Specularity Removal for Robust Road Detection

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Tencon
Nov 24, 2016

Outline

Introduction

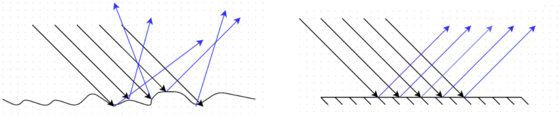
- Road detection for autonomous vehicles
- Important background segmentation stage for vehicle and pedestrian detection
- Vision based- Identify each pixel in image as belonging to road/ non road
- Past approaches: feature based and model based techniques
- Recent research efforts towards Illuminant invariant based approaches

Problem Definition

- Real-time road detection algorithm
- Address challenges in the road detection task
  1. Shadows
  2. Smooth merging of road into background (no discernible boundary)
  3. Issues related to intra-class variability - different shades, sizes, and wear down of road
  4. Specular reflections
  5. White lane markers/ arrows painted on road
- Paper on 'Road detection by illuminant invariant'[1] addresses 1,2 and 3 and identifies 4 and 5 as the limitations of their method
- Solution: Specularity removal

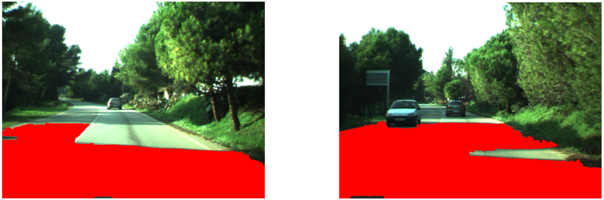
[1] J.M.A. Alvarez and A.M. Lopez. Road detection based on illuminant invariance. Intelligent Transportation Systems, IEEE Transactions on, 12(1):184–193, March 2011.

Problem Definition



(a) (b)

Figure 1: (a) Diffuse v/s (b) Specular Reflection



(a) (b)

Figure 2: Results of road detection applied in presence of specularity

Illuminant Invariant Feature Space

- Given a colour image with shadows, we'd like to get an illumination independent representation containing just the chromaticity information at each pixel
- A shadow is a change in the illuminant colour and intensity
- So, if we can factor out the illumination locally (at a pixel) it should follow that we remove the shadows.
- This is possible given that the camera and the illuminant follow certain restrictions

Assumptions About the Illuminant and Surface

- **Lambertian surface model**- image pixel values are linearly related to the intensity of the incident light, and images are free of specularities.
- Imaging device has perfectly **narrow-band sensors** or delta sensitivity.
- **Planckian light source** model which states spectral power distribution (power per unit area per unit wavelength) of light emitted by a blackbody heated to a given temperature is given by

$$E(T, \lambda) = Ic_1\lambda^{-5}[exp(-c_2/\lambda T)]$$

  where T is the temperature in kelvins, I is the overall intensity of the light, λ is the wavelength and c_1 and c_2 are two constants. Accurate estimation for most illuminants including daylight.

Imaging System

- Camera response depends on 3 factors- Illuminant (E), Surface reflectivity (S) and the sensor spectral sensitivity(R,G,B).

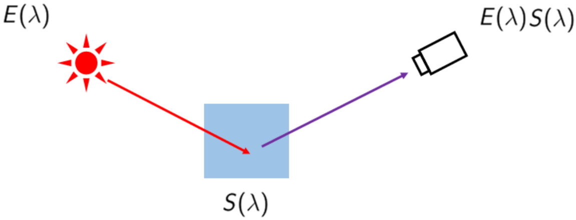


Figure 3: Image capture procedure

$$r = \int R(\lambda)E(\lambda)S(\lambda)d\lambda \quad g = \int G(\lambda)E(\lambda)S(\lambda)d\lambda$$

$$b = \int B(\lambda)E(\lambda)S(\lambda)d\lambda$$

Delta Sensitivity

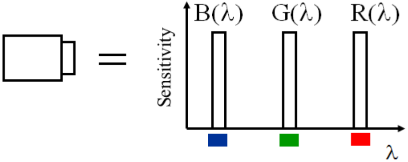


Figure 4: Camera with delta sensitivities

$$R(\lambda) = \delta(\lambda - \lambda_R) \implies r = E(\lambda_R)S(\lambda_R)$$

$$G(\lambda) = \delta(\lambda - \lambda_G) \implies g = E(\lambda_G)S(\lambda_G)$$

$$B(\lambda) = \delta(\lambda - \lambda_B) \implies b = E(\lambda_B)S(\lambda_B)$$

Illuminant Invariant

For, delta function sensors and Planckian Illumination we have

$$r = S(\lambda_R) I c_1 \lambda_R^{-5}[exp(-c_2/\lambda_R T)]$$

Taking logarithm on both sides,

$$log(r) = log(I) + log(S(\lambda_R) c_1 \lambda_R^{-5}) - c_2/\lambda_R T$$

$$\begin{bmatrix} log(r) \\ log(g) \\ log(b) \end{bmatrix} = \begin{bmatrix} k \\ k \\ k \end{bmatrix} + \begin{bmatrix} \alpha_s \\ \beta_s \\ \gamma_s \end{bmatrix} + \frac{1}{T} \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

$$\begin{bmatrix} r' \\ b' \end{bmatrix} = \begin{bmatrix} log(r) - log(g) \\ log(b) - log(g) \end{bmatrix} = \begin{bmatrix} \alpha_s - \beta_s \\ \gamma_s - \beta_s \end{bmatrix} + \frac{1}{T} \begin{bmatrix} a - b \\ c - b \end{bmatrix}$$

Illuminant Invariant

With some algebra,

$$r' - \frac{(a-b)}{(c-b)} b' = f(\alpha_s, \beta_s, \gamma_s),$$

$\alpha_s = log(r), \quad \beta_s = log(g)$ and $\gamma_s = log(b)$

There exists a weighted difference of log chromaticities that depends only on the surface reflectance.

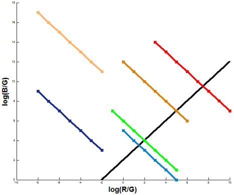


Figure 5: Chromaticity plot

Illuminant Invariant estimation by entropy minimization

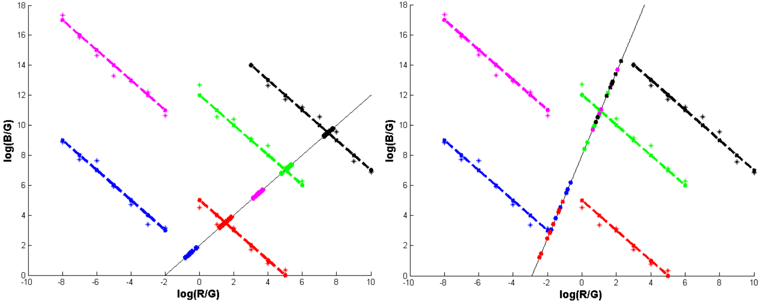


Figure 6: Entropy minimization

Key is to find the invariant angle θ for which the entropy is minimized.

Road Detection Algorithm[1]

1. Compute I from I_{RGB} using θ.
2. Build the road model $p(I(p)|road)$ using the normalized histogram of a set of N_s seeds placed at the bottom part of the image.
3. Obtain I_r by thresholding I according to $p(I(p)|road)$ and a fixed threshold λ.
4. Obtain I_{cc} by performing a connected-component procedure on Ir. The same set of N_s seeds is used as starting points.
5. Fill in small holes in I_{cc}: a closing operation followed by a flood fill.

[1] J.M.A. Alvarez and A.M. Lopez. Road detection based on illuminant invariance. Intelligent Transportation Systems, IEEE Transactions on, 12(1):184–193, March 2011.

Road Detection Algorithm

Figure 7: Illuminant invariant image

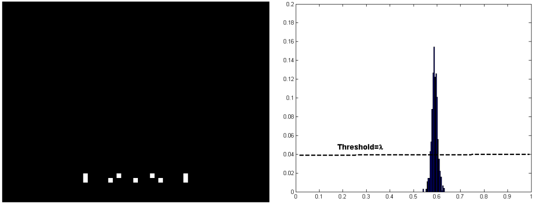


Figure 8: Seed points and histogram Thresholding

Limitations of Illuminant Invariant Method

- Because of lambertian assumption for road surface, fails in case of specular reflection. (common occurence during noon time)
- Fails to detect lane markers as white color of markers is not modelled.
- Two methods of overcoming these limitations:
    1. Graph cut- shape constraints in form of priors
    2. Detection and removal of specular reflection

Inclusion of Priors into Graph Cut

- Priors containing information about road shape added to graph cut[1]
- Shrinking constraint- Width of road in the upper row cannot be greater than that in the lower row
- Consistency constraint- region between two road boundaries is always road region

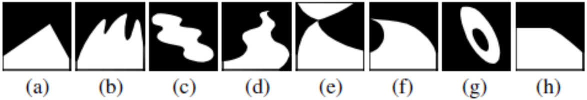


Figure 9: Examples of some segmented images[1]. The white regions in (a), (d), (f), and (h) look more like roads than those in (b), (c), (e), and (g).

[1] Zhen He, Tao Wu, Zhipeng Xiao, and Hangen He. Robust road detection from a single image using road shape prior. In Image Processing (ICIP), 2013 20th IEEE International Conference on, pages 2757–2761, Sept 2013.

Road Shape Prior-Failure Cases

(a) (b) (c)

Figure 10: Failure cases for: Shrinking constraint ((a) and (c)) and consistency constraint ((a) and (b)).The upper row shows the original images and the lower row the ground truth of the detected road region.

Proposed Solution

Specularity Removal Algorithm

1. Let $\mathcal{I}_{\mathcal{RGB}}$ be the original image with dimensions $m \times n$. If
$$min(I_r(x,y), I_g(x,y), I_b(x,y)) > \eta \implies s(x,y) = 1$$
$$else \quad s(x,y) = 0$$
where $x \in [m/2, m], \quad y \in [0, n]$ and $s(x,y)$ is a binary image showing the specular regions in white.
2. Find all connected components of specularities $(CC_1, CC_2 ..., CC_n) \quad s.t. \quad size(CC_k) > C_t \quad \forall k \in \{1, 2, ...n\}$. C_t is the minimum size of connected component.
3. Find the bordering pixels
$$CCsd_k = Dilate(CC_k, strsmall)$$
$$CCld_k = Dilate(CC_k, strlarge)$$
$$(Border)_k = CCld_k - CCsd_k$$
4. Fill the connected component CC_k with this mean value of $(Border)_k$.

Specularity Removal

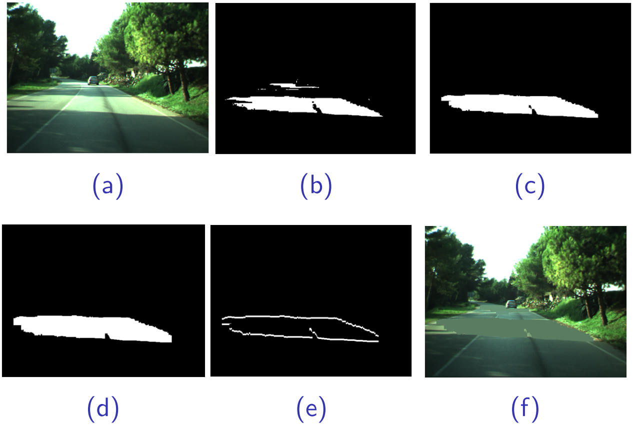


Figure 11: (a) Original Image $\mathcal{I}_{\mathcal{RGB}}$ (b) Detected specular regions s (c) Connected component 1 dilated by strsmall $CCsd_1$ (d) Connected component 1 dilated by strlarge $CCld_1$ (e) Boundary of CC_1, $Border_1$, (f) Image with specularity removed

Lane Markers + Specularity Removal

(a) (b) (c)

(d) (e) (f)

Figure 12: Input images (a) , (b) and (c) and specularity/ lane markers removed images (d), (e) and (f)

Results- Improvement in Detection Accuracy

(a)

(b)

(c)

(d)

Figure 13: Result of road detection applied on original image (a) and (c) and specularity removed image (b) and (d)

Quantitative Evaluation

Six performance measures are calculated for a set of 25 images containing specularity. Precision (P), Inverse Precision or True Negative Accuracy (TNA), Recall (R), Inverse Recall or True Negative Rate (TNR), Effectiveness (E) and Inverse Effectiveness (IE).

The proposed modification leads to improvement in both the f-measure and pseudo f-measure as shown in Table 1.

Performance Measure	Illuminant invariant based method	Proposed method
Precision $P = \frac{TP}{TP+FP}$	0.99	0.99
Recall (Sensitivity) $R = \frac{TP}{TP+FN}$,	0.78	0.93
Effectiveness (F measure) $E = \frac{2PR}{P+R}$	0.87	0.96
Inverse Precision $TNA = \frac{TN}{TN+FN}$	0.89	0.97
Inverse recall (Specificity) $TNR = \frac{TN}{TN+FP}$	1.0	0.99
Pseudo f measure $IE = \frac{2\times TNA\times TNR}{TNA+TNR}$	0.94	0.98

Table 1: Comparison of performance measures

Hardware Implementation

- As a proof of concept of the algorithm, we implemented it on the Beaglebone Black and Raspberry pi-2 development boards.
- Both are open-source hardware single-board computers.
- Low power consumption- 5V @ 1A at INR 4500
- Installed python+OpenCV on the preloaded Debian OS and used parallel processing.

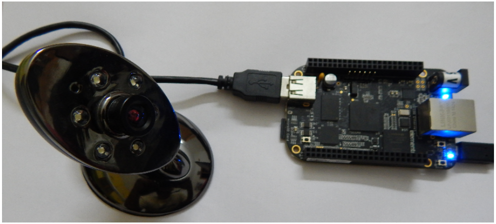


Figure 14: Beaglebone Black and webcam

Timing Considerations

- Python profiling gives the percentage time taken for each task:

Process	**Percent**
Specularity detection	5.06
Replacing regions by mean	12.66
Specularity Removal	**17.72**
Illuminant invariant computation	44.3
Histogram Thresholding	3.79
Connected component and morphology	34.17
Road Detection	**82.2**

Table 2: Timing breakdown

Timing Details

Platform	Resolution	Time taken to process 1 frame (ms)
Laptop-serial	480×640	160
Laptop-parallel	480×640	35
BBB-serial	240×320	680
BBB-parallel	240×320	109
RPi-2-serial	240×320	850
RPi-2-parallel	240×320	109

Table 3: Timing comparison

This shows a processing ability of 9 frames per second on mobile platforms.

Parallel Implementation

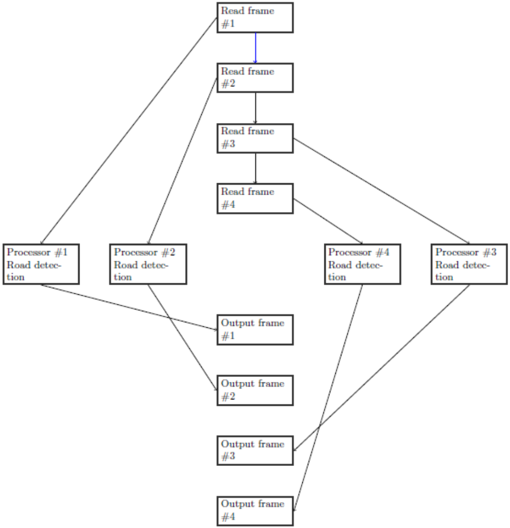


Figure 15: Parallel implementation flow: joblib

Conclusion

- Introduced an approach to make the illuminant invariant based road detection technique robust against specular reflections and lane markers.
- Performed a quantitative evaluation of the segmentation results, where the proposed method showed improvement in segmentation accuracy.
- Implemented the algorithm on the low cost-low power BBB and RPi-2 development boards. With parallel implementation, it is possible to process 9 frames per second.

References

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Acknowledgements

Thanks are due to...

- Prof. Pratik Shah for being a very patient and helpful guide.
- Prof. Rahul Dubey for the right motivation that made this hardware implementation possible.
- Prof. Aditya Tatu and Prof. M.V Joshi for teaching me DIP and vision concepts I used throughout my thesis work.
- Tencon organizers for this wonderful opportunity
- All my friends at DA-IICT for making this journey fun and enjoyable.

Thank You