A Vision-Based System to Detect Potholes and Uneven Surfaces for Assisting Blind People

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***Abstract*—Vision is one of the most advanced and important sensory input in humans. However, many people have vision problems due to birth defects, uncorrected errors, work nature, accidents, and aging. The white cane and guide dog are the most widely used means of navigation for the vision-impaired. With advancements in technology, electronic devices have been created using different sensors and technologies to help navigate the blind. Electronic Travel Aids (ETAs) assist in navigating a person by collecting information about the environment and relaying this information in a form that allows a blind or vision-impaired person to understand the nature of the environment. However, there is still a lack of devices to detect potholes and uneven pavements, which inhibits mobility after dark. This pilot study proposes a computer vision based pothole and uneven surface detection approach to assist blind people in meeting their mobility needs. The system includes projecting laser patterns, recording the patterns through a monocular video, analyzing the patterns to extract features and then providing path cues for the blind user. With over 90% accuracy in detecting potholes, the proposed system aims to assist blind people in real-time navigation.**

I. Introduction

Vision is the one of the most advanced sensory systems in humans [1]. Humans depend on vision predominantly, which is detailed and spatially specific, as compared to sound, smell, taste, and touch [2]. However, many people around the world are blind because of various reasons. These include birth defects, uncorrected errors, work nature, accidents, aging, and other. The World Health Organization (WHO) estimates that worldwide there are about 285 million vision-impaired people as of August 2014 [3]. WHO also estimates that around 39 million of the 285 million are blind, with 90% of the vision-impaired are from developing countries [3].

The white cane is the most popularly used tool to navigate in indoors and outdoors by detecting obstacles in and around the person. Also, guide dogs have been used extensively to travel in outdoor environments. Recently, many electronic devices have been created using different sensors and technologies to help blind people navigate. The research community has used sensors such as sound, ultrasound, image processing, and depth sensors to detect obstacles as well as pavement surfaces in the recent past. Most of these sensors were placed on head mounted displays (HMD), body-worn clothes, canes, and other portable devices. These devices can be broadly categorized as [4]: (1) Electronic Travel Aids (ETAs), (2) Electronic Orientation Aids (EOAs), and (3) Position locator devices (PLDs). ETAs assist in navigating a person by collecting information about the environment and relaying this information in a form that allows a blind or vision-impaired person to understand the nature of the environment. ETAs are being popularly used by visually impaired people for navigation purposes. EOAs provide orientation information that would assist traveling or other activities to be performed effectively. PLDs help locate the geographical position of a person. The Global Positioning System (GPS) is a good example.

Our interactions with the vision-impaired, and orientation and mobility specialists suggest that there is a lack of devices to detect potholes and uneven pavements, which inhibits mobility after dusk. To address this issue, we proposed a simple ETA system in [5] that exploits a laser pattern as a source of light, a video camera to record the laser patterns, and a computer vision algorithm to detect the laser patterns and infer the uneven surfaced pavements. The approach uses Hough transform to detect lines and a new feature descriptor to detect potholes and uneven surfaces. In this work, we conduct a pilot study of the proposed system that provides path cues for the blind. With > 90% accuracy in detecting potholes, the proposed system aims to assist blind people in real-time navigation using only monocular vision, thereby reducing cost, complexity and footprint of the system.

II. Related Work

In the development of ETAs, devices were primarily used to detect obstacles on the paths. Sonic-Torch [6], Pathsounder [7], Mowat Sonar Sensor [8], Nottingham Obstacle Detector [9], and Laser Cane [10] were the initial systems developed to detect obstacles. Sonic-Torch [6] is a hand-held device that uses sonar to detect obstacles and provides information about distance and surface texture by modulating the pitch and timbre of auditory signals fed to the user through headphones. The Pathsounder [7] uses a narrow beam (30°) of sonar to detect obstacles by suspending it from the user's neck. The Mowat Sonar Sensor [8] system is a potable device that senses the obstacles up to 4m ahead and informs the user using tactile (vibration) feedback. The Nottingham Obstacle Detector [9] is also a hand-held device similar to Mowat, but provides high-frequency 40 kHz sound pulses (in eight notes) instead of vibration. The Laser Cane detects obstacles based on the reflection of laser light from different objects, where the light receiver has a photodiode to discriminate the reflected light from objects up to 4m. The more recently introduced Sonic Pathfinder [11] finds obstacles using sonar and informs the user of the nearing obstacles through earphones.

With technological advancements, some advanced features have been incorporated into recent ETAs. The Echolocation system [12] uses ultrasonic sensors mounted on eyeglasses to detect obstacles. This system alters the ultrasonic signal intensities and timings to detect the direction and size of the obstacles, and the information is presented to the user through headphones. The Navbelt [13] uses eight ultrasonic sensors, a computer and earphones to detect obstacles in eight directions and information is relayed to the user through earphones. Meijer [14] developed an image-to-sound mapping system that uses eyeglasses with digital cameras to record images, converting them to auditory signals. The image signals are processed using a computer software and are relayed as auditory signals through headphones. Hub *et al.* [15] developed an orientation assisting system for indoor environments in the form of a cane. The device is portable and can be handled similar to flashlight. The system comprises two color cameras to detect color, object and size; and a digital compass, inclination sensor and orientation sensor to determine the position and orientation of the user. The system provides a text-to-speech feature: the characteristics of the objects in the 3D environments can be inquired from by pressing keys and the computer software would analyze and provide the information to the user via a loudspeaker.

Aguerrevere *et al.* [16] developed a portable Pocket PC-based navigation system to assist blind individuals. The system determines the objects based on six directional sonar sensors, whereby a spatial map of objects around the person is created and presented on the Pocket PC. Cardin *et al.* [17] developed a body-worn system to detect obstacles and inform users through tactile actuators placed on shoulders. Ultrasound sensors are used to detect the objects and the information is processed and sent to the wearable system to indicate the objects in the form of vibrations. Gonz´alez-Mora *et al.* [18] developed a system to create a sound map of the environment using eyeglasses, headphones, and a processor. The portable system captures the scenes using two color cameras. The images are then processed to find the depth, texture, and distance, and these are presented in the form of audio signals as feedback to the user. Sainarayanan *et al.* [19] developed an ETA system using a video camera, a headgear, and headphones. Furthermore, a vest was developed to hold a processing unit with rechargeable batteries. The system captures the color video and converts it into to grayscale images. The images are then downsampled to 32×32 images. The pixel images are then classified into either background and foreground (objects) using a fuzzy learning vector quantization (LVQ) neural network. Finally, the processed image is converted into stereo sounds and fedback to the user. Zelek *et al.* [20] developed a system using two cameras, a portable computer and a tactile hand glove with tactile sensors. The system uses a stereovision algorithm to find the depth and a map is created. The map is divided into five sections to provide the presence of objects in five spatial directions through the five actuators located in the hand glove.

Borenstein [21] developed a system called Guidecane to guide the blind people around obstacles. The system consists of a cane with wheels and ultrasonic sensors. The system detects obstacles and steers the cane away to avoid the obstacles. Meers and Ward [22] developed a system using cameras, a GPS receiver, and an electrotactile stimulation to create a depth map. The stimulating information is fedback to the user through tactile hand gloves, which has electrotactile sensors. Johnson and Higgins [23] developed a system consisting of a "tactor" belt with 14 tactile actuators. The system also included two cameras mounted on a waist belt, and a backpack to carry the laptop that processes the visual information. A 2D depth map is first created and then divided into 14 parts to feed the tactile actuators. The actuators provided high frequency vibrations for objects that are closer. The visual information processing included 10 frames/sec using a Matlab stereovision algorithm. Adjouadi [24] developed a computer vision system to detect upright and flat objects, shadows, drop-offs to help blind people navigate. This is achieved by processing the images acquired through two cameras; however, the mode of feedback to the user is yet to be determined. Adjouadi [24] uses path cues such as *safe step*, *obstacle ahead*, *turn left/right*. Yuan and Manduchi [25] developed a laser-based navigation system that can be held in the hand and the idea is similar to the white cane in that when the device is swung, the device alerts the users.

III. Methodology

According to the National Research Council (US) [26], for safe and efficient pedestrian navigation, there are six concepts, which an ETA design should address. They are:

1) Obstacle presence, location, and nature ahead of the traveler, from ground to head heights,
2) Ourface, such as gradient, texture, ups and downs (stairs), sidewalks (kerbs), *etc*,
3) Objects' position and nature along path sides,
4) Relative or absolute direction (such as traffic sounds) and aiming point,
5) Landmarks such as buildings, rooms, elevators, *etc*, and
6) Direction to build a mental map of the environments

From literature, it is evident that of the six concepts listed, limited work has been conducted on providing surface information of the path to the traveler. In this work, we focus on detecting the presence of potholes and uneven surfaces, e.g. stairs and curbs, using a newly developed computer vision algorithm. In addition, the system is targeted for night time scenarios, which is lacking in most of the existing systems.

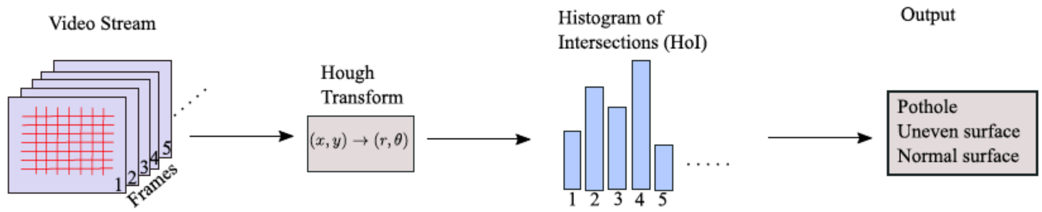

Fig. 1. Overview of the proposed approach to detect potholes and uneven surfaces.

A. Data Collection

Fig. 1 shows the overview of the proposed system. In order to detect uneven surfaces, a camera was used along with a laser to record surface data. Recorded paths included steps, potholes, curbs, small potholes and other surfaces. The experiment setup included two different laser patterns: (1) cross-hair output, as shown in Fig. 2, and (2) mesh (grid) output, as shown in Fig. 3. The camera was mounted on a handheld mount such that the angle between the vertical axis and the camera formed was approximately $30-45°$. The distance from the camera to the surface was approximately 0.5 m. The laser was mounted on top of the camera to project patterns.

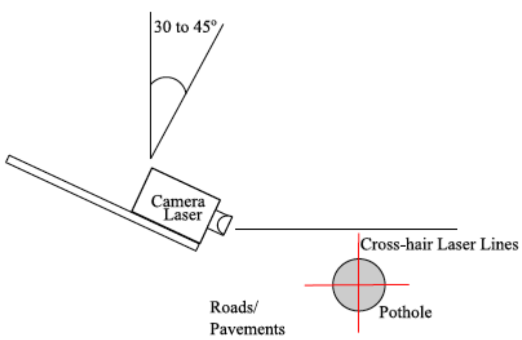

Fig. 2. Cross-hair laser pattern to detect pothole and uneven surfaces.

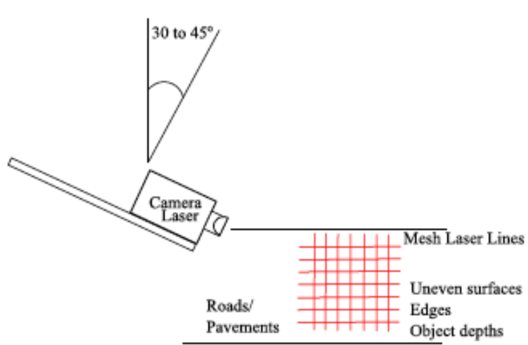

Fig. 3. Mesh laser pattern to detect pothole and uneven surfaces.

B. Feature Extraction

The underlying phenomenon to detect uneven surfaces is based on analyzing the recorded laser patterns. For example, a cross-hair pattern has four intersecting lines and when the same pattern in projected on a pothole, the intersection points break or fade depending on the pothole depth and size. Thus, it is important to detect lines and intersecting points in the image space.

1) Preprocessing: Let $I(x, y; t)$ denote a video frame at time t, where $I(x, y)$ represents a particular pixel of the frame. A video frame creation introduces noise in the frame due to scatter effects, color sensors, recording media, quantization errors, and management and storage of the data [27]. These noises usually result in blurred video frames. To deblur and also to strengthen the laser projected lines, a “bilateral” filter with $\sigma_d = 5$ and $\sigma_r = 10$ was used to preserve edges and simultaneously reduce variations in (laser) color pixels. In other words, a bilateral filter would enhance the sharpness of the video frames while protecting the edges from being deblurred.

2) Hough Transform: The next logical step is to detect the laser projected lines and the Hough Transform [28], [29], [30] is implemented for this task. The Hough transform aims to find lines passing through $(x_i,\ y_i)$ in an image space by using the parameters $(\rho,\ \theta)$ in the parametric space. The cartesian parameters and (r, θ) denotes the parameters in polar coordinates. A line in the cartesian coordinate can be represented as:

$$y = mx + c, \tag{1}$$

where m is the slope of the line and c is the intercept. The 2D line can be expressed in the polar coordinates as:

$$y = -\frac{\cos\theta}{\sin\theta}x + \frac{r}{\sin\theta}, \tag{2}$$

which can be rewritten as:

$$r = x\cos\theta + y\sin\theta. \tag{3}$$

Using (3), for a point (x_i, y_i) one can find the family of lines passing by varying parameters (ρ, θ). This results in an *accumulator* matrix or grid of ρ along the abscissa and θ along the ordinate axes of the parameter (Hough) space. Suppose $m, n \in \mathbb{R}$ represent the number of rows and columns of a video frame $I(x, y; t)$, the maximum value of ρ will be the diagonal length across the frame, i.e., $\rho \in [-\rho_{max}, \rho_{max}]$, where

$\rho_{max} = \sqrt{m^2 + n^2}$, and $\theta \in [0, \pi]$ degrees. The output from the Hough transform provides a number of lines intersecting at any point (x, y) of $I(x, y)$ in the form of accumulator matrix (ρ, θ), where each ρ and θ combination indicates the number of intersecting sinusoidal lines present in the image space. The ρ and θ combinations with peak values indicate the presence of straight lines in the image space.

3) Histogram of Intersections (HoI): In order to detect potholes and uneven surfaces, the intersecting points obtained from the Hough transform are binned to create a histogram for each frame. We dub this feature as *Histogram of Intersections (HoI)*. This HoI serves as the prime feature descriptor. Let $(\rho, \theta)^T = \mathbf{R}_\theta = [n_i, n_{i+1}, \cdots, n_N]$ where $n_i \in \mathbb{R}$ indicates the number of lines intersecting for ρ_i, θ_i combination. HoI can be expressed as:

$$H_t = \sum_{i=1}^{N} \mathbf{R}_\theta{}^T \mathbf{Q}, \tag{4}$$

where $\mathbf{Q} = [q_i, q_{i+1}, \cdots, q_N]$, $q_i \in \mathbb{R}$ is a row vector indicating the threshold values that determine as to which elements of an accumulator matrix considered, and t indicates the HoI for a particular frame. For a video of v frames, the HoI will be:

$$\text{HoI} = \mathbf{H} = [H_1, H_2, \cdots, H_v]^T \tag{5}$$

4) Learning and Classification: Once the feature descriptor corresponding to potholes/uneven surfaces is extracted, the system is designed to learn a model in order for it to identify safe and unsafe paths. Model learning from the HoI is performed by employing the Gaussian Mixture Model (GMM) technique. Using GMM, a model is learned that establishes a nonlinear relationship between the number of intersecting points and the type of event encountered. The rationale behind using GMM is that the system is designed to accommodate tolerance in establishing the relationship between input features and the output; establishing a linear regression would impose a hard threshold, which is not suitable in many practical scenarios. A GMM consists of a finite number (K) of convex combination of Gaussians to form a parametric probability density function. A GMM can be represented as [31]:

$$p(\mathbf{x}|\theta) = \sum_{i=1}^{K} w_i \cdot g(\mathbf{x}|\mu_{\mathbf{i}}, \mathbf{\Sigma_i}), \tag{6}$$

and

$$g(\mathbf{x}|\mu_{\mathbf{i}}, \mathbf{\Sigma_i}) = \frac{1}{(2\pi)^{D/2} |\sum_i|^{1/2}} e^{\left\{\frac{1}{2}(\mathbf{X}-\mu_{\mathbf{i}})^T \sum_i^{-1} (\mathbf{X}-\mu_{\mathbf{i}})\right\}}, \tag{7}$$

where X is a visible variable, θ is an assumed parameter of the model, $\sum_i w_i = 1$ and $0 \geq w_i \leq 1$, K is the number of mixtures, $g(\mathbf{x}|\mu_{\mathbf{i}}, \mathbf{\Sigma_i})$ are the Gaussian components, each Gaussian consisting of D-dimensional vector (D-variate) with mean $\mu_{\mathbf{i}}$ and covariance matrix $\mathbf{\Sigma_i}$. In this study, we have considered two separate cases of laser patterns: (1) cross-hair; and (2) mesh. The system uses a classifier based on the number of intersecting points. To determine the number of intersecting points that form a particular class, the mean value μ_i of the GMM is used to distinguish among different classes. In the case of the cross-hair and mesh laser patterns, four and five classes were realized, respectively. These classes are the *path cues* that will help the user to navigate. More specifically, the path cues for cross-hair and mesh patterns are given by:

$$\text{Cross-hair} = \begin{cases} 1 \leq |\mathbf{H}| < p_1, \text{Pothole detected,} \\ p_1 \leq |\mathbf{H}| < p_2, \text{Pothole possible,} \\ p_2 \leq |\mathbf{H}| < p_3, \text{Be careful,} \\ |\mathbf{H}| \geq p_3, \text{Safe} \end{cases} \tag{8}$$

and

$$\text{Mesh} = \begin{cases} 1 \leq |\mathbf{H}| < u_1, \text{Pothole detected,} \\ u_1 \leq |\mathbf{H}| < u_2, \text{Safe,} \\ u_2 \leq |\mathbf{H}| < u_3, \text{Objects present,} \\ u_3 \leq |\mathbf{H}| < u_4, \text{Objects are closing,} \\ |\mathbf{H}| \geq u_4, \text{Objects ahead} \end{cases} \tag{9}$$

IV. Experimental Setup and Results

The experiment setup for our pilot study, implementation details and discussion on the designed system is presented below.

A. Setup and Data Collection

A GoPro HERO 4 Silver camera mounted on the GoPro's 3-Way mount was used to collect the data. The data was collected in a HD mode (720p: 1280 x 720) and with narrow field of view (FoV). To generate a cross-hair laser projection, we used Edmund Optics' continuous wave, elliptical beam laser Diode (power: 3 mW; wavelength: 635 nm) [32] and a cross-hair. A battery pack (with four AA batteries generating 5V DC via USB) was attached to the laser diode to power the laser diode. Fig. 4 shows the entire setup with the laser, camera, battery pack and mount. To generate a laser grid projection, Ghost Stop's Laser Grid GS1 was mounted on top of camera and the video was recorded. Fig. 4 shows the setup with the camera and laser. The Laser Grid GS1 requires two AA batteries. The algorithms were implemented in OpenCV 2.4 on a Linux machine (Ubuntu 14.04 LTS).

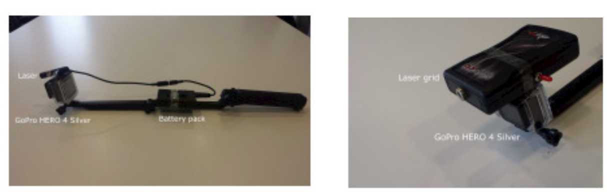

Fig. 4. Experiment setup to generate and collect video data: (a) cross-hair and (b) mesh pattern

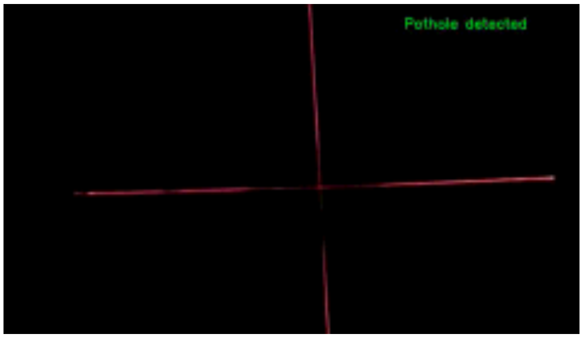

Fig. 5. Results of Experiment 1 using HoI: pothole detected ($|\mathbf{H}| \leq 1$).

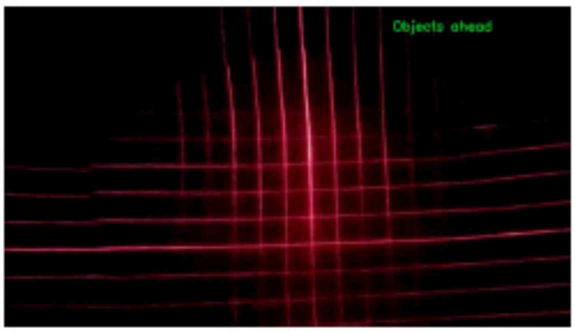

Fig. 6. Results of Experiment 2 using HoI: objects ahead ($|\mathbf{H}| > 121$).

B. Implementation

We conducted experiments using two laser projections: (1) cross-hair; and (2) mesh. An algorithm including the Hough Transform and decision-making was written to process the recorded videos offline. First, the lengths of recorded videos were trimmed to the actual events. Next, using Canny edge detection and Hough Transform, the lines were detected for each (x_i, y_i) by varying the polar coordinate parameters, $r > 0$ and $0 \leq \theta \leq 2\pi$ (with one radian increments). The threshold chosen for the edge detector was based on the domain knowledge. Later, for each frame, the number of intersection based on the HoI were determined. For cross-hair and mesh laser experiments, the variable values of p_i's and q_i's were determined using the GMM model in (6) and (7). The initial number of clusters, which is a parameter to be provided to GMM, was determined based on the combined knowledge of domain expertise and k-means clustering. In other words, k-means clustering was used to find the number clusters with sample videos to determine the number of clusters; furthermore, real-life examples were considered as to how many clusters would be appropriate. In the case of cross-hair experiment, the p_i's were set as $p_1 = 2$, $p_2 = 3$, and $p_3 = 4$, corresponding to path cues *Pothole detected*, *Pothole possible*, *Be careful* and *Safe*, respectively. Similarly, in the case of the mesh laser experiment, the q_i's were set as $q_1 = 10$, $q_2 = 60$, $q_3 = 90$, $q_4 = 120$ to the path cues *Pothole detected*, *Safe*, *Objects present*, *Objects are closing* and *Objects ahead*, respectively. The examples of outputs of Experiment 1 (cross-hair) and 2 (mesh) are shown in Figs. 5 and 6, respectively. Table I shows the accuracy of the proposed approach. Three videos (two cross-hair and one mesh patterns) were tested for pothole detection and the corresponding results show > 90% accuracy. Overall, the experiments from the pilot study achieved over 85% accuracy in classification output and over 90% accuracy in detecting potholes.

TABLE I
ACCURACY OF THE PROPOSED APPROACH ON 3 DIFFERENT VIDEOS IN DETECTING THE POTHOLES.

Dataset (laser pattern)	Detected	Ground truth	Accuracy
Video 1 (cross-hair)	3	3	100%
Video 2 (cross-hair)	2	2	100%
Video 3 (mesh)	9	10	90%

Existing ETAs lack the capability to detect potholes or uneven surfaces. This is mainly attributed to the mode of sensor input i.e. the sensors considered while designing the system. Vision-based system are promising as they closely resemble our human visual system, which is one of the highly developed system in human evolution [1]. Video-based systems such as [22] and [23] endeavor to detect obstacles using two cameras. The use of two cameras to detect obstacles is expensive and also the processing of video information becomes computationally expensive as the system designed has to do twice the amount of work in order to complete any task. For instance, the system designed by Meers and Ward [22] requires a laptop to process video information. In addition, the depth map created is similar to 3D depth map (using a disparity map, similar to our eyes), but with lack of information about surfaces. The system with a laptop becomes bulky and would hamper the mobility aspects, which is one of the primary objective of ETAs. One of the main limitations of the system [22] is that the 3D depth map could be lost if environmental features are less pronounced.

The backpack-based vision system designed by Johnson and Higgins [23] also requires the carry of a computer in the backpack. Here the system uses two cameras attached to the tactor belt, and becomes computationally burdensome (to compute stereo vision). The mobility of a blind person is also impacted because of the backpack. In addition, the system does not provide any information on potholes or uneven surfaces. One of the most closely resembling system was designed by Adjouadi [24], which was designed to detect upright and flat o bjects, s hadows a nd d rop-offs. A gain, t his s ystem uses stereo-vision (two cameras) and homography to map 3D to 2D coordinates. Moreover, the system requires three frames to determine obstacles. In contrast, our system does not require stereovision to compute depth and path cues are indicated to users just by using a single video frame. By this combined advantage, the computational complexity, time, and also the power consumption of the system is greatly reduced. Without the need for carrying any bulky objects such as a laptop, th3 mobility of the user is not hampered. Another advantage of our system is that it can be used during night times, which is lacking in the existing systems.

V. Conclusion

The paper reports on a pilot study conducted to detect potholes and uneven surfaces with the aim to assist blind people in meeting their mobility needs using a computer vision system. This system comprises projected laser patterns and recoding the patterns through a monocular camera, analysis of the patterns to extract features and then the provision of path cues for the blind user. Our approach uses a novel feature descriptor dubbed Histogram of Intersections (HoI) to detect potholes and uneven surfaces. With over 90% accuracy in detecting potholes, the proposed system aims to assist blind people in real-time navigation. One of the primary limitations of the proposed system is that the laser patterns are visible only in dark, i.e., it is suitable for night times only at this stage. Our future work involves investigating suitable laser sources that would provide good contrast in day time as well as at night, and optimal camera distance and angle from the surface, and speed of the video analytics without losing any important information.

Acknowledgements

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