ESTIMATION OF TERRAIN GRADIENT CONDITIONS & OBSTACLE DETECTION USING A MONOCULAR VISION-BASED SYSTEM

Final Demonstration

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Background

The ability for an autonomous robot to navigate from one location to another in a manner that is both **safe**, yet **objective** is vital to the **survivability** of the machine, and the **success of the mission** it is undertaking.

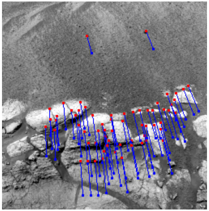


Figure 1: Tracked features from MER [**?**].

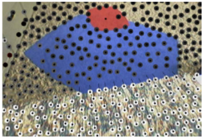
Vision based obstacle detection has enjoyed a high level of research focus over recent years. Less work has concentrated on providing a means of reliably detecting changes in terrain slope through the exploitation of observed changes in motion.

RELATED WORK

[1] *A Robust Visual Odometry and Precipice Detection System Using Consumer-grade Monocular Vision*, J. Campbell *et al.*, IEEE, 2005

[2] *Obstacle Detection using Optical Flow*, T. Low and G. Wyeth, School of Information Technology and Electrical Engineering, University of Queensland, 2011

[3] *Appearance-based Obstacle Detection with Monocular Color Vision*, I. Ulrich and I. Nourbakhsh, AAAI, 2000



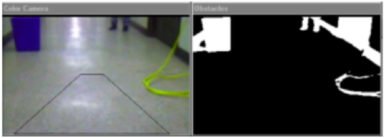


Figure 2: **Left:** Precipice detection [1], **Right:** Obstacle colour detection [3]

Focus

Investigation into a system capable of utilising a single, forward-facing colour camera to provide an estimation into current terrain gradient conditions, obstacle location & characteristics and robot ego-motion.

Potential Metrics For Observation

- Changes in terrain gradient (i.e. slopes).
- Location & characteristics of positive and negative obstacles (i.e. rock or pit respectively).
- Current robot speed of travel.
- Changes in robot orientation.

Working Hypothesis

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"From images captured using a ***non-calibrated*** *monocular camera system, analysis of optical flow vectors extracted using* ***localised appearance-based*** *dense optical flow techniques can provide certain estimates into the current condition of terrain gradient, the location and characteristics of obstacles, and robot ego-motion."*

Approach focussed on the effects of **motion parallax**.

i.e. Objects/features that are at a greater distance from the camera appear to move less from frame-to-frame than those that are closer.

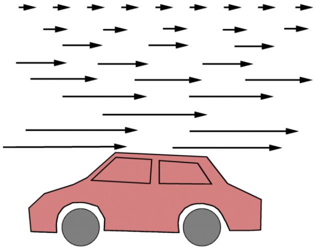


Figure 3: Typical example of motion parallax. **Courtesy**: http://www.infovis.net.

Key Aspects

1. The exclusive use of appearance-based template matching techniques to provide a localised variant of dense optical flow analysis over the use of sparse optical flow techniques relying upon a high number of available image features.
2. The use of a formalised model to represent detected changes in vertical displacement as part of efforts to estimate changes in terrain gradient in addition to the location characteristics of potential obstacles.

Provides a mechanism by which to evaluate the prediction:

"Features captured towards the ***bottom*** *of an image will show* ***greater displacement*** *between subsequent frames, than those features captured towards the* ***top*** *of the image."*

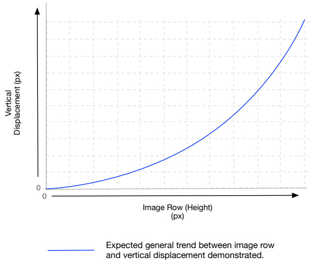


Figure 4: Tracked features from MER [?].

INVESTIGATION AIMS

Experiment Methods

EXPERIMENT METHODS

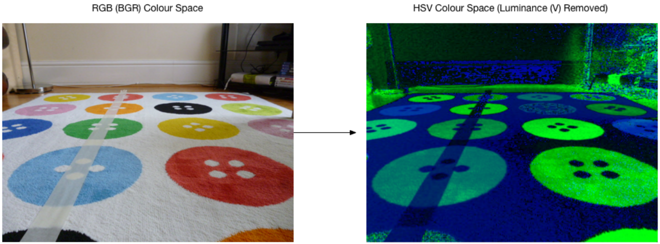
EXPERIMENT 1

EXPERIMENT 2

EXPERIMENT 3

Stage One

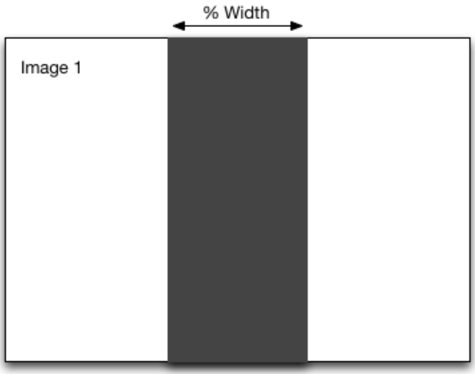
Import two consecutive images, and convert from RGB (BGR in OpenCV) colour space to HSV.



The 'V' channel is then removed in order to improve robustness to lighting changes between frames.

Stage Two

Extract a percentage-width region of interest (ROI) from centre of first image.



Why do we need to extract a ROI?

Focus-of-expansion: Objects in images do not actually move in 1-dimension (i.e. straight down the image).

This effect is minimised towards the centre of the image.

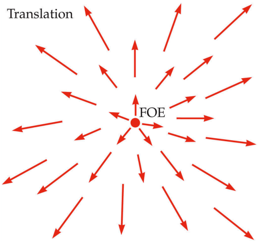


Figure 5: **Courtesy:** J.Pillow, University of Texas

Stage Three

Extract patches of a fixed size around each pixel within the extracted ROI.

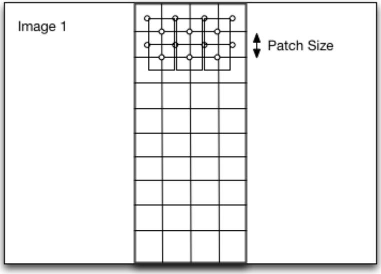


Figure 6: Simplified example of patch extraction within ROI.

Stage Four

For each patch extracted from *image one*, move down through a localised search window (column) in *image two* searching for the best match against the template patch.

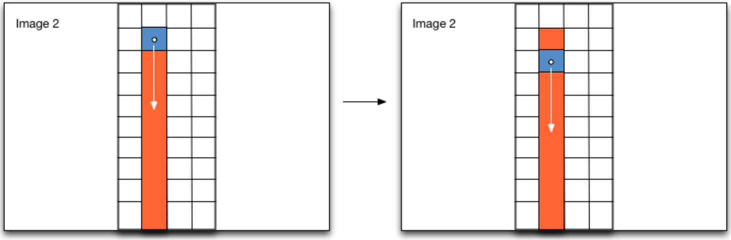
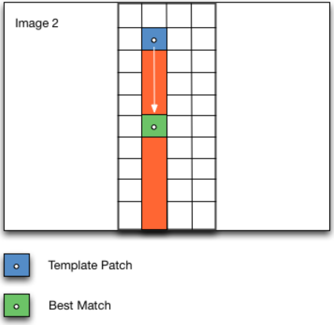


Figure 7: Example of "best match" search within local column.

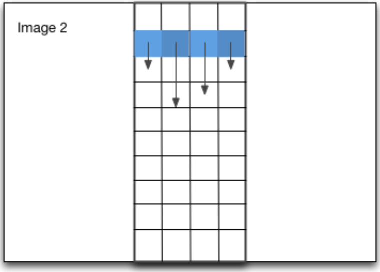
Stage Five

Identify the patch within the localised search window that provides the "best match" via correlation-based matching (e.g. Euclidean Distance, SSD or Correlation coefficient).



Stage Six

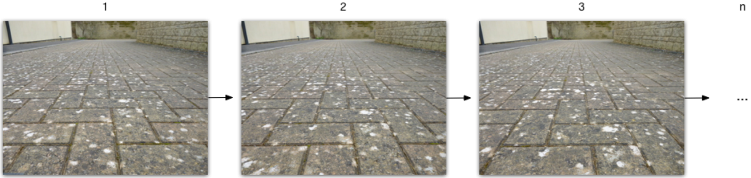
Average all measured displacements for each pixel along a given row.



Outliers are removed by ignoring any displacements that lie outside of (2 x Standard Deviation) of the mean.

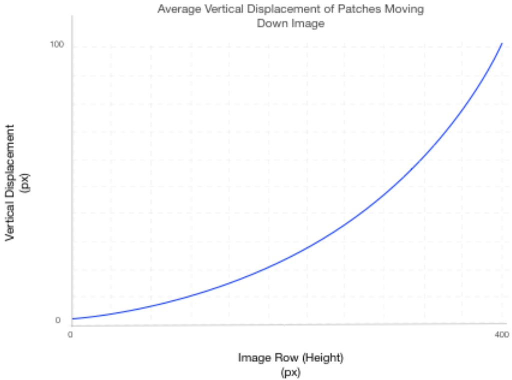
Repeat Stages 1-6

Repeat stages 1-6 for an entire collection of “calibration” images taken of *flat, unobstructed* terrain.



Stage Seven

Plot the *average displacement* for each ROI row, calculated from the displacements recorded over all calibration images.



EXHAUSTIVE VS. NON-EXHAUSTIVE

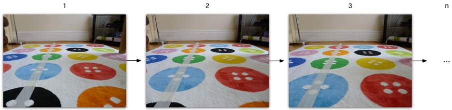
Investigation Results

Generally “mixed” results at this stage.

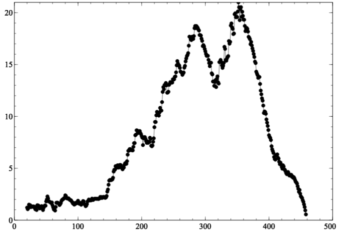
From the results obtained, we have learned:

1. It is possible to potentially establish a relationship between row height in an image, and average downwards pixel displacement.
2. The current approach to appearance-based tracking using multiple “small” patches**does not work well** for many typical terrain conditions (i.e. outside).

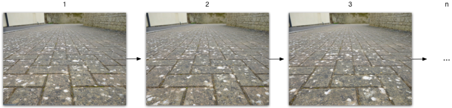
Input Collection:



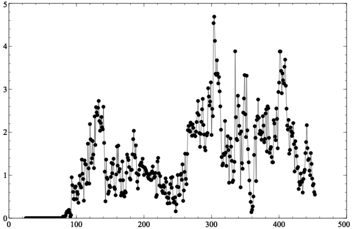
Result:



Input Collection:



Result:



Evaluation & Conclusion

FUTURE WORK

FUTURE WORK

SUMMARY

Questions?

Project Blog

Slide Design: Matthias Vogelgesang - (Github)