Outdoor Mobile Robot Localization and Environment Mapping using a Single Camera

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Outline of Topics

1. Introduction
2. Methodology
3. Implementation Results
4. Conclusion

Motivation

- More than 10,000 landmines planted by Nepal Army and about the same number by the-then Maoist rebels
- 500 deaths from 1996-2004 [http://www.icbl.org/lm/2004/nepal]
- Low cost robotic system
- Efficient implementation using SLAM

Problem Statement

The problem here is to build a simulation model of a robotic system which can accurately build a feature map of its environment using a vision sensor, i.e., a camera mounted on the robot. This involves

- extracting stable features from the robot's environment,
- establishing correspondence among the extracted features,
- detecting and removing outliers (if any) and
- reconstructing the 3D shape and camera motion.

Objectives

- To use SIFT for extraction of scene features.
- To use BBF search for 2D correspondences matching and fundamental matrix based RANSAC for outlier detection and removal.
- To use iterative para-perspective factorization for Euclidean reconstruction.
- To evaluate the performance of the system based on synthetic as well real data.

Assumptions and Limitations

- Camera movement is limited in subsequent frames.
- Sufficient texture is needed in the environment for reliable feature extraction.
- At least three views are required for reconstruction of the scene.

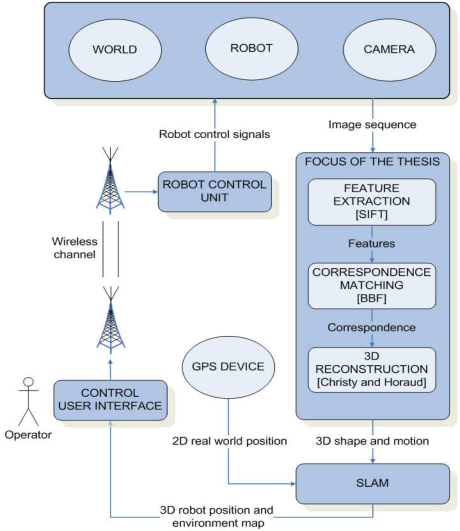

Figure: System Model

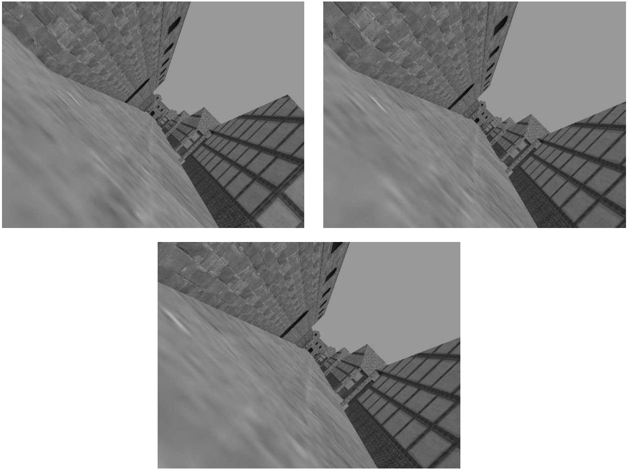

Figure: A sample image triplet from simulation - *VRML model [http://www.bbc.co.uk/ history/3d/houstead.shtml]*

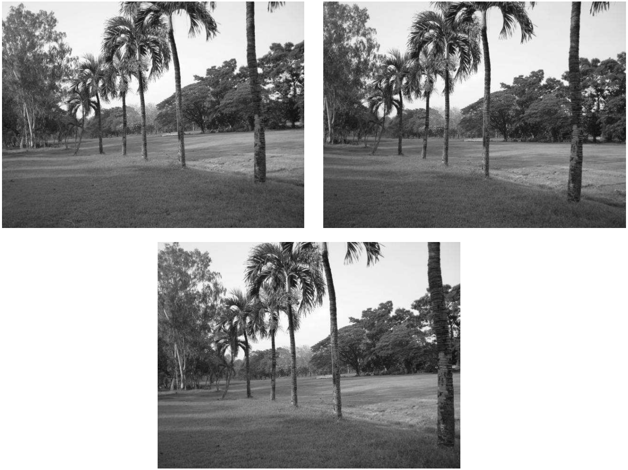

Figure: A sample image triplet from real world - *AIT Golf Course*

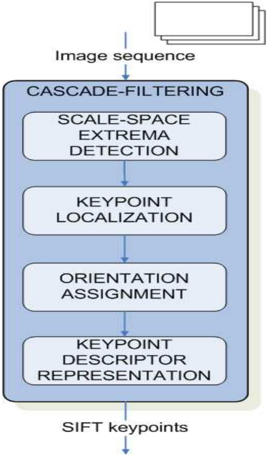

Figure: SIFT feature extraction process [Lowe(2004)]

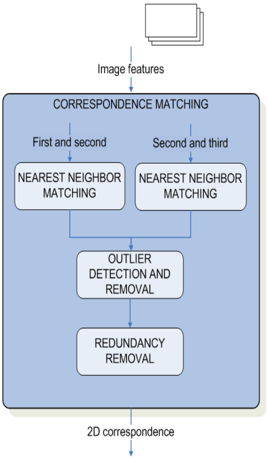

Figure: 2D correspondence matching using BBF search [Beis and Lowe(2003)] and RANSAC [Ruzgienė and Förstner (2005)]

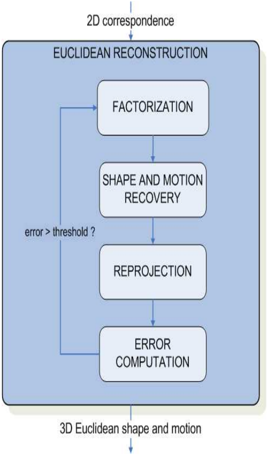

Figure: Euclidean reconstruction using iterative paraperspective factorization [Christy and Horaud(1996)]

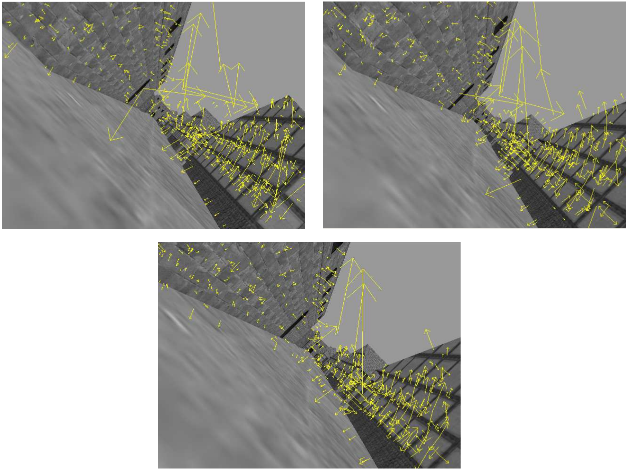

Figure: SIFT features from simulation

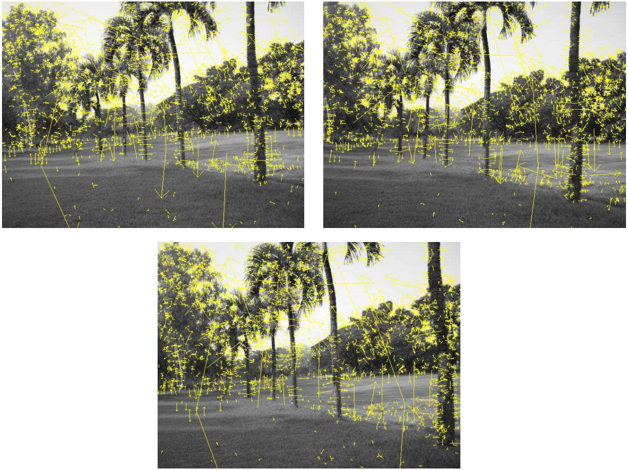

Figure: SIFT features from real images

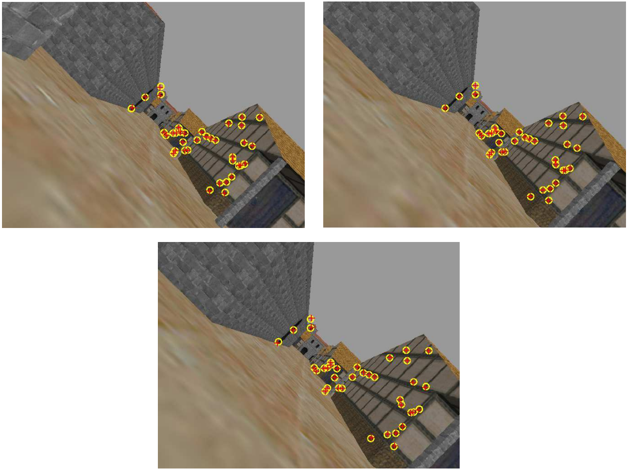

Figure: Reprojection of constructed 3D points: *circles - observations, crosses - reprojections*

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3D Reconstruction Error

3D reconstruction is tested using

$$e_{3D} = \sqrt{\min_T \sum_j \|P_j - \alpha_j T P_j{}^*\|^2} \tag{1}$$

where P_j is the ground truth 3-D points and α_j is the scale factor for normalizing the fourth component of $TP_j{}^*$ to 1. The root mean square (RMS) 3D error is defined as

$$e_{3D\,rms} = \frac{e_{3D}}{\sqrt{n}} \tag{2}$$

where n is the number of 3D points being considered.
[Tang and Hung (2006)]

2D Reprojection Error

$$e_{2D} = \sqrt{\frac{1}{n} \sum_{i,j} \|X_{i,j} - X_{i,j}{}^*\|^2} \tag{3}$$

where $X_{i,j}$ and $X_{i,j}{}^*$ represent i^{th} point extracted and reprojected, respectively from and onto j^{th} image, and n is the number of points under consideration.

Synthetic Data

Test using 10 uniformly distributed sphere points.

- Test 1: *Robot moving along a straight line*
  3D RMS error: 0.35cm
- Test 2: *Robot moving along an arc*
  3D RMS error: 0.81cm

Simulation and Real Images

S.N	Image Type	Number of Images	SIFT Features Extracted	Initial Match	After Outlier Detection	Outlier %	RMS error
1	Simulation	42	438	63	29	51.69	1.17352
2	Real image (before undistortion)	20	1913	269	132	49.74	2.52370
3	Real image (after undistortion)	20	2321	265	121	54.87	2.14390

Figure: Overall system performance

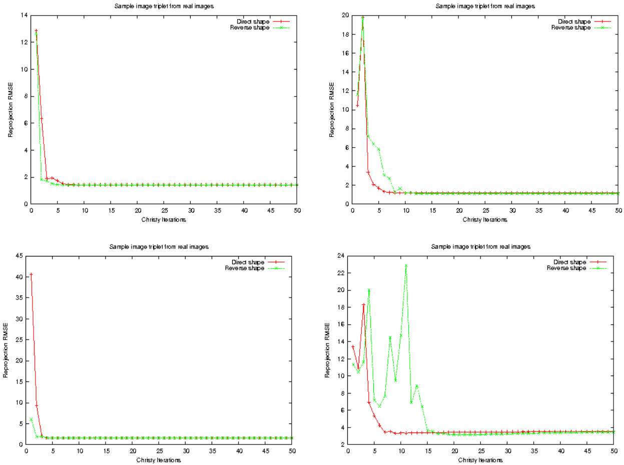

Figure: RMS error plot

In conclusion:

- SIFT proved to be a promising technique for extraction of highly distinctive and stable features.
- Fundamental matrix based RANSAC helped in detection and removal of many of the outliers present, but still left out some wrong matches to be removed.
- Performance of iterative para-perspective factorization algorithm used for Euclidean reconstruction was satisfactory, but needs to be improved to make it acceptable for the system to be used in real applications.

We recommend:

- To use trifocal tensor [Hartley and Zisserman (2000)] based RANSAC, which plays analogous role in case of three-view vision system as fundamental matrix does in two-view system.
- To use the improvement suggested in [Aanæs et al. (2002)] to upgrade the performance of Euclidean reconstruction.
- To compare performance of reconstruction process with similar techniques suggested in [Han and Kanade (1999), Poelman and Kanade(1997)] and subspace method proposed by [Tang and Hung (2006)].

Thank You

That was my last slide..

Thank you for your attention!

Aanæs, H., Fisker, R. and Åström, K. (2002) Robust Factorization, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 24, no. 9.

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