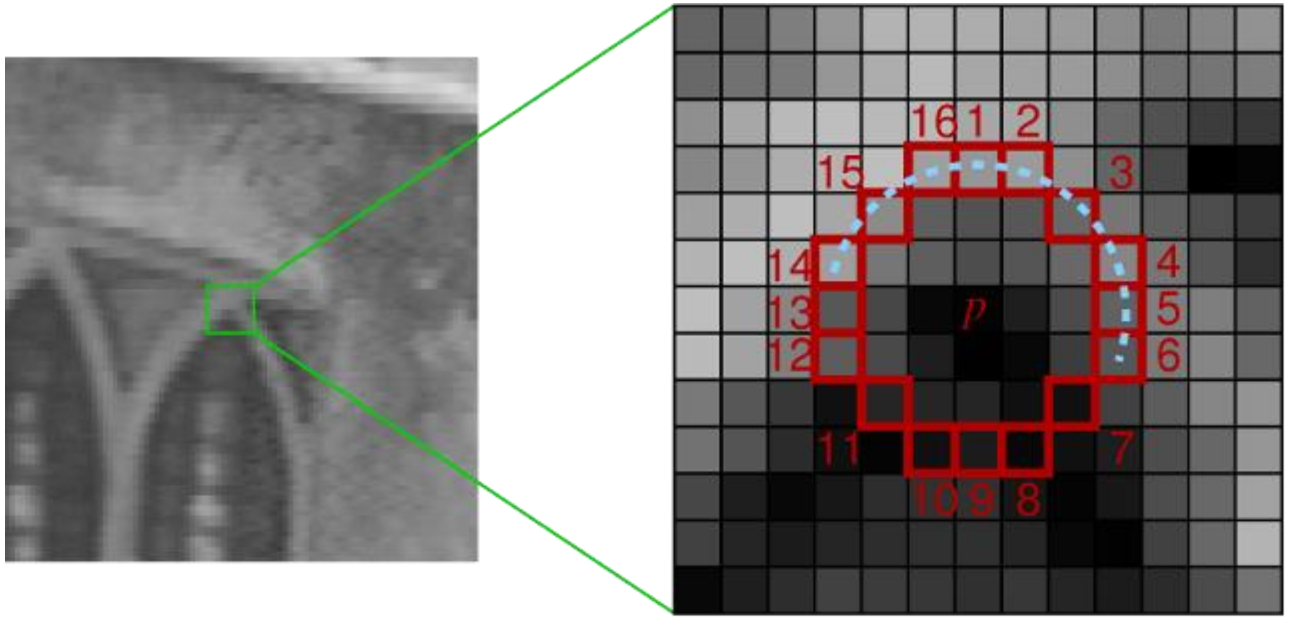
3D Scanning & Motion Capture

Exercise - 4

Armen Avetisyan, Dejan Azinović

Feature Detection/Extraction

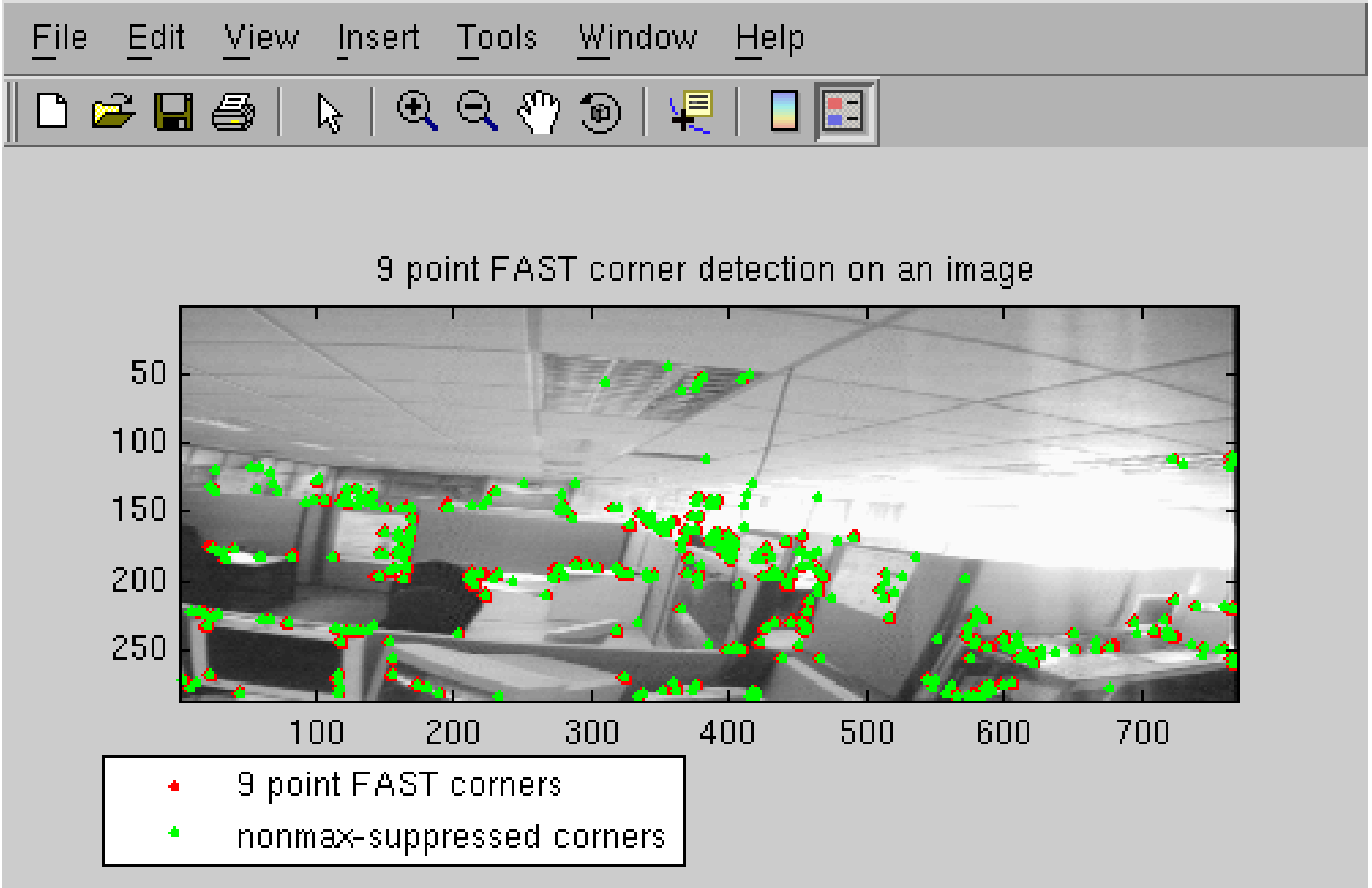


$$S_{p\to x} = \begin{cases} d, & I_{p\to x} \le I_p - t \quad \text{(darker)} \\ s, & I_p - t < I_{p\to x} < I_p + t \quad \text{(similar)} \\ b, & I_p + t \le I_{p\to x} \quad \text{(brighter)} \end{cases}$$

$S_{p\to x}$ is the state, $I_{p\to x}$ is the intensity of the pixel x. and t is a threshold.

http://homepages.inf.ed.ac.uk/rbf/CVonline/LOCAL_COPIES/AV1011/AV1FeaturefromAcceleratedSegmentTest.pdf

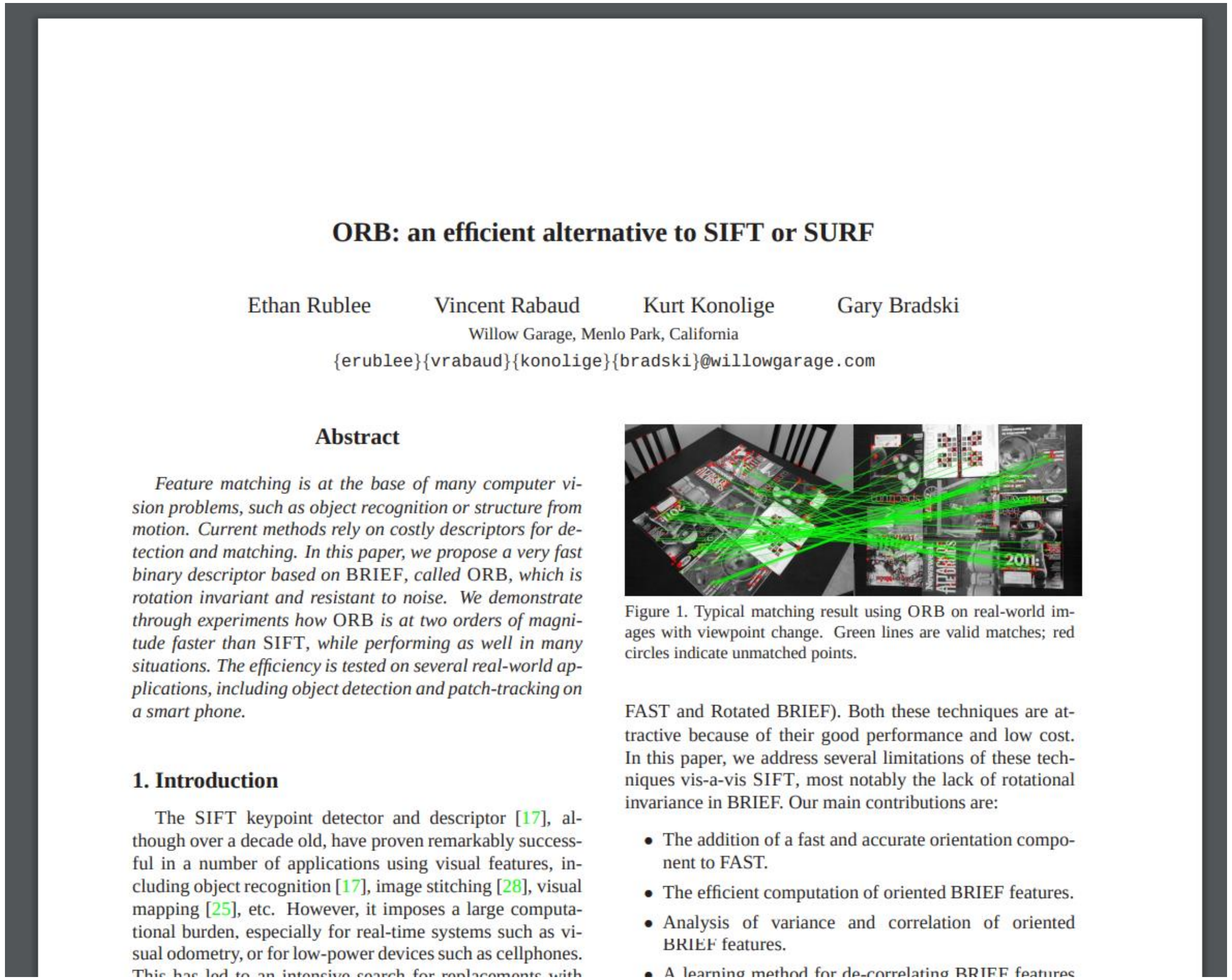
Feature Detection/Extraction



Feature Detection/Extraction

Feature Description

- Generates a vector that describes the local surrounding of a feature
- Vector length typically dim=256
    - Often binary vectors!
    - Hamming distance



ORB: an efficient alternative to SIFT or SURF

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Abstract

Feature matching is at the base of many computer vision problems, such as object recognition or structure from motion. Current methods rely on costly descriptors for detection and matching. In this paper, we propose a very fast binary descriptor based on BRIEF, called ORB, which is rotation invariant and resistant to noise. We demonstrate through experiments how ORB is at two orders of magnitude faster than SIFT, while performing as well in many situations. The efficiency is tested on several real-world applications, including object detection and patch-tracking on a smart phone.

1. Introduction

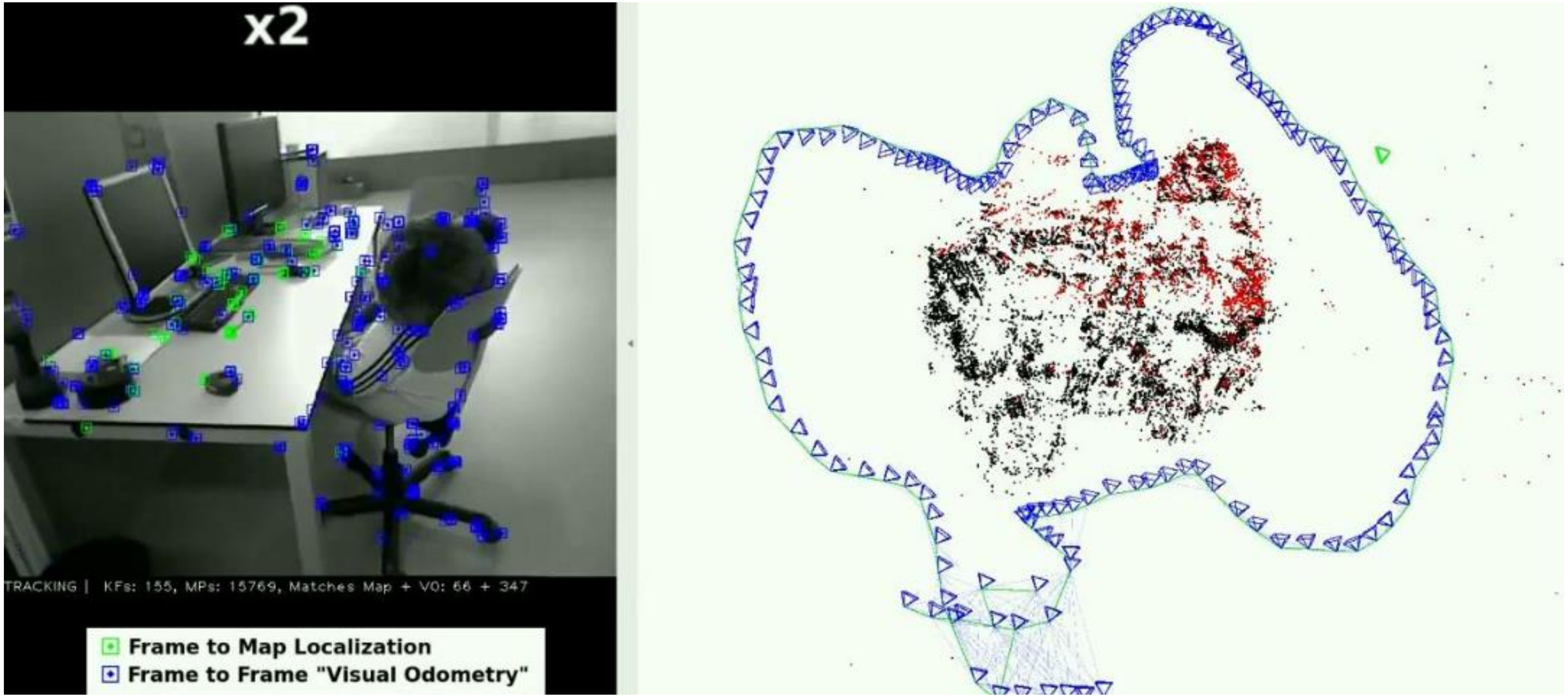
The SIFT keypoint detector and descriptor [17], although over a decade old, have proven remarkably successful in a number of applications using visual features, including object recognition [17], image stitching [28], visual mapping [25], etc. However, it imposes a large computational burden, especially for real-time systems such as visual odometry, or for low-power devices such as cellphones. This has led to an intensive search for replacements with

Figure 1. Typical matching result using ORB on real-world images with viewpoint change. Green lines are valid matches; red circles indicate unmatched points.

FAST and Rotated BRIEF). Both these techniques are attractive because of their good performance and low cost. In this paper, we address several limitations of these techniques vis-a-vis SIFT, most notably the lack of rotational invariance in BRIEF. Our main contributions are:

- The addition of a fast and accurate orientation component to FAST.
- The efficient computation of oriented BRIEF features.
- Analysis of variance and correlation of oriented BRIEF features.
- A learning method for de-correlating BRIEF features

Feature Description (ORB-SLAM 2015)



https://arxiv.org/abs/1502.00956

Feature Matching

- ORB generates dim=256 binary vectors!
- A match between a keypoint i in frame0 and a keypoint j in frame1 is determined if the Hamming distance is low.
- approx. $O(N^2)$ operation!
  - Every keypoint of frame0 has to be checked with every keypoint in frame1

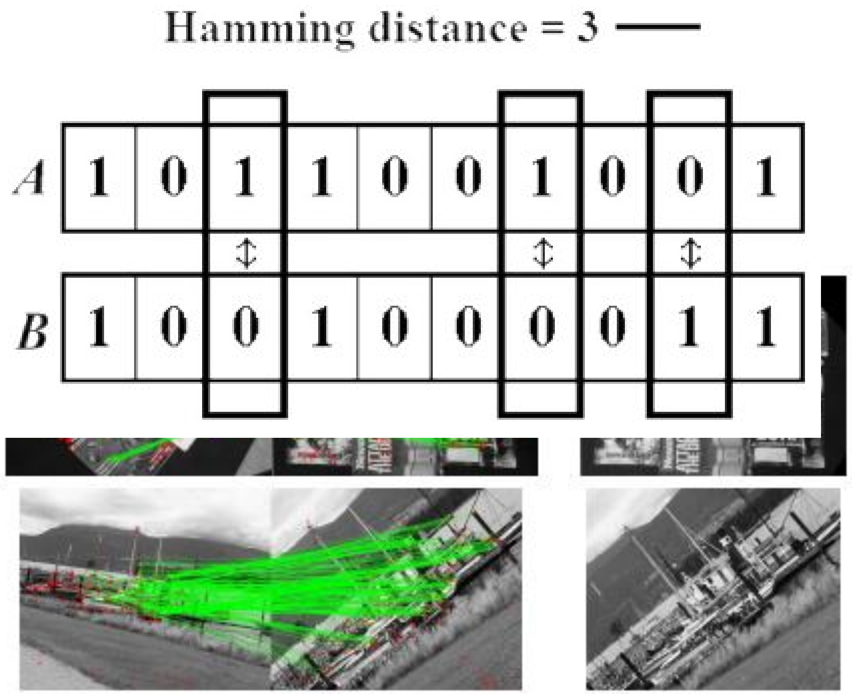
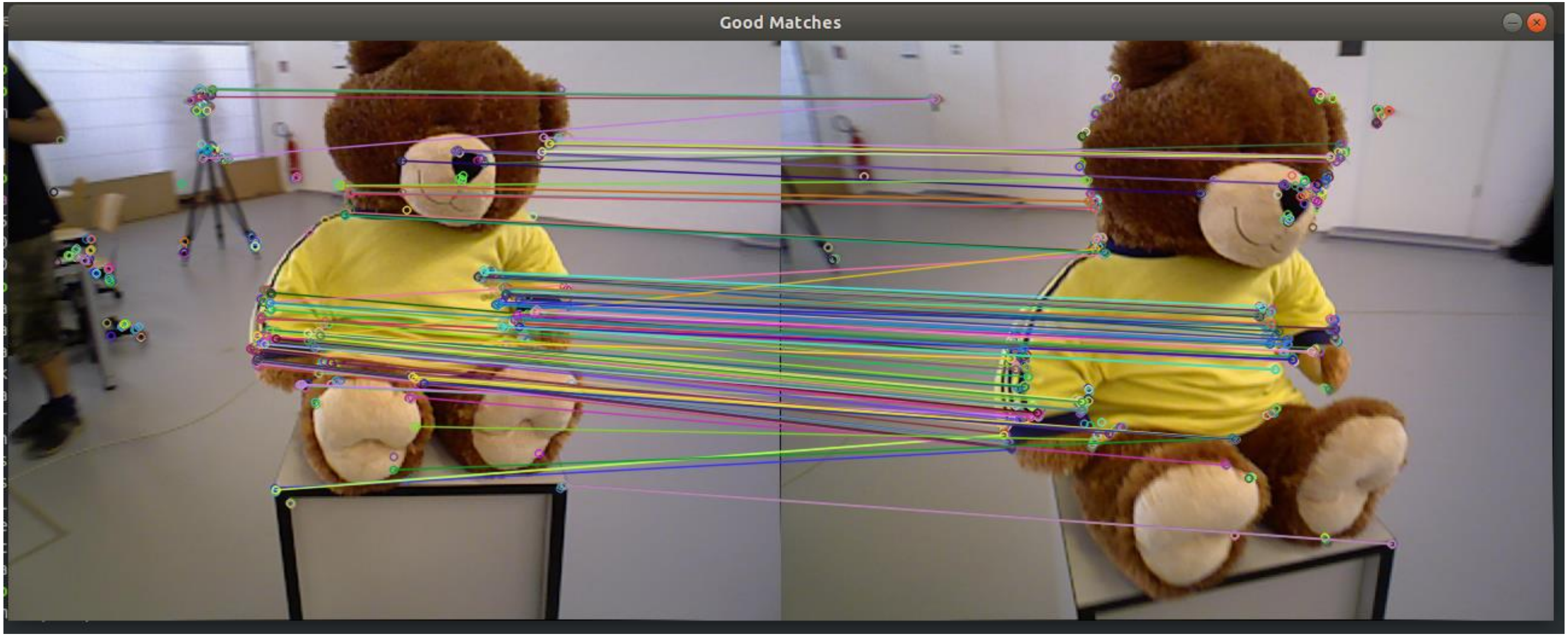
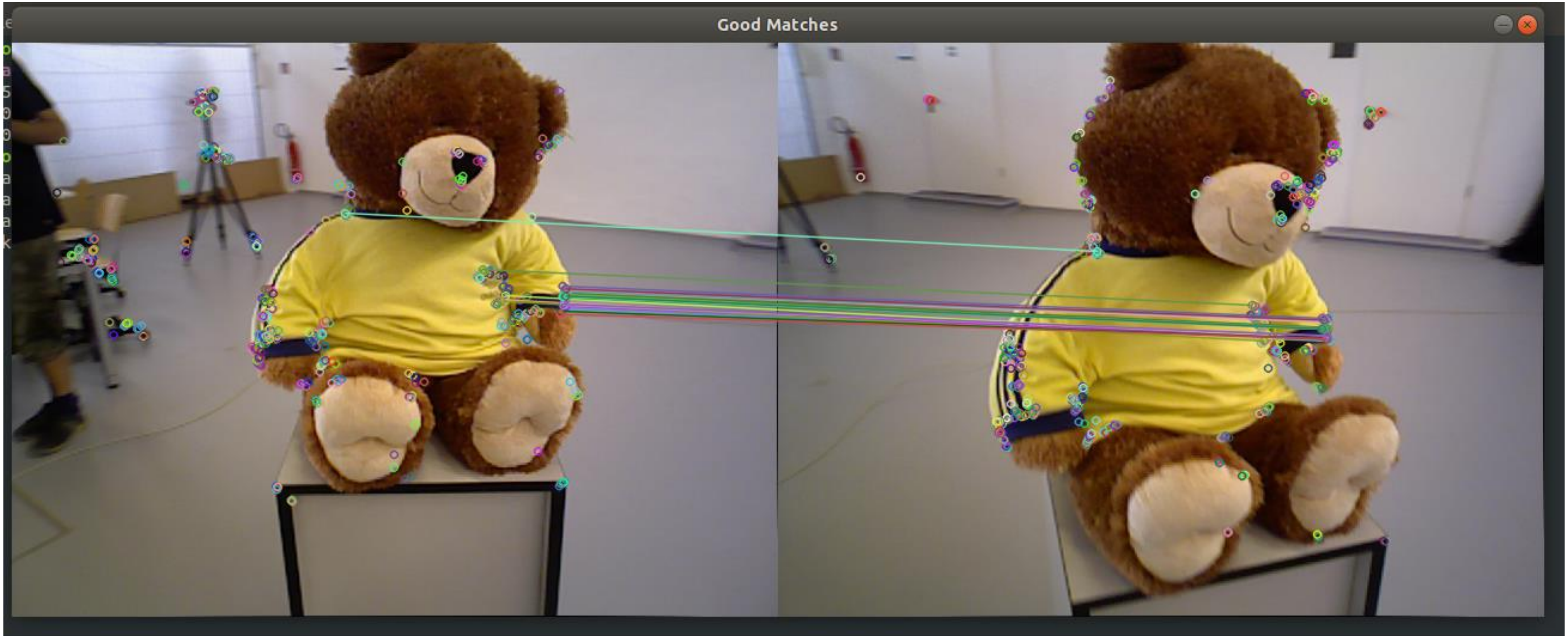


Figure 9. Real world data of a table full of magazines and an outdoor scene. The images in the first column are matched to those in the second. The last column is the resulting warp of the first onto the second.

Feature Matching (before Filtering)



Feature Matching (after Filtering)



Global Tracking

- Minimizing reprojection error!
  - Optimizing over 6 parameters * Num-frames

$$E(\mathbf{P},\mathbf{X}) = \sum_{i=1}^{m}\sum_{j=1}^{n} D\left(\mathbf{x}_{ij}, \mathbf{P}_i\mathbf{X}_j\right)^2$$

- m = num-keypoints in frame0
- n = num-keypoints in frame1