

## Chapter 8

# Calculating Absolute Scale and Scale Uncertainty for SfM Using Distance Sensor Measurements: A Lightweight and Flexible Approach

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### ABSTRACT

*Capturing details of objects and surfaces using structure from motion (SfM) 3D reconstruction has become an important part of data gathering in geomapping, medicine, cultural heritage, and the energy and production industries. One inherent problem with SfM, due to its reliance on 2D images, is the ambiguity of the reconstruction's scale. Absolute scale can be calculated by using the data from additional sensors. This chapter demonstrates how distance sensors can be used to calculate the scale of a reconstructed object. In addition, the authors demonstrate that the uncertainty of the calculated scale can be computed and how it depends on the precision of the used sensors. The provided methods are straightforward and easy to integrate into the workflow of commercial SfM solutions.*

### INTRODUCTION

Structure from Motion (SfM) techniques have matured throughout the years to become viable commercial solutions for 3D reconstruction. This is due to the techniques' scalability, relative ease of use and the fact that they do not rely on specialized equipment. This positions SfM as a useful substitute for other reconstruction approaches that require both specialized hardware and software, like structured

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light (Sarbolandi, 2015), stereo (Sarker, 2017) or time-of-flight cameras (Corti, 2016), when real-time performance is not necessary.

The algorithm pipeline for SfM is extensively documented by (Özyeşil, 2017) and the accuracy of different solutions for varying use cases are discussed by (Nikolov I. A., 2016), (Knapitsch, 2017). There are several approaches to performing SfM reconstruction, but a typical algorithm takes 2D images looking at the reconstructed object or surface, from different positions and directions. Another important feature of SfM is the possibility to use it both with images from precisely calibrated capturing setups (Martell, 2018), as well as with in the wild image datasets (Makantasis, 2016), requiring more post-processing in filtering the image data and clustering it, but saving on long capturing times.

In the SfM processing pipeline, a number of feature points are extracted from each image and matched with features from the input images. These feature matches are filtered and together with the intrinsic parameters of the cameras are used in a bundle adjustment algorithm to triangulate the camera positions in 3D space, as well as a sparse point cloud. A depth map and dense point cloud are then computed. Finally, if needed, the dense point cloud is meshed and a texture is calculated from the images. One drawback of using only uncalibrated 2D images as input is that the scale of the reconstruction is ambiguous. To calculate the absolute scale, additional information is needed. This information can be captured manually, by using objects of known sizes in the images or by using additional sensors.

This chapter focuses on using additional sensors for calculating the absolute scale of the 3D reconstruction. It demonstrates a step-by-step solution which uses external distance sensors to provide the necessary information. In addition, the authors take into consideration that real-world sensors' readings contain level of uncertainty, which in turn is transferred to the calculated scale. The discussed solutions take this into consideration and demonstrate that these uncertainties can be quantified.

The chapter's contributions to the field of SfM can be summarized as:

- A lightweight and easy to implement method for finding the absolute scale of a SfM reconstruction using distance sensors;
- The method is easy to integrate into existing commercial SfM solutions, as it requires only simple outputs, such as a 3D mesh and camera positions and orientations;
- The method is flexible and can be used both with expensive LiDAR solutions, as well as cheap distance measurement sensors, as it does not require capturing the object surface;
- The uncertainty of the computed absolute scale can be calculated, when high precision is required.

## **STATE OF THE ART**

All state of the art SfM solutions, both open-source (Wu, 2011), (Sweeney, 2015), (Schonberger, 2016) and commercial (Agisoft, 2010), (Bentley, 2016), (CapturingReality, 2016), contain some kind of built-in way to manually scale the final 3D reconstruction using information captured from the environment. Normally, users can manually measure parts of the real and reconstructed objects and compute the resultant scaling factor. Another widely used method is relying on markers with predefined shapes and sizes. These markers are put on the reconstructed object or surface and are captured in the images. Later the scale of the object can be calculated from the ratio between the real-world size of the marker and the captured size. Both methods rely on the fact that the real object is easily accessible and are time

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