Supporting Drivable Region Detection by Minimising Salient Pixels Generated Through Robot Sensors

Omowunmi Falola
Department of Computer Science
University of Cape Town
Cape Town, South Africa
Email:wunmi.falola@uct.ac.za

Isaac Osunmakinde
Modelling and Digital Sciences Department
Council for Scientific and Industrial Research (CSIR)
P O Box 395 Pretoria 0001, South Africa
Email:iosunmakinde@csir.co.za

Antoine Bagula
Department of Computer Science
University of Cape Town
Cape Town, South Africa
Email:bagula@cs.uct.ac.za
Telephone: +21 650 4315
Fax: +21 689 9465

***Abstract*—The role of robots, automatically guided machines able to perform tasks on their own cannot be over emphasized. In particular, if robotic vehicles are to work effectively, the way they are required to perform their jobs and their ability to reach the desired destination where the job is to be performed are of utmost importance. This necessitates the need to facilitate proper navigational aid for robotic vehicles. Various navigational approaches have been proposed in robotics literature, but this work serves to provide an assistive pre-processing strategy for the detection of drivable region through minimisation of salient pixels in a colour feature extraction. Salient pixels are pixels occupying the non-drivable region particularly those having same grayscale value as road images. Salient pixels provide difficulties during colour feature extraction on road images captured by a robot's camera (sensor). In our method, a stream of road images is captured, pixels are extracted based on a RGB (red, green, blue) colour space, edges of objects are detected using Sobel operator. Salient pixels are minimised using some heuristic which is based on a threshold parameter. In a series of experiments using our method, a stream of real life road images is obtained and results show that good drivable regions, which facilitate proper robotic navigation, can be detected.**

keywords: Robotics, Image Processing, Salient Pixels, and Drivable Region Detection

I. Introduction

In today's world, the role of robots in our everyday activities cannot be over emphasized. Robots have been used in motivating applications for new algorithms and formalism. This is evident in the use of learning in high-profile competitions such as RoboCup and the Defence Advanced Research Projects Agency (DARPA) challenges [5]. The successful completion of a task by a robot is highly dependent on its ability to effectively navigate to the point where the operation or task is to be performed. Consequently, it is important to ensure that a robot, in particular an autonomous robot, with little or no human support or intervention, gets to the desired destination. This is an ongoing key challenge as depicted in Figure 1 and stressed by researchers [10]. An autonomous vehicle intended for driving off-road (e.g., for military reconnaissance) should still be able to identify roads and drive along them when conditions allow, this ability will minimize terrain-based dangers and maximize speed [3]. However, the challenges of salient pixels remain a key issue in detecting drivable region. Salient pixels are the pixels in the non-drivable region sharing the same characteristics as road pixels. These pixels are salient as they are very conspicuous. This provides difficulties in detecting drivable region.

Recognising objects in a complex scene is the purpose of a general image understanding system [2]. This process is carried out effortlessly by the human visual system (HVS). However, it becomes a challenging task when computer vision algorithms are designed to imitate this action. Typically, one of the first steps in such a system is edge detection. Edge detection is the process of identifying and locating areas of sharp transitions (intensity contrast) within an image. Once the edges of an object are detected, other processing such as region segmentation can easily be carried out. Various methods of edge detection are available but the performance of edge detectors depends on the application at hand. Minimisation of salient pixels in a road frame is a sound basis for assisting drivable region detection for autonomous robotic navigation.

(a) Robotic vehicle

(b) A sample road frame for autonomous navigation

Fig. 1. A sample road frame with salient pixels (e.g. houses and vegetation) which provides difficulties in autonomous navigation

In the succeeding sections, we have the following: Section II presents some related work. In section III, we present the methodology used in achieving the main goal of this paper as well as the analytic and theory of the edge detection technique adopted to achieve the desired result. Section IV illustrates experimental results and further evaluate the outcome measures to assess the adequacy of the proposed method. Section V concludes the paper and future work are also presented.

II. Related Work

The need to improve drivable region detection for autonomous navigation has led to the development and emergence of different models, heuristics and methods by different researchers and practitioners. Osunmakinde and Ndhlovu [6] investigated the task of improving the vision of a robot for autonomous navigation in complex environments inclined with flexed far-field (or bent) terrains. They used the Emergent Situation Awareness (ESA) technology as a supportive strategy for autonomous robotic navigation. Experiments were conducted on five flexed terrains (tarred and coarse) including the Council for Scientific and Industrial Research (CSIR) real life road frames captured locally and public road frame collected by a robotic vehicle.

Conner *et al.* [4] developed a method of composing simple control policies, applicable over a limited region in a dynamical system's free space, such that the resulting composition completely solves the navigational and control problem for the given system operating in a constrained environment.

Hong *et al.* [3] investigated a synonymous problem by using a sensor based system developed to identify roads and to enable a mobile robot drive along them. A light detection and radar (LIDAR) sensor, which produces range measurements, and a colour camera are used in conjunction to locate the road surface and its boundaries.

A. Contributions and Outline

In general, a drivable detection system intended for autonomous robots should be capable of effectively integrating data captured at the different navigational layers of the operational system. In a broader research perspective, challenges of salient pixels removal still remain one of the key issues to be addressed in computer vision.

In this paper, we obtain reduced salient pixels in road frames in a series of experiments conducted, for different scenarios, using an edge detection technique and salient pixels reduction heuristic. In particular, the Sobel edge detection technique which gives a good approximation of the image boundaries is adopted in this work. Ultimately, these combined methods are needed by the robot in making a crucial decision for detecting drivable region. The major goals of this paper are as follows:

1) The identification, using Sobel filter, and reduction of salient pixels on road frames in order to assist algorithms for effective detection of drivable regions for mobile robots.
2) Qualitative and quantitative evaluation of the combined methods on a number of road frames in a series of experiments conducted.

III. Proposed Methodology

A. Image Acquisition

A digital image consists of an array (N $\times$ M) of pixels. For the image data in this work, a number of road frames (of different scenarios, down-sampled to 300 $\times$ 227 resolution) were captured and features were computed at each pixel location, P_i. Figure 2 describes the interlinked streams of the functional components of the methods adopted in this paper. This work is a pre-processing strategy which serves as an input to the machine learning algorithm layer in the drivable detection system depicted in Figure 2.

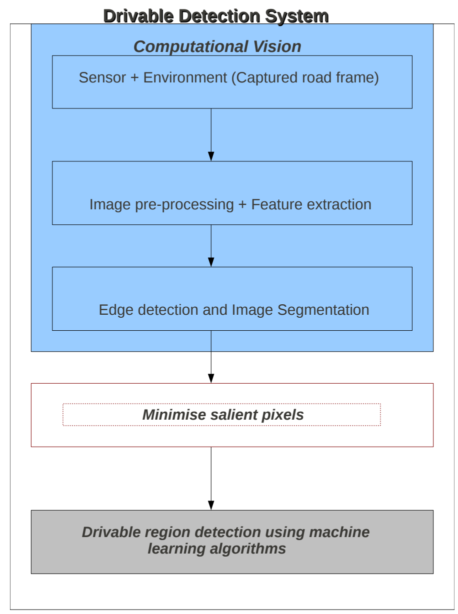


Fig. 2. Overall process of drivable region detection

B. Colour Feature Extraction

Colour is an important component containing a great deal of information. Consequently, it is a highly important property in identifying certain objects in an image. This feature (colour) was chosen, based on some prior knowledge of a road frame as discussed in [3], on the assumption that roads (which have a grey-like colour) would be more-or-less consistent in their mixture of colours. In this work, we use gray level images for further processing after submitting the coloured road frame captured by a digital camera to our drivable region detector software (Laptop Computer- AMD Turion(tm) 64 x2 Mobile Tech TL-50 1.60 GHz-1GB-Operational System: Ubuntu 10.04).

C. Road Frame Edge Detection (Image segmentation)

Edge detection is a task of fundamental importance in image processing. Edge detection serves to identify and locate areas of sharp intensity contrast in an image[1] and contains three steps namely, Filtering, Enhancement and Detection [7]. To determine the edges in an image, one intuitive characteristic one might consider is that the respective brightness values of two neighbouring pixels are significantly different[14].

Edge Detection Techniques: Various techniques for edge detection have been proposed [12]. The majority of the different edge detection methods may be grouped into two categories which are, Gradient and Laplacian.

The Sobel operator is a gradient operator which consists of a pair of 3×3 convolution kernels as shown in Table I. The Sobel operator is applied by convolving the image with a small, separable, and integer valued filter in horizontal and vertical directions and is therefore relatively inexpensive in terms of computations. One kernel is simply the other rotated by $90°$ [9]. The kernels can be applied separately to the image in order to obtain the gradient component in each orientation, say, Gx and Gy.

The gradient magnitude is given as below:

$$|G| = \sqrt{Gx^2 + Gy^2}. \tag{1}$$

Relative to the pixel grid, the angle of orientation (θ) of the edge giving rise to the spatial gradient is given by:

$$\theta = \arctan\left(\frac{Gy}{Gx}\right). \tag{2}$$

TABLE I
SOBEL HORIZONTAL AND VERTICAL OPERATORS

$Mx =$

-1	0	+1
-2	0	+2
-1	0	+1

$My =$

+1	+2	+1
0	0	0
-1	-2	-1

Let $\otimes$ represent the convolution operation to be performed on the image $G(x, y)$ to obtain $G'(x, y)$. The 2-D convolution operation is described below,

$$G'(x, y) = G(x, y) \otimes M(k, l) = \sum_{k=-N}^{N} \sum_{l=-N}^{N} M(k, l) G(x-k, y-l) \tag{3}$$

where

- $M(k, l)$ = convolution kernel (i.e. Sobel horizontal or vertical operator)
- $G(x, y)$ = original image
- $G'(x, y)$ = filtered image .

The convolution operation, $\otimes$, as described above is adopted in the Sobel filter method to convolve the image and it returns uniform value of zero along the edges of the road frame images. This is further exploited during the elimination of salient pixels in the road frame. The Sobel operator is relatively inexpensive in terms of computation and less sensitive to isolated high intensity point variations [11] since the local averaging over sets of three pixels tends to reduce this. Also, it gives an estimate of edge direction as well as edge magnitude at a point which is more informative, as evident in Figure 3, and it has been successfully applied in all the three channels in RGB space [8]. Each of the Sobel masks, Mx and My, is slid over an area of the input image at each iteration. The mask coefficients is used in a weighted sum of the value of pixels (i, j) as depicted in Table II.

TABLE II
3×3 MASK WITH COORDINATES

(i-1,j-1)	(i-1,j)	(i-1,j+1)
(i,j-1)	(i,j)	(i,j+1)
(i+1, j-1)	(i+1, j)	(i+1, j+1)

Pseudo-code for Sobel Edge Detection:

INPUT: Sample road frame image, G.
OUTPUT: Road frame with detected edges, $E(G)$.

Step 1: Read in and load image, G.
Step 2: Extract feature matrix, $A(G)$.
Step 3: Convolution process: apply Sobel operators
Step 4: Compute $|G| = \sqrt{Gx^2 + Gy^2}$

D. Salient Pixels Removal

In this study, salient pixels are referred to as the non-drivable (non-road) region in road frame images, which creates dificulties in drivable region detection. Having determined the edges in the digital road image, we look for a way of removing the salient pixels. The value of zero returned along the edge region of road frames after segmentation is concentrated on in-order to minimise salient pixels. That is, we need to replace the values of the pixels representing the salient pixels with zeros or a uniform value other than actual road pixel value for a clear distinction between the road and non-road region. In this work, various heuristics were employed in order to achieve our aim. The feature matrix is iterated through, using a column-wise bottom-up approach with respect to the neighbouring pixels of each pixel's location. At each iteration, salient pixels values are replaced with some uniformly defined colour value. It is worth mentioning that the method adopted in this work is not to present algorithms with perfect results but to find larger amount of white pixels (considered as drivable region in our work) in a safe propotion. The salient pixels are minimised using the following algorithm:

Pseudo-code for minimising salient pixels:

INPUT: Original feature matrix, $E(G)$.
OUTPUT: Feature matrix without salient pixels, $E(G')$.

Step 1: Extract the edge-detected frame matrix, $E(G)$.
Step 2: Scan each column in a bottom-up approach.
Step 3: Replace values above a pixel value by zero:
if pixel value at a location is zero (an edge pixel)
OR absolute difference in neighbouring pixels is greater than some threshold.
Step 4: Repeat for all columns until all salient pixels are minimised.

The basic idea illustrated in the above algorithm is experimentally determined. Using the assumed notion of the prior knowledge that road images have grey-like colours, it is expected that cluster of grey colour values will be observed at a concentrated region of the road frame while some grey colours around the bush appear as salient pixels. The choice of the threshold centers around the fact that road pixels are consistent in their mixture of colours. We compare the absolute difference between current pixel (i, j) and neighbouring pixels $(i-1, j)$ and $(i-2, j)$. If the absolute difference is greater than or equal to threshold, say $t = 90$, we replace pixel values above pixel (i, j) with zeros. This is achievable due to the fact that road has certain width and area and have consistent grayscale values. More advanced methods can be used to make the choice of the threshold for better results.

E. Scoring and Evaluation Mechanism

The notion of probability such as confusion matrix which was used in [6] for performance evaluation is used to evaluate how efficient our method is with respect to the experimental results obtained. A confusion matrix is a validating tool which contains information about actual and predicted classifications done by a classification system. An example of a confusion matrix is depicted in Table III.

TABLE III
SCHEMATIC OF A CONFUSION MATRIX

		Actual	
		Parameter x	*Parameter y*
Predicted	*Parameter x*	A	B
	Parameter y	C	D

The performance accuracy (AC) of the minimised salient pixels in a confusion matrix is the proportion of the total number of predictions that were correct. This is generally expressed as :

$$AC = \frac{\sum(\text{left-diagonal-entries})}{\sum(\text{All-entries})} \times 100\%. \quad (4)$$

Thus, the performance accuracy (AC) of the confusion matrix in Table III is given in Equation (5):

$$AC = \frac{A+D}{A+B+C+D} \times 100\%. \quad (5)$$

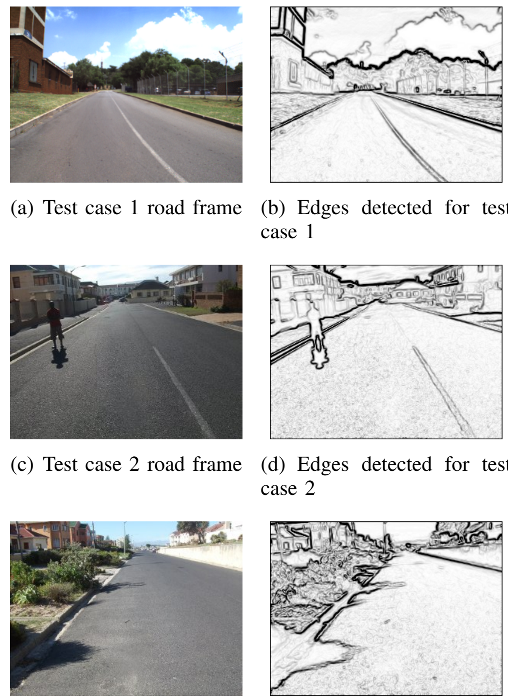
The qualitative and quantitative evaluations of the experimental results are also put into account. Quantitative research produces data in the form of numbers while qualitative research tends to produce data that are stated in prose or textual forms [17]. These two evaluation methods help yield insights that neither approach would produce on its own [16]. A proper integration of qualitative and quantitative methods can therefore help provide a more comprehensive evaluation of an intervention. In [15], qualitative and quantitative approaches were used in poverty analysis.

IV. EXPERIMENTAL EVALUATIONS

This section evaluates the effectiveness of the earlier described techniques in minimising salient pixels. In order to test the flexibility of our method, experiments were conducted on different scenarios of such road frames. Part of the scenarios involve obstacles (occlusion), which appear as salient pixels on the road feature matrix extracted. In one, there is a physical obstacle (a pedestrian) along the surface of the road as depicted in Figure 3(c) and another involves an optical obstacle (shadow of an object off the road) as depicted in Figure 3(e).

A. Experiment 1: Qualitative Evaluation of Road Frame Edges Detected

The computed edge magnitude produced the results shown in Figures 3(b), 3(d) and 3(f). This clearly outline the boundaries of the objects in the images. By visual inspection, one can see that the edges on Figures 3(b), 3(d) and 3(f) are detected adequately when compared with the original frames in Figures 3(a), 3(c) and 3(e) respectively.



(a) Test case 1 road frame
(b) Edges detected for test case 1
(c) Test case 2 road frame
(d) Edges detected for test case 2
(e) Test case 3 road frame
(f) Edges detected for test case 3

Fig. 3. Test Cases: Road frames and the corresponding image edges detected

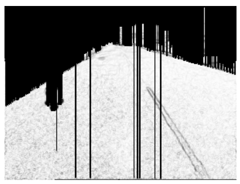
B. Experiment 2: Road Frames with Minimised salient Pixels

The algorithm in this work is tested on a stream of road frames but this paper presents, in Figure 4 and Figure 5, the results (minimised salient pixels on the road frames) of some of the different scenarios experimented. The algorithm presented in the pseudo-code for minimising salient pixels is implemented here. It takes the edge feature matrix from the road frames edges detected as its input, operates on the edge lines as marked out in the matrix by replacing salient pixels with a uniform value, say zero (black) in our case. The value used for the replacement differs from the road colour intensity value, and consequently produces the road frames with minimised salient pixels as depicted in Figure 4 and Figure 5, respectively. Ultimately, all salient pixels should be replaced with zeros (black). These results show that complete drivable region for safe autonomous robotic navigation has been detected. It is worth mentioning that the result produced in this work is thought to serve as an input to the next (machine learning algorithm) layer in the drivable region detection system.

(a) Edges detected for test case 1

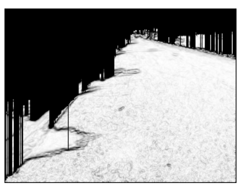
(b) Minimised salient pixels for test case 1

(c) Edges detected for test case 2



(d) Minimised salient pixels for test case 2

(e) Edges detected for test case 3



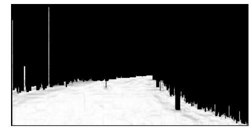
(f) Minimised salient pixels for test case 3

Fig. 4. Test Cases: Pre-processing results - minimised salient pixels for a complete drivable region detection

C. Experiment 3: Performance Accuracy of Salient Pixels Minimisation

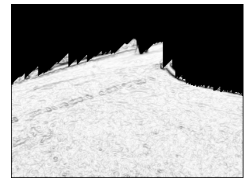
In the experiment conducted, two matrices were used as points of reference : the originally extracted road frame edge matrix, say M_1, whose values are depicted as Actual (pixel) value, and the minimised salient pixels matrix, say M_2, whose values are depicted as Final value in Table IV. Pixel points, P_i's (road pixels and salient pixels), are selected at random from M_1 with the aid of an automated code. The experiment is repeated in three(3) folds. A pixel location in the matrix is represented by a string of alpha-numeric characters, where the first set of integers denote the pixel row and the immediate character(s) after it denote the pixel column. The two variables rp and sp denote road and salient pixels, respectively. Thus, in Table IV, $204V - rp$ represents a road pixel (rp) on row 204, column V of the matrix. The chosen pixel value from M_1 is marked as either a road pixel or salient pixel accordingly. The marked pixel value, P_i in M_1, is then cross-checked in matrix M_2 to ascertain its value. Road pixels are expected to remain unchanged even after carrying out the operation of salient pixels minimisation, while salient pixels are expected to have been replaced with zeros. This is viewed in the confusion matrix, which gives the summary of the classification system and is important, as it validates the accuracy of our implemented algorithm and heuristic. Thus, it is expected that salient pixels would be minimised (replaced with zeros) while road pixels remain as they were. Table IV shows the result of the experiment for one of the test cases. Tables V, VI and VII with accuracies of 93%, 90% and 86% respectively, shows the confusion matrices for the first three test cases. The confusion matrix shows a cross-validation of the experiment performed for each of the test cases and reveals the amount of white pixels (naviagble region) acquired in a safe proportion. Further experiments from Figure 5 produce accuracies of 85 %, 80 % and 90 % respectively.

(a) Test case 4 road frame



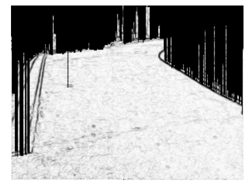
(b) Minimised salient pixels for test case 4

(c) Test case 5 road frame



(d) Minimised salient pixels for test case 5

(e) Test case 6 road frame



(f) Minimised salient pixels for test case 6

Fig. 5. Test Cases: Pre-processing results - minimised salient pixels for a complete drivable region detection

V. Summary and Conclusion

Machine vision as a research field remains a challenging area. Ability to construct robust algorithms for safe autonomous drivable region detection in real time is still an on-going process. This is significant from a number of publications in the area of machine vision which, in most cases, only addresses specific problems.

In this work, we have presented a simple solution directed towards addressing a specific machine vision problem, autonomous drivable region detection. Salient pixels in the non-drivable region appear as drivable because of the similarity they share with actual road pixels (drivable-region). In this domain of interest, heuristics were developed to minimise salient pixels in the non-drivable regions of road frames. The results of this work will be incorporated into a complete

TABLE IV

PERFORMANCE ACCURACY OF SALIENT PIXELS MINIMISATION FOR TEST CASE 1

Pixel-location	**Actual-value**	**Expected**	**Final value**
$72FD-sp$	195	0	0
$23CC-sp$	252	0	0
$204V-rp$	241	241	241
$22CH-sp$	250	0	0
$28FB-sp$	241	0	0
$6AB-sp$	0	0	0
$110CW-sp$	0	0	0
$149KG-sp$	196	0	0
$98EX-sp$	252	0	0
$77Q-sp$	239	0	0
Accuracy: 100 %			
$102FR-sp$	216	0	0
$214IP-rp$	243	243	243
$170AX-rp$	251	251	251
$19IW-sp$	242	0	0
$181GS-rp$	247	247	0
$188F-rp$	245	245	245
$17FD-sp$	242	0	0
$11CU-sp$	243	0	0
$102AQ-sp$	235	0	0
$74HO-sp$	170	0	0
Accuracy: 90 %			
$167IO-rp$	239	239	239
$133GA-rp$	253	253	253
$190JM-rp$	242	242	242
$127EA-rp$	248	248	248
$147AL-rp$	220	220	220
$156GP-rp$	240	240	0
$130AD-sp$	233	0	0
$97FS-sp$	215	0	0
$29CY-sp$	247	0	0
$210IN-rp$	242	242	242
Accuracy: 90 %			
Average Total Accuracy: 93.33 %			

TABLE V

TEST CASE 1: CONFUSION MATRIX WITH MINIMISED SALIENT PIXEL ACCURACY

		Actual	
		Road pixels	*salient pixels*
Predicted	*Road pixels*	10	0
	salient pixels	2	18

TABLE VI

TEST CASE 2: CONFUSION MATRIX WITH MINIMISED SALIENT PIXEL ACCURACY

		Actual	
		Road pixels	*salient pixels*
Predicted	*Road pixels*	17	2
	salient pixels	1	10

TABLE VII

TEST CASE 3: CONFUSION MATRIX WITH MINIMISED SALIENT PIXELS ACCURACY

		Actual	
		Road pixels	*salient pixels*
Predicted	*Road pixels*	16	1
	salient pixels	3	10

drivable region detection module as shown in Figure 2. This consequently improves autonomous robot navigation.

The images experimented with in this work are real life images of different scenarios where some of the scenarios involve obstacles (a physical obstacle and an optical obstacle) and some without obstacles. This demonstrates the level of reliability of this work as applied to the practical real world problem. For instance, qualitative edges are detected in Figures 3(b), 3(d) and 3(f), salient pixels are minimised adequately in Figures 4(b), 4(d) and 4(f) and validation on the performance accuracy of salient pixels minimisation gives a good approximation.

At the moment, the proposed heuristic for salient pixels removal has not been tested on coarse road frames. We are working on making our idea more universal and robust such that it becomes applicable to any kind of road frames. This work offers a pre-processing strategy for the detection of drivable regions for robotic vehicles and only tarred road images were used as sample frames. Special cases such as the influence of environmental factors (i.e. rain) on road frames can further be investigated and we intend to improve on the evaluation schemes.

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