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An examination of 3D reconstruction methods and their uses in civil engineering

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ABSTRACT
More frequently than not, three-dimensional (3D) reconstruction techniques—of which point cloud models constitute the foundation—have been utilized to create 3D representations of things in civil engineering as mesh models, point cloud models, and geometric models. To make clear the current state of the application and research One of the methods used in civil engineering is literature retrieval, which is carried out by utilizing the world's largest literature databases. The outcome is summed up by examining the abstracts or, if necessary, the complete publications. First, the framework of 3D reconstruction methodologies is constructed, and the research methodology is presented. Second, point cloud generation and processing 3D reconstruction approaches are covered, along with the corresponding algorithms and procedures. Third, the accomplishments are highlighted, and typical examples of their applications are provided, including the management and reconstruction of construction sites and the reconstruction of pipes for Mechanical, Electrical, and Plumbing (MEP) systems. Lastly, the difficulties are examined and the main lines of inquiry for further study are suggested. By methodically summarizing the most recent advancements and difficulties in the use of 3D reconstruction techniques in civil engineering and suggesting important future research avenues to be pursued in the field, this paper adds to the body of knowledge in the field of 3D reconstruction.

Keywords:3D reconstruction techniques Civil engineering Point clouds Achievements Challenges

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I. INTRODUCTION

The process of creating 3D representations of an object's 3D appearance from the outputs of data gathering devices is known as three-dimensional (3D) reconstruction [1,2]. The most common formats for 3D representations are point cloud models, mesh models, and geometric models, with point cloud models serving as the foundation. The methods have been used in various domains, including medical engineering [5] and survey engineering [4], due to their cost-effectiveness and efficiency [3] in producing 3D representations of objects. They have also been used in civil engineering in recent years. For instance, the 3D models produced by using the approaches have been used to preserve historic structures [6–8], assess a building's energy efficiency [9], and obtain the surface roughness of pavements [10]. These applications are still in their infancy, but it is expected that they will have a lot of promise. Clarifying the current state of the research and technique application through a literature review is crucial to improving such applications.

Several reviewed publications have provided an overview of 3D reconstruction methods in civil engineering and their uses. The 3D reconstruction methods for generating as-built building information models (BIM) using laser scanner point clouds were compiled by Tang et al. [11]. The image-based methods for creating as-is BIM for existing buildings were examined by Lu and Lee [3]. However, they skipped over several of the procedures, such mesh reconstruction and point cloud preprocessing, in the two reviews. Furthermore, they limited their target objects to buildings. Parn and Edwards [12] examined the fundamentals, price, requirements, and uses of laser scanning, including quality control, progress tracking, structural health monitoring, and the creation of as-built BIM. Son et al. [13] examined the uses of 3D reconstruction methods based on images, videos, and laser scanning, such as reconstruction of Mechanical, Electrical, and Plumbing (MEP) systems, progress monitoring, and dimensional quality control.

A few publications have also provided summaries of the other methods that are pertinent to 3D reconstruction methods in civil engineering and their uses. Teizer [14] provided an overview of computer vision-based equipment tracking, personnel tracking, and detection on building sites. The computer vision-based flaw detection and condition evaluation of civil infrastructure, such as precast concrete tunnels, reinforced concrete bridges, underground concrete pipes, and asphalt pavements, was examined by Koch et al. [15]. Koch et al. [16] discussed recent developments and unresolved issues in machine vision-based large-concrete structure inspection. 3D reconstruction techniques were used as one of the methods in all three of these reviews. In their evaluation of 3D image-based technologies for pavement distress detection and measures, Mathavan et al. [7] discussed methods linked to 3D reconstruction, such as stereo imaging, laser scanning, and structured light systems.

Two crucial elements of 3D reconstruction methods are absent from the review papers listed above: (1) some crucial phases for 3D reconstruction methods, such as absolute scale recovery, feature matching, and camera motion estimates; (2) the main avenues for future study into the methods and their uses. Of these, the latter is undoubtedly significant to the civil engineering world, while the former's steps have been considered essential in a particular study [18]. Considering these constraints, this study provides a systematic overview of 3D reconstruction techniques, current advancements and obstacles in their use in civil engineering, and important avenues for future research in the area.

The process, algorithms, and techniques of 3D reconstruction approaches, as well as their successes and difficulties in civil engineering, are the key topics of the remaining portion of this work. The structure of the procedures in civil engineering is described in Section 2, along with the methods utilized for literature retrieval and identifying the research focus.

The methods for 3D reconstruction are presented in Sections 3 and 4, which also cover the methods for creating point clouds and processing them, respectively, along with the relevant algorithms and methodologies. As typical instances, Section 5 shows how the strategies are applied to managing and rebuilding construction sites and reconstructing MEP system pipelines, highlighting the accomplishments. The difficulties in using the techniques in civil engineering are covered in Section 6, which also suggests the main areas of future research. The paper is concluded in Section.

II. METHODOLOGY

2.1: LITERATURE REVIEW

Using keywords like "3D reconstruction," "three-dimensional reconstruction," and "3-D reconstruction," one can retrieve a list of publications from 2000 to the present from the world's largest databases, such as Web of Science, Engineering Village, and China Knowledge Resource Integrated Database. These papers are then filtered by reading the abstracts to eliminate those that are unrelated to the civil engineering fields, as the keywords do not limit the target objects of the research and use of 3D reconstruction techniques in civil engineering.

2.2: RESEARCH SCOPE

Table 1 displays the frequency of publications in terms of data collection equipment types based on an analysis of the 95 articles overall that were gathered from Section 2.1. It is worth noting that another name for laser scanners is Light Detection and Ranging (LiDAR) [18,19]. "Laser scanners" is the term that will be used in this paper going forward because it is used more often than "LiDAR" in the evaluated literature.

The chart shows that whereas CT, ultrasonic tomography, Kinect, and total stations have been employed infrequently for 3D reconstruction techniques in civil engineering, monocular cameras, binocular cameras, video cameras, and laser scanners have been utilized frequently. Only methods used in civil engineering that rely on the following data collecting tools—monocular cameras, binocular cameras, video cameras, and laser scanners—are examined in this work to concentrate on the main 3D reconstruction techniques.

Data collection equipment types	2000–2004	2005–2009	2010–2014	2015-prseent	Total
Monocular cameras	–	4	22	15	41
Binocular cameras	–	3	3	3	9
Video cameras	–	2	7	1	10
Laser scanners	–	3	15	9	27
Computerized Tomography (CT)	–	1	1	2	4
Ultrasonic tomography	1	–	–	1	2
Kinect (based on structured light)	–	–	–	1	1
Total stations	–	–	1	–	1
Total	1	13	49	32	95

Table No.1 - The frequency of publications in terms of data collection equipment types per five years since 2000.

Based on their underlying concepts, binocular and video cameras can be divided into two groups: line-based and point-based. The feature lines in the outputs of monocular, binocular, and video cameras are extracted and processed in subsequent steps [20] in the latter case, whereas the feature points in the outputs of these cameras are extracted and processed in subsequent steps [19–20] in the former. This work does not examine the latter category of 3D reconstruction techniques because there have been relatively few applications for them up to this point. This study has cited other publications in addition to the 95 papers, such as the Scale Invariant Feature Transform (SIFT) algorithm publication, in case certain algorithms and approaches need to be quoted.

2.3: FRAMEWORK OF 3D RECONSTRUCTION TECHNIQUES IN CIVIL ENGINEERING

The framework of 3D reconstruction approaches in civil engineering is constructed by examining the chosen articles, as seen in Fig.1.The framework breaks down 3D reconstruction techniques into two major processes: creating and processing point clouds. Each major step can be further broken into several smaller steps. The first major stage involves processing the outputs from video, binocular, and monocular cameras to create the point clouds that correspond to a particular scene. The outputs of 3D reconstruction techniques for the scene's objects of interest are produced in the latter big step by processing point clouds from laser scanners or the preceding big phase. The 3D reconstruction approaches will be reviewed in this large, step-by-step framework for ease of reading, with Sections 3 and 4 devoted to the two major processes, respectively.

III. TECHNIQUES FOR GENERATING POINT CLOUDS

Typically, the outputs of data gathering devices serve as the inputs for 3D reconstruction procedures. In civil engineering, monocular pictures, stereo images, video frames, and point clouds are the inputs of techniques that are used frequently. These techniques correlate to monocular cameras, binocular cameras, video cameras, and laser scanners, respectively. It is worth noting that while stereo, monocular, and video frames are all digital images, they differ in certain ways. In fact, video pictures contain a sequence of monocular images or a sequence of stereo images, whereas stereo images contain monocular images in pairs. This section presents the procedures for creating point clouds from monocular, stereo, and video frames as well as the algorithms and techniques employed.

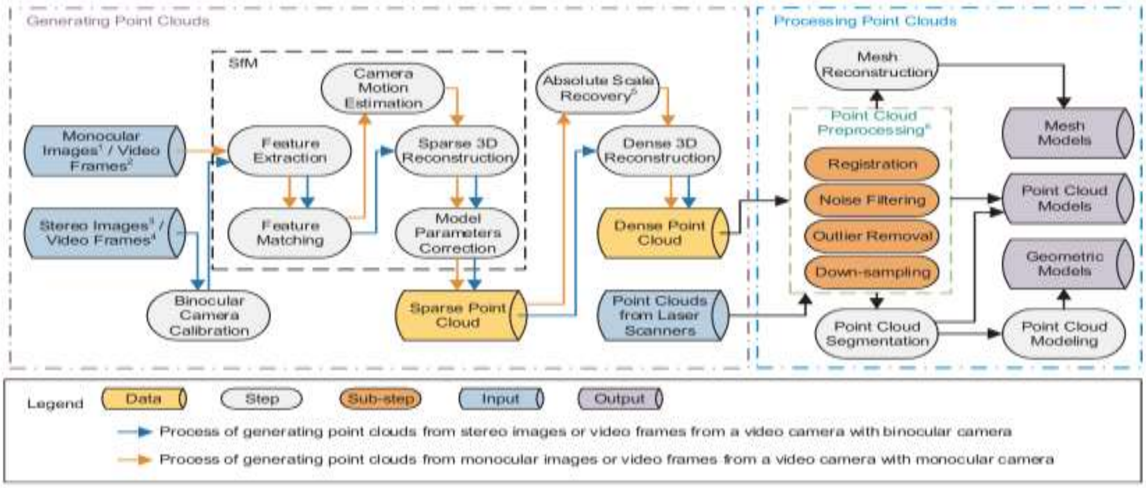

Figure No. 1 - the foundation of civil engineering 3D reconstruction methods. One, two, three, and four of the following were produced using monocular cameras, video cameras with monocular cameras, binocular cameras, and video cameras with binocular cameras, respectively; 5. In certain situations, the step is not required; Six sub-steps are not required here; the sub-steps that are required rely on the quality of the point clouds and the requirements of the application.

3.1: GENERATING POINT CLOUDS FROM MONOCULAR IMAGES

The articles claim that there are minor differences in the methods used to create point clouds from monocular images.

Feature extraction, feature matching, camera motion estimation, sparse 3D reconstruction, model parameter adjustment, absolute scale recovery, and dense 3D reconstruction are the seven general steps of the procedure, as illustrated in Fig. 1. Typically, as illustrated in Fig. 1, Structure from Motion (FM) is the result of combining the processes of feature extraction, feature matching, camera motion estimation, sparse 3D reconstruction, and model parameter correction [9]. The outcome of the earlier steps must be used as the input for every phase starting with the second step. Table 2 lists the algorithms and techniques applied in each phase.

The step's objective is to extract feature points—which represent the scene's original structure—from the pictures of a particular scene [18]. The step's algorithms fall into two categories: feature point detectors, which identify the locations of an image's feature points, and feature point descriptors, which produce the vectors or strings that describe the feature points that feature point detectors have found.

Affine Scale Invariant Feature Transform (ASIFT), Harris corner detector, SIFT detector, Speeded-Up Robust Features (SURF) detector, and Features from Accelerated Segment Test (FAST) are the feature point detectors utilized for the step. In the SIFT detector [3], Gaussian convolution creates a scale space from an original image that contains images of different scales. Adjacent images in the scale space are then subtracted to create difference-of-Gaussian images. Next, each pixel in the difference-of-Gaussian pictures is compared to its neighbors to identify the feature point candidates. Following that, feature point candidates are refined to yield feature points. A scale space is created using integral pictures in the SURF detector [1], and the approximated determinant of the Hessian of every pixel in the scale space is computed. The approximated determinant of each pixel's Hessian is then used to identify feature points. The SIFT detector's variant is called ASIFT [3]. This method creates simulated images of each original image with every distortion that could result from shifting the direction of the camera's optical axis. The SIFT detector then processes each simulated image to identify feature points. As a result, ASIFT can extract more feature points than SIFT detectors for images with changing viewpoints [34]. The Harris corner detector [5] uses the variations in image intensity surrounding each pixel to identify corners. FAST [36], a corner detector that is quicker than the Harris corner detector, recognizes a pixel as a corner if the threshold is met by the number of pixels in the circle made up of sixteen pixels surrounding the pixel.

SIFT, SURF, Fast Retina Key point (FREAK), and Multi-Scale Descriptor (MSD) are the feature point descriptors utilized for the step. By calculating the gradient magnitude and orientation for each image pixel in the area surrounding the feature point, the SIFT descriptor [3] produces a vector for characterizing the feature point. By calculating the Haar-wavelet responses in a region surrounding a feature point, the SURF descriptor [31] produces a vector for characterizing the feature point. A binary string based on a retinal sampling pattern created by a series of one-bit differences of Gaussians is the result of the coarse-to-fine feature point descriptor

FREAK [7]. To characterize a feature point, MSD [8] creates a vector based on the intensity gradients over several scales.

Descriptors[1]	Dimensions of Vector	Robustness
SIFT descriptor	128	Robust to scale, rotation and translation changes
SURF descriptor	64	Robust to scale and rotation changes
FREAK	–[2]	Robust to scale and rotation changes
MSD	108	–

Table No. 2 - Comparison among feature point descriptors

By calculating the Euclidian distance of feature point descriptors between two images, an ANN is utilized to match the feature points of each image pair [18]. The ANN's outputs are matched feature points, but since the matching criteria only consider the Euclidian distance of feature point descriptors and ignores the image pair's peripolar geometry, which characterizes the uniqueness of the matched feature points in each image pair, there may be false matches in the results. FLANN and ANN have comparable functions [4], but FLANN's approximate nearest neighbor's search algorithm [6] makes it faster than ANN. RANSAC makes use of an image pair's peripolar geometry to eliminate false matches. The technique can lessen the effort of erroneous matches by iteratively estimating the peripolar geometry by randomly selecting matching feature points [16] as opposed to using all the matched feature points. When erroneous matches exceed 50% [2], ORSA, a version of RANSAC [4], is more effective than RANSAC in eliminating false matches.

Two matrices, known as the essential matrix and the fundamental matrix, can be employed, respectively, to characterize the correspondences between the matched feature points of an image pair in its peripolar geometry. The correspondences between the matched feature points of camera coordinates are described by the essential matrix [6], which contains extrinsic parameters, and the correspondences between the matched feature points of pixel coordinates are described by the fundamental matrix [3], which contains intrinsic and extrinsic parameters. Five matching feature points are used to compute the essential matrix in the five-point algorithm [2], and the singular value decomposition of the essential matrix is used to determine the extrinsic parameters, such as the translation and rotation matrices. To guarantee that the fundamental matrix is singular, the eight-point algorithm [5] computes a new fundamental matrix based on singular value decomposition after computing an initial fundamental matrix based on eight matched feature points using linear solution. Typically, extrinsic parameters are calculated using the five-point algorithm, while intrinsic and extrinsic parameters are computed using the eight-point algorithm. Put differently, the eight-point technique is preferred when the goal is to compute both intrinsic and extrinsic parameters, whereas the five-point algorithm is preferred when the intrinsic parameters are known, and the goal is to compute extrinsic parameters. While the five-point and eight-point algorithms do not require the 3D points of absolute coordinates in the scene, DLT [4] computes intrinsic and extrinsic parameters based on the least square method using the feature points of pixel coordinates and the corresponding 3D points of absolute coordinates in the scene.

IV. TECHNIQUES FOR PROCESSING POINT CLOUDS

In general, point clouds of objects acquired by laser scanners or utilising the methods in Section 3 are unable to satisfy the needs of the application. Point clouds, for instance, contain points from the surrounding environment, which will prevent the point clouds from being used in other ways. Four steps—point cloud preprocessing, mesh reconstruction, point cloud segmentation, and point cloud modeling—are required to ensure that the point clouds satisfy the application requirements. Table 4 lists the algorithms and techniques applied in each stage and sub-step.

Steps	Sub-steps	Algorithms and methods
Point cloud preprocessing	Registration	Iterative Closest Point (ICP) [43,52,78]
	Noise filtering	Removing points manually [79];
	Outlier removal	RANSAC [28]
	Down-sampling	Point spacing strategy [80];
Mesh reconstruction	–	Poisson surface reconstruction (PSR) [29,54,81]
Point cloud segmentation	–	Region growth [82,83]; K-means clustering [78]; Voxel-based algorithm [84]; Hough transform [85]; RANSAC [86]
Point cloud modeling	–	Obtaining the dimensions of objects [79,87,88]

Table No. 3 - Algorithms and methods used in the steps for processing point clouds.

4.1: POINT CLOUD PREPROCESSING

The step's objectives are to produce point cloud models or high-quality point clouds for use in later stages. The phase typically consists of four smaller steps: down sampling, noise filtering, outlier elimination, and registration. It is important to note that the application requirements and point cloud quality determine which of the four steps are required. For instance, registration is necessary if the application requirement calls for a combined point cloud and the current point clouds are distinct. The ICP algorithm [8] is commonly employed for registration; it iteratively estimates the rigid transformation between two-point clouds by minimizing the distance between matched points.

In addition to the points of interest, point clouds derived from Section 3 also include outliers [19] and points from the surrounds [9], also referred to as noise points. Noise filtering and outlier removal are the methods used to eliminate noise points and outliers, respectively. Since noise points and outliers are both undesirable points that are not from objects of interest, the algorithms and techniques employed for noise filtering may typically also be utilized for outlier removal, and vice versa. RANSAC [8] and manual point removal from the environment [9] are two algorithms and techniques used for noise filtering and outlier removal.

Furthermore, point cloud registration increases the density of overlapping regions, which lowers the processing efficiency of later steps.

Such issues must be resolved by down sampling. The point spacing strategy method [8], which can decrease points in congested areas, is typically used for down sampling. A point cloud is divided into equal-sized 3D grid cells using the method's algorithm, and points in each 3D grid cell with at least one point are decreased until the criteria are satisfied [9].

4.2: MESH RECONSTRUCTION

The step's goal is to use the point cloud from the previous step to create a mesh model of the object of interest. For certain application needs, mesh rebuilding is required for two reasons: Mesh models derived from mesh reconstruction are superior to dense point clouds in terms of visualizing the items of interest [2]; mesh models can be utilized for other applications, like crack detection [5]. PSR is the most often used mesh reconstruction algorithm [1], which uses the object's point cloud [9] to create a precise, triangulated approximation of its surface.

4.3: FEATURE-BASED SEGMENTATION

These algorithms group points with similar characteristics into a subset based on those characteristics. The curvature of the point [80,92,93], the angle between normal vectors [2], and the angle between the point's normal vector and a unit vector [4] are among the features utilized in feature-based segmentation methods. Region expansion [3] and clustering are often employed techniques for feature-based segmentation, but the voxel-based approach [4] is hardly employed. A seed point is chosen from the point cloud using predetermined criteria in the former algorithm, also known as region growth. Next, the same subset as the seed point is expanded to include all nearby points that satisfy the predetermined criteria of the seed point. A point that meets predetermined criteria in the subset—aside from the seed points then chosen as a new seed point. Until no point can be added to the subset, the procedure is repeated. The literature makes use of K-means clustering, a type of clustering method [7]. Every point in the point cloud is categorized into one of the predetermined number of clusters using K-means clustering, depending on how far away each cluster is from its centroid. The voxel-based approach divides a point cloud's space into equal-sized voxels, each of which has either no points or at least one point. Next, neighboring voxels with elevation differences below a threshold are repeatedly sorted into the same subset, and voxels with no points are eliminated. The points that are part of the same subset's voxels are separated from other points.

V. CONCLUSION

Because 3D reconstruction techniques make it easier to obtain 3D representations of things of interest, they are utilized in a wide range of applications. Nonetheless, the applications in civil engineering are still in their infancy. To ensure that the methods satisfy high application requirements, like complete automation, high accuracy, and reduced operating time, more research must be done.

This essay examines the successes and difficulties of 3D rebuilding methods in civil engineering. It was decided how to retrieve literature and define the scope of the study. 3D reconstruction approaches for creating and manipulating point clouds, as well as the corresponding algorithms and methodologies, were provided by examining the articles that were obtained. The accomplishments of the applications of 3D reconstruction techniques in civil engineering were compiled, and typical examples of their use were presented for the reconstruction and management of construction sites as well as for the reconstruction of MEP system pipelines.

Ultimately, the difficulties in applying the techniques in civil engineering were examined, and the main lines of future research were suggested.

This paper adds to the body of knowledge in two ways: first, it provides a systematic summary of the most recent successes and difficulties in applying 3D reconstruction techniques in civil engineering; second, it suggests important directions for future research in the field.

REFERENCE

[1]. Q. Lu, S. Lee, Image-based technologies for constructing as-is building information models for existing buildings, J. Comput. Civil Eng. 31 (4) (2017).

[2]. E. Kwak, I. Detchev, A. Habib, M. El-Badry, C. Hughes, Precise photogrammetric reconstruction using model-based image fitting for 3D beam deformation mon itoring, J. Surv. Eng. 139 (3) (2013) 143–155.

[3]. L. Humbert, J.A. De Guise, B. Aubert, B. Godbout, W. Skalli, 3D reconstruction of the spine from biplanar X-rays using parametric models based on transversal and longitudinal inferences, Med. Eng. Phys. 31 (6) (2009) 681–687.

[4]. X. Lu, Y. Wang, Y. Lu, X. Ge, B. Song, Qiyun pagoda 3D model reconstruction based on laser cloud data, Bulletin of Surveying and Mapping 9 (2011) 11–14 (in Chinese).

[5]. X. Brunetaud, L. De Luca, S. Janvier-Badosa, K. Beck, M. Al-Mukhtar, Application of digital techniques in monument preservation, Eur. J. Environ. Civil Eng. 16 (5) (2012) 543–556.

[6]. P. Ren, W. Wang, X. Bai, Reconstruction of imperial university of shanxi based on virtual reality technology, Comput. Simul. 29 (11) (2012) 20–23 (in Chinese).

[7]. Y. Ham, M. Golparvar-Fard, Three-dimensional thermography-based method for cost-benefit analysis of energy efficiency building envelope retrofits, J. Comput. Civil Eng. 29 (4) (2015).

[8]. Y. Liu, S. Han, O. Xu, Acquisition system for three-dimensional surface texture of asphalt pavement based on digital image processing, J. Southwest Jiaotong Univ. 49 (2) (2014) 351–357 (in Chinese).

[9]. P. Tang, D. Huber, B. Akinci, R. Lipman, A. Lytle, Automatic reconstruction of as built building information models from laser-scanned point clouds: a review of related techniques, Autom. Constr. 19 (7) (2010) 829–843.

[10]. E.A. Parn, D. Edwards, Vision and advocacy of optoelectronic technology developments in the AECO sector, Built Environ. Proj. Asset Manage. 7 (3) (2017) 330–348

[11]. V. Balali, M. Golparvar-Fard, J.M. De La Garza, Video-based highway asset re

cognition and 3D localization, in: Computing in Civil Engineering– Proceedings of the 2013 ASCE International Workshop on Computing in Civil Engineering, 2013, pp. 379–386.

[12]. N. Benmansour, R. Labayrade, D. Aubert, S. Glaser, D. Gruyer, A model driven 3D lane detection system using stereovision, in: 2008 10th International Conference on Control, Automation, Robotics and Vision, ICARCV 2008, 2008, pp. 1277–1282.

[13]. M. Hofer, A. Wendel, H. Bischof, Incremental line-based 3D reconstruction using geometric constraints, in: BMVC 2013– Electronic Proceedings of the British Machine Vision Conference 2013, 2013, pp. Dyson; HP; IET Journals– The Institution of Engineering and Technology; Microsoft Research; Qualcomm.

[14]. M. Hofer, M. Maurer, H. Bischof, Line3d: efficient 3D scene abstraction for the built environment, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2015, pp. 237–248.

[15]. Z.-Z. Hu, L. Zhang, D.-F. Bai, B. Zhao, Computation of road curvature from a se quence of consecutive in-vehicle images, J. Transport. Syst. Eng. Inform. Technol. 16 (1) (2016) 38–45 (in Chinese).

[16]. H. Bay, T. Tuytelaars, L. Van Gool, SURF: speeded up robust features, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2006, pp. 404–417.

[17]. E. Rosten, T. Drummond, Machine learning for high-speed corner detection, in: Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2006, pp. 430–443.

[18]. A. Alahi, R. Ortiz, P. Vandergheynst, FREAK: fast retina keypoint, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2012, pp. 510–517.

[19]. H. Bae, M. Golparvar-Fard, J. White, High-precision and infrastructure-independent mobile augmented reality system for context-aware construction and facility management applications, in: Computing in Civil Engineering– Proceedings of the 2013 ASCE International Workshop on Computing in Civil Engineering, 2013, pp. 637–644.

[20]. X. Du, Y.-F. Zhu, A flexible method for 3D reconstruction of urban building, in: International Conference on Signal Processing Proceedings, ICSP, 2008, pp. 1355–1359.