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A flexible technique based on fundamental matrix for camera self-calibration with variable intrinsic parameters from two views ☆

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ABSTRACT

We propose a new self-calibration technique for cameras with varying intrinsic parameters that can be computed using only information contained in the images themselves. The method does not need any a priori knowledge on the orientations of the camera and is based on the use of a 3*D* scene containing an unknown isosceles right triangle. The importance of our approach resides at minimizing constraints on the self-calibration system and the use of only two images to estimate these parameters. This method is based on the formulation of a nonlinear cost function from the relationship between two matches which are the projection of two points representing vertices of an isosceles right triangle, and the relationship between the images of the absolute conic. The resolution of this function enables us to estimate the cameras intrinsic parameters. The algorithm is implemented and validated on several sets of synthetic and real image data.

1. Introduction

Motivation. Self-calibration is an important task in computer vision for providing a powerful method for the recovery of 3*D* models from image sequences. Many applications exist which require these models, including robotics, medicine (medical imaging), security (face detection and recognition), etc. In general, these works can be classified into two categories: self-calibration of camera with constant parameters and self-calibration of camera with varying parameters. A variety of self-calibration approaches will be discussed with details in Section 2. In this paper, we are interested to work freely in the domain of self-calibration without any prior knowledge about the scene and with fewer constraints (the number of images used, the characteristics of the cameras, and the type of scene). This new approach does not require constraints on the scene or on the cameras which shows that our methods minimizes the constraints on the self-calibration system.

Contribution. In this work, we present a new method for self-calibration of cameras with varying intrinsic parameters, by using an unknown 3*D* scene and two images only to estimate the intrinsic parameters of cameras. Our method is based on the use of an unknown isosceles right triangle ABC belonging to the semicircle $C(O,r)$ to perform the self-calibration procedure. After detecting the control points by the Harris algorithm [15] and the matching of these points by the correlation measure ZNCC [29,9] and then we eliminate the false matches by using the RANSAC algorithm [13,53,44]. The projection of two points of the 3*D* scene in images plans taken by different views and estimation of the Fundamental matrix are exploited to formulate a system of linear equations. Solving these equations allows us to obtain the projection matrices. The relations between the projection matrices, projections of two points of the 3*D* scene of an isosceles right triangle and the images of the absolute conic allow the formulation of a nonlinear cost function. The minimization of this function by the Levenberg–Marquardt algorithm [40] lead to estimate the intrinsic parameters of the cameras used.

The remainder of this paper. The paper is organized as follows. In Section 2, we reviewed some most techniques and work of self-calibration made in these last years. In Section 3 we study the basic structure of the camera model and camera self-calibration tools. Section 4 presents the proposed method of camera self-calibration for 3*D* scene addressed in this paper. Section 5 describes the experimental framework used to evaluate the performance of the approach. Finally, in Section 6 we conclude

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some comments are made based on the study carried out in this paper.

2. Related work on camera self-calibration

Obtaining three dimensional ($3D$) models of scenes from images has been a long lasting research topic in computer vision. Many applications exist which require these models. Traditionally robotics and inspection applications were considered. In this section an overview of the literature in the area of camera self-calibration is given. The self-calibration of cameras characterized by two types of parameters constant or varying intrinsic parameters. Nowadays however more and more interest comes studies based on self-calibration of cameras with varying intrinsic parameters.

2.1. Overview

Camera self-calibration was originally introduced by Faugeras et al. [12] in computer vision. The methods based on the Kruppa equation were later developed by Maybank and Faugeras [39], Heyden and Aström [21] and Luong and Faugeras [34]. All this methods introduced the idea of self-calibration, where the camera calibration can be obtained from the image sequences themselves (a camera could be calibrated using only point matches between images), without requiring knowledge of the scene, or any knowledge of the camera motion. This has allowed the possibility of reconstructing a scene from pre-recorded images sequences, or computing the camera calibration during the normal vision tasks. The original method by Faugeras et al. [12] involved the computation of the Fundamental matrix, which encodes epipolar geometry between two images Faugeras [11], Hartley [18], Luong and Faugeras [33]. From three views a system of polynomial equations is constructed called Kruppa's equations Kruppa [27] (Kruppa's equations are based on the relationship between the image of the absolute conic and the epipolar transformation). Since then, Luong [32] has used an iterative search technique to solve the set of polynomial equations, but results were limited by the choice of initial values and the complexity of the equations. The self-calibration technique described in this article Zeller and Faugeras [56] is the generalization to a large number of images of the algorithm developed by Faugeras et al. [12] based on the Kruppa equations and solved the equations using energy minimization. Hartley [19] uses a set of matched points from images taken with the same camera but from different positions. There is no constraint on the motion allowed between the camera positions. Each set of matched image points has a corresponding point in $3D$. The method involves an iterative search to find a set of calibrated camera matrices and $3D$ world points consistent with the image points. This approach of Hartley [19] was extended for purely rotating cameras with varying intrinsic parameters by Agapito et al. in De Agapito et al. [7,5,6]. The work of Agapito et al. proposed is the first and mostly referred approach for self-calibration of a purely rotating camera with varying intrinsic parameters. This technique uses the Frobenius norm of the difference of the mapped dual image of the absolute conic and the dual image of the absolute conic; and in De Agapito et al. [5] the infinite homography constraint for cameras j and i with varying intrinsic parameters was used for self-calibration. Recently Heyden and Åström [22] proved that self-calibration in the case of continuously focusing/zooming cameras is possible even when the aspect ratio was known and no skew was present. Hartley [20] presented a method of self-calibration using a rotating camera. When there is no translation of the camera between views, there is an image-to-image projective mapping which can be calculated using point matches. Luong and Viéville [35] showed that a camera can be calibrated using two or more rotated views of an affine structure. A stratification approach was proposed by Pollefeys and Van Gool [43] and refined recently by Chandraker et al. [4]. Triggs [52] develops a practical algorithm for the self-calibration of a moving projective camera, from $m \geqslant 5$ views of a planar scene. This technique based on some constraints involving the absolute quadric and the scene-plane to image-plane collineations. Sturm and Maybank [48] and Zhang [57] independently proposed to use planar patterns in $3D$ space to calibrate cameras. Triggs [51] introduced the absolute (dual) conic as a numerical device for formulating auto-calibration problem. These early works are however quite sensitive to noise and unreliable Bougnoux [3], Hartley and Zisserman [16]. Li and Hu [30] propose a linear camera self-calibration technique based on projective reconstruction that can compute the 5 intrinsic parameters. In this method, the camera undergoing at least a pure translation and two arbitrary motions. The numerical solution using interval analysis was presented in Fusiello et al. [14], but this method is quite time consuming. Other techniques, use different constraints, such as camera motion Hartley [20], Stein [47], Horaud and Csurka [23], De Agapito et al. [5], plane constraints Triggs [52], Sturm and Maybank [48], Knight et al. [26], concentric circles Kim et al. [25] and others Pollefeys et al. [42], Liebowitz and Zisserman [31]. Malis and Cipolla [37] present a technique to self-calibrate cameras with varying focal length. This method does not need any a priori knowledge of the metric structure of the plane. Moreover Malis and Cipolla [38,36] extend their work into allow the recovering of the varying focal length and propose to impose the constraints between collineation using a different iterative method. Jiang and Liu [24] presents a method of self-calibration of varying internal camera parameters that based on quasi-affine reconstruction, this method does not require a special scene constraints or a special movement informations to achieve the goal of self-calibration. El Akkad et al. [10] proposes a self-calibration method of camera having varying intrinsic parameters from a sequence of images of an unknown $3D$ object. Applicative domains are numerous, including robotics or autonomous driving, using some efficient video encoding techniques Yan et al. [55,54].

3. Camera self-calibration tools

3.1. The camera model

A camera is modeled by the usual pinhole model, see Fig. 1. The mapping is a perspective projection from $3D$ projective space $\mathcal{P}^3$ (the world), to $2D$ projective space $\mathcal{P}^2$ (the image plane). The world point denoted by $B = (X, Y, Z, 1)^T$ is mapped to the image point denoted by $b = (x, y, 1)^T$ by a 3×4 matrix M_i in homogeneous coordinates, which is:

$$b = M_i\ B \tag{1}$$

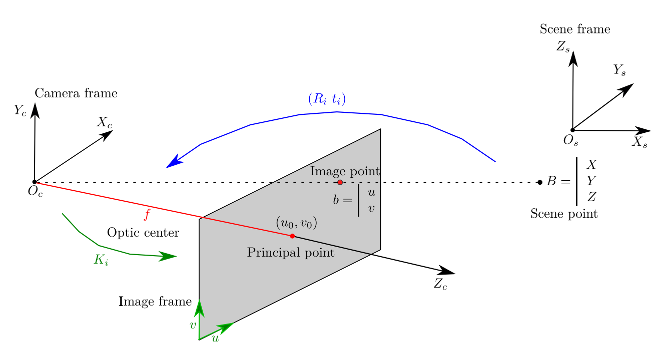

Fig. 1. Pinhole model of camera.