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

Final Demonstration

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Background

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.

[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

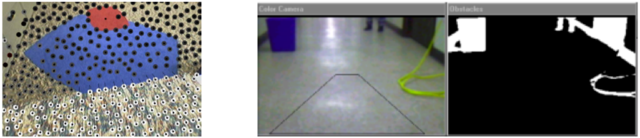


Figure 1: **Left:** Precipice detection [1], **Right:** Obstacle colour detection [3]

Working Hypothesis

WORKING HYPOTHESIS

*"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.

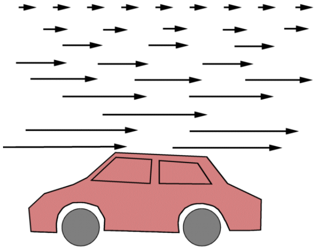


Figure 2: Typical example of motion parallax [4].

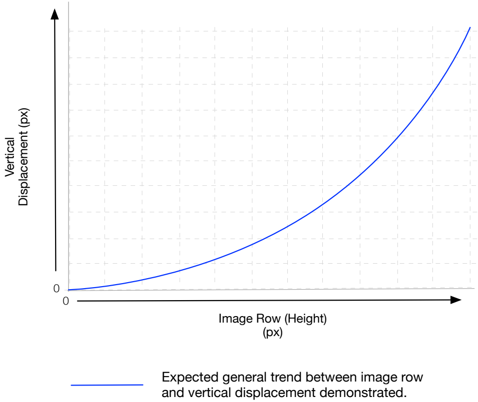
Key Aspects

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.

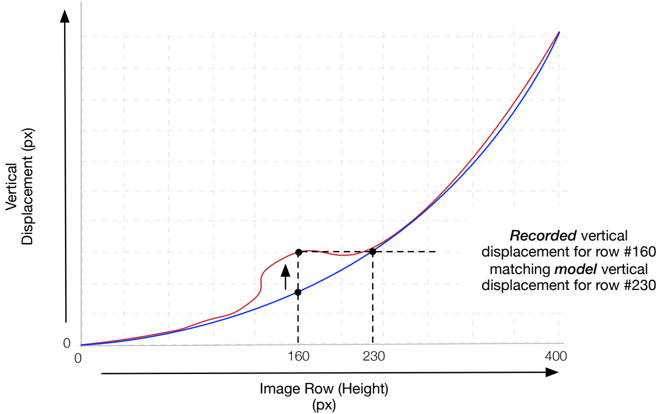
2. The use of a **formalised model** to represent detected changes in vertical displacement as part of efforts to estimate changes in terrain gradient in addition to the location characteristics of potential obstacles.

Provides a mechanism by which to evaluate the prediction:

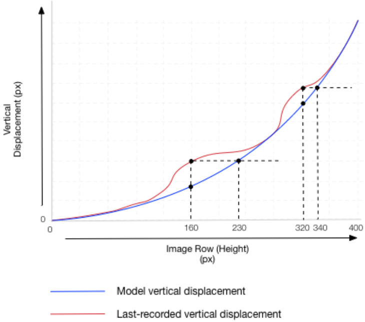
*"Features captured towards the **bottom** of an image will show **greater displacement** between subsequent frames, than those features captured towards the **top** of the image."*

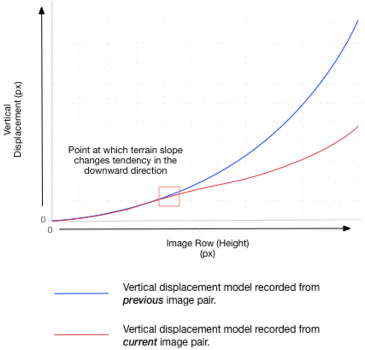


From observing discrepancies between the current model and "baseline" model, it should be possible to infer the presence of potential obstacles:



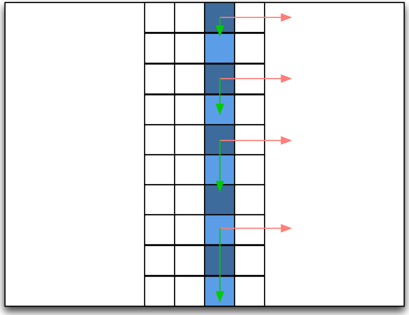
Differences in model discrepancy behaviour should provide enough information to establish between a potential obstacle and a change in terrain slope:





Two types of observed motion:

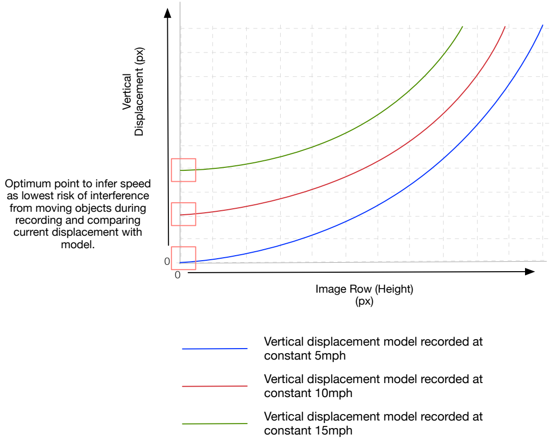
- **Translation** (*Vertical* component of optical flow vectors)
- **Rotation** (*Horizontal* component of optical flow vectors)



Horizontal component of optical flow vector (Rotation)

Vertical component of optical flow vector (Translation)

By recording multiple "calibration" models at different speeds, it should be possible to later infer the current speed using the standard *speed-distance-time* equation.



Primary Aims

1. Establish which out the following appearance-based template matching similarity measures:

   - Euclidean Distance
   - Correlation Coefficient
   - Histogram Correlation
   - Histogram Chi-Square

   best supports the predicted positive correlation between the vertical position of features within an image, and the level of vertical displacement demonstrated.

2. Use the generated model of vertical displacement to identify potential obstacles and changes in terrain gradient based upon the predicted ‘comparative trend’ behaviour.

Secondary Aims

1. Further extend the capabilities of the vertical displacement model to provide estimates into the current speed of travel demonstrated by the robot.
2. Add support for providing an estimation into the change in orientation.

Experiment Methods

No existing imagery datasets were found to be suitable, therefore new sets had to be collected.

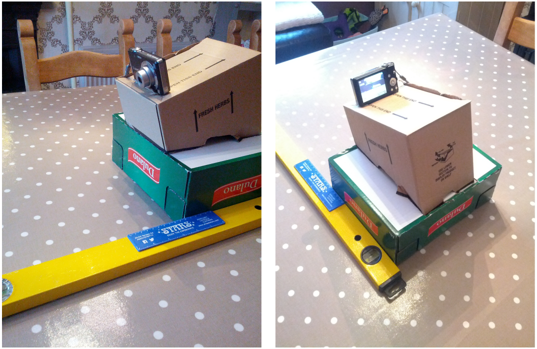


Figure 3: Camera-rig setup used to capture the experiment datasets from front and back profiles.

Images taken at a number of locations, but **four** were eventually selected based upon their variety in terms of **terrain texture** and **lighting conditions**.

Site 1: Living Room Rug | Site 2: Brick Paved Road | Site 3: Asian Rug | Site 4: Slate Tile Footpath

Figure 4: Examples of the first frame captured from each of the four location datasets.

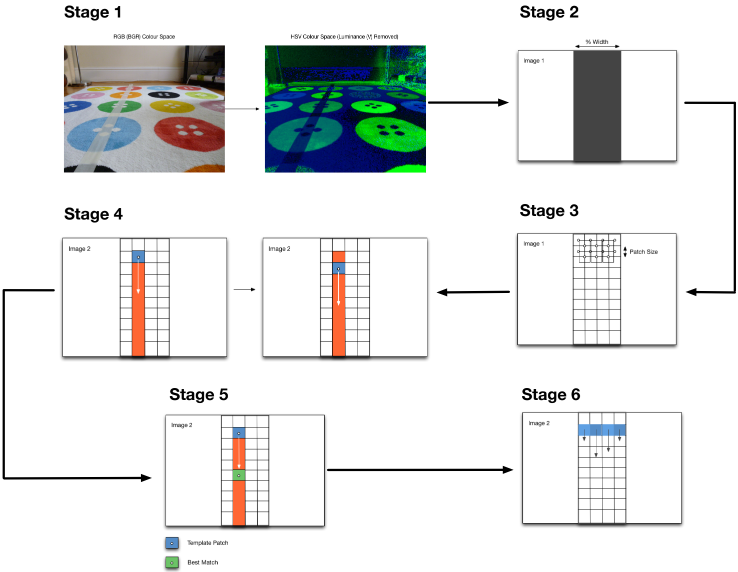
Over time, **investigation focus changed** from exploring a series of reasonably "generalised" research aims, to instead concentrating almost exclusively on one small, but very important aspect;

Ensuring that accurate results for appearance-based motion displacement could continue to be achieved, across terrain lacking any significant features and/or demonstrating highly repetitive patterns.

Three Experiments

1. Template Matching - **Multiple Small Patches**
2. Template Matching - **Full-width Patches (Non-Scaled)**
3. Template Matching - **Full-width Patches (Geometrically Scaled)**

EXPERIMENT ONE - MULTIPLE SMALL PATCHES



EXPERIMENT TWO - FULL-WIDTH PATCHES (NON-SCALED)

Focus

Establishing if adopting ***larger*** patches in fewer numbers provided better appearance-based matching accuracy than using many more, but critically much ***smaller*** overlapping patches.

While the underlying method remained the same as in the first experiment, some key changes were made:

- Extracting a central region of interest relative to the **ground plane**, as opposed to extracting a fixed-width column from the *image plane*.
- Moving away from multiple *overlapping small patches*, in favour of adopting a single, **full-width** patch to represent a single row in the image.

To extract a region-of-interest along the *ground plane*, the system would need to take account of **perspective distortion**. Therefore, a simple **calibration tool** was implemented, enabling users to define the required region of interest within an image.

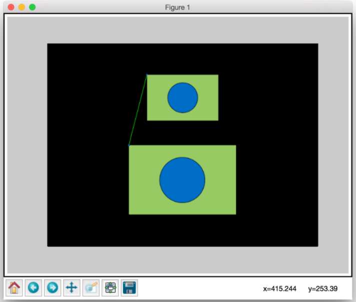
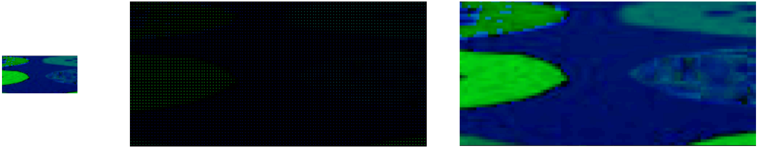


Figure 5: Results of the verification test for the approach towards geometric scaling of template patch pixel coordinates.

EXPERIMENT THREE - FULL-WIDTH PATCHES (SCALED)

Focus

Add **geometric scaling** of template patch in order to account for objects appearing *larger* as they approach the camera.



Original Template Patch   Re-scaled Template Patch (Geometric Transformation of Pixel Coordinates)   Re-scaled Template Patch (Linear Interpolation)

Figure 6: Comparison between various approaches of performing scaling of the original template patch image. In the case of linear interpolation, additional information has been added to image as a result of “estimating” the colour that lies between two original pixels.

Testing of Scaling Approach

A simple test was devised to confirm geometric scaling worked as expected under “perfect” conditions.

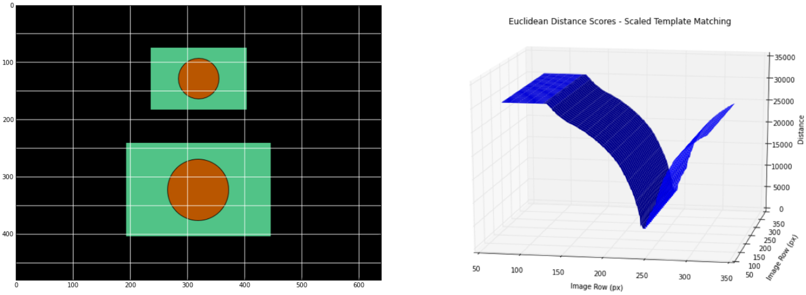


Figure 7: Results of the verification test for the approach towards geometric scaling of template patch pixel coordinates.

Issue discovered regarding the use of **non-exhaustive** searching causing erroneous results. All tests in experiments two and three were conducted using both exhaustive and non-exhaustive approaches.

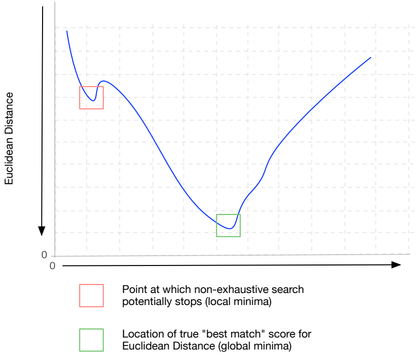


Figure 8: Example of potential early termination of non-exhaustive search due to entering local minima caused by noise, rather than global minima which represents to true best match.

Investigation Results

View Results (Courtesy: nbviewer)

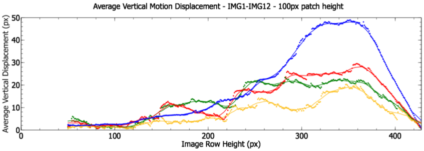
From the results obtained, we have learned:

1. Under certain terrain conditions, it is possible to potentially establish a relationship between row height in an image, and average downwards pixel displacement.

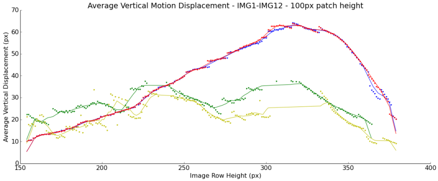
2. The performance of each appearance-based similarity measure can vary widely, based upon factors including:

    - Terrain texture (e.g. highly patterned, isotropic or homogenous)
    - Patch size (Balance between reducing “noise” and representing true displacement behaviour)
    - Exhaustive vs. Non-exhaustive search
    - Scaling vs. Non-scaling

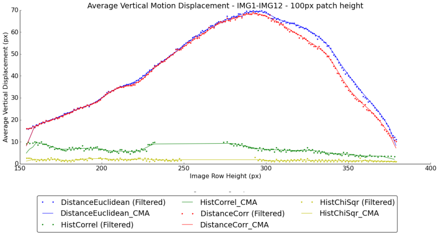
RESULTS: APPROACH COMPARISON – ‘LIVING ROOM RUG’ DATASET



(1)

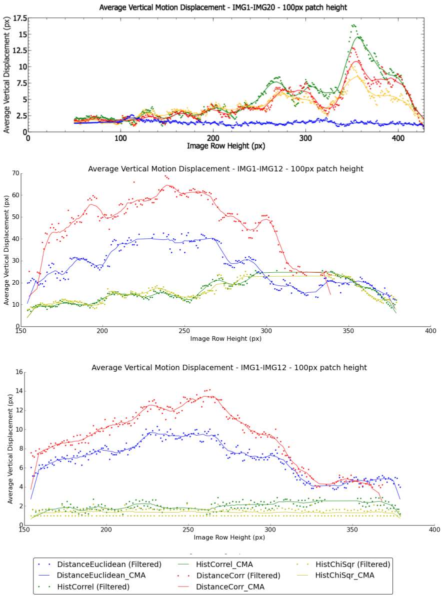


(2)



(3)

RESULTS: APPROACH COMPARISON – ‘BRICK-PAVED ROAD’ DATASET

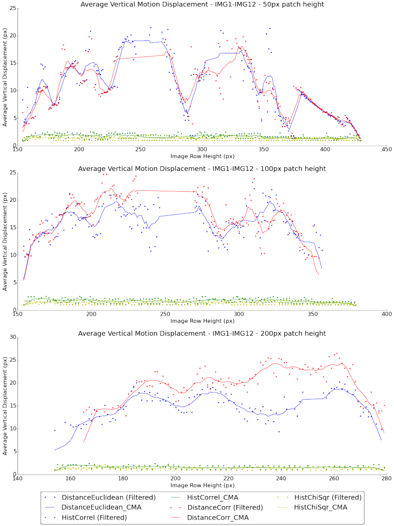


(1)

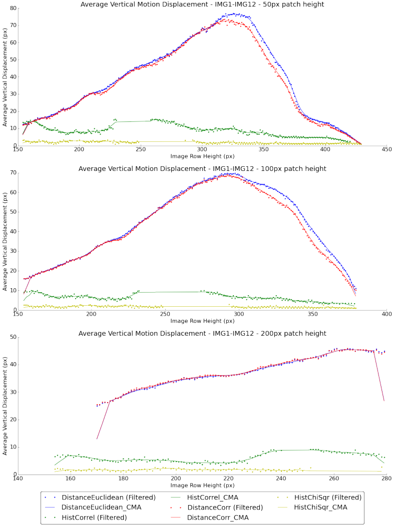
(2)

(3)

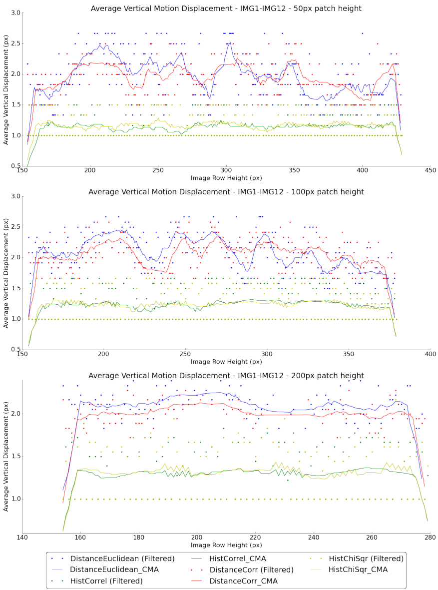
Non-Exhaustive



Exhaustive



RESULTS: PATCH SIZE COMPARISON – 'SLATE FOOTPATH' DATASET



Conclusion

Great potential for future work, most likely focussing on areas including:

- Further experimentation to establish most appropriate combination of similarity-measure, search approach and patch size for a **given terrain type**.
- Development of a system to identify "significant" changes in vertical displacement model that are potentially indicative of a potential obstacle or change in terrain gradient.
- Development of system to estimate change in robot heading.
- Development of system to estimate current robot speed.

Project has laid the groundwork upon which further development can subsequently be conducted.

While not all of the original aims were accomplished, research efforts had to be focussed on confirming the underlying hypothesis, which as a general concept, has been proven.

Not one single approach or solution will suffice for all terrain conditions.

Questions?

Project Blog

Slide Design: Matthias Vogelgesang - (Github)

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[1] Jason Campbell, Rahul Sukthankar, Illah Nourbakhsh, and Aroon Pahwa. A robust visual odometry and precipice detection system using consumer-grade monocular vision. In *Robotics and Automation, 2005. ICRA 2005. Proceedings of the 2005 IEEE International Conference on*, pages 3421–3427. IEEE, 2005.

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[4] Jonathan Pillow. Motion Perception 2. `http://homepage.psy.utexas.edu/homepage/faculty/pillow/courses/perception09/slides/Lec13A_Motion_part2.pdf`, October 2009.

[5] Akshay Roongta. Depth Cue Theory. `http://akshayroongta.in/notes/depth-cue-theory/`, October 2013.