# Machine Measuring Method for Norm-Position of Targets

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**Abstract.** Current methods for targets location in real-life scenarios are still based on the point-level location, which regard the target as a mass point and perform its position via 2D/3D coordinates. However, point-level location cannot describe the spatial structure or three-dimensional position of targets, which is not enough to provide location services that meet higher requirements in some special areas, such as scene regeneration and precision operation. In this paper, we propose a novel position measure called Norm-Position for this task. Norm-position describes the target location information by spatial structure and three-dimensional position, which no longer regards the target as a mass point. Norm-position measurement surveys the position of all surface points belonging to the same object. It does not only rely on traditional position measurement methods, but a novel machine measurement approach that combines key technologies such as high-precision positioning and timing based on Beidou navigation satellite, computer vision, lidar, artificial intelligence, 5G communications, big data, and cloud computing, to name a few. The presentation of norm-position measuring results is to calculate the three-dimensional coordinates, spatial structure and space occupation of multiple targets in the real scenes. In this paper, we also present a machine measuring method for norm-position and verify its effectiveness. Finally, we discuss the potentials of norm-position measurement in practical applications such as real-scene information management, unmanned precision operation and reverse control engineering.

**Keywords:** Norm-position·real-life scene · Multiple targets · Machine measurement

## 1 Introduction

High-precision positioning technology can provide basic location-based services for applications such as autonomous driving [1], automatic navigation [2], security monitoring [3] and emergency rescue [4] etc. On 23 June 2020, China successfully launched the 55$^{th}$ BDS navigation satellite and the final Beidou-3 satellite of Beidou navigation network was launched for global coverage. On 31$^{st}$ July 2020, President Xi Jinping announced the official commissioning of the BeiDou-3 global navigation satellite system, starting a new phase in China's satellite navigation applications. With the promotion of BDS time service and positioning technology, high-precision position measurement


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technology, computer vision and artificial intelligence [5], 5G [6], blockchain [7] and other key technologies are more closely integrated and more widely used in smart cities [8], smart agriculture [9], smart logistics [10] and other fields. The real-time and accurate measurement of the spatial position of multiple targets in real scenes helps realize deep integration of location information and attribute information of multiple targets and promotes accurate identification and dynamic management of spatial objects. Therefore, realizing real-time and accurate positioning of spatial objects is one of the most basic and important issues in location application scenarios.

At present, there are two categories of positioning technologies, i.e. outdoor positioning and outdoor positioning, based on different application scenarios. Outdoor positioning is generally used in outdoor and other openair scenarios and its main positioning technologies include satellite positioning [11] and base station positioning [12]. Satellite positioning receives satellite signals sent from the Global Navigation Satellite System (GNSS) through the receiver to resolve the current location (latitude and longitude). The current mainstream global satellite navigation systems mainly include the Chinese BeiDou navigation satellite system (BDS), the U.S. Global Positioning System (GPS), the Russian GLONASS system and the European GALILEO system. As another important technology for outdoor positioning, the base station positioning is achieved by using the "three-point positioning" to resolve the position with the support from the base stations established by mobile communication operators. Since 1996, the United States, Japan, the European Union and other countries or organizations have successively legislated to require mobile operators to provide positioning services. In recent years, with the popularization and application of 5G, a lot of results have been achieved in the research on positioning based on 5G cellular networks [13], such as 5G applications in high-precision positioning of urban trains [14]. The outdoor positioning technologies represented by satellite positioning and base station positioning have become more mature, but are still affected by factors such as blocking and multipath effects, which makes indoor application impossible and has therefore given rise to the development of indoor positioning technology. In 2006, China launched the "Xihe" plan, proposing to achieve sub-meter level indoor positioning accuracy during the 13th Five-Year Plan period. In recent years, a variety of location measurement technologies have emerged for indoor positioning, which can be divided into wireless positioning technologies and non-wireless positioning technologies. Typical wireless positioning technologies include WIFI [15], bluetooth [16], Ultra Wide Band (UWB) [17], and Radio Frequency Identification (RFID) [18], while non-wireless positioning technologies are mainly based on vision [19], inertial components [20], geomagnetic [21], ultrasonic [22] and other technologies. These indoor positioning technologies are also widely used in the commercial market, for example, UWB positioning is widely used in industrial, logistics, and smart city scenarios and companies such as Apple, Huawei, and Xiaomi are gradually adding UWB modules to their smartphones to achieve high-precision positioning of mobile devices.

Although there are currently more mature positioning technologies for both indoor and outdoor target position measurement, there still exists a common problem: positioning by regarding the target as a mass point. These positioning methods equate the target with a mass point in 2D or 3D space, i.e., they do not consider information such as the spatial structure and spatial occupation of the target. This type of positioning method is widely used in applications that involve the provision of only location-based services of targets, but proves hard to meet the requirements of applications such as 3D sensing of targets, real-world scene twinning and reverse control. For example, if a person is equated to a mass point in the center of the body for position measurement, the 3D position information of the same person is the same when the person is standing up and standing upside down, but the position of the person in space is completely different; similarly, the position information obtained through point positioning is the same for two cubic products of different sizes in an industrial production line, but the spatial occupation of the two targets is actually different. The point position alone cannot provide accurate operation information for the control equipment. Therefore, a comprehensive three-dimensional measurement of the target is needed and the spatial structure and spatial occupation information of the target can be accurately described by measuring the position of all surface points of the target. Based on this, this paper proposes the machine measurement of the norm position of the spatial object to describe the three-dimensional position, spatial structure and spatial occupation of the target.

## 2 Norm Position

### 2.1 Definition of Norm Position

The norm position defined in this paper is the set of positions of all surface points belonging to the same target object. The norm position no longer presents the target as a mass point, but instead describes the target location information by spatial structure and spatial occupation. The norm-position measurement is equivalent to locating all the points that make up the target and the combination of the positions of all surface points belonging to the same target (i.e. the target norm position information), through which the three-dimensional structure of the target in three-dimensional space will be restored. Compared with the traditional target point positioning method, the norm position of spatial objects has the following characteristics:

(1) Target materialization. Unlike the positioning method that treats the target as a mass point, the norm position measurement treats each target as an entity of a different category of object, which has preserved the structured and semantic characteristics of the entity.

(2) Position structuring. Norm-position measurement is about the measurement of the coordinates of all constituent points on the surface of an entity and is able to construct the spatial form of the target based on the coordinates of surface points. Although the point cloud scan of the object can reconstruct the three-dimensional structure and spatial location of the target, the norm position measurement of the object is not equivalent to the point cloud scan of the object; what makes it different from the results of point cloud scan of the target is that the norm position measurement also includes the semantic features of the target.

(3) Target-scene association. The norm position measurement obtains the target information directly from the real scenes, while using the spatial position of reference points in the scene to obtain the spatial position information of the target; on the other hand, the norm position of each target in the scene can be used to restore the real scenes.

### 2.2 Key Technologies for Norm-position Machine Measurement

The norm-position measurement of spatial objects is different from the traditional object position measurement in that it is a kind of realistic target monolithic, structured and semantic machine measurement based on multi-technology fusion. The core technologies supporting the machine measurement of spatial object norm position include the following:

(1) BDS-based high-precision positioning and time services. For the machine measurement of spatial object norm position, BDS-based high-precision positioning and time service technology can provide position and time reference frame, which is the basis for norm position measurement. Using BDS-based high-precision point positioning [23] and the differential positioning based on BeiDou ground –based augmentation-based system [24], the centimeter-level position information of outdoor targets can be obtained. Based on BDS-based time service technology, a unified timestamp of multiple targets and devices in the scene is established to achieve nanosecond-level time synchronization [25].

(2) Instance segmentation and 3D perception of targets. Through multi-camera acquisition of RGB images or RGB-D images in the scene, the 3D structure of the target is reconstructed and restored through machine vision technology to sense the spatial occupation of multiple targets, such as realized by SFM algorithm [26]; instance segmentation of targets based on deep learning, such as realized by Mask R-CNN [27], the individual targets in the scene are monolithized and semanticized to obtain the individual attribute information of each target. The artificial intelligence technology represented by deep learning is the main technical means used to acquire the semantic information for norm position measurement.

(3) Indoor and outdoor positioning based on multi-sensor fusion. BDS-based high-precision positioning technology can accurately obtain the location information of outdoor targets. However, indoor applications of BDS-based high-precision positioning have certain limitations due to the influence of indoor blocking and multipath effects. For indoor positioning, other sensors such as UWB, Bluetooth, vision sensors, LIDAR, WIFI, etc. are required for positioning. Based on the deep integration of Beidou and other positioning, sensing and measurement technologies, multi-source positioning models such as "Beidou+UWB+vision" [28] and "Beidou+vision+inertial navigation" [29] can be built to make up for the limitations of single location measurement technology and realize the sensing of the position of indoor and outdoor targets.

(4) High-speed transmission and information connectivity based on 5G and IoT. Realizing norm position measurement of multiple targets in real scenes requires real-time acquisition and transmission of on-site radio signals, images, videos and other data. For the concurrent transmission of large amounts of data, the transmission method requires higher bandwidth and transmission rate. For example, according to the average bit rate of 5 Mbps for each channel of HD video, 1 Gbps of bandwidth is required for real-time transmission of 200 channels of the video. At the same time, the need for information exchange between different targets in the process of norm position measurement also puts higher requirements on the real-time transmission of information. In recent years, the development of 5G technology has provided a solution for high-speed data transmission. 5G technology, with its high speed, low latency, high reliability and other characteristics

[30], has become one of the key technologies involved in the norm position measurement of spatial objects.

(5) Intelligent cloud computing technology based on massive data. For the real-time measurement of norm position of multi-target entities in real scenes, the accumulated scene information needs to be processed efficiently, which requires intelligent computing platforms with strong computing power support. For example, according to each high-performance server's ability of processing 10 channels of high-definition videos in real time, the processing of 200 channels of video will require at least 20 servers with cloud computing capability. Therefore, the strong computing power and technology of the cloud-computing platform provides an important computing support to ensure real-time norm position measurement.

### 2.3 Resolution Methods for Norm Position

Compared with the traditional object point positioning method, the norm position measurement of the target involves more items to be resolved as well as higher computational complexity and more computational volume. Therefore, it is necessary to optimize the position resolution method. Based on this, the paper proposes the following resolution methods for norm position measurement:

(1) Using static targets to resolve norm position of dynamic targets. The targets in the real scenes include a large number of static targets in addition to dynamic targets. The absolute position of the static targets remains constant and the static targets can be used as a reference to quickly determine the norm position of the dynamic targets based on the motion state of the dynamic target in relation to the static target. At the same time, the relative motion between two moving targets can also be used to resolve the norm position of a certain object.

(2) Using the targets whose structures are known to resolve the norm position of all of the target surface points. For the norm position measurement of some targets, after the semantic information of the target is identified, the spatial structure of the target can be obtained through semantic features, so that only the coordinates of some control points will need to be calculated and the spatial structure of the target is assembled to help obtain all of the position information of the target surface points. This resolution method is suitable for resolving the norm position of some targets whose structures are known, such as products in the industrial field. The norm positions of these industrial products can be obtained quickly because they have uniform standard structure dimensions.

(3) Using the targets in the 2D image to resolve the norm position of targets in the 3D image. The 2D image of the scene is collected, the instance segmentation of the target in the image is conducted and the spatial coordinates of the surface points of the target are resolved through the mapping of pixel points in the image onto the coordinates of the 3D spatial points. A typical implementation method such as the EPnP algorithm [31] is used to resolve the actual spatial coordinates of the target points by utilizing the pixel coordinates of multiple points in the image.

# 3 Study of Measurement Methods

Based on the above-mentioned resolution methods, this paper designs a feasible method for machine measurement of the norm position of spatial objects: the RGB-D camera is used to capture the scene images and the instance segmentation of multiple targets in the space is realized based on YOLACT; on the basis of the instance segmentation result of each object, the depth information of each target is obtained through the depth map; combined with the pixel coordinates and depth information of the target, the PnP algorithm is used to calculate the 3D spatial coordinates of all surface points of the target.

## 3.1 Principles and Methods

### 3.1.1 Instance Segmentation of Targets

Although Mask R-CNN, which is widely used in instance segmentation, has been able to achieve good results, it mainly focuses on detection accuracy, with poor real-time performance and the detection speed of less than 10 FPS. In order to ensure the real-time performance of instance segmentation, YOLACT algorithm [32] is used as the implementation path in this study.

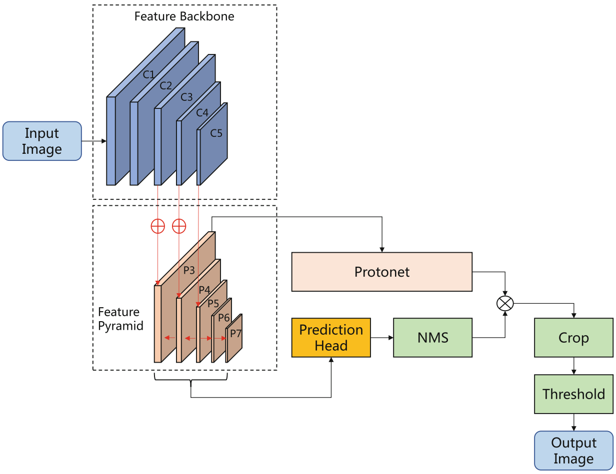


**Fig. 1.** YOLACT architecture

The network structure of YOLACT is shown in Fig. 1: In this model, ResNet-101+FPN is used as the backbone, and the instance segmentation is achieved by two branches, i.e. the prototype generation branch and the mask coefficient branch. The prototype generation branch Protonet is mainly implemented based on FCN to generate mask prototypes; the mask coefficient branch mainly implements mask coefficient prediction through anchor-based target detector. The two branches are calculated independently and then the mask synthesis is performed by the use of matrix multiplication and Sigmoid function and the segmentation results is exported finally.

### 3.1.2 Principles of Position Resolution

The pixel-level position of each target in the image can be obtained through the instance segmentation of the object. The 3D position of the target in the world coordinate system can be obtained by transforming the coordinate system for pixels.

For the pixel coordinates (u, v), the transformation into the image coordinate system can be realized by the following equation:

$$\begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \begin{pmatrix} 1/dx & 0 & u_0 \\ 0 & 1/dy & v_0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} \tag{1}$$

in which dx and dy are the actual physical dimensions of the pixels on the light-sensing components, u0 and v0 are the image plane centers and x and y are the image coordinates. The conversion relationship between the image coordinate system and the camera coordinate system can be calculated by the following equation:

$$Z_c \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} fx & 0 & 0 & 0 \\ 0 & fy & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} X_c \\ Y_c \\ Z_c \\ 1 \end{pmatrix} \tag{2}$$

in which fx, fy are the focal lengths of the camera in x-axis and y-axis and Xc, Yc, Zc are the coordinate values of the target in the camera coordinate system. The conversion relationship between the camera coordinate system and the world coordinate system can be calculated according to the following equation:

$$\begin{pmatrix} X_c \\ Y_c \\ Z_c \end{pmatrix} = \mathbf{R} \begin{pmatrix} X_w \\ Y_w \\ Z_w \end{pmatrix} + \mathbf{T} \tag{3}$$

where Xw, Yw, and Zw are the coordinate values of the target in the world coordinate system, **R** is a $3 \times 3$ rotation matrix, and **T** is a $3 \times 1$ translation matrix. The matrices **R** and **T** can be combined into one external reference matrix, and then Eq. (3) can be rewritten as

$$\begin{pmatrix} X_c \\ Y_c \\ Z_c \\ 1 \end{pmatrix} = \begin{pmatrix} \mathbf{R} & \mathbf{T} \\ \mathbf{0} & 1 \end{pmatrix} \begin{pmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{pmatrix} \tag{4}$$

Based on Eqs. (1)–(4), the equation for conversion of the pixel point into the 3D spatial position can be obtained as:

$$Z_c \begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \begin{pmatrix} fx/dx & 0 & u_0 & 0 \\ 0 & fy/dy & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} \mathbf{R} & \mathbf{T} \\ \mathbf{0} & 1 \end{pmatrix} \begin{pmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{pmatrix} \tag{5}$$

In Eq. (5), the matrix consisting of the parameters of the camera itself is called the internal reference matrix, which can be obtained through camera calibration. According to Eq. (5), the pixel coordinates (u, v) of the target and the internal reference matrix of the camera are both known. In order to resolve the 3D coordinates (Xw, Yw, Zw) of the target in the world coordinate system, the depth value Zc of the target in the camera coordinate system and the external reference matrix need to be calculated.

### 3.1.3 Target Depth Acquisition

The depth value of the target in the camera coordinate system can be obtained with the depth camera. To calculate the 3D position of each point on the target surface, this study uses a binocular camera to acquire depth information. The binocular camera is able to export aligned RGB-D images, i.e. the images in which each pixel point in the color image corresponds to the depth value at the same location in the depth map.

In the measurement of depth values, depth is usually noisy and there are some pixel locations where depth values cannot be obtained due to target reflections and other reasons. In order to obtain stable depth values, a neighborhood window is used to estimate the depth value at each pixel location, i.e., for a target at coordinates (i, j), the depth value Z(i, j) can be calculated as:

$$Z(i,\ j)\ =\ \frac{\sum_{x\ =\ i-S}^{i\ +\ S}\sum_{y\ =\ j-S}^{j\ +\ S}\varphi(x,y)\cdot Z(x,y)}{\sum_{x\ =\ i-S}^{i\ +\ S}\sum_{y\ =\ j-S}^{x\ =\ i-S}\varphi(x,y)} \tag{6}$$

In this equation, S is the size of the neighborhood window. φ(x, y) is the sign function, which is calculated as:

$$\varphi(x,y)=\begin{cases}1,\ Z(x,y)\neq 0\\ 0,\ Z(x,y)=0\end{cases} \tag{7}$$

### 3.1.4 Calculation of External Reference Matrix

To calculate the external reference matrix of the camera, this study performs pose estimation of the camera by the use of PnP (Perspective-n-Point) algorithm. This method performs camera pose estimation by a set of n 3D points in the world coordinate system and their corresponding 2D coordinates in the image. Based on the known control point coordinates, the camera pose can be estimated by combining the internal parameters of the camera. There are many methods of resolution of PnP algorithm, such as P3P with three sets of point pairs, direct linear transformation, EpnP and UpnP etc. In this study, the EPnP (Efficient PnP) algorithm is used for pose estimation.

For N sets of control points, let the image coordinates of the $i^{th}$ control point be v[i] and the world coordinates be cwi. According to the EPnP algorithm, there is the equation

$$\left\|\sum_{k=1}^{N}\beta_k v_k^{[i]}-\sum_{k=1}^{N}\beta_k v_k^{[j]}\right\|^2=\left\|c_i^w-c_j^w\right\|^2 \tag{8}$$

Resolve β based on the known coordinates of the control point. Calculate the coordinates of the control point in the camera coordinate system based on β:

$$c_i^c = \sum\nolimits_{j=1}^{N} \beta_k v_k^{[i]} \tag{9}$$

For the reference point, according to the EPnP algorithm, there is the equation

$$\begin{cases} p_i^w = \sum_{j=1}^4 \alpha_{ij} c_j^w \\ p_i^c = \sum_{j=1}^4 \alpha_{ij} c_j^c \end{cases} \tag{10}$$

According to the above equation, the coordinates of the reference point in the camera coordinate system can be obtained. The center of gravity and matrix of the reference point in the world coordinate system and camera coordinate system are calculated separately as follows:

$$\begin{cases} p_o^w = \frac{1}{n} \sum_{i=1}^n p_i^w \\ p_o^c = \frac{1}{n} \sum_{i=1}^n p_i^c \end{cases} \tag{11}$$

$$\mathbf{A} = \begin{pmatrix} p_1^{wT} - p_o^{wT} \\ p_2^{wT} - p_o^{wT} \\ \vdots \\ p_n^{wT} - p_o^{wT} \end{pmatrix}, \ \mathbf{B} = \begin{pmatrix} p_1^{cT} - p_o^{cT} \\ p_2^{cT} - p_o^{cT} \\ \vdots \\ p_n^{cT} - p_o^{cT} \end{pmatrix} \tag{12}$$

Calculate the **H** matrix:

$$\mathbf{H} = \mathbf{B}^T \mathbf{A} \tag{13}$$

Perform the SVD of the matrix **H**:

$$\mathbf{H} = \mathbf{U} \Sigma \mathbf{V}^T \tag{14}$$

Then the rotation matrix **R** in the external reference matrix can be calculated as:

$$\mathbf{R} = \mathbf{U}\mathbf{V}^T \tag{15}$$

The translation matrix **T** can be calculated as:

$$\mathbf{T} = p_o^c - \mathbf{R} p_o^w \tag{16}$$

#### 3.1.5 Norm Position Measurement

Based on the pixel-level segmentation of the target, all the pixel points of the target surface can be obtained and the actual 3D coordinates of each point on the surface of each target in space can be obtained based on the conversion relationship between pixel coordinates and 3D spatial coordinates. By managing the set of 3D coordinates of each point on the surface of each target, the spatial structure of the target and the actual spatial occupation can be obtained.

## 3.2 Experimental Verification

### 3.2.1 Equipment and Implementation

To test the effectiveness of the design method used in this study, a simple verification system has been built for the experiment. The scene image acquisition is performed by a binocular camera, ZED2, which has a maximum resolution of 4416 × 1242 and a frame rate of 15FPS at 2K resolution, a depth measurement range of 0.5–20 m, and USB 3.0 output. The processing system is Ubuntu 18.04 with 64 GB of RAM and NVIDIA GeForce RTX 2080Ti GPU with 11 GB of video memory and Python programming language.

In this study, the verification system has been built indoors and the world coordinate system has been established in a right-handed right-angle coordinate system and the ZED2 camera is mounted on the top of the tripod with a height of 2.1 m, as shown in Fig. 2.

After the fixation of the camera, the camera is calibrated. Four control points have been selected in the site to obtain the world 3D coordinates onsite and 2D coordinates in the image. The external reference matrix of the camera is obtained by the use of EPnP algorithm. At the same time, the internal reference matrix of the camera is obtained by utilizing Zhang Zhengyou's method of camera calibration based on the checkerboard.

**Fig. 2.** ZED2 installation

### 3.2.2 Results and Analysis

Firstly, the accuracy and detection time of target detection were calculated to verify the effectiveness and real-time performance of target instance segmentation. Secondly, the accuracy of three-dimensional space point positioning was tested. Finally, the validity of the norm-position measurement was tested via the twin test of human body's real spatial pose.

In the first step, different targets were placed in the site, and instance segmentation was performed on the targets through YOLACT. In the experiment, each target was moved 20 times, and the segmentation detection results of each target in 20 groups of different positions were counted. In the experiment, a total of 193 targets were correctly segmented, 7 targets were missed, and the detection accuracy was 96.5%. As shown in Fig. 3, this method could correctly detect all the targets placed in the segmented scenarios. Figure 4 shows the undetected target in the scenario, which is the basketball in the field. The average detection time was 55 ms. The frame rate of ZED2 camera was 15FPS at 2K resolution, so the segmentation speed of YOLACT could match the real-time speed of ZED2 camera.

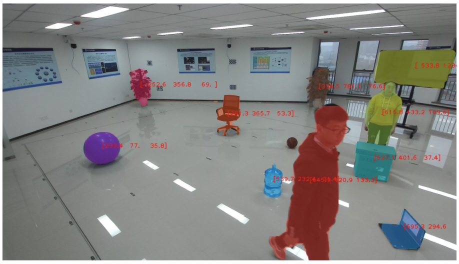

**Fig. 3.** Result of instance segmentation: all detected accurately

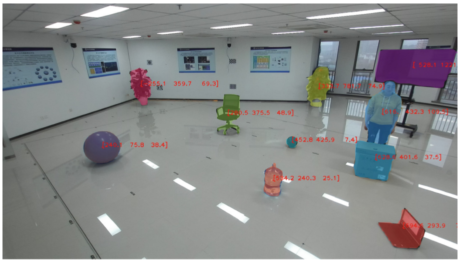

**Fig. 4.** Result of instance segmentation: basketball is omitted

Then the accuracy of 3D positioning was verified. Five targets were selected in the experiment, including a big ball, a basketball, a human, a water bottle and a chair, to measure their positioning accuracy. An error test was carried out on 20 measurements of those 5 targets. To measure the errors, the errors between the measured value and the actual value on three coordinates $\Delta X$, $\Delta Y$, and $\Delta Z$ were respectively calculated, as well as the spatial Euclidean distance between the actual values and the measured values $\Delta S$. It was found from Fig. 5 that the positioning error on the Z-axis was the smallest, while the positioning error on the X-axis was the largest. The spatial positioning error was 22.75 cm.

Finally, the validity of the norm-position measurement method was verified by regenerating the spatial position of human body. The pixel coordinates of the key points of the target human were obtained from the image with the algorithm of extracting human body key points [33]. According to the norm-position measurement method proposed in this study, each key point can be converted into three-dimensional coordinates, and human body pose can be quickly reconstructed in space. As shown in Fig. 6, real-time digital twin of human motion state and spatial pose can be made by measuring the human body's norm-position.

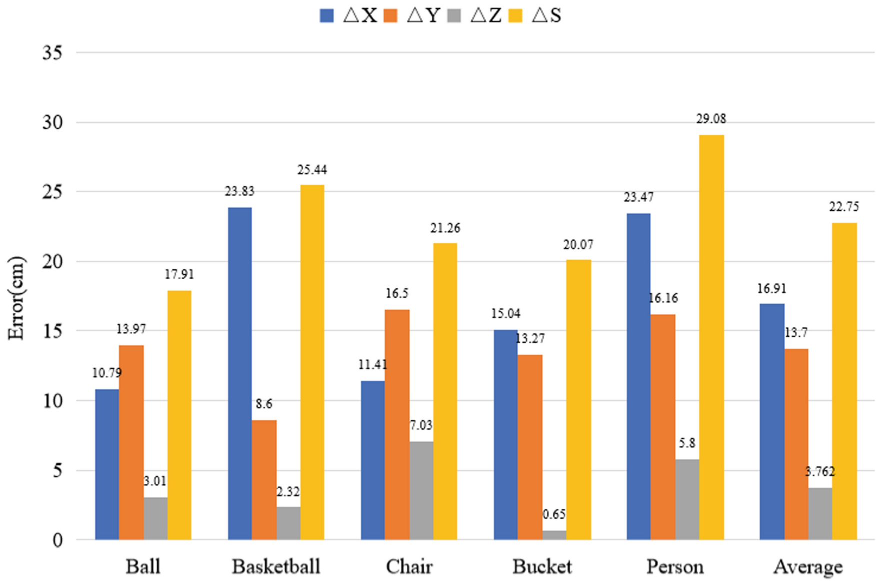


**Fig. 5.** Result of 3D location

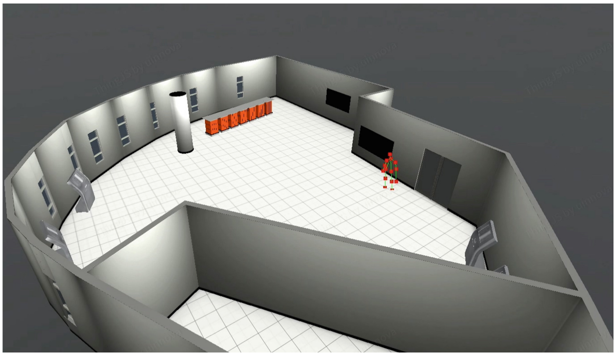

**Fig. 6.** Result of digital twin based on norm-position

### 3.3 Discussion

The norm-position measurement method designed in this study, combined with artificial intelligence and visual positioning technology, embodies its idea of solving problem "from a known to an unknown state, and from two-dimensional to three-dimensional," and the feasibility of the method was verified by building a simple verification system. It needs to be clarified that the complexity of the real scenarios can largely increase the difficulty of the norm-position measurement, and cause huge challenges to the method. However, the innovation and iteration of various advanced measurement methods also provide strong technical support for the method. Challenges and opportunities coexist.

The research on norm-position machine measuring method will attract more researchers' attention.

# 4 Analysis of Applications

## 4.1 Real Scenario Information Management

In the application of target management, it is usually necessary to manage the various elements of interest in the scenario. The attributes and position information of each target entity can be obtained by machine-measuring the norm-position of the spatial objects, which is helpful in the accurate management of the target elements. For example, in the application of real-time management of tourist information in scenic areas, measuring the norm-position of tourists to single them out and obtain their individual attributes and location information can help achieve the accurate management of tourists. At the same time, the norm-position information of tourists can also provide field information for the safety and emergency management of scenic areas, supporting scientific decision-making.

## 4.2 Unmanned Precision Operation

In the modern industrial automatic production, the unmanned precision operation of machines has become an important sign of intelligent manufacturing. In the typical application scenario where the robot arm automatically identifies, locates and grabs goods, the simple point positioning can no longer meet the complex and diverse operation requirements. For example, the operation system needs to use different capturing schemes for different materials and product structures. At the same time, different parts of the same object can be very different. By measuring the norm-position of the goods, the space pose of the goods and the space coordinates of each point can be obtained, based on which the robot arm then selects the corresponding grabbing operation scheme, making the operation adaptive and precise. In unmanned precise operation scenarios, the norm-position machine measurement method mainly provides precise target space position and three-dimensional structure information for operation equipment, so as to realize targeted selection of operation methods.

## 4.3 Reverse Control of Targets

The real-time scene can be reconstructed based on the digital twinning of the target and the three-dimensional regeneration of the scenario. Furthermore, the reverse control of the target in the real scenario can be realized by controlling the twin target in the regenerated scenario. Typically in autonomous driving, the norm-position information of the target vehicle and other vehicles can be obtained in real time.

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