Multi-View Stereo: A Tutorial

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Contents

Abstract

This tutorial presents a hands-on view of the field of multi-view stereo with a focus on practical algorithms. Multi-view stereo algorithms are able to construct highly detailed 3D models from images alone. They take a possibly very large set of images and construct a 3D plausible geometry that explains the images under some reasonable assumptions, the most important being scene rigidity. The tutorial frames the multi-view stereo problem as an image/geometry consistency optimization problem. It describes in detail its main two ingredients: robust implementations of photometric consistency measures, and efficient optimization algorithms. It then presents how these main ingredients are used by some of the most successful algorithms, applied into real applications, and deployed as products in the industry. Finally it describes more advanced approaches exploiting domain-specific knowledge such as structural priors, and gives an overview of the remaining challenges and future research directions.

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1

Introduction

Reconstructing 3D geometry from photographs is a classic Computer Vision problem that has occupied researchers for more than 30 years. Its applications range from 3D mapping and navigation to online shopping, 3D printing, computational photography, computer video games, or cultural heritage archival. Only recently however have these techniques matured enough to exit the laboratory controlled environment into the wild, and provide industrial scale robustness, accuracy and scalability.

Modeling the 3D geometry of real objects or scenes is a challenging task that has seen a variety of tools and approaches applied such as Computer Aided Design (CAD) tools [3], arm-mounted probes, active methods [110, 131, 11, 10] and passive image-based methods [162, 165, 176]. Among all, passive image-based methods, the subject of this tutorial, provide a fast way of capturing accurate 3D content at a fraction of the cost of other approaches. The steady increase of image resolution and quality has turned digital cameras into cheap and reliable high resolution sensors that can generate outstanding quality 3D content.

The goal of an image-based 3D reconstruction algorithm can be described as *"given a set of photographs of an object or a scene, estimate*

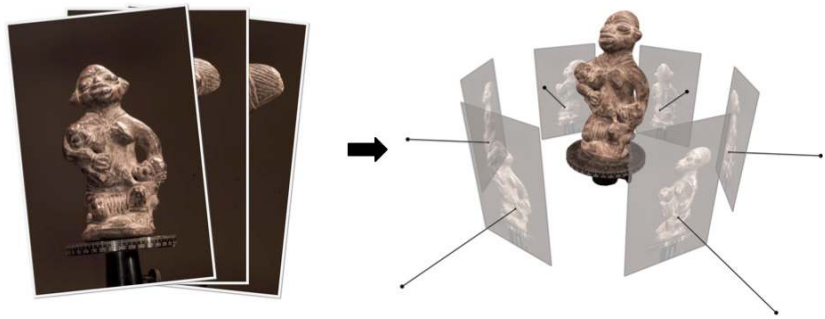

Figure 1.1: Image-based 3D reconstruction. Given a set of photographs (left), the goal of image-based 3D reconstruction algorithms is to estimate the most likely 3D shape that explains those photographs (right).

the most likely 3D shape that explains those photographs, under the assumptions of known materials, viewpoints, and lighting conditions" (See Figure 1.1). The definition highlights the difficulty of the task, namely the assumption that materials, viewpoints, and lighting are known. If these are not known, the problem is generally ill-posed since multiple combinations of geometry, materials, viewpoints, and lighting can produce exactly the same photographs. As a result, without further assumptions, no single algorithm can correctly reconstruct the 3D geometry from photographs alone. However, under a set of reasonable extra assumptions, e.g. rigid Lambertian textured surfaces, state-of-the-art techniques can produce highly detailed reconstructions even from millions of photographs.

There exist many cues that can be used to extract geometry from photographs: texture, defocus, shading, contours, and stereo correspondence. The latter three have been very successful, with stereo correspondence being the most successful in terms of robustness and the number of applications. Multi-view stereo (MVS) is the general term given to a group of techniques that use stereo correspondence as their main cue and use more than two images [165, 176].

All the MVS algorithms described in the following chapters assume the same input: a set of images and their corresponding camera parameters. This chapter gives an overview of an MVS pipeline starting from

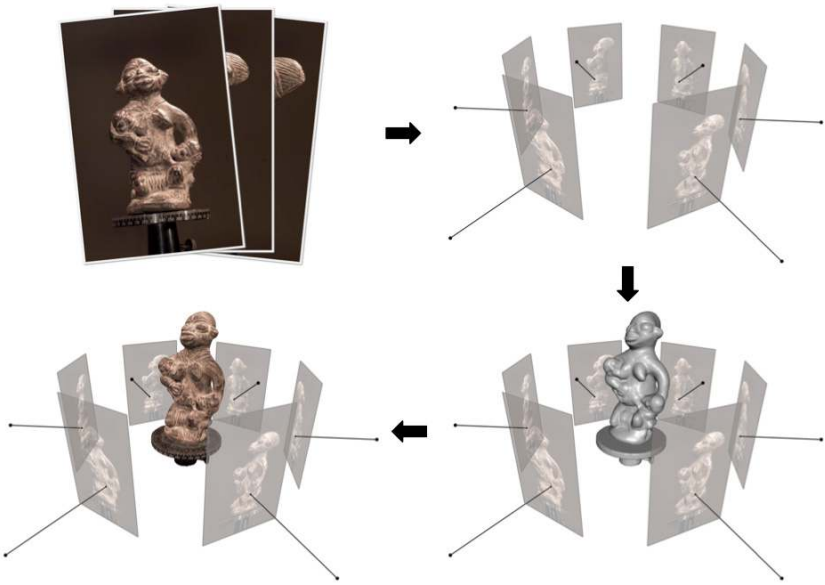

Figure 1.2: Example of a multi-view stereo pipeline. Clockwise: input imagery, posed imagery, reconstructed 3D geometry, textured 3D geometry.

photographs alone. An important take-home message of this chapter is simple: An MVS algorithm is only as good as the quality of the input images and camera parameters. Moreover, a large part of the recent success of MVS is due to the success of the underlying Structure from Motion (SfM) algorithms that compute the camera parameters.

Figure 1.2 provides a sketch of a generic MVS pipeline. Different applications may use different implementations of each of the main blocks, but the overall approach is always similar:

- Collect images,
- Compute camera parameters for each image,
- Reconstruct the 3D geometry of the scene from the set of images and corresponding camera parameters.
- Optionally reconstruct the materials of the scene.

Figure 1.3: Different MVS capture setups. From left to right: a controlled MVS capture using diffuse lights and a turn table, outdoor capture of small-scale scenes, and crowd-sourcing from online photo-sharing websites.

In the chapter we will give more insight into the first three main stages of MVS: imagery collection, camera parameters estimation, and 3D geometry reconstruction. Chapter 2 develops the notion of photo-consistency as the main signal being optimized by MVS algorithms. Chapter 3 presents and compares some of the most successful MVS algorithms. Chapter 4 discusses the use of domain knowledge, in particular, structural priors in improving the reconstruction quality. Chapter 5 gives an overview of successful applications, available software, and best practices. Finally Chapter 6 describes some of the current limitations of MVS as well as research directions to solve them.

1.1 Imagery collection

One can roughly classify MVS capture setups into three categories (See Figure 1.3):

- Laboratory setting,
- Outdoor small-scale scene capture,
- Large-scale scene capture using fleets or crowd-sourcing, e.g., cars, planes, drones, and Internet.

MVS algorithms first started in a laboratory setting [184, 147, 58], where the light conditions could be easily controlled and the camera

could be easily calibrated, e.g. from a robotic arm [165], rotation table [93], fiducial markers [2, 43, 192], or early SfM algorithms [62]. MVS algorithms went through two major developments that took them to their current state: They left the laboratory setting to a small-scale outdoor scenes [174, 102, 85, 169, 190], e.g. a building facade or a fountain, then scaled up to much larger scenes, e.g. entire buildings and cities [129, 153, 97, 69].

These major changes were not solely due to the developments in the MVS field itself. It was a combination of new hardware to capture better images, more computation power, and scalable camera estimation algorithms.

Improvements in hardware: Two areas of hardware improvements had the most impact on MVS: digital cameras and computation power. Digital photography became mainstream and image digital sensors constantly improved in terms of resolution and quality. Additionally, mass production and miniaturization of geo positioning sensors (GPS) made them ubiquitous in digital cameras, tablets, and mobile phones. Although the precision of commercial units is not enough for MVS purposes, it does provide an initial estimate on camera parameters that can be refined using Computer Vision techniques. The second significant hardware improvement was computation power. The rise of inexpensive computer clusters [5] or GPU general computation [6] enabled SfM algorithms [25, 64] and MVS algorithms [69] to easily handle tens of thousands of images.

Improvements in Structure-from-Motion algorithms: Researchers have been working on visual reconstruction algorithms for decades [183, 182]. However, only relatively recently have these techniques matured enough to be used in large-scale industrial applications. Nowadays industrial algorithms are able to estimate camera parameters for millions of images. Two slightly different techniques have made great progress in recent years: Structure-from-Motion (SfM) [88] and Visual Simultaneous Localization and Mapping (VSLAM) [53]. Both rely on the correspondence cue and the assumption that the scene is rigid. SfM is most commonly used to compute camera models of unordered sets of images, usually offline, while VSLAM specializes in computing the

location of a camera from a video stream, usually real-time. In this tutorial we focus on SfM algorithms, since a large majority of MVS algorithms are designed to work on unordered image sets, and rely on SfM to compute camera parameters. Note however that VSLAM has made very quick progress recently in the context of MVS [145, 180].

The term "camera parameters" refers to a set of values describing a camera configuration, that is, camera pose information consisting of location and orientation, and camera intrinsic properties such as focal length and pixel sensor size. There are many different ways or "models" to parameterize this camera configuration. In the following section, we discuss some of the most common camera projection models used in MVS applications.

1.2 Camera projection models

As mentioned in the introduction, MVS algorithms need additional knowledge in order to make the reconstruction problem well posed. In particular, MVS algorithms require that every input image has a corresponding camera model that fully describes how to project a 3D point in the world into a 2D pixel location in a particular image. The most commonly used camera model for MVS is the pinhole camera model, which is fully explained by a 3x4 projection camera matrix [88], defined up to a scale. This is the model commonly used with off-the-shelf digital cameras capturing still photographs. Any 3×4 projection matrix P can be decomposed into the product of a 3×3 upper triangular matrix K and a 3×4 pose matrix $[R|T]$

$$P = \underbrace{\begin{pmatrix} f_x & s & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{pmatrix}}_{K} \cdot \underbrace{\left(\begin{array}{ccc|c} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{array}\right)}_{R \quad T}. \tag{1.1}$$

The matrix K is commonly referred to as the intrinsics matrix, because it is composed of quantities intrinsic to the camera: vertical and horizontal focal lengths (f_x, f_y), principal point (c_x, c_y), and skew s. The matrix $[R|T]$ is commonly known as the extrinsics matrix, where R is

Figure 1.4: Common deviations from pinhole camera model. Left: a fish eye lens exhibiting large radial distortion (top) and a rectified version of the same image after removing radial distortion (bottom). Right: rolling shutter artifacts caused by a fast moving object in the scene [155].

the rotation of the camera and T is the translation of the camera. Note that, due to the quality of digital sensors, one rarely estimates the 11 parameters of the projection matrix. In particular, pixels are assumed to have no skew ($s = 0$), and be square ($f_x = f_y$). Also, if an image has not been cropped, it is safe to assume the principal point is at the center of the image. As a result, a common pinhole camera model is just composed of 7 parameters: the focal length f, the rotation matrix R and the translation vector T.

If the attached lens is low quality, or wide-angle (See Figure 1.4 left), the pure pinhole model is not enough and often extended with a radial distortion model. Radial distortion is particularly important for high-resolution photographs, where small deviations from the pure pinhole model can amount to multiple pixels near the image boundaries.

Radial distortion can typically be removed from the photographs before they enter the MVS pipeline. If the radial distortion parameters of an image have been estimated, one can undistort the image by resampling as if it had been taken with an ideal lens without distortion (See

Figure 1.4 bottom left). Undistorting the images simplifies the MVS algorithm and often leads to faster processing times. Some cameras, e.g. those in mobile phones, incorporate dedicated hardware to remove radial distortion during the processing of the image just after its capture. Note however that rectifying wide-angle images will introduce resampling artifacts as well as field of view cropping. To avoid these issues MVS pipelines can support radial distortion and more complicated camera models directly, at the expense of extra complexity.

Finally, rolling shutter is another source of complexity particularly important for video processing applications (See Figure 1.4 right). A digital sensor with an electronic rolling shutter exposes each row of an image at slightly different times. This is in contrast to global shutters where the whole image is exposed at the same time. A rolling shutter often provides higher sensor throughput at the expense of a more complicated camera model. As a result, if the camera or the scene are moving while capturing the image, each row of the image captures effectively a slightly different scene. If the camera or scene motion is slow w.r.t. the shutter speed, rolling shutter effects can be small enough to be ignored. Otherwise the camera projection model needs to incorporate the effects [63].

1.3 Structure from Motion

There is a vast literature on Structure-from-Motion algorithms, and it is not our intention to throughly review it here. In the following, we will discuss some of the key aspects of SfM and how they relate to MVS algorithms.

SfM algorithms take as input a set of images and produce two things: the camera parameters of every image, and a set of 3D points visible in the images which are often encoded as tracks. A track is defined as the 3D coordinates of a reconstructed 3D point and the list of corresponding 2D coordinates in a subset of the input images. Most of the current state-of-the-art SfM algorithms share the same basic processing pipeline (See Figure 1.5):

- Detect 2D features in every input image.
- Match 2D features between images.
- Construct 2D tracks from the matches.
- Solve for the SfM model from the 2D tracks.
- Refine the SfM model using bundle adjustment.

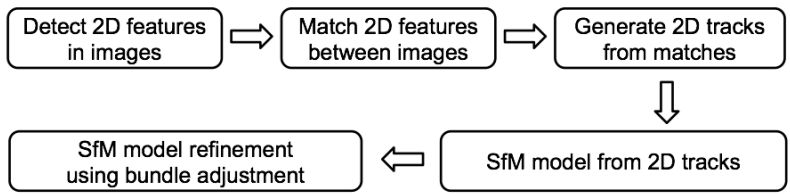

Figure 1.5: Main stages of a generic SfM pipeline, clockwise: feature detection, feature matching, track generation, structure-from-motion and bundle adjustment.

Initial work on SfM mainly focused on the geometry of two and three views under the assumption of a rigid scene [88]. Carlo Tomasi's technical perspective on visual reconstruction algorithms [182] presents an overview of the early work. One of the key developments for SfM was the use of RANSAC [61] to robustly estimate the epipolar geometry between two or three views given noisy matches.

Efforts then focused on two key components of the SfM algorithm: 1) computing a Euclidean reconstruction (up to a scale) from multiple cameras, that is, estimating both the camera parameters and 3D positions of the tracks, and 2) building longer 2D tracks. By the end of the 20th century, SfM algorithms were able to robustly compute models from large structured sets of images, e.g. from sequences of images or video sequences [62, 152] and the first SfM industrial solutions started to be commercialized for applications such as movie editing and special effects [4].

These initial systems were mainly designed for structured sets of images i.e., sets where the order of images matters, such as a video

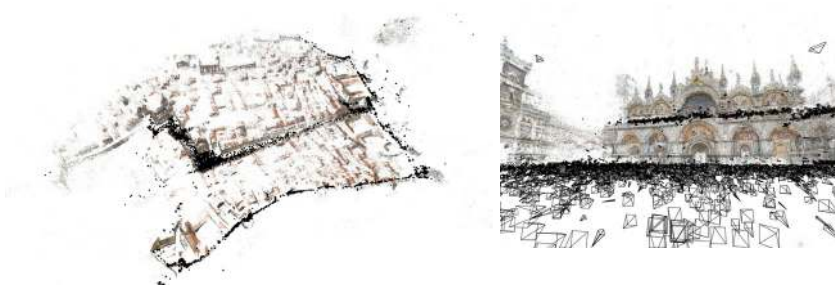

Figure 1.6: Large scale SfM examples from [25]. Left: SfM model of the city of Dubrovnik. Right: SfM model of San Marco Square in Venice.

sequence. Although some MVS applications can define such an order, for example, Google's StreetView [81] or Microsoft's Streetside [143], many recent MVS applications also use unordered sets of images captured at different times with different hardware, e.g. 3D maps from aerial images [108, 144, 30]. The development of fast and high quality feature detectors [87, 135, 57] and descriptors [135, 36, 159, 130, 26] was a crucial development towards making SfM work with unstructured datasets. High quality descriptors enabled building longer and higher quality tracks from images captured with very different pose and illumination.

The final ingredient to tackle large-scale SfM of unstructured photo collections was to improve the matching stage. In the case of unstructured photo collections, one does not have any prior knowledge of nearby candidate images that should be matched against. Therefore, every image has to be matched to every other image, which is computationally very expensive. Efficient indexing [146] combined with high quality descriptors allowed efficient pairwise matching of millions of images. Further work on simplifying the connectivity graph of the tracks [172] and parallelization [25, 64] lead to the current state-of-the-art SfM pipelines used in the industry, for example, Microsoft's photosynth [16] and Google's photo tours [15] (See Figure 1.6).

1.4 Bundle Adjustment

Although bundle adjustment [183] is not strictly a part of SfM, it is a very common step used to refine the initial SfM model. Given a set of camera parameters $\{P_i\}$, and a set of tracks $\{M^j, \{m_i^j\}\}$, where M^j denotes the 3D coordinate of a track, and m_i^j denotes the 2D image coordinate of its image projection in the i_{th} camera, bundle adjustment minimizes the following non-linear least squares error

$$E(P, M) = \sum_j \sum_{i \in V(j)} |P_i(M^j) - m_i^j|^2. \tag{1.2}$$

$V(j)$ is the list of camera indices where point M^j is visible, and $P_i(M^j)$ represents the projected 2D image coordinate of 3D point M^j in camera i using the camera parameters P_i.

$E(P, M)$ is typically measured in squared pixels, but a more common metric to express the accuracy of the estimation is to use the Root Mean Square Error or RMSE, which is measured in pixels and is defined as:

$$RMSE(P, M) = \sqrt{\frac{E(P, M)}{N}}, \tag{1.3}$$

where N is the number of residual terms being summed up in (1.2). Typical RMSE values before bundle adjustment are in the order of several pixels, while values after bundle adjustment are often sub-pixel.

The bundle adjustment framework enables the combination of multiple sensors with the SfM objective in a principled optimization framework. One way to fuse GPS and IMU constraints with SfM constraints is to simply add additional terms to (1.2) that penalize deviations of P_i from the predicted camera models from the GPS and IMU signals.

MVS algorithms are very sensitive to the accuracy of the estimated camera models. The reason is that, for efficiency purposes, they use the epipolar geometry defined by the camera models to restrict the 2D matching problem into a 1D matching problem (See Section 1.5 for more details). If the reprojection error is large, a pixel might never be compared against its real match, significantly degrading the MVS performance. The robustness of MVS to camera reprojection error depends mainly on how tolerant the matching criterion (namely the photo-

consistency measures presented in Chapter 2) is to misalignments. Usually, the larger the domain Ω of the photo-consistency measure (See equation 2.1), the more robust the measure is. Unfortunately, large domains also tend to produce over smoothed geometry, so there is a compromise between accuracy and robustness.

Since MVS is so sensitive to reprojection errors, bundle adjustment is often a requirement for MVS, with the goal of sub-pixel reprojection errors. Note that, because reprojection error is measured in pixels, one can downsample the input images and rescale the camera parameters until the reprojection error drops below a certain threshold. This approach will work as long as the downsampled images still contain enough texture and details for MVS to work [72].

1.5 Multi-View Stereo

The origins of multi-view stereo can be traced back to human stereopsis and the first attempts to solve the stereoscopic matching problem as a computation problem [139]. Until this day, two-view stereo algorithms have been a very active and fruitful research area [162]. The multi-view version of stereo originated as a natural improvement to the two-view case. Instead of capturing two photographs from two different viewpoints, multi-view stereo would capture more viewpoints in-between to increase robustness, e.g. to image noise or surface texture [184, 147]. What started as a way to improve two-view stereo has nowadays evolved into a different type of problem.

Although MVS shares the same principles with such classic stereo algorithms, MVS algorithms are designed to deal with images with more varying viewpoints, such as an image set surrounding an object, and also deal with a very large number of images, even in the order of millions. The difference in the nature of the MVS problem ends up producing significantly different algorithms than the classic stereo counterpart. As an example, industrial applications for 3D mapping [108, 144, 30], process millions of photographs over hundreds of kilometers at a time, effectively reconstructing large metropolitan areas, countries and eventually the entire world.

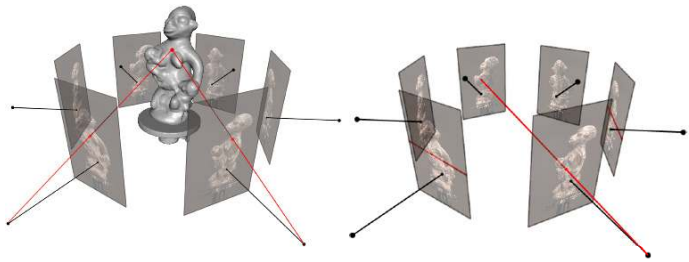

Figure 1.7: Matching images with known camera parameters. Left: The 3D geometry of the scene defines a correspondence between pixels in different images. Right: when camera parameters are known, matching a pixel in one image with pixels in another image is a 1D search problem.

Matching pixels across images is a challenging problem that is not unique to stereo or multi-view stereo. In fact, optical flow is another very active field in Computer Vision, tackling the problem of dense correspondence across images [33]. The main differences with MVS being that optical flow is typically a two image problem (similar to two-view stereo), cameras are not calibrated, and its main application is image interpolation rather than 3D reconstruction.

Note that in the case of MVS, where the camera parameters are known, solving for the 3D geometry of the scene is exactly equivalent to solving the correspondence problem across the input images. To see why, consider a 3D point belonging to the 3D scene geometry (See Figure 1.7 left). Projecting the 3D point into the set of visible cameras establishes a unique correspondence between the projected coordinates on each image.

Given a pixel in an image, finding the corresponding pixels in other images needs two ingredients:

- An efficient way to generate possible pixel candidates in other images.
- A measure to tell how likely a given candidate is the correct match.

If the camera geometry is not known, as is typically the case in optical flow, each pixel in an image can match any other pixel in another

image. That is, for each pixel one has to do a 2D search in the other image. However, when the camera parameters are known (and the scene is rigid), the image matching problem is simplified from a 2D search to a 1D search (See Figure 1.7 right). A pixel in an image generates a 3D optic ray that passes through the pixel and the camera center of the image. The corresponding pixel on another image can only lie on the projection of that optic ray into the second image. The different geometric constraints that originate when multiple cameras look at the same 3D scene from different viewpoints are known as epipolar geometry [88].

As for measures to tell how likely a candidate match is, there is a vast literature on how to build so called *photo-consistency* measures that estimate the likelihood of two pixels (or groups of pixels) being in correspondence. Photo-consistency measures in the context of MVS are presented in more detail in Chapter 2.

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