Performance Evaluation of RANSAC Family

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Random Sample Consensus (RANSAC) [3] has been popular in regression problem with samples contaminated with outliers. M-estimator, Hough transform, and others had been utilized before RANSAC. However, RANSAC does not use complex optimization as like M-estimator. It does not need huge amounts of memory as like Hough transform to keep parameter space. RANSAC is simple iteration of two steps: hypothesis generation and hypothesis verification. It is now widely applied to many vision problem such as epipolar geometry estimation, motion estimation, structure from motion.

Many researches on robust estimation have followed after RANSAC, but there are a few and old survey and performance evaluation [4, 8, 9]. An insightful view of the RANSAC family is described in this paper. The view categorizes them into their research objectives: being *accurate*, being *fast*, and being *robust* (Figure 1). It can be useful to analyze the previous works and develop the new method. Each viewpoint are also examined according to tactics to achieve the objectives. For example, guided sampling and partial evaluation have been tactics to accelerate RANSAC. Computing time of RANSAC is

$$T = t(T_G + NT_E)\,, \tag{1}$$

where T_G is time for generating a hypothesis from sampled data, T_E is time for evaluating the hypothesis for each datum, t is the number of iteration, and N is the necessary number of data to verify a hypothesis. Guided sampling tries to reduce t and partial evaluation focuses on N to make RANSAC fast. Guided MLESAC [7], PROSAC [2], NAPSAC [5] and GASAC [6] are representative estimators which substitute random sampling as guided sampling. Among them, Guided MLESAC and PROSAC need prior or domain-specific knowledge, but NAPSAC and GASAC do not use it.

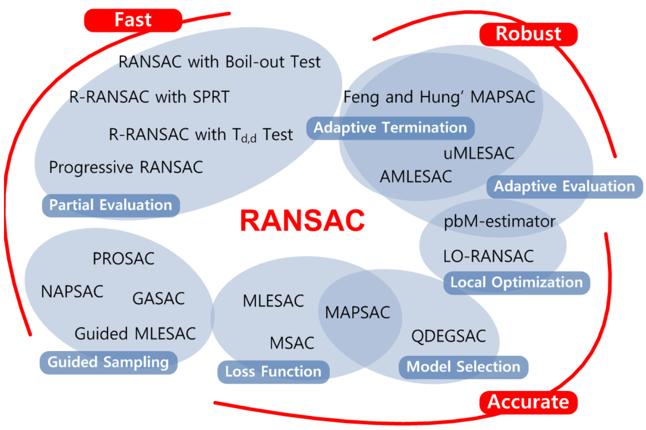

Figure 1: RANSAC Family

Performance evaluation on 12 estimators was executed on line fitting (synthesized data) and planar homography estimation (real data). Line fitting was performed on various combination of outlier ratio and magnitude of inlier noise (Figure 2). Oxford VGG *Graffiti* images were utilized for estimating planar homography (Figure 3). The results of two experiments were also analyzed in three viewpoints. Accuracy was quantified through *the normalized squared error of inliers* (NSE),

$$\mathrm{NSE}(M) = \frac{\sum_{d_i \in \mathscr{D}_{in}} \mathrm{Err}(d_i; M)^2}{\sum_{d_i \in \mathscr{D}_{in}} \mathrm{Err}(d_i; M^*)^2}\,, \tag{2}$$

where M^* and M are the true line and its estimation, $\mathscr{D}_{in}$ is a set of inliers. NSE comes from Choi and Kim' problem definition [1]. NSE is close to 1 when the magnitude of error by the estimated line is near the magnitude of error by the truth. Computing time was measured using MATLAB `clock` function at Intel Core 2 CPU 2.13GHz. Robustness (or adaptiveness) was observed via variation of accuracy in varying configuration. Experimental results and discussion were described in the paper.

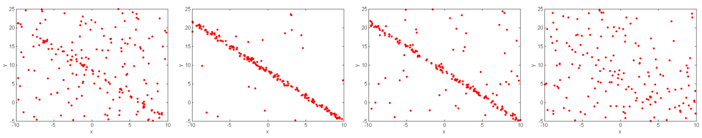

Figure 2: Examples of Line Fitting Data

Figure 3: Oxford VGG *Graffiti* Images

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