**MARSHALL PLAN SCHOLARSHIP**

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# Application of Computer Vision in Roller Operation Management


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**ABSTRACT**

Compaction is the last and possibly the most important phase in construction of asphalt concrete (AC) pavements. Compaction densifies the loose (AC) mat. This process strongly affects the AC performance properties. Too much compaction may cause aggregate degradation and low air void content facilitating bleeding and rutting. On the other hand too little compaction may result in higher air void content facilitating oxidation and water permeability issues, rutting due to further densification by traffic and reduced fatigue life. Therefore, compaction can be a critical issue in AC pavement construction.

The usual practice for applying the right level of compaction to the mat is to establish a roller pattern. At the beginning of the paving job a specific area designated as the control strip. The density of the surface within this area is checked and verified against the number of passes made by the roller(s), in either static or vibration mode, to meet the specification requirements. Once the pattern is established, it is the contractor's responsibility to maintain the roller pattern uniformly over the entire mat. Unless any of the other effective parameters such as temperature or material property changes or further density tests reveal that modification of the roller pattern is required, the operator must keep rolling the surface using the same pattern.

Generally roller operators are responsible for keeping track of the number of roller passes, the starting and the end point of each pass and the total number of coverages. Despite the importance of uniform compaction to achieve the expected durability and performance of AC pavements, having the roller operator as the only mean to manage the operation can involve human errors in the process. With the advancement of technology in recent years, the concept of intelligent compaction (IC) was developed to assist the roller operators and improve the construction quality. Commercial IC packages for construction rollers are available from different manufacturers. Common denominators for these packages include an accelerometer mounted on the drum, infrared thermometers and a computer system that collects the feedback from the sensors and adjusts the roller operation accordingly. The state of the art IC packages also implement global positioning system (GPS) for count pass mapping. The GPS integrated IC packages are able to combine the data collected from the sensors with local coordinates for quality control purposes. Moreover they can interactively modify the roller pattern to achieve the best compaction results. The precise count pass mapping improves the compaction uniformity greatly and eliminates the majority of the human errors associated with maintaining the roller pattern. Commercial GPS for roller count pass mapping is also available in the market.

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## NOMENCLATURE/LIST OF ACRONYMS

# Chapter 1: INTRODUCTION

## 1.1. COMPACTION SIGNIFICANCE

Asphalt concrete (AC) is a mixture of aggregate and asphalt binder. The AC is the major material used in paving surface of roads, airfields and parking lots. AC pavements are required to be stable under the traffic loads, smooth, durable and impermeable unless designed otherwise. To achieve the expected properties and performance, the loose AC mixture need to be compacted during the construction.

Compaction is the process of reducing the volume of loose AC material under an external force. The compaction force squeezes loose asphalt-coated aggregates together providing increased aggregate interlock and stronger asphalt bonds for higher stability to endure traffic loads.

In the compaction process, mixture air voids are reduced to the design level for higher durability. Compaction to the design level assures enough room to accommodate binder expansion at higher seasonal temperatures while reduces the chance of water susceptibility issues and premature surface distresses by reducing permeability. Moreover, lower air void and surface impermeability avoid accelerated binder oxidation and aging which let the surface undergo repeated loads without cracking for a longer service life.

## 1.2. INTELLIGENT COMPACTION

Rollers are used to densify the AC mat during the construction at field. In order to achieve the required density, a rolling pattern must be defined. The rolling pattern is specific to each project and it may require modification upon change in material properties, temperature, environmental condition and underlying surface stiffness. Once the rolling pattern is established, the roller operator is in charge for maintaining it as consistent as possible. Remembering the rolling zone limits and keep track of number of passes and coverages is tedious, but it is essential to achieve the target density and compaction uniformity. To assist the roller operators with this monotonous task and minimizing human errors intelligent compaction (IC) was developed.

Currently different commercial IC packages are available in the market from several manufacturers. Figure 1 describes the most comprehensive package introduced yet. This IC system is comprised of data acquisition sensors, automatic feedback control (AFC) and output devices such as a display screen and a printer. The data acquisition part may include an accelerometer for drum vibration measurement, infrared temperature detectors, and GPS. The AFC unit analyzes the acquired data and adjusts vibration accordingly. The operator screen also displays helpful information such as the mat temperature, estimated mat density, vibration frequency and amplitude, vibration mode, count pass mapping and density map.

In practice not all the IC packages cover all the activities in Figure 1. The AFC unit can only be used on rollers with directional compaction technology, which are not very common. IC upgrade packages mostly focus on pass count mapping, developing temperature profiles, and possibly density map for vibratory rollers.

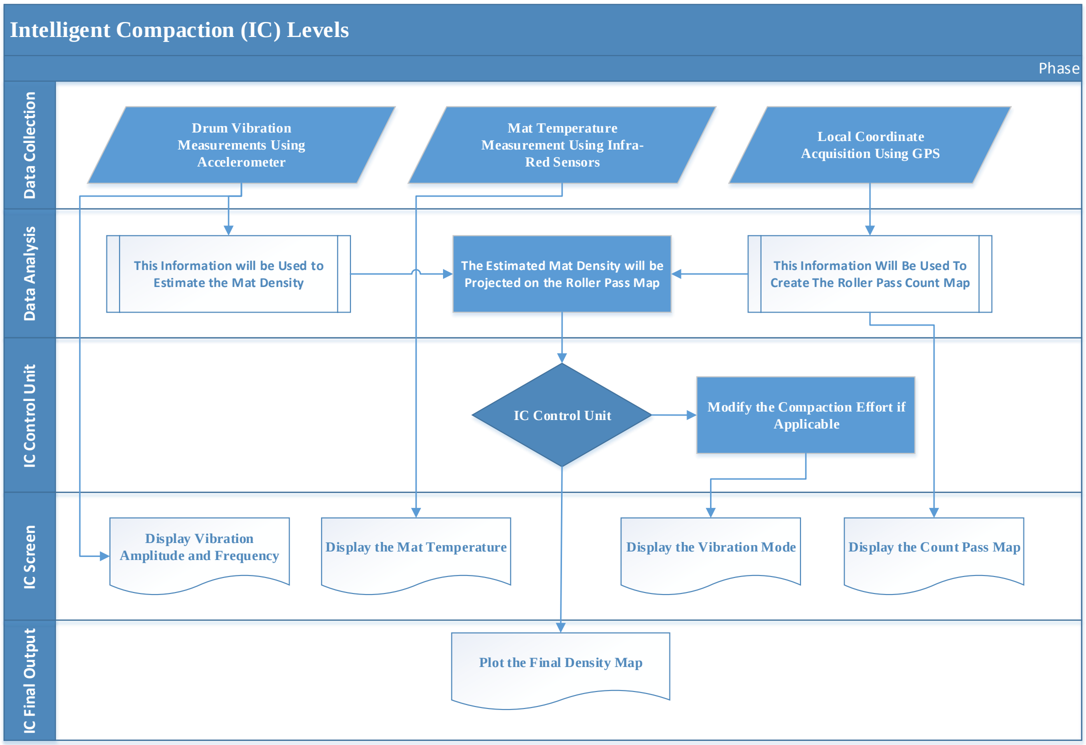



Figure 1 Comprehensive IC Flowchart

## 1.3. PROBLEM STATEMENT

The current IC packages available use global positioning system (GPS) to map the roller location. Despite the satisfactory results, these systems have two disadvantages that make contractors reluctant to adopt this technology. First, because the functionality of these packages highly depends on the precision of the real time location information, a sophisticated GPS antenna is required. This increases the price of typical new vibratory tandem asphalt roller by almost 20%-25% (based on the quotation for Trimble CSS Flex, dated August 2012). For most of the contractors who already own a compaction fleet, the investment is greater, relative to the current value of their equipment.

Moreover, the GPS device integrated into the IC require stationary support. Single or multiple reference stations on the job site are needed to constantly correct the satellite data acquired by the GPS mounted on the roller. To maintain the system functionality, it is essential to keep the radio line of sight between the antenna mounted on the roller and stationary GPS antennas clear. This is the other shortcoming of the system which requires labor on the ground to relocate and reset the reference station.

## 1.4. OBJECTIVES

The focus of this research project is to design and build an economical IC upgrade package that can be used on any asphalt compaction roller. The primarily objective is to produce pass count mapping.

# Chapter 2: LITERATURE REVIEW

## 2.1. INTRODUCTION

Due to the wide variety of the topics discussed in this chapter, the materials are organized in two sections. Section 1 discusses the asphalt concrete (AC) compaction. Section 2 covers the computer vision application and focuses on methods of perceiving the environment, image processing and simultaneous localization and mapping.

### 2.1.1. Rolling operation

In general, using rollers to compact the AC layer on the field takes place in 3 steps “break -down”, “intermediate” and “finish”. The break-down roller gets the initial and the majority of the density, the target density is supposed to be achieved with the intermediate rolling and finally the finish roller removes the marks and surface defects. Single or multiple rollers can be assigned to the tasks depending on the time available for compaction and the paving rate [1].

In order to achieve the specified density uniformly all over the surface, a plan for compaction is required. This plan is called rolling pattern and should define the quantity of rollers, roller types, rolling sequences, speed, the starting point and number of passes made by each roller. A “pass” is referred to the roller passing over a surface **point** once. The total passes required to cover the whole width of mat being paved is one “coverage”. The rolling pattern the number of coverages required to achieve the target density [1].

The rolling pattern is unique for each project, since the mixture type and properties, lift thickness, environment, underlying surface density and rollers availability vary. Therefore, it is essential to establish a rolling pattern for each project and maintain it while the initial conditions are still valid. For this purpose, a test strip needs to be built at the beginning of each project to simulate the rolling operation using the actual material, thickness, environmental and underlying surface conditions. Then the non-destructive density gauges are used to measure the in-place density after each pass. The data collected helps to find the optimum number of passes for each participating roller to establish the rolling pattern and approximate rolling zone area [2].

### 2.1.2. Roller Types

Mix compaction in field is achieved through use of rollers. The roller drums (wheels) sink to the loose mat due to its weight and create three distinct zones shown in Figure 2. Drum (wheel) moving forward creates shear displacement of aggregate in the mat providing major de-compaction in the front zone, compaction in the middle zone and minor de-compaction in rear zone of contact area. The bearing capacity increases as the mat become denser with subsequent roller passes reducing drum penetration depth which minimizes de-compaction [11].

To do the compaction task in the field several different roller types have been developed to raise the process efficiency. Generally, the asphalt compaction rollers are categorized as:

- Tandem steel rollers
- Pneumatic rollers
- Combination of steel drum and tires

In addition the construction rollers can be classified into static and vibratory rollers in terms of the state of compaction energy they implementation.

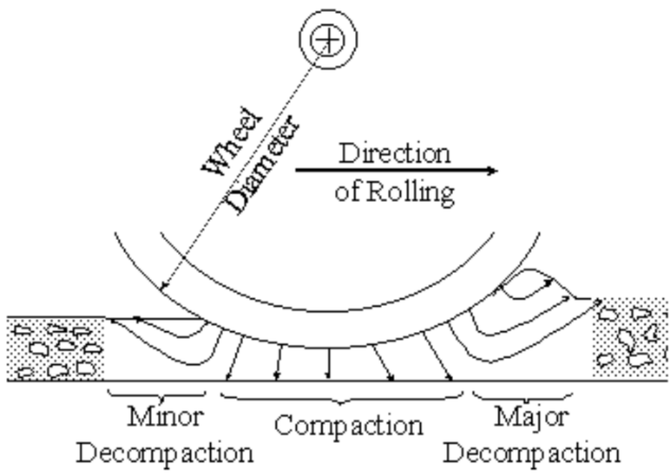
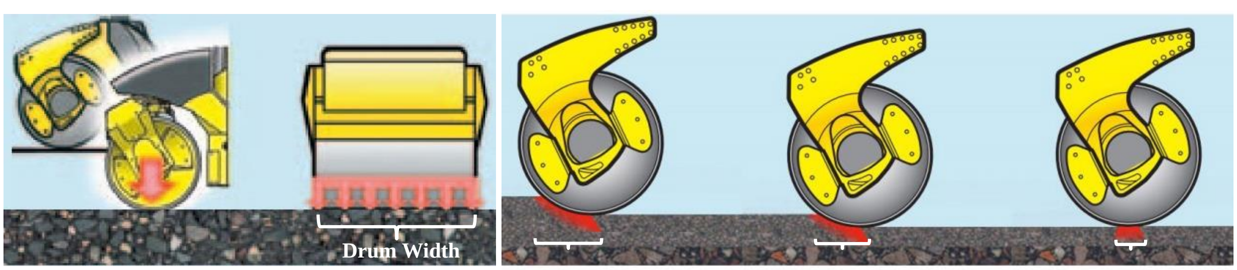



Figure 2 Drum Action

***Static Tandem Roller***

The static tandem steel rollers use their gross weight and possibly add-on loads to press down the mat in order to get the density. The term static indicates the compaction force is due to the static weight of roller. As shown in Figure 3-(a) the exerted compaction force for this type of rollers is expressed in terms of static linear load, which is a factor of roller gross weight, and the width and diameter of the drums. The drum contact area is a narrow band which contracts in length as the loose mat become densified with the subsequent roller passes, see Figure 3-(b) for illustration. As the contact area reduces, the contact pressure on the surface increases [1].



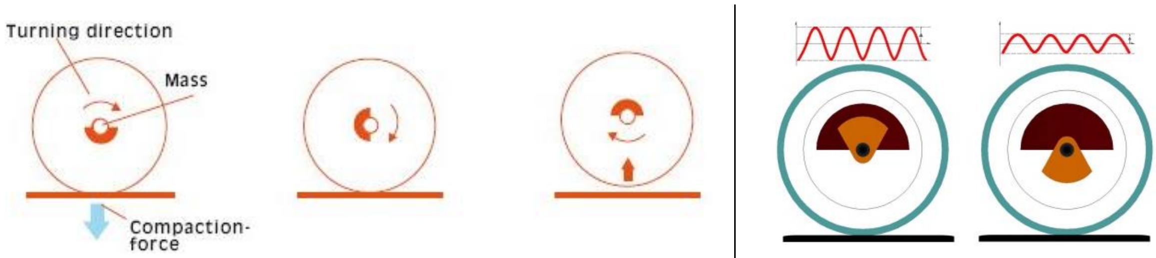

(a) Linear Load (b) Drum Contact Length

Figure 3 Static Tandem Roller (BOMAG)

***Dynamic rollers***

Traditional dynamic rollers have either one or two drums with a system of eccentric weights spinning around the center shaft. The centrifugal force created by the spinning eccentric weight(s) causes vertical displacement of the drum. In fact, drum in vibratory mode not only rolls over the mat but it also beats the surface. Dynamic compaction can greatly improve the compaction results. The vibration helps the aggregate to relocate and reorient to find a denser configuration. Moreover, because of the impact action due to drum vertical displacement the compaction force increases considerably.

Figure 4-(a) shows the mechanism used in traditional vibratory rollers. These type rollers normally come with a single circular exciter at the center of the drum. Spinning the exciter at high speed induces vibration in the drum. The vibration frequency or in other words the time period between two drum's impacts can be controlled by changing the exciter spinning speed. Counter weights shown in Figure 4-(b) might be used to adjust the magnitude of the impacts.




(a) The Exciter Full Cycle (b) The Counter Weight Action

Figure 4 Traditional Vibratory Rollers (HAMM)

The later generation of vibratory rollers takes the advantage of a new vibration mechanism often known as directed vibration. Figure 5 displays the directed vibration mechanism. Such systems use two counter-rotating eccentric weights. The magnitude of the centrifugal force reaches its maximum peak when the two weights spin in the same direction. They can also balance each other out if rotated at opposite direction. Directional systems are also capable of adjusting the vibration magnitude, within the minimum and maximum, by changing the orientation of the whole vibration system. As the system orientation deviates from the vertical axis, the produced centrifugal force breaks down into horizontal and vertical vectors reducing the magnitude of the vertical impact. The horizontal vibration improves the surface finish. The ability to adjust the vertical magnitude of vibration increases the roller versatility on variety of projects with different compaction requirements [15].

Despite all the benefits associated with vibration, it comes with two problems. First, the drum loses contact with the surface between consecutive impacts. Second, the surface marks created by drum impacts, especially when operating the roller at high vibration amplitude. To solve these issues oscillatory rollers were introduced.

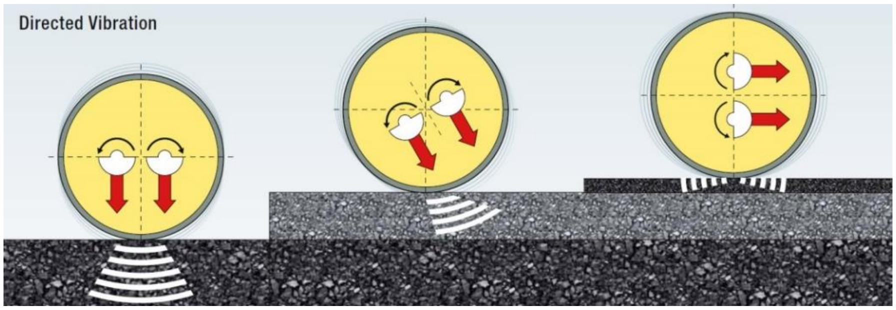
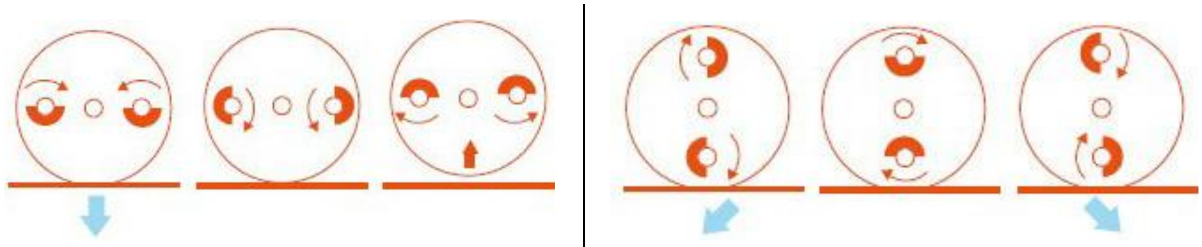



Figure 5 Directed Vibration (BOMAG)

Figure 6, compare oscillation and vibration mechanisms. Oscillation only induces horizontal displacements of the drum but it keeps the drum in contact with the surface all the time. Compared to the vibratory rollers, oscillatory rollers can greatly improve the surface finish but their compaction influence depth is shallower [15].



(a) Vibration Mechanism

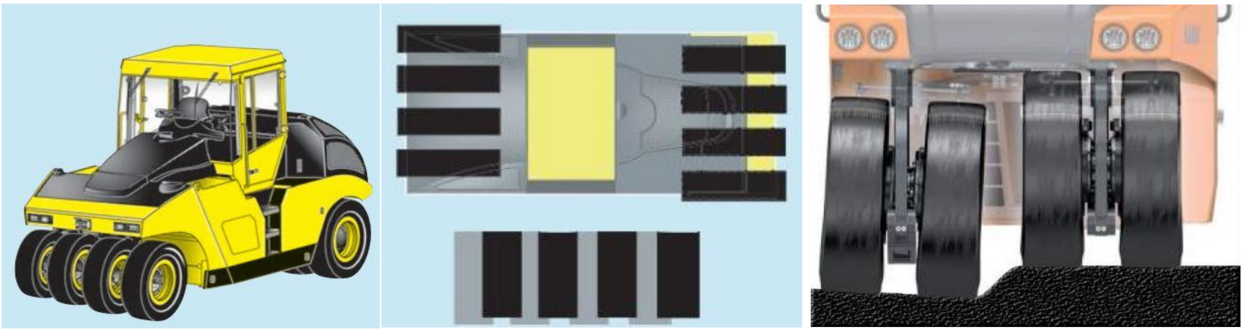
(b) Oscillation Mechanism

Figure 6 Comparison of Vibration and Oscillation (HAMM)

All dynamic steel wheel rollers can also be operated in static mode, therefore they can be used for all phases of compaction process.

***Pneumatic Tire Roller***

The pneumatic rollers, in Figure 7-(a), generally serve as the intermediate roller operating behind the break down roller. The rear tires are shifted to cover the areas not compacted by the front wheels, see Figure 7-(b) for illustration.



(c) Pneumatic Roller

(d) Tires Formation

(e) Tires on Uneven Surfaces

Figure 7 Pneumatic Tire Roller Illustration

The compaction force of the pneumatic rollers is applied by tires; the compaction energy is a factor of roller gross weight, tire pressure and tire design. As displayed in Figure 7-(c), unlike the steel drum rollers where the solid cylinder will bridge over hollow areas the tires act independently allowing compaction of the mat on uneven surfaces. Pneumatic rollers produce higher uniformity in density, improved surface sealing and superior aggregate orientation. The space between wheels provides room for the aggregate to move and reach a more stable orientation. Figure 8 displays the influence fields of the tires.

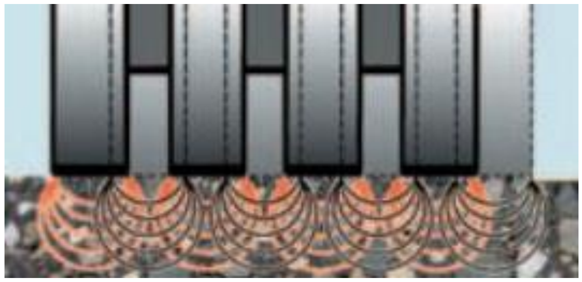


Figure 8 Front and Rear Tires

## 2.2. INTELIGENT COMPACTION (IC)

In mid-1980s a compaction documentation system (CDS) was introduced in Sweden. CDS task was to keep track of rolling operation. There was no sensor used in CDS and all of the records including lane change, direction change and number of passes, beginning and the end of rolling zone were to be entered into the system by the operator [16]. Since this beginning, the technology in this area has come a long way. Today, according to the Federal Highway Administration (FHWA), IC is a technology which acquires real-time kinematic global positioning system (GPS), continuous compaction control (CCC) device and onboard real-time display of IC parameters to improve the compaction uniformity. IC records compaction measurements including number of roller passes, roller integrated measurement value (ICMV), GPS location of the roller, roller vibration parameters and surface temperature profile. Based on the information provided by the IC on the display screen, operator can either manually, or let the IC automatically, adjust the roller operation for optimum performance. Roller pass count mapping on the operator screen allows the operator to match the rolling pattern accurately and assure the compaction uniformity [17].

### 2.2.1. Monitoring Roller Location

Operating roller back and forth for hours, while at the same time keeping track of the number passes, coverages and the rolling zone limits is challenging and prone to human error. This leads to non-uniform compaction and finally causing non-uniformity in the density of the surface being compacted. To solve the issue, GPS was integrated into the IC in order to provide the operator with a real time mapping of the roller passes on the mat. Using the map, operator can assure to make equal passes all over the surface. In addition, if the surface density can be estimated in real time then the operator will be able to modify the roller pattern to achieve the highest uniformity in the density [18].

*Introduction to GPS application*

A global positioning system (GPS) is a system comprised of three segments: space, control and user. The space segment is a constellation of minimum 24 operational satellites. At least 4 operational satellites are place in each of the 6 orbital planes. This arrangement allows 4 to 10 satellites being accessible from any place on the earth. Each satellite transmits a unique identifying signal containing its location coordinates as a function of time generated by a high precision atomic clock. The control segment of the GPS includes one master control station (MCS) located at Schriever Air Force Base at Colorado, USA and also operational control segments (OCS) around the world. OCS units are distributed around the world in a way that each satellite can be monitored from at least two OCS simultaneously. Each satellite passes over an OCS twice a day. The OCS units monitor the satellite location and compare it with the information received from the satellite. MCS collects this information from the OCS units around the world and update the atomic clock on the satellite accordingly. Finally, the user is anyone or any object that uses a GPS antenna and a GPS receiver to find its location [19].

Once a GPS antenna is connected to at least three satellites, the receiver analyzes signals from each satellite to measure the satellite distance from the antenna location, Figure 9. Knowing the satellite locations and the distances of the desired point to each of the satellites, it is possible to find the location using the resection concept. The resection concept is a geometrical method commonly used in surveying to find a position on a map based on the grid azimuths of two or more well-defined locations.

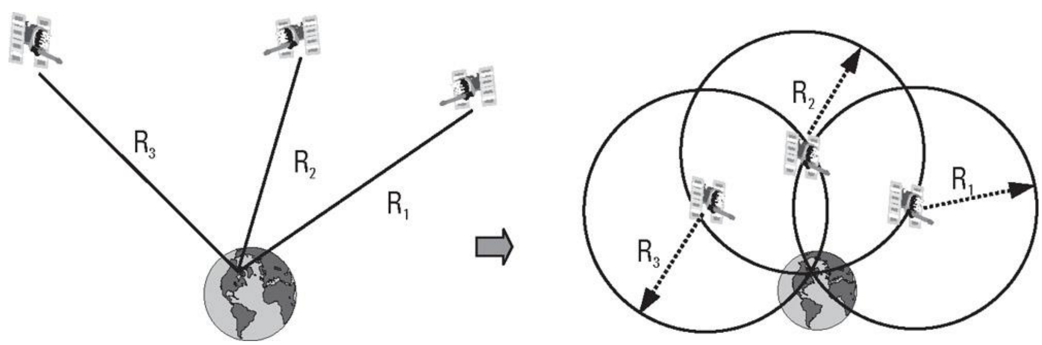



Figure 9 the Basic Idea of GPS Positioning [19]

GPS devices fall into four categories based on their precession. The “Autonomous” type includes devices with a horizontal precession tolerance around 10 to 15 meters. “DGPS” devices present a relatively higher accuracy with an error tolerance ranging from 0.5 to 4 meters. “Float” devices’ error is maximum a meter. The highest level of accuracy is gained the “Fixed” type which has an error range of 1 to 3 centimeters [17].

Point positioning or autonomous positioning involves a GPS device which simultaneously tracks four or more GPS satellites to find its location, Figure 10.

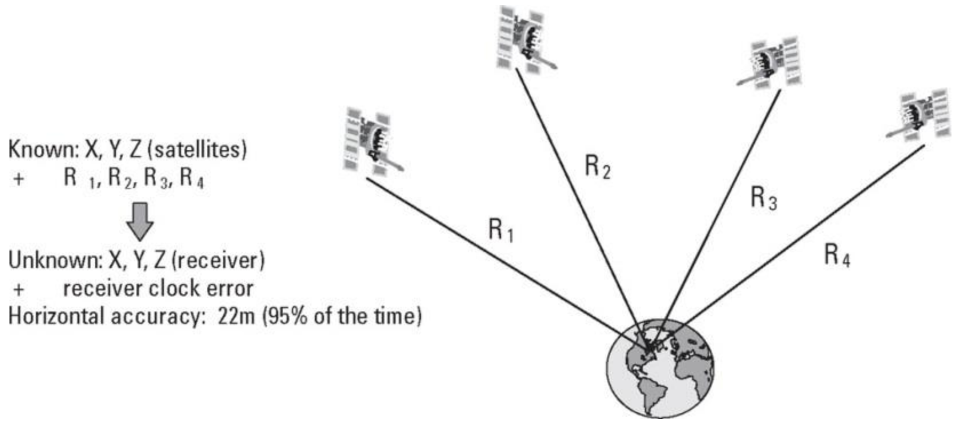



Figure 10 Autonomous Positioning [19]

Relative positioning or differential positioning is the technique used by the fixed type GPS. It involves two or more GPS receivers simultaneously tracking the same satellites to find their relative coordinates. One of the receivers serves as stationary reference fixed at a location with precisely known coordinates. The location of the other receiver known as the rover or remote receiver, is desired. The rover coordinates are determined relative to the stationary reference using measurements recorded simultaneously at the two receivers [19].

For the purpose of mapping roller passes on the mat surface, both high level of data precession and real-time positioning are required. The solution to these requirements is Real-Time Kinematic (RTK) GPS [17]. RTK is a mode of relative positioning where remote station is traveling. The positioning measurements are done in real-time instead of gathering satellite signals for a specific period of time and then taking them to a computer for post calculations in order to produce maps. Shorter signal reception time for a traveling remote station, compared to a static one, reduces the data accuracy from millimeters to few centimeters [19]. The RTK GPS operation is demonstrated in Figure 12.

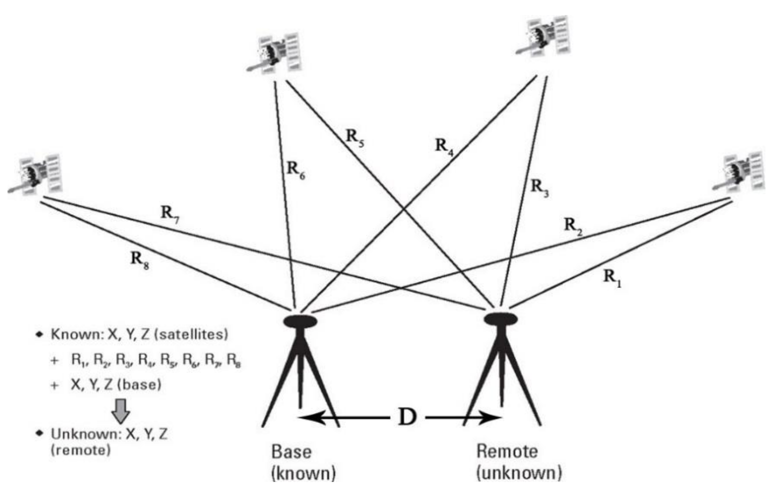



Figure 11 Relative Positioning [19]

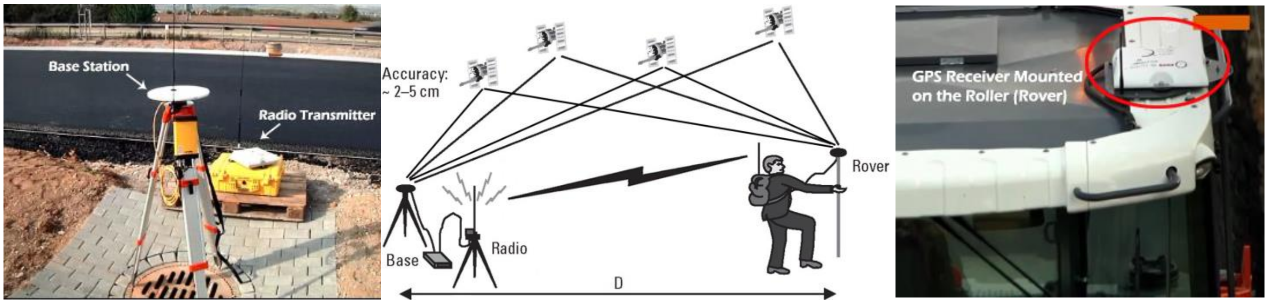



Figure 12 RTK Demonstration (HAMM), [19]

It is essential for the remote station to stay within 2 miles of the base station and also the line of the sight between the two stations must be almost obstacle free. If the connection between the two stations is lost then the GPS configuration simply demotes to "Autonomous" mode [17].

## SECTION 2: COMPUTER VISION APPLICATION

Developing a cost effective, accurate and self-sufficient solution for roller path mapping is analogues to the research in the field of robotics and autonomous vehicles. The literature presented here discusses the science and technology used in robotics for mapping.

### 2.3. PERCEIVING THE ENVIRONMENT

Perception and localization often rely on each other. Building a map is constructing a presentation of the environment. Once the environment is perceived, the robot can match the information with the preset map for localization. There are also situations where the robot constructs the map and localize itself at the same time. It is called simultaneous localization and mapping (SLAM) [38]. The first step in mapping is perceiving or sensing the environment. Sensors in robotics are classified as proprioceptive and exteroceptive. Proprioceptive sensors provide information about internal state of the machine such as the position of the wheels. The exteroceptive sensors acquire information from the surrounding environment such as the spatial information or the colors [39].

#### 2.3.1. Vision Based Methods

Images are detailed, accurate and compact sources for automated data collection [45]. Development of cheap digital cameras and high capacity storage devices has made images and videos great means for progress measurement, claim reports, safety and training on construction sites [40]. Computer vision (CV) is defined as the field of techniques for acquiring, processing, analyzing, and understanding images and, in general, high-dimensional data from the real world in order to produce numerical or symbolic information. A general idea in development of this area has been to mimic the ability of human vision by electronically perceiving and understanding of a scene [46]. In terms of application in construction field, CV has become quite popular as it provides the opportunity to collect a vast amount of data from site videos and images. For instance, CV has been used in construction progress monitoring defect detection, automated image retrieval and productivity measurements [40]. Some other instances of using CV in civil engineering includes pavement distress surveying [47], health monitoring of structures [48], strain measurement of loaded samples [49], structural assessment of underground pipes [50], movement of sediment particles [51] and many more.

With regard to vision perception, currently three major categories monocular, omnidirectional and stereo vision systems are available. Both monocular and omnidirectional vision systems have a single camera whereas the stereo vision systems use two cameras. The omnidirectional and monocular systems can only generate 2D information. In monocular systems the camera is placed horizontally which results in a view field less than 180 degrees. In omnidirectional vision systems, to achieve a 360 degree field of view, the camera is mounted vertically pointed upward at a convex mirror [52]. Comparing to the monocular images the retrieved images by omnidirectional cameras have lower resolution. On the other hand, the stereo vision systems are inspired by human vision and use a pair of images from two specially mounted cameras to perceive the world in 3D [53].

Monocular vision is mainly used for landmark recognition. Landmarks are environmental features that are familiar to the machine and will be used as navigational aids. Once a land mark is detected the machine will be able to approximate its current location. This approach is called selective visual attention landmark recognition (SVALR) and is frequently used in vision based autonomous robots [54]. Vision based robots' architecture consists of five essential components:

- **Maps**: The system needs some internal knowledge of the surrounding environment in order to perform tasks. A sequence of images can be used to automatically generate a 2D CAD geometric representation of the machine path.
- **Data Acquisition**: The system captures the surrounding environment using a camera.
- **Feature extraction**: Significant features such as edges, texture and colors can extracted from images.
- **Land mark recognition**: The system looks for matches between the extracted features and the expected landmarks based on the predefined criteria.
- **Self-localization**: The self-localization algorithm calculates the robot's current position relative to the detected land mark and its earlier position in real time.

## 2.4. IMAGE PROCESSING

Image processing which normally refers to digital image processing is the process of analyzing digital images or video frames using a computer to produce either manipulated images or extracting a set of desired characteristics or parameters. Image processing can be used wherever visual information are needed. Examples of image processing applications are in quality control for counting particles and measuring the size distribution, in many medical diagnosing such as tomography, exploring dynamic processes such as plant growth in botany, in climatology to study the cloud patterns and so on [55]. In CV image processing is used for feature extraction. Some of the popular techniques and tools used in image processing for feature extraction are discussed in the following:

### *Edge Detection*

In processing images, edge is a collection of points where an abrupt change in pixels' intensity occurs. Therefore edges can be detected by taking partial derivatives from an image function with regard to x and y axes. In other words, a change in the image function can be described by a gradient that points toward the largest growth. To detect an edge, the behavior of the image function is investigated within the neighborhood of the target pixel. An edge is a vector variable with magnitude and direction components.

Various different operators including: Roberts, Laplace, Prewitt, Sobel, Robinson and Kirsch have been used for edge detection. The Roberts operator is very simple and easy since it only investigate a 2x2 pixel neighborhood for edge. The Laplace operator is very popular and uses second derivative. Therefore it is only based on magnitude and not direction. Prewitt operator uses the first derivative and estimates the gradient in different directions to find the greatest magnitude. Sobel operator is often used to estimates edges in horizontal and vertical directions [56].

Canny [57] introduced a computational approach to edge detection, Figure 13. The algorithm is optimal for step edges. The performance of the detector depends on detection criterion, localization criterion and one response criterion. Detection criterion determine which edges are important. Localization criterion minimizes the distance between the actual and the detected edge. Lastly, the one response criterion determines a unique response to the detected edge. Canny algorithm uses Laplace operator which is based magnitude and not direction.

Figure 13 Canny Edge Detection at Two Different Scales [57]

### *Segmentation*

Segmentation divides an image into regions where there are a strong correlation with the objects or areas of the real world captured in the image. There are complete and partial segmentation. In complete segmentation, the problem is looking for contrasted objects plotted on a uniform background. In partial segmentation, the image is divided into separate homogeneous regions based on a sectioning criterion such as brightness, color, reflectivity, texture, etc [57].

### *Hough Transform*

Hough transformation is a segmentation tool that can be used to find an object in a scene when the object's shape and size are known. This technique is particularly helpful for feature extraction [57].

### *Region of Interest*

Region of interest (ROI) is a technique that saves time and increases the productivity of the computation process by only analyzing that part of image that contain useful information [57].

## 2.5. SIMULTANEOUS LOCALIZATION AND MAPPING

Simultaneous localization and mapping (SLAM), is the method used by mobile robots placed in an unknown environment to incrementally construct a consistent map of this environment and simultaneously marking its location on the map being developed [58]. SLAM consists of multiple parts; Landmark extraction, data association, state estimation, state update and landmark update. The formulation of the SLAM problem and the solution are discussed in the following:

### *SLAM problem*

Figure 14 shows a mobile device moving through an environment and taking relative observations of a number of unknown landmarks using a sensor attached to the device.

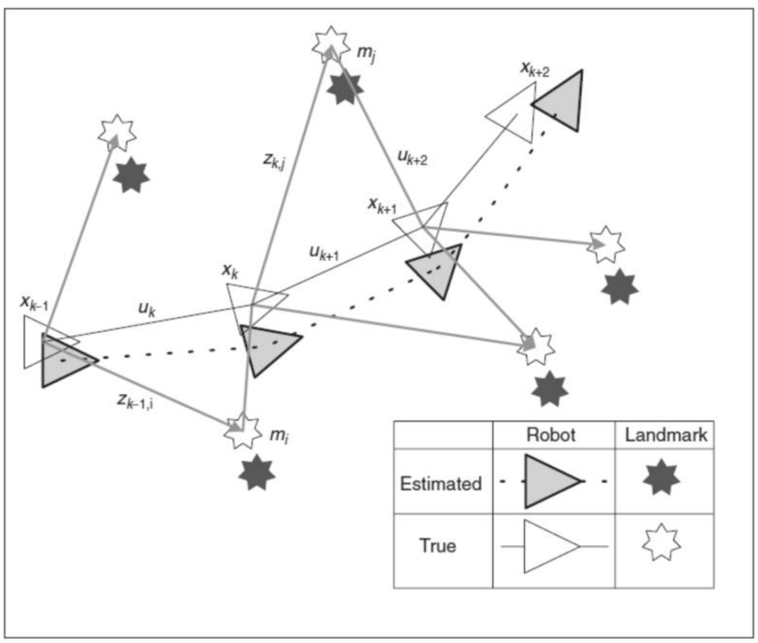



Figure 14 SLAM Problem [58]

$x_k$ : The state vector describing the location and orientation of the mobile device
$u_k$ : The transit vector, applied at time $k-1$ to transfer the mobile device to a state $x_k$ at time $k$.
$m_i$ : Vector describing the location of the ith landmark whose true location is assumed time invariant

$z_{ik}$ : An observation of the location of the ith landmark, taken from the mobile device at time $k$. If there are multiple landmark observations at any one time or when the specific landmark is not relevant to the discussion, the observation will be written simply as $z_k$

The history of data is also recorded in form of series:

$\mathbf{X}_{0:k} = \{\mathbf{x}_0, \mathbf{x}_1, \cdots, \mathbf{x}_k\} = \{\mathbf{X}_{0:k-1}, \mathbf{x}_k\}$
$\mathbf{U}_{0:k} = \{\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_k\} = \{\mathbf{U}_{0:k-1}, \mathbf{u}_k\}$
$\mathbf{m} = \{\mathbf{m}_1, \mathbf{m}_2, \cdots, \mathbf{m}_n\}$
$\mathbf{Z}_{0:k} = \{\mathbf{z}_1, \mathbf{z}_2, \cdots, \mathbf{z}_k\} = \{\mathbf{Z}_{0:k-1}, \mathbf{z}_k\}$

### *Probabilistic SLAM*

In probabilistic form of SLAM, the probability distribution of $P(x_k, m|Z_{0:k}, U_{0:k}, x_0)$ must be computed for all times $k$. The process can start with an estimate for the distribution of $P(x_{k-1}, m|Z_{0:k-1}, U_{0:k-1})$ at time $k-1$, the joint posterior and the next system state $u_k$ and observation $z_k$ are computed using the Bayes' theorem. To perform the analysis, a state transition model and an observation model are defined. The observation or the measurement model $P(\mathbf{z}_k|\mathbf{x}_k, \mathbf{m})$ describes the probability of making an observation $\mathbf{z}_k$ with known location of the mobile device and the landmark. The motion or the transition model $P(\mathbf{x}_k|\mathbf{x}_{k-1}, \mathbf{u}_k)$ describes the change in the system state [58].

The formulated probabilistic SLAM problem is a standard two-step recursive (sequential) estimation (time-update) presented in Equation 1 and correction (measurement-update) by Equation 2.

<u>System state based on time-update</u>

$$P(\boldsymbol{x}_k, \boldsymbol{m}|\boldsymbol{Z}_{0:k-1}, \boldsymbol{U}_{0:k}, \boldsymbol{x}_0) = \int P(\boldsymbol{x}_k|\boldsymbol{x}_{k-1}, \boldsymbol{U}_k) \times P(\boldsymbol{x}_{k-1}, \boldsymbol{m}|\boldsymbol{Z}_{0:k-1}, \boldsymbol{U}_{0:k-1}, \boldsymbol{x}_0) dx_{k-1} \qquad \text{Equation 1}$$

<u>Measurement update</u>

$$P(\boldsymbol{x}_k, \boldsymbol{m}|\boldsymbol{Z}_{0:k}, \boldsymbol{U}_{0:k}, \boldsymbol{x}_0) = \frac{P(z_k|x_k, m) P(\boldsymbol{x}_k, \boldsymbol{m}|\boldsymbol{Z}_{0:k-1}, \boldsymbol{U}_{0:k}, \boldsymbol{x}_0)}{P(\boldsymbol{z}_k|\boldsymbol{Z}_{0:k-1}, \boldsymbol{U}_{0:k})} \qquad \text{Equation 2}$$

### *Solutions to the SLAM Problem*

Solutions to the SLAM problem must provide appropriate presentation for both observation and motion models, efficient computation of prior and posterior distributions. So far the best solution is provided by extended Kalman filter (EKF). The extended Kalman filter (EKF) is the heart of SLAM process [58].

Kalman filter (KF) is an optimal linear estimator. KF consists of an algorithm for recursively estimating the state of a dynamic system from noisy measurements. The filter combines all available measured data, plus any prior knowledge about the system and the measuring devices to make an estimate of the variable of interest with minimized statistical error [38]. To illustrate the KF algorithm, assume a measurement describing the system state partially or entirely is available at least on an intermittent basis. The current and the last system state or measurements are denoted with time $t_k$ and $t_{k-1}$. $x$ and $z$ are system state and measurement. For a linear system:

$$\begin{cases} \underline{\hat{x}}_{k+1} = \varphi_k \underline{\hat{x}}_k + G_k \underline{w}_k \\ \underline{z}_k = H_k \underline{x}_k + \underline{v}_k \end{cases} \qquad \text{Equation 3}$$

Where:

$\underline{\hat{x}}_k$= State vector estimate at time $t_k$

$\Phi_k$ = Transition matrix (relates $\underline{x}_k$ to $\underline{x}_{k+1}$)

$G_k$ = Process noise distribution matrix (transforms the $\underline{w}_k$ vector into the coordinates of $\underline{x}_k$)

$\underline{w}_k$= Disturbance sequence or process noise sequence

$z_k$ = Measurement at the time $t_k$

$H_k$= Measurement matrix or observation matrix (relates $\underline{x}_k$ to $\underline{z}_k$ in the absence of measurement noise)

$\underline{v}_k$= Measurement noise sequence

Kalman filter equations for a linear system are as follows:

$$\mathit{System\ Model} \begin{cases} \underline{\hat{x}}_{k+1} = \varphi_k \underline{\hat{x}}_k & \mathit{Predict\ State} \\ P_{k+1} = \Phi_k P_k\ \Phi_K^T + G_k Q_k G_k^T & \mathit{Predict\ Covariance} \end{cases} \qquad \text{Equation 4}$$

$$\mathit{Kalman\ Filter} \begin{cases} K_k = P_k^- H_k^T \left[H_k P_k^- H_k^T + R_k\right]^{-1} & \mathit{compute\ Kalman\ gains} \\ \underline{\hat{x}}_k^+ = \underline{\hat{x}}_k^- + K_k\left[\underline{z}_k - H_k \underline{\hat{x}}_k^-\right] & \mathit{update\ state\ estimate} \\ P_k^+ = [1 - K_k H_k] P_k^- & \mathit{update\ its\ covariance} \end{cases} \qquad \text{Equation 5}$$

Where $Q_k$ is the matrix describing the uncertainty in the system, whereas the $R_k$ matrix models the uncertainty associated with measurements. The developer must develop these matrices based on knowledge of the system and sensors.

Figure 15, displays the KF algorithm. The linear model is split into two groups, the system model and the KF. The system model and KF do not run at the same time. The system model runs at high frequency to report the system state with time. The system model proceeds solely based on time measurements. On the other hand the KF runs when measurements are a both available and acceptable. In that case KF runs after the state has been predicted by the system for that cycle [38].

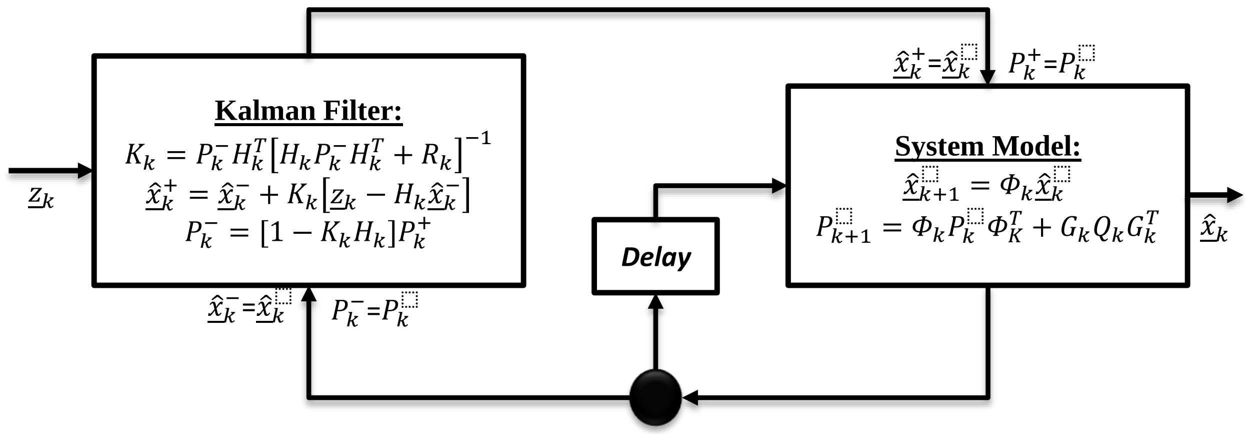



Figure 15 KF Algorithm

Extended Kalman filter (EKF) deals with non-linear motion and observation models [58]. Equation 6 shows the general model for non-linear system state and observation.

$$\begin{cases} \dot{\underline{x}} = \underline{f}(\underline{x}, t) + \underline{g}(\underline{w}, t) \\ \underline{z} = \underline{h}(\underline{x}, t) + v(t) \end{cases} \qquad \text{Equation 6}$$

Where:

*f*, *g* and *h* are vector valued non-linear functions
*w* and *v* are noises

Equation 6 is used to develop the EKF form the KF presented in Equation 4 and Equation 5. In the EKF, the trajectory error estimates are used to update the reference trajectory with time. Equation 7 and Equation 8 describe the EKF [38].

$$\mathit{System\ Model} \begin{cases} \hat{\underline{x}}_{k+1} = \varphi_k \hat{\underline{x}}_k & \mathit{Predict\ State} \\ P_{k+1} = \Phi_k P_k\ \Phi_K^T + G_k Q_k G_k^T & \mathit{Predict\ Covariance} \end{cases} \qquad \text{Equation 7}$$

$$\mathit{Kalman\ Filter} \begin{cases} K_k = P_k^- H_k^T \left[H_k P_k^- H_k^T + R_k\right]^{-1} & \mathit{compute\ Kalman\ gains} \\ \hat{\underline{x}}_k^+ = \hat{\underline{x}}_k^- + K_k\left[\underline{z}_k - h(\hat{\underline{x}}_k^-)\right] & \mathit{update\ state\ estimate} \\ P_k^+ = [1 - K_k H_k] P_k^- & \mathit{update\ its\ covariance} \end{cases} \qquad \text{Equation 8}$$

***Visual Odometry***

Visual odometry or egomotion is the estimation of camera motion. Egomotion is usually the base for recovering the motion and structure in monocular setting. Generally, there are two approaches toward egomotion, feature matching between consecutive frames and tracking features over stack of frames. The earlier method suffers from higher drift rates since it is based on the data from only two images. The feature track over a sequence of frames results in higher accuracy but requires higher computational capacity. To solve this issue a bundle adjustment algorithm that optimize the analysis over a limited number of images is applied. Some other algorithms also use GPS or INS data to reduce the drift [65]. For on road applications with a single camera pointed downward, a planer vision is analyzed which results in reduced degrees of freedom for camera motion estimation and provides improved results. Kitt et al, [65] proposed an algorithm for egomotion estimation solely from monocular image stack. The algorithm reduces the degrees of freedom with the assumption of planarity for the road surface and fixed camera hight. The results shows no significant drift from the true path. Lovegrove et al, [66] used a rear parking camera for visual odometry and demonstrated results close to the ground truth path. He also improved the system accuracy by fusing the visual odometry with GPS.

# Chapter 3: RESEARCH METHODOLOGY

## 3.1. INTRODUCTION

In this chapter first the objectives of the research are defined. Then research methodology will be discussed and finally the proof of concept will be presented.

## 3.2. RESEARCH OBJECTIVES

Despite the importance of roller pass mapping, it has not become popular among the contractors. Mainly because of the high cost of acquisition and the technology used in the packages available in the market. Currently, the only positioning system used for roller tracking is GPS based, which requires on ground labor to set up the base station and assure constant connection between the base and the roller at any time during the operation.

In this study, a relative positioning system is proposed to map the roller position. It is expected that the proposed package can perform the roller track mapping cost effectively and independently. The task includes both hardware setup and software development.

## 3.2. SENSING THE ENVIRONMENT

Different technologies including machine control sensors, GPS, ultra-wideband (UWB), radio frequency identification (RFID) and computer vision based techniques have been used for automated data collections in construction practices [40]. Table 1, summarizes the advantages and disadvantages of the methods described above. The comparison suggests a combination of CV and cheap inertial sensors or GPS to achieve the objectives of this research.

Table 1 Comparison of Tracking Technologies

| | Major Advantage | Major Disadvantage |
|---|---|---|
| Machine Control Sensors | Low cost, do not rely on external sources | Provide limited information of the surrounding environment |
| Dead reckoning sensors | Low cost, do not rely on external sources | Accuracy drops with time and distance, Susceptibility to vibration, |
| ToF based | Accurate range measurement | Incapable of spectral measurements |
| GPS | Accuracy | Expensive for high precision applications, |
| UWB | Reliable tracking data | Requires a network around the site |
| RFID | Low cost | Low range |
| CV | Low cost, Spectral measurement | Accumulated error for tracking |

For self-localization using CV the device needs to detect a land mark and then calculates the device location relative to that land mark. As shown in Figure 16, edges of the lane being paved can serve as the land mark required to find the roller position across the lane.

a) Open Scene, Contrast Between the Old and the New Surface, Distinct Edges

b) Shadow, Relativly Distinct Edges

Figure 16 Paving Lane View from Top of the Roller on Different sites (Taken by GoPro HERO3)

### 3.3. VISION RIG

The rig displayed in Figure 17 was used to capture the real-time roller operator’s vision.

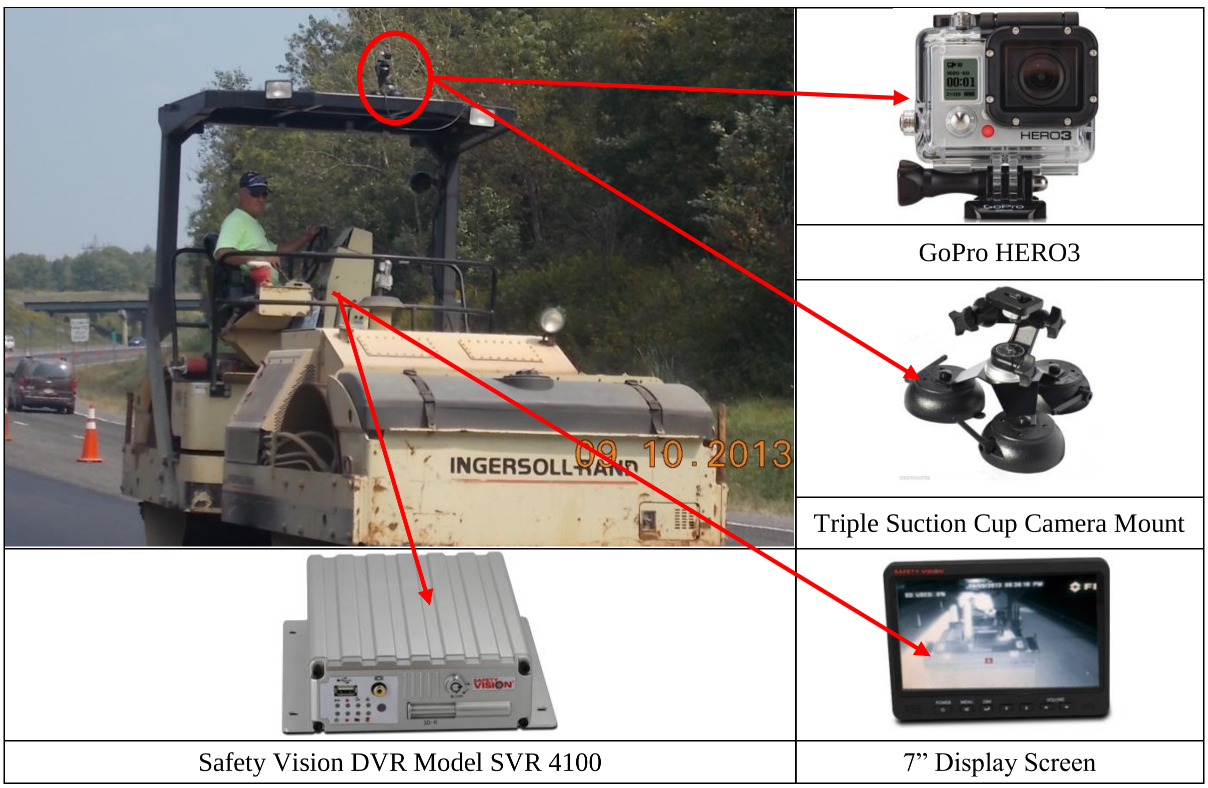



Figure 17 Camera Setup on the Roller

The proposed rig consists of:

1. GoPro HERO3for capturing regular (visual spectrum) images

2. Triple suction cup camera mount which allows adjustments around 3 axis
3. A digital video recorder (DVR) integrated with GPS and accelerometer that records the IR videos and allows input from other sensors
4. A 7" display screen that displays the real time IR view of the surface right behind the roller.

### 3.4. SOFTWARE DEVELOPMENT

Open source computer vision library (OpenCV) is a powerful image processing tool that was used inside the C# programing language to develop the software package in this study. Figure 18, presents a snapshot of the software graphical user interface (GUI).

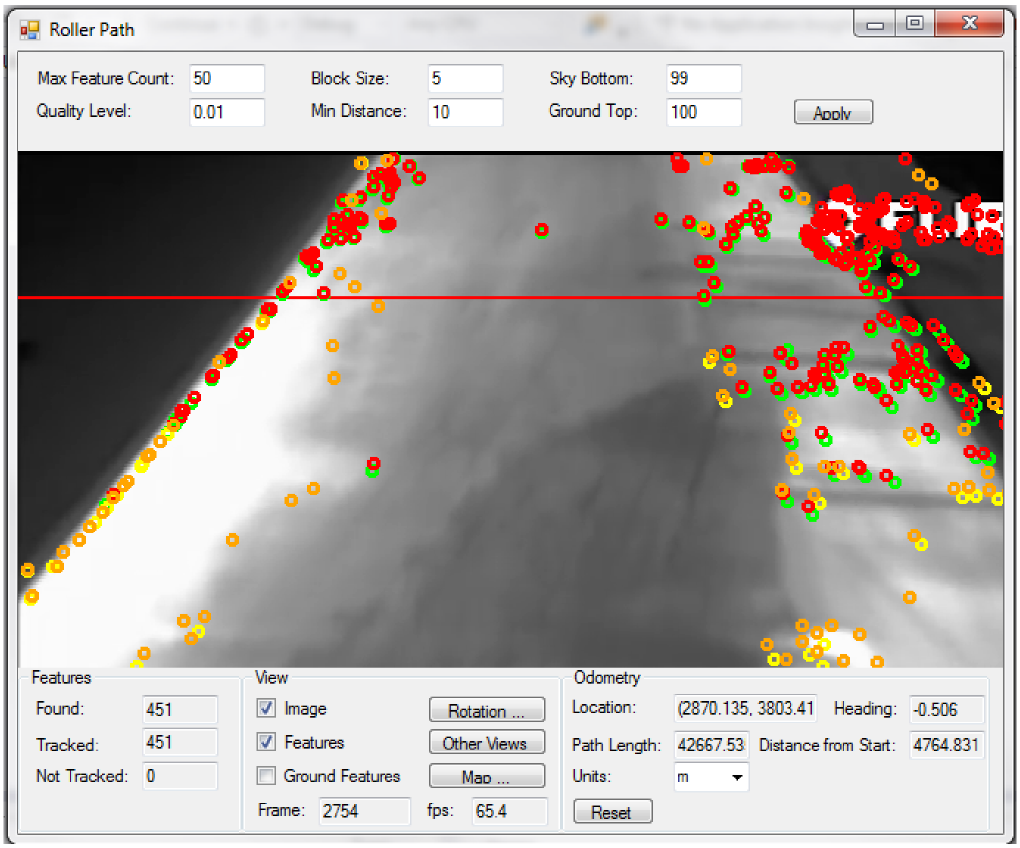



Figure 18 a snapshot of the graphical user interface (GUI)

The software estimates and record the roller location based on the self-localization algorithm described in the previous chapter. These data can be plotted to visually track the roller path on the screen.

### 3.5. EVALUATION OF THE RESULTS

The accuracy of the results and performance of the proposed method must evaluate on the job site. At the time of this report due to the weather considerations in winter, asphalt paving projects are shut down. It is expected that the evaluation results to be available during the month of April 2015.

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