



A General Method for Geometric Feature Matching and Model Extraction

CLARK F. OLSON

*University of Washington, Bothell, Department of Computing and Software Systems, 18115 Campus Way NE,
Box 358534, Bothell, WA 98011-8246, USA*

cfolson@u.washington.edu

Received March 3, 2000; Accepted June 15, 2001

Abstract. Popular algorithms for feature matching and model extraction fall into two broad categories: generate-and-test and Hough transform variations. However, both methods suffer from problems in practical implementations. Generate-and-test methods are sensitive to noise in the data. They often fail when the generated model fit is poor due to error in the data used to generate the model position. Hough transform variations are less sensitive to noise, but implementations for complex problems suffer from large time and space requirements and from the detection of false positives. This paper describes a general method for solving problems where a model is extracted from, or fit to, data that draws benefits from both generate-and-test methods and those based on the Hough transform, yielding a method superior to both. An important component of the method is the subdivision of the problem into many subproblems. This allows efficient generate-and-test techniques to be used, including the use of randomization to limit the number of subproblems that must be examined. Each subproblem is solved using pose space analysis techniques similar to the Hough transform, which lowers the sensitivity of the method to noise. This strategy is easy to implement and results in practical algorithms that are efficient and robust. We describe case studies of the application of this method to object recognition, geometric primitive extraction, robust regression, and motion segmentation.

Keywords: divide-and-conquer, feature matching, generate-and-test, geometric primitive extraction, Hough transform, model extraction, motion segmentation, object recognition, randomized algorithm, robust regression

1. Introduction

The generate-and-test paradigm is a popular strategy for solving model matching problems such as recognition, detection, and fitting. The basic idea of this method is to generate (or predict) many hypothetical model positions using the minimal amount of data necessary to identify unique solutions. A sequence of such positions is tested, and the positions that meet some criterion are retained. Examples of this technique include RANSAC (Fischler and Bolles, 1981) and the alignment method (Huttenlocher and Ullman, 1990).

The primary drawback to the generate-and-test paradigm is its sensitivity to noise. Let us call the data points (or other features, in general) that are used in predicting the model position for some test the *distin-*

guished features, since they play a more important role in whether the test is successful. The other features are *undistinguished features*. Errors in the locations of the distinguished features cause the predicted model position(s) to be in error. As the error grows, the testing step becomes more likely to fail.

To deal with this problem, methods have been developed to propagate errors in the locations of the distinguished features (Alter and Jacobs, 1998; Grimson et al., 1994). Under the assumption of a bounded error region for each of the distinguished features, these methods can place bounds on the locations in which various model features can be located in an image. If we count the number of image features that can be aligned with the model (with the constraint that the distinguished features must always be in alignment up