A review of machine vision pose measurement

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ABSTRACT

This review paper provides a comprehensive overview of machine vision pose measurement algorithms. The paper focuses on the state-of-the-art algorithms and their applications. The paper is structured as follows: the introduction in provides a brief overview of the field of machine vision pose measurement. Describes the commonly used algorithms for machine vision pose measurement. Discusses the factors that affect the accuracy and reliability of machine vision pose measurement algorithms. Summarizes the paper and provides future research directions. The paper highlights the need for more robust and accurate algorithms that can handle varying lighting conditions and occlusion. It also suggests that the integration of machine learning techniques may improve the performance of machine vision pose measurement algorithms. Overall, this review paper provides a comprehensive overview of machine vision pose measurement algorithms, their applications, and the factors that affect their accuracy and reliability. It provides a valuable resource for researchers and practitioners working in the field of computer vision.

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1. INTRODUCTION

Pose measurement is a technique used to determine the position and orientation of an object in three-dimensional space [1]. Traditional methods of pose measurement involve the use of sensors, but they suffer from low precision, high cost, and poor real-time performance, which make it difficult to meet the current demands for high precision, low cost, and real-time performance in the industrial and technological sectors [2]. To address these issues, researchers have turned to computer vision technology and introduced the concept of visual pose measurement [3]. Visual pose measurement is a method that uses computer vision technology to perform pose measurement, typically employing a camera as a sensor [4]. The target object's position and direction are determined by capturing scene images and performing image processing and calculations. Compared to traditional methods, visual pose measurement offers advantages such as non-contact operation, high precision, high speed, and low cost [5]. It is widely used in fields such as robotics [6], autonomous driving [7], virtual reality [8], and aerospace [9].

The research focus on visual pose measurement includes the development of accurate scene models [10], robust image processing and matching algorithms [11], and real-time pose measurement [12]. Building an accurate scene model is a significant challenge since it serves as the foundation for matching real images with theoretical models and extracting pose information [10]. Maintaining high-precision pose measurements in the presence of interference from motion blur, illumination changes, and noise is another significant challenge [13]. To address these issues, visual pose measurement researchers are working to improve the algorithm's accuracy and stability, develop new image processing and matching algorithms, and enhance the system's real-time and robustness.

2. THE COMMONLY USED MACHINE VISION POSE MEASUREMENT ALGORITHMS

This paper presents a detailed algorithm for machine vision pose measurement. It encompasses four main aspects: image feature extraction method, camera calibration method, vision system global calibration method, and visual pose parameter estimation. Each category contains commonly used algorithms that are further introduced and explained in this article.

2.1. The method based on image feature extraction

Image feature extraction is a critical step in machine vision pose measurement, as it involves identifying and extracting key points, lines, surfaces, and other features from an image to enable object recognition and pose estimation [14]. Commonly used image features in machine vision include edges, corners, SIFT features, SURF features, ORB features, and more. These features are often invariant, repeatable, and discriminative, making them ideal for matching and identification. Table 1 is an introduction to the advantages and disadvantages of these commonly used methods.

Table 1. The advantages and disadvantages of commonly used machine vision pose measurement methods based on image feature extraction

Method	Advantage	Diadvantage
Harris corner detection [15]	(1) Robustness (2) Scale invariance (3) Independence	(1) Insensitive to rotation changes (2) Sensitive to scale changes (3) Computational complexity (4) Sensitive to noise
Shi-Tomasi corner detection [16]	(1) Ranking of corner responsivity (2) Robustness (3) Scale invariance (4) Suitable for tracking	(1) Insensitive to rotation changes (2) Sensitive to scale changes (3) Computational complexity (4) Sensitive to noise
Sobel operator [17]	(1) Simple and efficient (2) Edge positioning is accurate (3) Direction sensitivity (4) Noise suppression	(1) Gray level smoothness is poor (2) The gradient boundary response is discontinuous (3) Sensitive to edge width (4) Applicable only to grayscale images
Canny edge detection	(1) Accurate edge positioning (2) Single edge response (3) Low error rate (4) Multi-scale processing	(1) Computational complexity (2) Parameter selection (3) Sensitive to noise (4) slower speed
Scale-invariant feature transform (SIFT) [18]	(1) Scale invariance (2) Uniqueness (3) Not affected by light changes (4) Efficiency	(1) Computational complexity (2) Scale space extremum selection (3) Sensitive to image distortion
Speeded up robust feature (SURF) descriptor [19]	(1) Fast performance (2) Scale invariance (3) Rotation invariance (4) Robustness	(1) Poor spatial invariance (2) The feature expression ability is relatively weak (3) Sensitive to light changes (4) Parameter selection
SIFT descriptor [20]	(1) Scale invariance (2) Rotation invariance (3) Uniqueness and distinguishability (4) Robustness	(1) Computational complexity (2) Parameter selection (3) Sensitive to light changes (4) Higher feature dimension
HOG descriptor [21]	(1) Invariance (2) Robustness to illumination changes (3) Local texture features (4) Low-dimensional representation	(1) Sensitive to viewing angle changes and deformation (2) Requires explicit target labeling (3) Low-level feature representation (4) Sensitive to noise

In feature-based pose estimation, feature points of the target object are extracted from the input image, and the pose of the object is calculated by matching these feature points with the corresponding points in the target model. Matching methods like nearest neighbor matching, nearest neighbor distance ratio matching, and RANSAC are commonly used, but the accuracy and robustness of matching can be affected by noise, occlusion, deformation, and other factors, which must be addressed for optimal performance [22]. Deep learning-based image feature extraction methods, such as those based on convolutional neural networks (CNNs), can also be used to improve the accuracy of object recognition and pose estimation. These methods learn feature expressions from input images through deep learning, leading to more accurate and effective pose estimation [23]. The image gradient method is a widely used method for pose estimation in machine vision [24]. This method calculates the pose of an object by using the gray value change rate at the edge of the object in the image. To use this method, the image needs to be processed first to extract the edge information, which is then used to calculate the pose of the object. The first-order derivative and second-order derivative information of the image are used to calculate the pose of the object, which correspond to the gray-scale gradient and gray-scale Laplacian of the image, respectively [25]. The commonly used image gradient methods include the Canny operator, Sobel operator, Prewitt operator, and more, which can smooth the image to different degrees to reduce the influence of noise, calculate the gradient value and direction information of each pixel in the image, and finally determine the pose of the object through statistical analysis of the gradient information [26]. However, this method has high requirements on image quality and continuity of the edges of objects in the image. Additionally, since the image gradient method can only calculate the pose of the object, but cannot determine its position, it usually needs to be used in combination with other methods [27].

Bok *et al.* [28] presents a corner sub-pixel extraction method that utilizes image gradients. This method exploits the characteristic that the vector pointing to any nearby pixel from a corner point is perpendicular to the gradient direction between the corner point and the pixel point. It selects the neighborhood of the pixel-level corner point as the region of interest and employs a series of mathematical processing methods and optimization techniques to iteratively obtain the sub-pixel localization of the corners. In the iterative process, the sub-pixel positioning coordinates of the corner points obtained in the previous operation are used as the center of the region of interest in the next operation. The iteration stops when the center coordinates converge and remain within the preset range. Xu *et al.* [29] proposes a sub-pixel corner extraction method based on the Harris operator. The method starts iterative calculation from a given initial corner position, and uses the structural tensor principle of block sampling for optimization. The goal of the method is to obtain the location of the maximum gradient value and locate the sub-pixel corners. The method adopts direct gradient interpolation, which significantly improves the calculation efficiency compared with the traditional method that performs image interpolation first and then performs gradient calculation.

Gray-scale symmetry is a widely used pose measurement method in industrial manufacturing processes, which uses image gray-scale information to calculate the pose information of objects with high precision, robustness, and adaptability [30]. The method involves obtaining the grayscale image of the target object and using image processing techniques to extract the grayscale symmetry line on its surface. The grayscale symmetry line is a line on the object surface where the gray-scale values on both sides are equal or nearly equal. By using the properties of the grayscale symmetry line, the position and rotation angle of the object on the plane can be determined, and its pose information can be obtained [31].

In previous studies, researchers have proposed various methods to improve the accuracy and robustness of the grayscale symmetry algorithm [32], [33]. Moreover, the grayscale symmetry method has been combined with other techniques, such as stereo vision [34] and contour features [35], to further enhance its performance in pose estimation. Huang *et al.* [36] employs a method that directly utilizes the grayscale symmetry of the area surrounding corners for sub-pixel localization. As the center of the square pixel block approaches the corner, the gray symmetry increases. Therefore, the algorithm defines a region of interest with a fixed window radius around the pixel-level corner. Within this region, a square pixel block is extracted with each pixel as the center, and its gray-scale symmetry degree is calculated as the gray-scale symmetry factor. By using the gray symmetry factors of all pixels as weights, the coordinates are then weighted to obtain the sub-pixel positioning coordinates of the corner points. The gray-scale symmetry method has been widely studied and applied in the field of industrial manufacturing due to its high precision, robustness, and adaptability. Moreover, the gray-scale symmetry method can be combined with other pose measurement methods, such as the point cloud registration method [37] and the structured light method [38], to improve the accuracy and reliability of the pose measurement.

The polynomial fitting method is a widely used approach for attitude measurement, which involves fitting the attitude angle curve to obtain the object's attitude information [39]. The basic principle of the polynomial fitting method is to collect the object's attitude angle data during its movement, fit it into a polynomial function, and then solve for the object's attitude information. In practice, quadratic or cubic polynomials are typically used since they can better approximate the real attitude angle curve. The polynomial fitting method offers several advantages, including high precision and reliability, and its applicability to various object attitude measurement problems. Moreover, since the polynomial fitting method only requires fitting the attitude angle curve, it has a small calculation amount and operates at high speeds. However, this method also has some disadvantages, such as the need for high-quality attitude angle curve data, and the potential for overfitting or underfitting in some cases [40]. One of the advantages of the polynomial fitting method is its high precision and reliability. This method has been applied successfully in various attitude measurement problems, such as the control of a quadrotor unmanned aerial vehicles (UAV) [41], the measurement of satellite attitude [42], and the estimation of vehicle dynamics [43]. Another advantage of this method is its high computational efficiency since only fitting the attitude angle curve is required. As a result, this method is suitable for real-time applications that require a fast response. However, the polynomial fitting method also has some limitations. One major limitation is the requirement for high-quality attitude angle curve data. The accuracy of the attitude estimation heavily relies on the accuracy and quality of the collected data. Therefore, the noise and bias in the data can lead to significant errors in the estimated attitude information. Another limitation is the potential for overfitting or underfitting, which can cause the polynomial function to fit the noise instead of the actual attitude angle curve. Various regularization techniques, such as L1 and L2 regularization, have been proposed to address this issue [44].

2.2. The camera calibration method

The camera calibration method is a technique used for pose measurement, enabling the conversion from the camera image to the actual three-dimensional space of the object by calibrating the internal and external parameters of the camera [45]. To perform pose measurement, it is necessary to know the camera's internal parameters, such as focal length and pixel size, and the camera's external parameters, namely, its position and orientation relative to the object. Table 2 is an introduction to the advantages and disadvantages of these commonly used methods.

Table 2. The advantages and disadvantages of commonly used machine vision pose measurement methods based on camera calibration

Method	Advantage	Shortcoming
Zhang's calibration [46]	(1) High precision (2) Easy to use (3) Scalability (4) Open source code	(1) Higher requirements on the calibration board (2) There are more requirements for calibration images (3) High requirements for computing resources (4) Strong assumptions about the distortion model
Tsai's calibration [47]	(1) High precision (2) Scalability (3) Intuitive mathematical model (4) Wide application	(1) Higher requirements on the calibration board (2) A large number of calibration images are required (3) High requirements for computing resources (4) Strong assumptions about the camera model
Direct linear transform (DLT) [48]	(1) Simple and easy to implement (2) Wide application range (3) Scalability (4) Based on geometric relationship	(1) Higher requirements for calibration data (2) Sensitive to noise and errors (3) Restrictions on the distortion model (4) Does not consider the distribution of camera parameters
Bouguet's stereo calibration [49]	(1) High precision (2) Scalability (3) Comprehensive multiple calibration parameters (4) Open source code	(1) Higher requirements on the calibration board (2) A large number of calibration images are required.
Extended calibration method [50]	(1) High precision (2) Polynomial distortion model (3) Adaptive optimization (4) Scalability	(1) Complex calculation and data processing (2) Higher requirements for calibration boards and images (3) Complicated calibration process (4) Calibration accuracy is limited

The tensor-based camera calibration method is a camera calibration method that estimates the intrinsic and extrinsic parameters of the camera by using corresponding points in multiple views and tensor decomposition. The method requires at least two different viewpoints, and performs feature matching on images in these viewpoints to obtain corresponding point pairs. Then, the intrinsic and extrinsic parameters of the camera are computed using the tensor decomposition of these corresponding points [51]. The basic idea of this method is to represent the 3D coordinates of corresponding points as a function of the camera intrinsic parameter matrix and extrinsic parameters (ie rotation and translation vectors). These 3D coordinates are then represented as a product of tensors, using the tensor decomposition technique of corresponding points, where one tensor is the camera intrinsic parameter matrix and the other tensor is a vector containing the 3D coordinates of each corresponding point. Then, by decomposing the tensor, the intrinsic and extrinsic parameters of the camera can be estimated simultaneously [52]. Tensor-based camera calibration methods have the advantages of high accuracy and robustness, and can handle multiple images from different viewing angles. Furthermore, the method is able to eliminate calibration errors due to feature matching errors and can be used for various types of cameras, including nonlinear ones. The disadvantage of this method is that it is computationally intensive and therefore requires powerful computers and optimization algorithms [53]. The camera calibration method based on feature points is a widely used and effective approach for camera calibration [54]. It involves extracting feature points from images taken at different viewing angles and calculating the internal and external parameters of the camera based on the correspondence between these feature points. The basic idea of this method is to project known 3D points onto the image plane using the camera projection model and match them with their corresponding 2D feature points. By solving the matching point pairs, the internal and external parameters of the camera can be determined. The feature point-based camera calibration method has several advantages, including its ease of implementation and high accuracy, which makes it a fundamental tool for many computer vision tasks, such as 3D reconstruction [55], object detection [56], and tracking [57]. However, this method also has some limitations. For example, it may produce matching errors in low-texture areas or under large illumination changes. Furthermore, it requires a large amount of computing resources to achieve high-precision calibration. Thus, it is important to weigh the advantages and disadvantages of this method and choose an appropriate calibration method based on specific application requirements.

2.3. The global calibration method for vision system

The global calibration of a vision system is a process of obtaining its internal and external parameters by capturing images of multiple objects in different positions and orientations [58]. This calibration requires the use of multiple calibration boards or calibration points. By capturing images of these calibration objects at different positions and angles, the camera's internal and external parameters can be determined, including its focal length, distortion, rotation, and translation. Internal parameters are camera-specific and independent of the scene being captured, while external parameters are scene-specific and related to the camera's position and direction. The accuracy and stability of pose measurement largely depend on the results of global calibration, which makes it crucial for practical applications. Therefore, choosing appropriate calibration objects, methods, and algorithms is essential for achieving the desired accuracy and stability in different scenarios. Table 3 is an introduction to the advantages and disadvantages of these commonly used methods.

Table 3. The advantages and disadvantages of commonly used machine vision pose measurement methods based on global calibration

Method	Advantage	Shortcoming
Multi-camera calibration [59]	(1) Accurate camera alignment (2) 3D reconstruction and stereo vision (3) Flexible multi-camera configuration (4) Wide application	(1) The calibration process is complicated (2) A large amount of calibration data is required (3) Higher requirements for calibration boards and images (4) High computational complexity
Camera-laser calibration [60]	(1) High precision (2) Non-contact calibration (3) Real-time (4) Scalability	(1) High equipment requirements (2) The calibration device is complex (3) Higher requirements on the scene (4) Affected by environmental factors
Camera-inertial measurement unit [61]	(1) High-precision attitude estimation (2) Real-time (3) Environmental adaptability (4) Multiple applications	(1) Cumulative error (2) Sensing range limitation (3) Equipment complexity and cost
Multi-sensor fusion calibration [62]	(1) High precision and accuracy (2) Diversity and redundancy (3) Environmental adaptability (4) Wide application	(1) Computational complexity (2) Data inconsistency (3) Sensor selection and configuration (4) Calibration data requirements

The calibration method of precision measuring instruments refers to the method of determining the measurement error of the instrument and correcting its measurement results by comparing a set of standard objects of known size or position with the measured instrument [63]. It is a key step to ensure the measurement accuracy and reliability of the instrument. The calibration method of precision measuring instruments usually includes the following steps: first, select a suitable standard object and measure its exact size or position; then, collect multiple sets of data at different positions and angles; analyze and process, calculate the internal error and external error of the instrument; finally, correct according to the error value to improve the measurement accuracy and stability of the instrument. Liu *et al.* [64] mentioned, a global calibration is performed using a laser rangefinder and a planar target. This method involves adjusting the target pose to ensure the laser rangefinder's emitted light spot precisely falls on the target working surface, facilitating distance data measurement.

Motion recovery structure calibration, also known as multi-view geometric calibration, is a 3D reconstruction and pose recovery method that relies on the geometric relationship between multiple views. This method typically requires multiple cameras to simultaneously capture multiple views of the same object and extract common feature points or feature lines. By matching these features, the internal and external parameters of the camera can be recovered to determine the position and orientation of the camera. Additionally, performing 3D reconstruction on these features allows for the extraction of 3D structure information of the observed object. The motion recovery structure calibration method is widely used in applications such as 3D modeling, computer vision, and robotics. Svoboda *et al.* [65], the proposed method aims to achieve global calibration by leveraging a freely moving light point to construct a 3D control point cloud. It employs the RANSCA algorithm and fourth-order matrix factorization to robustly recover motion and estimate the projected structure. Moreover, a hierarchical algorithm with geometric constraints is introduced to further enhance the accuracy and robustness of the calibration, ultimately obtaining global calibration parameters. Conversely, in [66], a movable auxiliary camera is utilized to collect landmarks within the multi-camera system's global field of view. By calculating the three-dimensional coordinates of these landmarks, the global calibration is accomplished. Artificial public field of view calibration is a technique used in computer vision and computer graphics to determine the intrinsic and extrinsic parameters of a camera in order to transform an object from a three-dimensional space into a two-dimensional image. These parameters include the camera's focal length, field of view angle, pixel size, image distortion, and more. Kumar *et al.* [67] proposes a method for global calibration of multi-camera systems without a common field of view, using planar mirror groups. In this method, a target object is placed in the field of view of the main camera, and the mirror position of the target object in the sub-camera is directly imaged and processed by adjusting the mirror. This generates a virtual camera. The method first calculates the pose relationship between the target object, the main camera, and the virtual camera, and then solves the global parameters using the mirror image relationship between the virtual camera and the sub-camera. Agrawal [68] presents a global calibration method that utilizes a spherical mirror of known curvature. This method is capable of simultaneously solving for the position of the spherical mirror and the external parameters of the camera using a mathematical model, which eliminates the need for precise estimation of the mirror position beforehand. The artificial public field of view calibration method uses a special calibration object, usually an object such as a checkerboard or a sphere of known geometry and size. By placing these objects in different positions and angles, the internal and external parameters of the camera can be determined, thereby calibrating the camera [69]. When using the artificial public field of view calibration method, it is necessary to take multiple images and analyze these images to calculate the camera parameters. These parameters can be used for applications such as correcting image distortion [70].

2.4. The vision pose parameter estimation

Machine vision pose parameter estimation is the process of obtaining the pose information of an object in three-dimensional space by processing image or point cloud data in computer vision [71]. This process includes two approaches: 2D image-based pose parameter estimation and 3D point cloud-based pose parameter estimation. Table 4 is an introduction to the advantages and disadvantages of these commonly used methods.

Table 4. The advantages and disadvantages of commonly used vision pose parameter estimation

Method	Advantage	Shortcoming
Perspective-n-point [72]	(1) Efficiency	(1) Sensitive to noise and mismatch
	(2) High accuracy	(2) Sub-pixel precision limitation
	(3) Does not depend on the scene structure	(3) Complex scene challenges
	(4) Suitable for various camera configurations	(4) Lack of scale information
Direct methods [73]	(1) High precision	(1) Robustness challenges
	(2) Global consistency	(2) Computational complexity
	(3) Real-time	(3) Memory requirements
	(4) Scale consistency	(4) Limited by texture
Filtering methods [74]	(1) Robustness	(1) Computational complexity
	(2) Data association	(2) Data association problem
	(3) System modeling	(3) Accumulation of errors
	(4) State estimation	(4) Selection of parameters
Optical flow methods [75]	(1) Motion continuity	(1) Lighting changes
	(2) Speed estimation	(2) Occlusion problem
	(3) Real-time	(3) Multi-scale problem
	(4) No need for feature points	(4) Cumulative error

The methods for estimating pose parameters based on two-dimensional images can be broadly categorized into feature point matching methods and deep learning methods. Feature point matching is a traditional approach where robust feature points are extracted from two images and the pose parameters are computed by matching these points [76]. The most widely used feature point algorithms include SIFT [77], SURF [78], and ORB [79]. These algorithms extract feature points from images, which are then matched to compute the pose parameters. Deep learning methods are a newer approach where deep neural networks are used to directly estimate the pose parameters from input images [80]. This method bypasses the feature point matching process and requires a large amount of labeled data and computing resources. However, in some scenarios, such as object detection, deep learning methods can be more robust and accurate than traditional methods. In addition to these two basic methods, there are some derivative methods, such as direct methods [81] and depth map methods [82], which use depth information to estimate pose parameters. 3D point cloud-based pose parameter estimation involves estimating camera pose by matching a known 3D model with the 3D point cloud [83]. It mainly includes the iterative closest point (ICP) algorithm [84] and methods based on deep learning [85]. The ICP algorithm is a classic point cloud registration algorithm that matches point clouds by iteratively finding the transformation matrix that minimizes the sum of squared distances between point clouds.

3. THE FACTORS AFFECTING THE ACCURACY OF MACHINE VISION POSE MEASUREMENT ALGORITHMS

Machine vision pose measurement algorithm is one of the very important technologies in modern industry. It can realize the attitude measurement and positioning of objects through image processing and computer vision algorithms, and provides basic technical support for automated production. However, the accuracy of machine vision pose measurement algorithms is affected by various factors.

Image quality is an important factor affecting the accuracy of machine vision pose measurement algorithms. The quality of the image directly affects the accuracy of attitude measurement. When the image quality is not good, there may be problems such as noise, blur, and distortion, which will lead to an increase in the error of the pose measurement. Therefore, when performing machine vision pose measurement, images with better image quality should be selected and the influence of image quality problems should be minimized. The distortion of the camera refers to the difference between the shape and position of the pixels in the image when the camera is imaging and the shape and position of the actual object [86]. Camera distortion is mainly divided into radial distortion and tangential distortion. Radial distortion refers to the distortion caused by irregularities in the shape of the lens, while tangential distortion is the distortion caused by the deflection of the camera lens. These distortions affect the actual size and position of objects in the image, which in turn affects the accuracy of pose measurement. Camera parameters are one of the key factors affecting the accuracy of machine vision pose measurement. Camera parameters include camera intrinsic parameters and camera extrinsic parameters. Camera intrinsic parameters refer to the inherent parameters of the camera itself, including focal length, and principal point coordinates; camera extrinsic parameters refer to the pose information of the camera in the world coordinate system, including the position and direction of the camera in space. The accuracy of camera parameters has a significant impact on the accuracy of pose measurements. Therefore, before attitude measurement, camera parameters need to be calibrated to ensure the accuracy of camera parameters. At present, commonly used camera parameter calibration methods include Zhang Zhengyou calibration method [87], Tsai calibration method [88]. Attitude calculation algorithm is the core part of machine vision attitude measurement, which has a decisive impact on measurement accuracy. At present, commonly used attitude calculation algorithms include three-point algorithm [89], quaternion-based algorithm [90], and rotation vector-based algorithm [91]. Different algorithms have different precision and computational complexity, so they need to be selected according to specific needs in practical applications.

4. CONCLUSION

Machine vision attitude measurement is a rapidly growing field that is becoming increasingly important in multiple industries such as robotics, autonomous vehicles, and augmented reality. This review paper delves into the field, highlighting state-of-the-art algorithms and their applications. First, this paper describes in detail common algorithms for machine vision attitude measurement. Different object detection and tracking methods such as feature-based, model-based and template matching techniques are discussed. Next, factors affecting the accuracy and reliability of machine vision pose measurement algorithms are discussed. Finally, this paper explores the application of machine vision attitude measurement in various fields such as robotics, augmented reality, and motion analysis. The importance of accurate attitude measurement in these industries is highlighted and examples are provided of how it can be exploited to improve efficiency and safety. This paper is instructive for researchers, engineers, and practitioners interested in the field of machine vision attitude measurement.

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