A Robust Scheme of Model Parameters Estimation Based on the Particle Swarm Method in the Image Matching Problem

A. S. Chernyavskiy
Federal State Unitary Enterprise State Scientific Research Institute for Aviation Systems,
ul. Viktorenko 7, Moscow, 125319 Russia

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Abstract—A new iterative method for robust estimation of image transform parameters based on particle swarm optimization is proposed. The main distinction of the method from the RANSAC method of random search which is frequently applied to solving problems of robust parameters estimation in computer vision problems, consists in the fact that at each iteration the test samples are generated with taking into account the information about model quality, constructed based on samples at all previous iterations, rather than randomly. The rules for refinement of samples are motivated by the behavior of swarm (schooling) living creatures. The efficiency of the new SwarmSAC algorithm is illustrated by an example of stereo matching of two images when matching errors (outliers) are present. The results of comparison of the algorithm with the RANSAC method demonstrate the advantage of the new algorithm in solving the image matching problem. The new method is generic and can be applied to various problems of robust parameters estimation of parameters and filtering of outliers.

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INTRODUCTION

In many computer vision problems it is necessary to eliminate unwanted abnormal data. In particular, in the orientation problem it is necessary to find orientation parameters (fundamental matrix) based on the coordinates of points on a pair of images of the same scene obtained from different angles. To determine the model parameters most accurately, the coordinates of the corresponding points of the stereo pair have to be known with high accuracy. For different reasons, the coordinates may be strongly affected by noise. In addition, sometimes, points are identified erroneously, which is connected with the fact that their numerical features, descriptors, may take close values for different image pixels.

The data that can be explained by the hypothetical model are called inliers of this model. The other points, e.g., those generated by matching errors are called outliers. The outliers are caused by external effects not related to the investigated model. There are several methods for identifying points as inliers or outliers. In particular in computer vision the RANSAC estimation method is widely applied. In contrast to similar methods applied in mathematical statistics, in computer vision, as a rule, no assumptions about the distribution to which outliers satisfy are made, since either there is no information about measurements or it does not follow obvious physical laws. In the RANSAC algorithm, random data samples, based on which the model parameters are calculated, are employed. Since actually we deal with random search, a large number of iterations are required to investigate a representative subset of noisy data and to find a reliable model that could explain the most part of available data. In this paper, we propose a method of directed search based on particle swarm optimization (PSO). The advantage of applying the PSO compared with a pure random search consists in the fact that the search is conducted among the data samples that give more inliers with a greater probability.

1. ROBUST MODEL PARAMETERS ESTIMATION

Consider a linear regression problem in which it is necessary to reject (filter) outliers from noisy data. Assume that a cloud of points is given which is distributed in a random way about a hidden straight line, and the distribution parameters are unknown. We can consider two problems: the problem of rejection of points that are located too far from the line, and, precisely, the problem of deriving the equation of the line passing through the cloud of points in an optimal way according to a defined criterion (Fig. 1). The cost functions that allow one to discriminate inliers from outliers depend on the particular problem at hand. In the problem considered above, this criterion can be based on the distance of a point to the hidden straight line. The problem of rejection (filtering) of outliers consists in dividing all the points into two classes. Inliers that lie at a reasonable distance to the straight line should be referred to the first class. The outliers, i.e., the points that lie far from the straight line should fall into the second class.
In essence, it is necessary to find the model parameters (the line coefficients in this case) to conduct the rejection process. It is obvious that it is necessary to find the model parameters as precisely as possible for successful filtering. The search process should be stable with respect to outliers. This means that the presence of a large number of points whose coordinates are distributed in the search domain in a random way should not affect the values of the found model parameters. In addition, we should remember that the distribution of samples cannot be described exactly.

The general problem of determining model parameters based on available data can be written as follows. It is required to find a vector of parameters \( \theta \) such that

\[
F(Z, \theta) = 0,
\]

where \( Z = \{Z_1, Z_2, \ldots, Z_N\} \) is a data vector, the function \( F(Z, \theta) \) implicitly describes the investigated mathematical model. In the problem of finding the straight line passing through a cloud of points, the coordinates of points play the role of \( Z \), \( F(Z, \theta) \) and \( \theta \) specify the line equation and its coefficients.

Figure 1 demonstrates two cases of finding the straight line passing through a cloud of points, without outliers (Fig 1a) and with them (Fig. 1b). Figure 1b implies that the maximum likelihood method is unstable to the presence of outliers. A small number of outliers are sufficient to lead the method in the wrong direction. Without loss of generality, in what follows, point means a point in a two-dimensional space, e.g., a pixel of a digital photo image.

What properties should an appropriate algorithm for automatic rejection possess? First of all, as small number of outliers classified as inliers as possible should remain after its operation. On the other hand, it is desirable not to classify inliers as outliers. Denoting by \( \gamma \in [0, 1] \) the fraction of inliers in the source data, we call a method of parameter estimation robust if it is possible to determine stably the model parameters by it if \( \gamma < 1 \). In other words, methods that are low-sensitive to outliers among useful data are called robust.

The RANSAC (RANdom Sample Consensus) algorithm for robust parameters estimation [1] was proposed in 1981. This algorithm solves the problem of model parameters estimation by finding the best hypothesis \( \theta \) among the set of all possible hypotheses \( \Theta \) generated by the source data. Since the source data are noisy, then in order to find the hypothesis about the unknown parameters, samples of the minimum size required for model estimation are taken (for example, a sample of only two points is sufficient to draw a straight line). Thus, the probability of presence of an outlier in the sample is reduced. The number of possible samples of the fixed minimum size \( M \) of a data set of length \( N \) is enormous, and the exhausting testing of all samples for a reasonable time is impossible. Therefore, only \( K \) samples are randomly chosen and tested. Algorithms of the RANSAC family consist of \( K \) iterations of the following cycle [2]:

1. construct a sample \( X_k \subset Z \) consisting of \( M \) different elements;
2. construct a hypothesis \( \theta_k \) based on the sample \( X_k \);
3. estimate the degree of agreement \( f_k \) of the hypothesis \( \theta_k \) with the set of all source data \( Z \).

After construction and estimation of all \( K \) hypotheses, a hypotheses

\[ \theta_{opt} = \arg \max_{k=1, \ldots, K} f_k(Z, \theta_k) \]

with the best degree of agreement is chosen among them, which is taken as the result of robust estimate of the model parameters. The maximization of the degree