Tracking Using Gaussian Mixture Model and Kalman Filter

Indrabayu, Bakti, Areni and Prayogi [39] tested a system for detection and tracking vehicles as part of an Intelligent Transport System (ITS). They applied the Gaussian Mixture Model (GMM) method to detect vehicles while the Kalman Filter method would carry out the object tracking for both light and heavy traffic conditions. They further used the Receiver Operating Characteristics (ROC) analysis for the validation of the system using the parameters of precision, sensitivity, specificity, and accuracy. The results under light traffic showed that the system achieved 100% precision, 94.44% sensitivity, 100% specificity, and a 97.22% accuracy.
Further, the heavy traffic scenario resulted in 75.79% precision, 88.89% sensitivity, specificity of 70.37%, and 79.63% accuracy. However, the system recorded 100% consistency in the tracking of objects. Therefore, the researchers concluded that the system was applicable for vehicle detection and tracking under light traffic conditions but inefficient in heavy traffic.

The system presented the advantage of having discernible parameters against which its effectiveness could be assessed. Apart from that, it presents an effective and objective detection and tracking under light traffic. However, it faces the drawback of not being too accurate under conditions of high traffic.

2.2.4 Real-Time Vehicle Detection and Tracking Using Deep Neural Networks

Gu, Chen, Ma, Li and Yan [40] presented a system for detecting and tracking vehicles in real time. Their solution relies on Convolutional Neural Networks (CNN) which would make it possible to get vehicle candidates, probabilities, and coordinates in real time. The system's design means that it could process live video and make it suitable for computer vision application. Features are extracted from the image using the system's convolutional layers. Another unique feature of the system is its use of four kinds of inception modules. Thirdly, a Spatial Pyramid Pooling (SPP) layer resizes the images of vehicles into their real sizes. Lastly, the system includes fully connected layer whose work is to predict the probability and coordinates of the vehicle. The authors believe that their proposed system has applicability in various aspects of road and traffic management. First, it can be used for intelligent road routing, which can be a vital solution for managing traffic. Secondly, it could also prove useful in traffic control, and road planning as well as other aspects of traffic management and road use. This method has limitation when dealing with small objects or objects close by in group despite its robust architectural layout. Therefore, that
problem could significantly diminish its ability to predict the probability and coordinates of vehicles.

**2.2.5 Vehicle Detection and Tracking Based on Color Feature**

Anandhalli and Baligar [41] propose a vehicle detection and tracking model that includes an algorithm which would detect vehicles and track them in real time. In designing their system, the authors sought to address the issue of the determination of vehicle density that is cited as a major concern in intelligent transportation systems. The system tracks vehicles purely based on their color features with tracking carried out by a Kalman filter with the data association.

Undoubtedly, the system that Anandhalli and Baligar proposed only uses color as the only parameter in vehicle detection. One feature is the conversion of the input frame from RGB to HSV color spaces which then makes it possible to differentiate between the vehicle colors. Further splitting of the HSV color into three channels and filtering them facilitates the extraction of the vehicle colors only. All the vehicles captured in the video are calculated with the system. However, it is limited by imperfect merging and in the splitting of the blobs in the binary images that are captured.

**2.2.6 Close Range Vehicle Detection and Tracking by Vehicle Lights**

Lee, Wu, Hsieh and Chien [42] propose a model that can be used to detect vehicles at night, that tracks them by the location of their tail lights. The researchers were responding to the fact that front vehicle detection is harder at night compared to the daytime. In the darkness, the environment offers little support regarding tracking vehicles. This system is designed on an algorithm that estimates the intensity of the diffused tail lights and then use the data to track the vehicle's location. After conducting tests using video recorded at night, the researchers concluded that the algorithm
they used performed quite well and could provide a reliable solution. The system that was designed could detect vehicles using the information from their lamps. The cameras can detect light at close range and not just pick sources located far away. Another important aspect is that the system would perform better once non-vehicle light was eliminated. Therefore, it would be able to isolate the effects of light sources such as streetlights or signals. However, the system is not 100% accurate and that would mean that it may miss some vehicles at night.

2.2.7 Research on Edge Tracing Based on Scan-Line Algorithm

Wang [43] proposed a system that would aid in the extraction of edge vectors in an image. The system’s design was driven by the realization that extracting the edge vectors of the regions of the image can be quite difficult due to the many regions in the image. However, the solution that the authors proposed would make it easy by extracting all the edge vectors at the same time. The system itself would be based on scan-line of the image for vehicle recognition. Utilizing the system can produce the desired results in a relatively short amount of time. The main departure point for this system is the tracing of an image. Prior models have been based on tracking an object recognition process which works by obtaining the edges through seed tracing of the images' boundaries. The new method would see the tracing of the boundaries at the same time. Therefore, the characteristic vectors would be obtained in a relatively shorter time. In doing so, the image processing time would be significantly cut, and makes it possible to get the required results faster. However, the system faces the limitation of being unable to trace the edges of regions that have intersections. Apart from that, it may be limited when it comes to sensing the inner part of the region of an image.
2.3 Background on Distance Estimation

This section reviews different methods that are being used for depth estimation. Depth extraction or estimation is referred to as the collection of algorithms and techniques that are aimed at obtaining a representation of the scene’s spatial structure. It is considered for depth estimation procedure to be an important task in different applications and industries. For instance, in vehicles navigation, it can be an effective preventive measure system for collision evasion and it can be ideal as dynamic high-beam assistance systems. The methods reviewed throughout will consist of their working procedures and the outcomes they will provide.

2.3.1 Analysis of Distance Measurement System of Leading Vehicle

Deshmukh [44] proposed a system that would enhance the measurement of the distance of the leading vehicle. The researchers carried out the project as guided by the requirements of intelligent vehicle technologies. The technique was based on digital image processing theory to identify and map the leading vehicle. Edge enhancement and morphological transformation were used to establish the input image for this method. The researchers applied obstacle detection and decision tree to identify and calibrate the target vehicle. The application of the ray angles established the relationship between coordinate values within the image space and the actual space plane. The calculation of the leading vehicle distance was measured based on a model of inverse perspective mapping. As part of the project, the researchers used the VC++ software to come up with an experiment for measuring the leading vehicle distance. However, the system has a disadvantage of a growing relative error between the actual and measured distances as the distance between the vehicles increases.
2.3.2 Real-time Depth Estimation and Obstacle Detection from Monocular Video

The paper by Wedel, Franke, Klappstein, Brox and Cremers [45] researched the detection of arbitrary static objects in traffic scenes. In their study, the researchers relied on monocular video that used structure from motion. In this case, a camera with known translation depth observes the road course ahead. One of the most impressive aspects of this system is its focus on detecting stationary objects. Most of the available options out there focus on the detection of nearby or moving objects. Obviously, the challenge of small subpixel motion between frames makes it harder to target stationary objects. The researchers devised a way of estimating scene depth which is possible from the scaling of supervised image regions. The method as proposed was found to have the capability of detecting obstacles that were at distances of 50m or more away using a standard focal length. However, the major drawback of the system is the fact that it becomes hard to detect moving objects in a monocular scenario.

2.3.3 Automatic Fog Detection and Estimation of Visibility Distance through Use of an Onboard Camera

Hautière, Tarel, Lavenant and Aubert [46] developed and patented a system that would aid in the measurement of visibility distances in foggy weather conditions. The system that the researchers developed was limited to addressing the visibility problem that drivers face while driving during the day due to fog. Implementing Koshmieder's Law, the researchers came up with a solution that could compute the meteorological visibility distance, making it safer to drive when one cannot see too far ahead. Another important feature of the system is the fact that it only relied on the use of a single camera mounted on the vehicle's dashboard. The downside of the system is that it cannot be used at night due to the darkness or used in circumstances of significant road
masking. Its inoperability at night is a considerable hurdle since one is more likely to struggle more with visibility at night than during the day.

**2.3.4 Catadioptric Stereo System**

Stereo imaging is considered as the permanent solution for the depth perception of mobile robotics. It uses multiple images from the same scene that are taken from different camera locations, specifically to create disparity. The disparity is a concept that involves the relative movement of an object in multiple views. In the present method, the camera is set in such a way that they are spatially separated so that the function of depth is ensured. There are numerous methods within the stereo imaging procedure; however, the present analysis was conducted on a Catadioptric stereo system. The system uses mirrors and lenses together for focusing on elements. Both entities are arranged in such a way that both images will appear on the same location [47].

The benefit of Catadioptric Stereo system is that the images are automatically captured, which provides a quicker update rate. However, the method also has numerous disadvantages. One of the disadvantages is that the sensor is fragmented, which reduces the resolution to half of the original. Furthermore, there is also a convergence problem that makes some of the sensor areas, vanish [47].

**2.3.5 Markov Random Field (MRFs)**

The 3D depth of images is a major issue when it comes to computer visions, especially due to its application in the field of robotics and 3D reconstruction. The method which is under the review is Markov Random Fields (MRFs), which is largely based on machine learning. The method is used for solving many issues, such as object classification, text segmentation, and image labelling. First, the method uses a 3D distance scanner for the collection of data. The data consists
of a large set of images, with their respective ground-truth depth maps. The MRF is trained to predict depth. This method can evaluate the interaction potentials, capture depths, and capture interactions between those depths on multiple spatial scales [48].

In the research study of Saxena et al [48] the method was applied by using two mathematical models, i.e. the Gaussian model and the Laplacian model, where the interaction performance improved by using the latter one. The algorithm easily predicts the depth of the objects, but it has a problem in determining absolute depths. Furthermore, the method also produces errors in those 3D images, which consist of irregular trees.

2.3.6 Predicted Semantic Labels

As mentioned beforehand, recovering a scene from a 3D picture is a problem in the concept of computer vision, specifically when it is used in robotics and surveillance. Furthermore, determining the structure from raw images is very different, particularly due to the lack of local appearance in the images. However, semantic procedures provide an essential role for the perception scale as well as 3D structure. To determine the depth reconstruction of the images, the predicted semantic label is used, firstly on determining the separate depth estimator. It works collaboratively with the MRFs, which discover both pixel and super pixel-based variants of the model. By using the following formulation, it becomes easier to incorporate smoothness and reduces the number of variables to use as well [49].

This method has many advantages. Firstly, it can be conducted by using simple features because the depth perception is based on semantic modelling after using MRFs. Secondly, it is not necessary to include modelling occlusions, since these can be obtained by the semantic labels mentioned above. Lastly, coplanar shapes can easily be imposed, due to the usage of semantic
labels. The drawback of this method is that it works based on accurate ground information and prior strengths, which is not possible in every kind of image data [49].

2.3.7 Pixel Location Method

There are many techniques to determine depths in various images. Considering that many methods do not give accurate results, the pixel location method differs from the rest. The process begins with placing a camera on the platform at a height of 11.5 cm and at an angle of 24°. Firstly, the images are converted to grayscale then the grayscale images are converted to binary form and compared to the object’s threshold value. Each pixel will then measure by the threshold if it is greater or equal to it. It is considered as an object otherwise it will be considered as the background. The image below provides a comparison between the original and the grayscale image, where the red dot determines the pixel, which is the object base of the image [50].

Pixel location method is deemed better than the rest of the monocular vision methods, for depth estimation of images. The estimated depth provided by this method is accurate to that of the real depth of the image. The only disadvantage of the method is that it can only work on one object at a time. It needs to be improved by using multiple objects placed at the same time on different locations [50].

2.3.8 Color Shifting Property of a Multiple Color-Filter Aperture

Another approach for figuring out the depth of the image is by using the color-filter aperture camera, which not only provides the depth information but also provides the color intensity of the image. The multiple color-filter aperture (MCA) cameras are placed between the imaging sensor and the lens to provide the geometric information regarding the color shifting property. The aperture is adjusted so that the light entering the camera is determined, and its center
is attached with the lens’s optical axis. The convergence pattern will then be placed in the form of a point or even a circular region, subjected to the distance between the object and focus plane [51].

The major advantage of using this method is that the MCA camera provides excess depth information estimated from the direction and the amount of deviation in color from the optical axis of the camera. Hence, it focuses on the light. Furthermore, it also improves the misaligned color in the images and provides photorealistic color pictures. This method has been fruitful for determining the depth of 3D images among various methods that are also used [51].

2.3.9 An Omnidirectional Stereo Vision System

The omnidirectional vision approach provides a wider Field of View (FOV), which enables it to be applicable in many areas. Mostly, this method is implemented by using one 360° FOV with a catadioptric imaging system where multiple mirrors are used to portray the large field view on the image sensor. There are various methods that can be used to implement this concept; however, the method which is discussed in the study of Yi, and Ahuja [52]. The study utilizes a simple combination of a concave lens and convex mirrors. To summarise, the concave lens stops the ray of light at some vertical angles, which creates an opaque ring. By sloping the lens from the vertical side, the blocked angle can be minimised, and the thickness or depth of the ring can be determined.

The advantage of using the system consists of the reduced complexity of the approach. This method also provides users with no limitation benefit, so far, and many other techniques are being developed with the same approach that the Omnidirectional stereo vision system is developed with [52].
This chapter discusses the proposed method to improve low visibility in images and frames caused by poor weather conditions such as snow, rain, and fog. This method is focused on reducing low visibility from images and frames to increase driver’s visibility during storms. The method preserves the most original image details. This method is divided into 5 steps. These steps are preprocessing, using Retinex Enhancement Techniques, post processing, detection and tracking objects, and calculating front vehicle distance. Figure 8 is a flowchart of the proposed method.
Figure 8. Flowchart of Proposed Method
3.1 Pre-processing

This first step is a multi-operation that is not designed to increase the image information contrast. In fact, it will decrease the image and frame information. It is mainly concerned with noise reduction, which allows the algorithm used in the next stage to perform better. Noise occurs in the image during the acquisition process and due to light diffusion under the specific weather conditions. There are many ways that noise can influence an image or frame, depending on how the image or frame is originated [53]. In this case, it depends on the specific weather, for example, snow versus rain. In this step, a Gaussian low pass filter is proposed to reduce noise effect.

3.1.1 Gaussian Low Pass Filter

Gaussian low pass filter is used to eliminate or reduce noise that effected images or video and it is also used to smooth the images. The Gaussian function is expressed as:

\[
G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x-\mu)^2 + (y-\mu)^2}{2\sigma^2}} \quad (17)
\]

Where \(\mu\) is the mean and \(\sigma^2\) is the variance [54].

The value of \(\sigma\) is determines the width of the Gaussian filter kernel. For instance, when \(\sigma\) is large that means the Gaussian filter is wider and smoother. Figure 9 shows an example of a Gaussian filter with different width values [55] [56]. The zero mean Gaussian function is expressed as:

\[
G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}} \quad (18)
\]
Figure 9. Example of Gaussian Low Pass Filter with Different Width Values

3.2 Modified Retinex-Based Enhancement Technique

In this step, the Retinex technique is used to enhance and increase the visibility of images and frames. The Retinex theory decomposes the image into two images illumination and reflectance. This decomposition allows us to control the illumination effects. The Retinex algorithm has been used in image enhancement for many years due to good results that were achieved. Retinex algorithm is based on using a surrounding function to estimate the background illumination via the logarithmic space operations in a similar manner to the nonlinear operations of the Homomorphic filters. A major shortcoming is the “halo” artifacts that appear on the edges in the displayed output image. This artifact is mainly due to the essence of Retinex operations, which is the convolution with the surround function [57-59]. This “halo” effect can be prevented
or reduce its appearance by inserting other processes in the system such as using an averaging filter to soften the edges and thus producing similar results as the surround function with image smooth areas [60] [61].

The average computation can be expressed by:

\[ G(x, y) = \sum_{i} \sum_{j} I(x, y) W(x - i, y - j) \]  

(19)

The average filter is designed according to the Roberts gradient operator. The Robert method finds edges using the Robert approximation to the derivative. It returns edges at those points where the gradient of an image is at maximum [62]. The gradient function is:

\[ \nabla I(x, y) = \left( \frac{\partial I}{\partial x}, \frac{\partial I}{\partial y} \right) \]  

(20)

where \( \frac{\partial f}{\partial x} \) is the partial derivative for x point and \( \frac{\partial f}{\partial y} \) is the partial derivative for y point. The edges are calculated by taking the magnitude of the gradient.

\[ \|\nabla I\| = \sqrt{\left( \frac{\partial I}{\partial x} \right)^2 + \left( \frac{\partial I}{\partial y} \right)^2} \]  

(21)

The adaptive filter makes it possible to enhance the visibility while keeping most of the image and frame details. In this method, the proposed surround function \( F_A(x, y) \) is:

\[
F_A(x, y) = \begin{cases} 
F(x, y) = k e^{-\frac{x^2+y^2}{\sigma^2}} & \|\nabla I\| \leq T \\
F(x, y) = \sum_i \sum_j W(x - i, y - j) & \|\nabla I\| > T 
\end{cases}
\]  

(22)
3.3 Post-processing

The post-processing step is the final step applied to enhance the quality of images or video. In this step, the aim is to sharpen and adjust the contrast of images and frames were used. Gaussian High Pass Filter (GHPF) is used to sharpen the output displayed images and frames and will enhance some details in images. The GHPF has the same effect as ideal High Pass Filter (HPF) except GHPF has smoother transition than the ideal HPF [63]. On the other hand, adjusting of the images and frames is used to improve the contrast and intensity values of the output [64].

3.3.1 Gaussian High Pass Filter

The high frequency components in images contain fine details and edges. The Gaussian High Pass Filter is used to enhance and sharpen some details or edges in an image. The GHPF is the reverse of Gaussian Low Pass Filter [65]. So, the function of the GHPS is expressed as:

\[ G(x, y) = 1 - \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 - y^2}{2\sigma^2}} \]  

(23)

Figure 10 shows the example of Gaussian high pass filter.
3.4 Detecting and Tracking Vehicles

This step is to detect and track the vehicles in front of the driver with bounding box. In this step, the Gaussian Mixture Models (GMMs) and blob analysis were used to detect and track cars. This is shown in Figure 11. The Gaussian Mixture Model is a function of parametric probability density, which is represented as a weighted sum of Gaussian component densities. GMMs are used to separate the background and foreground pixels in images and frames. GMMs are commonly used as a parametric model of the probability distribution to make continuous measurements. This algorithm works by comparing each pixel to the mean value. After comparing each pixel, the value of the Gaussian weight along with the mean and standard deviation values are updated to reflect the new obtained pixel value. Then threshold is applied to determine which pixels are foreground and background [66] [67].

![Flowchart](image)

**Figure 11. Gaussian Mixture Model Used in Step 4 to Achieve Detecting and Tracking Objects**
The Gaussian mixture model formula is expressed as:

\[ P(X_t) = \sum_{i=1}^{K} \omega_{i,t} \eta(X_t; \mu_{i,t}, \Sigma_{i,t}) \]  \hspace{1cm} (24)

where,

\[ \sum_{i=1}^{K} \omega_{i,t} = 1 \]  \hspace{1cm} (25)

\[ M_t = \sum_{i=1}^{K} \omega_{i,t} \mu_{i,t} \]  \hspace{1cm} (26)

K is the number of distribution (K=3), t is the time, \( \omega_{i,t} \) represents the ith Gaussian weight at time t, \( \mu_{i,t} \) is the mean value of the ith Gaussian at time t and \( \Sigma_{i,t} \) is the covariance matrix of the ith Gaussian in the mixture at time t.

### 3.4.1 Blob Analysis

A blob in image processing is defined as a group of connected pixels. This blob is used to trace the movement of an object within a frame. This algorithm can distinguish between foreground and background pixels by the value of each pixel. Also, it groups pixels that have similar values such as light values and color values to create the blob. The blob analysis works by searching through an entire image or frame and detecting all particles (blobs). Then it builds a detailed report of information for each blob including the blob’s location, size, and shape. After identifying the blobs contain vehicles in the image or frame, the rectangular box around them is used [67] [68].
3.5 Front Vehicle Distance Calculation

The last step is to find and calculate the distance of the front car. Different colors of the bounding box are used to determine how close the front car is. Red is used for distance less than 10 feet, green is used for distance less than 15 feet and green is used for distance over than 15 feet. Depth estimation algorithm has been used to find the car distance. Depth estimation, also known as extraction, defines the algorithms and techniques used for achieving a scene’s spatial structure representation. Simply put, performing a depth estimation procedure means obtaining a distance measurement, ideally of every point accessible in the scene [69].

As described in a study by Tiwari, the Pixel Depth of an object being photographed is mapped with the Real Depth of this object using a camera lens based on an interpolation function. Various lines placed at a specific distance from the camera help in determining the interpolation function parameters which in turn helps in calculating the distance of these lines from the picture’s bottom edge. The interpolation function is expressed as:

\[ y = \sum_{n=0}^{M} a_n x^n \]  

(27)

where \( x \) is the distance of the object from the camera and \( M \) is the order of the polynomial.

Pixel Depth with respect to its image is defined as the distance between this object’s foot and photograph edge (see Figure 12). The Pixel Depth is calculated as:

\[ \text{pixel depth} = R - R_i \]  

(28)

where \( R \) the image size and \( R_i \) is the object’s foot distance from the image’s periphery.

In the real depth approach, the horizontal distance existing between the photographed object and the camera lens is defined as an object’s Real Depth. The camera is placed horizontally
above the ground at a height as shown in Figure 13. The rays that are emitted from the camera are known as the camera’s vision region. The interpolation approach comprises of two steps. The first step is the calculation of the interpolation function depending on the camera’s horizontal angle and its height. The second step is applying this function for calculating the distance between the camera and the object [69-71].

Figure 12. The Pixel Depth [70]

Figure 13. The Real Depth [70]
This approach is test by taking videos and measuring the front car with different distances. Each test data contains 5 videos that taken with same distance. Table 3 shows the calculation result of test data. One of each test data result is shown in Figures 14 to 18 and Table 4. The error of distance in this algorithm is less than 3.4%.

Table 3. Depth Distance Calculation for Test Data

<table>
<thead>
<tr>
<th>Test Data</th>
<th>Real Distance (Feet)</th>
<th>Depth Estimation (Feet)</th>
<th>Error %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test Data 1</td>
<td>10</td>
<td>10.11 - 10.34</td>
<td>1.1 - 3.4</td>
</tr>
<tr>
<td>Test Data 2</td>
<td>15</td>
<td>15.06 - 15.23</td>
<td>0.4 - 1.5</td>
</tr>
<tr>
<td>Test Data 3</td>
<td>20</td>
<td>20.10 - 20.15</td>
<td>0.5 - 0.75</td>
</tr>
<tr>
<td>Test Data 4</td>
<td>25</td>
<td>25.07 - 25.17</td>
<td>0.35 - 0.68</td>
</tr>
<tr>
<td>Test Data 5</td>
<td>30</td>
<td>30.10 - 30.20</td>
<td>0.33 - 0.66</td>
</tr>
</tbody>
</table>

Figure 14. Depth Estimation Example (a) Original Frame with Real Distance = 10 Feet, (b) Distance Result After Running Depth Estimation Algorithm
Figure 15. Depth Estimation Example (a) Original Frame with Real Distance = 15 Feet, (b) Distance Result After Running Depth Estimation Algorithm

Figure 16. Depth Estimation Example (a) Original Frame with Real Distance = 20 Feet, (b) Distance Result After Running Depth Estimation Algorithm
Figure 17. Depth Estimation Example (a) Original Frame with Real Distance = 25 Feet, (b) Distance Result After Running Depth Estimation Algorithm

Figure 18. Depth Estimation Example (a) Original Frame with Real Distance = 30 Feet, (b) Distance Result After Running Depth Estimation Algorithm
Table 4. Depth Distance Calculation

<table>
<thead>
<tr>
<th>Figure</th>
<th>Real Distance (Feet)</th>
<th>Depth Estimation (Feet)</th>
<th>Error %</th>
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<tbody>
<tr>
<td>Fig 14</td>
<td>10</td>
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<td>Fig 15</td>
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<td>15.23</td>
<td>1.5</td>
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<td>Fig 16</td>
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<td>Fig 17</td>
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<td>Fig 18</td>
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<td>30.20</td>
<td>0.66</td>
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</table>
CHAPTER IV

IMPLEMENTATION AND EXPERIMENTAL RESULTS

In this chapter, the implementation setup and simulation results of the proposed method are presented. Extracted video frames that are captured using dashboard cameras during poor weather conditions such as snowstorms are used. Videos have a frame rate of 30fps and the frame size is equal to 512 x 512 x 3. A sample set of frames that display weather conditions are shown in Figure 19. In our proposed algorithm, the number of scales is assumed to be equal to 3 representing the RGB colors. The weights were assumed to be equal to 1/3 since our proposed method deal with true color frames. The average filter window size is chosen to be 3 x 3. This proposed method is implemented using MATLAB software on a computer with 4GB memory RAM and 1.7 Intel® core™ i7 CPU. The proposed method is simple, and the execution time is 0.51 second allows for real time processing.

Figure 19. an Extracted Frame Showing a Very Low Visibility Conditions Under a Snowstorm
4.1 Experimental Results in Snow Conditions

The results show improved visibility even in frames with extremely low visibility. In Figure 20 the input frame (a) has extremely low visibility during snowstorm. The first step is to reduce the noise by using Gaussian low pass filter as shown in (b). The three channels figures, which are red, green, and blue, are shown in (c). Then the combined frame of the three channels is shown in (d). The result shown in (e) after applying the Gaussian High Pass Filter and in (f) after applying Gaussian Mixture Model and blob analysis, which is used to detect and track vehicles and find the vehicle depth estimation for the front vehicle’s distance. Another sample result is shown in Figure 21 extracted data from another video under snow conditions.
Figure 20. Proposed Method Sample Results Showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image (e) Output Frame, and (f) Result Distance with Bounding Box Around the Vehicle
Figure 21. Proposed Method Sample Results Showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image (e) Output Frame, and (f) Result Distance with Bounding Box Around the Vehicle
Other results are shown in Figures Figure 22 to Figure 25 shows different frames with low visibility during a snowstorm.

Figure 22. Proposed Method Sample Results Showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image (e) Output Frame, and (f) Result Distance with Bounding Box Around the Vehicle
Figure 23. Proposed Method Sample Results Showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image (e) Output Frame, and (f) Result Distance with Bounding Box Around the Vehicle
Figure 24. Proposed Method Sample Results Showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image (e) Output Frame, and (f) Result Distance with Bounding Box Around the Vehicle
Figure 25. Proposed Method Sample Results Showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image (e) Output Frame, and (f) Result Distance with Bounding Box Around the Vehicle
4.2 Experimental Results in Sandstorm Conditions

Figure 26 is taken during a sandstorm and the input frame (a) has extremely low visibility. The first step is to reduce the noise by using Gaussian Low Pass Filter as shown in (b). The three-channel figures, which are red, green, and blue, are show in (c). Then the combined frame of the three channel figures is shown in (d). The result shown in (e) is after applying the GMM and blob analysis, which is used for detecting and tracking vehicles and finding depth estimation for the front vehicle’s distance.
Figure 26. Proposed Method Example (a) Original Frame, (b) Gaussian LP Filter, (c) Red, Green and Blue Channel, (d) Combined Retinex Image, (e) Result Frame, and (f) Result Distance with Bounding Boxes Around the Vehicles
Other results are shown in figures Figure 27 and Figure 28 show different frame with low visibility during a sandstorm.

Figure 27. Proposed Method Example (a) Original Frame, (b) Gaussian LP Filter, (c) Red, Green and Blue Channel, (d) Combined Retinex Image, (e) Result Frame, and (f) Result Distance with Bounding Boxes Around the Vehicles
Figure 28. Proposed Method Example (a) Original Frame, (b) Gaussian LP Filter, (c) Red, Green and Blue Channel, (d) Combined Retinex Image, (e) Result Frame, and (f) Result Distance with Bounding Box Around the Vehicle
4.3 Experimental Results Validation

A validation using quantitative measures such as peak signal to noise ratio (PSNR) and the Structure Similarity (SSIM), were used along with common visual enhancements. The PSNR represents the ratio between the maximum power of a signal and the power of noise that affect the signal. The PSNR usually used for measuring the quality of reconstruction of lossy images. The SSIM is a method for measuring the quality of digital images and videos. SSIM is used for measuring between the result image and the initial image or reference image. Table 4 and table 5 show the calculation for the PSNR and the SSIM for all figures on this chapter. The proposed method provides the PSNR and the SSIM with greater values than the Histogram Equalization and Multi Scale Retinex methods.

Table 4. PSNR Calculation

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Table 5. SSIM Calculation

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To evaluate the proposed method fifty videos and one hundred images were used. The proposed method’s performance was compared with a histogram equalization [19] and an MSR [26]. The results are shown in Figure 20 to Figure 28, and tables 4 and 5.

Figures 20(a) to 25(a) shows that the frames have low visibility and are taken from videos during snowstorms. Figures 20(b) to 25(b) frames after using a Gaussian Low Pass Filter to reduce the noise that occurs during the acquisition process. Figures 20(c) to 25(c) demonstrate the three of channels figures, which are red, green, and blue, before running a Retinex algorithm. Frame results after running a Retinex algorithm are shown in figures 20(d) to 25(d). Figures 20(e) to 25(e) show the result after running a gaussian high pass filter. The results in figures 20(f) to 25(f) show the frames after running the GMM and the depth estimation, which is used to detect and track vehicles. Then it calculates the distance of the front vehicle.
Figures 26(a), 27(a) and 28(a) show frames taken during sandstorms. The same process was applied on these frames as in the snowstorm frames. The results shown in figures 26(f), 27(f), and 28(f) depict what vehicles detected with their distances.

The quality parameters used for comparison are the Peak Signal to Noise Ratio (PSNR) and the Structural SIMilarity (SSIM). The results of the comparison are shown in Figure 29 and Figure 30. The proposed method gives better values compared to a Histogram Equalization and an MSR.

Figure 29. PSNR Comparison Result
Results of the simulations show that the proposed system can improve visibility during snowstorms and sandstorms as well. It performs better when the image or video frame size is 512 x 512. Also, the proposed system does not require prior knowledge about the scene condition or references. This system has the advantage over other systems because it requires no user interaction. In addition, the simulation results can effectively recover the scene and reduce the halo artifacts caused by the Retinex technique. However, this system requires many parameters for adjustment to produce optimal results depending on weather conditions such as snow, rain and fog. In fact, using constant parameters in different weather conditions will produce results with saturated colors due to some pixels with values equal to or near 0, then jumping to 255, and vice versa. The proposed system failed to detect objects when the objects are too far from the camera. Experimental results not only show that the proposed method increases the visibility and contrast intensity of images and videos, but also that their quality is increased as well.
CHAPTER V

CONCLUSION AND FUTURE WORK

Low visibility during inclement weather can lead to serious multi-vehicle accidents as evident by the data provided by several resources from USA and worldwide agencies. The proliferation of advanced technology can be utilized to facilitate safer driving conditions. Real-time image processing of scenes during inclement weather can be used to enhance the driving conditions which will lead to saving lives. Therefore, a real time system to provide drivers with safer driving conditions by improving visibility in poor weather conditions is truly a must.

This dissertation presents a reliable framework that may be deployed within a smart driver-assistant system capable of improving visibility under several weather conditions such as snow, fog, rain, and sand storms. The proposed system is composed of five stages as follows:

1. Preprocessing was used to achieve noise reduction: A Gaussian low pass filter is used to reduce the noise effect during video acquisition, along with other types of filters that can be used depending on the specific weather condition.
2. Modified Retinex algorithm: This the core process of the proposed system aiming to reconstruct the scene with a clearer view on the display screen of the smart driver-assistant system.
3. Post Gaussian filtering process: The video frames are then filtered with yet another Gaussian high pass filter during the third stage to sharpen image content through the output video.
4. Object detection and tracking: Gaussian mixture models and blob analysis were used to detect and track cars with a bounding box technique.
5. Depth estimation: This stage was used to calculate the distance between the system and other vehicles.

Ultimately, our goal is to save lives by providing better visibility to drivers and thus improving decision making while driving during inclement weather conditions. The benefits from this technique include improving the readability of road signage in addition to the visibility of other vehicles and objects on the road. This framework successfully addressed low visibility during severe weather as was demonstrated by the experimental results. Our proposed system preserves most image/frame details unlike other proposed methods. In addition, the algorithm is not computationally expensive, as the average execution time is only 0.51 seconds, which still allows for real time processing during storms. Improvements to the speed can be accomplished by code optimization and better hardware system realization. Therefore, this dissertation contributes a practical framework for enhancing visibility of roads during inclement weather conditions, which is an advancement that we are in a dire need for.

Beyond this research and for ongoing development, future directions may include:

1. Integrate storm-custom design pre-processing and post-processing to minimize noise impact on algorithm performance from the generalization of the algorithm.

2. Further parallelization of the code could decrease the execution time of this method to allow for better real time system usage.

3. Explore dedicated camera system for the underlying weather conditions to maximize benefits, and increase capabilities to address other visibility challenges such as thick smoke in large space such as fire or underwater conditions.
REFERENCES


Figure A-1. Proposed Method Example (a) Original Frame, (b) Gaussian LP Filter, (c) Red, Green and Blue Channel, (d) Combined Retinex Image, (e) Result Frame, and (f) Result Distance with Bounding Boxes Around the Vehicles
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Figure A-8. Proposed Method sample results showing the (a) Original Frame, (b) Gaussian LP Filtered frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image and (e) Result Frame
Figure A-9. Proposed Method sample results showing the (a) Original Frame, (b) Gaussian LP Filtered frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image and (e) Result Frame
Figure A-10. Proposed Method sample results showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels frames, (d) Combined Retinex Image and (e) Result with Bounding Boxes Around the Vehicles
Figure A-11. Proposed Method sample results showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels frames, (d) Combined Retinex Image and (e) Result Frame
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Figure A-14. Proposed Method Example (a) Original Frame, (b) Gaussian LP Filter, (c) Red, Green and Blue Channel, (d) Combined Retinex Image, (e) Result Frame, and (f) Result Distance with Bounding Boxes Around the Vehicles
Figure A-15. Proposed Method sample results showing the (a) Original Frame, (b) Gaussian LP Filtered Frame, (c) the Red, Green and Blue Channels Frames, (d) Combined Retinex Image and (e) Result Frame
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