Overview of the RANSAC Algorithm

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The *RANdom SAmple Consensus* (RANSAC) algorithm proposed by Fischler and Bolles [1] is a general parameter estimation approach designed to cope with a large proportion of outliers in the input data. Unlike many of the common robust estimation techniques such as M-estimators and least-median squares that have been adopted by the computer vision community from the statistics literature, RANSAC was developed from within the computer vision community.

RANSAC is a resampling technique that generates candidate solutions by using the minimum number observations (data points) required to estimate the underlying model parameters. As pointed out by Fischler and Bolles [1], unlike conventional sampling techniques that use as much of the data as possible to obtain an initial solution and then proceed to prune outliers, RANSAC uses the smallest set possible and proceeds to enlarge this set with consistent data points [1].

The basic algorithm is summarized as follows:

Algorithm 1 RANSAC

1: Select randomly the minimum number of points required to determine the model parameters.
2: Solve for the parameters of the model.
3: Determine how many points from the set of all points fit with a predefined tolerance ϵ.
4: If the fraction of the number of inliers over the total number points in the set exceeds a predefined threshold τ, re-estimate the model parameters using all the identified inliers and terminate.
5: Otherwise, repeat steps 1 through 4 (maximum of N times).

The number of iterations, N, is chosen high enough to ensure that the probability p (usually set to 0.99) that at least one of the sets of random samples does not include an outlier. Let u represent the probability that any selected data point is an inlier and $v = 1 - u$ the probability of observing an outlier. N iterations of the minimum number of points denoted m are required, where

$$1 - p = (1 - u^m)^N \tag{1}$$

and thus with some manipulation,

$$N = \frac{\log(1 - p)}{\log(1 - (1 - v)^m)} \tag{2}$$

For more details on the basic RANSAC formulation, see [1, 2]. Extensions of RANSAC include using a *Maximum Likelihood* framework [4] and *importance sampling* [3].

References

[1] M.A. Fischler and R.C. Bolles. Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. *Communications of the ACM*, 24(6):381–395, 1981.

[2] R. Hartley and A. Zisserman. *Multiple View Geometry in Computer Vision*. University Press, Cambridge, 2001.

[3] P. Torr and C. Davidson. IMPSAC: A synthesis of importance sampling and random sample consensus to effect multi-scale image matching for small and wide baselines. In *European Conference on Computer Vision*, pages 819–833, 2000.

[4] P. Torr and A. Zisserman. MLESAC: A new robust estimator with application to estimating image geometry. *Computer Vision and Image Understanding*, 78(1):138–156, 2000.