Minimum Uncertainty Triangle Paths for Multi Camera Calibration

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Multi camera systems become increasingly important in computer vision. For many applications, however, the system has to be calibrated, i.e. the intrinsic and extrinsic parameters of the cameras have to be determined. We present a method for calibrating the extrinsic parameters without any scene knowledge or user interaction. In particular, we assume known intrinsic parameters and one image from each camera as input.

The difficulty of the problem is mainly caused by the need to extract point correspondences from images in a medium or wide baseline situation. The typically high portion of outliers in such correspondences poses a challenge to the subsequent calibration. As the relative pose of two cameras can be estimated even in presence of very many outliers [1], we first estimate relative poses between some camera pairs and subsequently compose these to the extrinsic calibration. The quality of the results, of course, highly depends on the precision of the relative pose estimates, which varies a lot depending on the quality of the extracted point correspondences.

We assess the quality of relative pose estimates using an uncertainty measure, which is computed by a sampling-based relative pose estimation algorithm. Based on that, we propose a discrete optimization criterion for selecting good relative pose estimates for the calibration. We will roughly describe both of these aspects. Fig. 1 gives an overview of the whole system. For details, the reader is referred to the literature [2,3].

After extracting point correspondences from the images (using e.g. SIFT matching), we apply the five point algorithm embedded into a RANSAC-like robust sampling procedure to estimate relative poses. The main difference to RANSAC consists of evaluating the following probabilistic model based on the outlier-robust Blake-Zisserman distribution instead of computing support sets:

$$p(\boldsymbol{R}, \boldsymbol{t}^* \mid \mathcal{D}) \propto \left(\prod_{\boldsymbol{d} \in \mathcal{D}} \left(\exp\left(-\frac{s(\boldsymbol{R}, \boldsymbol{t}^*, \boldsymbol{d})}{\sigma^2} \right) + \epsilon \right) \right)^{|\mathcal{D}|^{-\phi}} p(\boldsymbol{R}, \boldsymbol{t}^*) \quad , \tag{1}$$

where $\boldsymbol{R}, \boldsymbol{t}^*$ denotes the relative pose (rotation and translation direction), $\mathcal{D}$ is the set of correspondences, $s(\boldsymbol{R}, \boldsymbol{t}^*, \boldsymbol{d})$ computes the Sampson approximation of the reprojection error, and σ, ϵ and ϕ are parameters. During the sampling process, we also compute a discrete approximate marginalization $p(\boldsymbol{t}^* \mid \mathcal{D})$ of $p(\boldsymbol{R}, \boldsymbol{t}^* \mid \mathcal{D})$. We use the entropy of $p(\boldsymbol{t}^* \mid \mathcal{D})$ as a measure for the uncertainty of the relative pose estimate.

As calibration is possible only up to a 3D similarity transformation, we can choose one of the cameras as world coordinate system. The extrinsic calibration is equivalent to computing relative poses with consistent scales from that reference camera to all other

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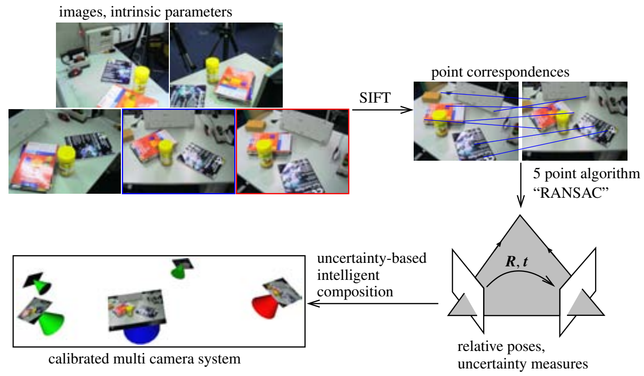

Fig. 1. An overview of the whole calibration algorithm.

cameras. We represent cameras and known relative poses in the *camera dependency graph*, which contains cameras as vertices connected according to known relative poses.

In order to compute consistent scales, we use triangles in the camera dependency graph. Two of the three unknown scale factors can be computed relative to the third one via triangulation. Hence, we set one scale factor to one and move from triangle to triangle to compute all other scale factors and compute missing relative poses via concatenation. As this triangle-based traversal of the graph implies a selection of relative pose estimates used for the calibration, we suggest using a more sophisticated traversal order based on the uncertainty of the relative pose estimates. Calibrating one camera relative to the reference camera involves a sequence of triangles, which we call *triangle path*. Using the uncertainties as edge weights, we choose triangle paths with minimum total uncertainty, which is defined as the sum of the uncertainties of all involved relative poses. We efficiently compute such shortest triangle paths by constructing a suitable auxiliary graph. Shortest ordinary paths in that graph correspond to shortest triangle paths in the camera dependency graph. Hence, the Dijkstra algorithm can be applied. We use a further minimum uncertainty criterion to choose the reference camera (pair).

Experiments [2,3] show that this selection criterion gives greatly improved results compared to breadth first search on the auxiliary graph.

References

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