Towards a Standalone Methodology for Robust Algorithms Evaluation: A Case Study in 3D Reconstruction

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Abstract—In the field of 3D reconstruction there are two main challenging tasks that require careful consideration, namely, feature detection and matching. The corresponding automatic process introduces noise resulting from the image capture and spurious features matching. A number of robust algorithms for hypothesis evaluation have been suggested; they would deal with these limitations by removing outliers. Most of these works are merely comparisons to previous algorithms and lack any standalone evaluation. This paper attempts to fill this gap by introducing a novel and robust statistical methodology. It has the advantage of evaluating related algorithms using non-dimensional metrics for fixed and continuous intervals. In addition, the proposed methodology is validated using a proof of concept scenario based on the 3D pose estimation phase in the 3D reconstruction pipeline. The obtained results are very promising and emphasize the methodology’s generic nature, clearing the way for its application in a multitude of scenarios, such as computer vision and 3D reconstruction.

Keywords—robust algorithms; standalone methodology; statistical tests; hypothesis testing

I. INTRODUCTION

3D reconstruction from 2D images demands multidisciplinary knowledge from several areas, including image processing, computer vision, geometry, and linear algebra, and also demands knowledge relating to nonlinear systems optimization, among other areas. This broad and specific knowledge is required in all phases of the 3D reconstruction pipeline, from 2D image acquisition, to the end product, which is characterized by a cloud of 3D points and by the parameters of the cameras that make up the scene. An example of a 3D reconstruction pipeline can be seen in Figure 1. This pipeline is based on Structure from motion (SfM) which is a classical approach to compute the scene structure and camera motion assuming that this information is unknown [1].

This 3D reconstruction pipeline is composed of the following phases: Image Acquisition and Tracking, Fundamental Matrix Estimation, Pose Estimation, Triangulation, Dense Reconstruction and Texturing of the 3D Reconstruction. The first phase is responsible for image processing, since the view acquisition from an image sequence, and the extraction of features in an image, find the correspondent point in the following image. Once the matching point has been computed, the following phase is used to estimate the Fundamental Matrix that encapsulates the projective geometry between the two views, as defined by the epipolar geometry. The Pose Estimation phase is used to calculate the camera matrix [2].

Besides the camera’s calibration parameters, extrinsic parameters (the camera pose formed by camera positioning and orientation) are also recovered with 3D reconstruction. A 3D point is reconstructed by triangulation of corresponding points in each group of images and with each corresponding camera pose. The scene can be sparsely reconstructed if only a few thousand points have had their 3D positions computed, or it can be densely reconstructed (called the Dense Reconstruction phase) if the total 3D points extracted are in the millions. Finally, the next phase is to generate texture from the images and render it into the reconstructed 3D model. Further details can be found in [1].

When real data is used in the 3D reconstruction pipeline, there is an introduction of accumulative errors in each executed stage. It starts with image acquisition, which depends on parameters such as image resolution, camera sensor and illumination. The image being processed may have noise when passed on to the next stage of the pipeline. In the tracking phase, aspects such as feature occlusion, false matchings, and drift, due to areas in the image with poor textures or low significant gradients, can also introduce noise into the features positioning along the tracks. Therefore, once it has been acknowledged that there are errors in the data, which were introduced by acquisition and tracking, a new approach that take those errors into account during the calculation