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Article

Sizing and Positioning of Cylindrical Object Based on the Millimeter-Wave Radar System

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Abstract. In this article, we propose an algorithm to estimate the size and position of an object with the millimeter wave radar system. With the proposed algorithm, the size and position of objects is represented by cylinders with a single IWR1443 radar sensor module. From the estimated cylinder, the radius and center of the cross-sectional circle shows the approximate size and position. Raw data from IWR1443 show scanning of objects in the form of data points which cannot be directly used to determine the exact size or shape of the object. The data in one frame of the sensor provides many data points. With K-mean and selection of K, we can group the number of data points to each object and find the size and position by circle-fitting. The results of the algorithm show that the mean of a position of the object is close to the actual value, but the mean of the radius is rather smaller than the actual value.

Keywords: Object estimation, mmWave, k-means, circle-fitting, radar sensor.

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1. Introduction

The first step of the obstacle avoidance problem is sizing and positioning. Mostly used object detection algorithms employ the camera fusion with other sensors due to many algorithms available in image processing area with multi-sensor [1–6]. For some robots to use multi-sensor, it is too computational consuming, such as small drone. Using only one sensor may be the only option. Another object detection sensor, Lidar, can be used without a camera or another sensor. This sensor uses a laser to scan the object. Data from lidar can be used to estimate size, i.e., width and depth, of the object [7, 8]. In 2010, Rutzinger, *et al.* [9] proposed the tree modelling algorithm using laser scanning. The disadvantage of lidar is that it takes more time to detect an object than radar because lidar is a 3D laser scan. In the case of imaging radar, the sensors do not require GPU to process data and it also has less complexity. In this paper, we focus on cylindrical objects and the method is based on mmWave radar sensors.

Millimeter wave (mmWave) is a radiation of the electromagnetic waves with frequency ranging from 30 to 300 GHz. This band can avoid agitation from other communication bands. This radar system is a technology used to describe the velocity, position and angle of the objects. The mmWave radar sensor can be used to detect motion [10] or to give the position of an object [11, 12].

We propose a method to estimate the size and position of cylindrical objects based on mmWave radar systems. With the proposed algorithm, the number of objects can be grouped using K-means and K-selection. From the distribution of data from radar, we can estimate the size and location by least-square circle-fitting.

This paper is organized as follows. We describe the background of a millimeter wave radar system in Section 2. The description of clustering and estimation are explained in Section 3. The experiment results of estimating algorithm are described in Section 4. In the last section, we conclude the result of this paper and give suggestions for the future work.

2. Millimeter Wave (mmWave) Radar System

The millimeter-wave (mmWave) is used for the detection and providing the distance of an object. The mmWave transmits the millimeter-wavelength which is in the millimeter range. The transmitter signal can have many types of waveform. The frequency-modulated continuous-wave (FMCW) is one of the waveform examples [13]. FMCW consists of waves that change frequency with time, $f(t)$. In this paper, we consider linear frequency changes that are called chirp signals. The chirp signal is illustrated in Fig. 1. The frequency of sensor with time is illustrated in Fig. 2.

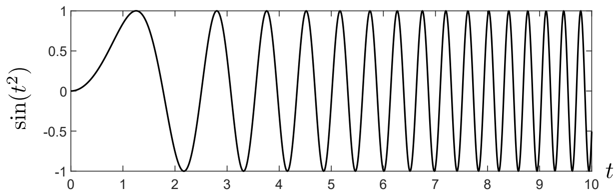

Fig. 1. Chirp signal with amplitude and frequency as a function of time, $f(t) = \frac{t}{2\pi}$.

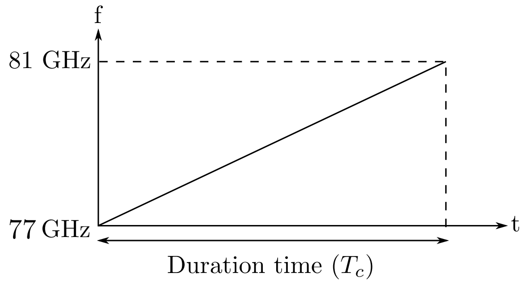

Fig. 2. Chirp frequency of IWR1443 in range of mmWave.

Objects can be detected after the sensor receives the reflected signal from each object. To compute the position of objects, we need two variables as shown in [13]. With this method, the sensor will detect objects when frequency is changed by movement or doppler frequency detection.

We propose to use the IWR1443 module to detect objects as shown in Fig. 3. This board is made by Texas Instrument. The bandwidth of 76- to 81-GHz coverage with 4-GHz Continuous Bandwidth [14]. The position of objects is computed by Python code from [15]. Figure 4 shows that the real environment. The distance between the radar and the tree was tested at approximately 2 meters. The raw data from the IWR1443 is shown in Fig. 5. It shows the result of detection in one frame of Fig. 4.

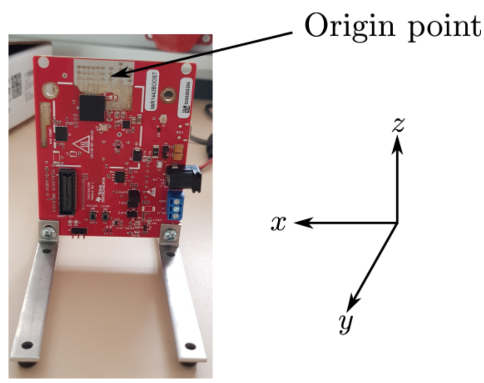

Fig. 3. IWR1443 module with the coordinate on radar sensor.

3. Clustering and Estimating Technique

The proposed algorithm to estimate the size and position of objects has three steps. The algorithm will be processed after IWR1443 collect the data point. From the previous section, IWR1443 gives the position of the objects in

Fig. 4. Sample environment for testing IWR1443 in Chulalongkorn university.

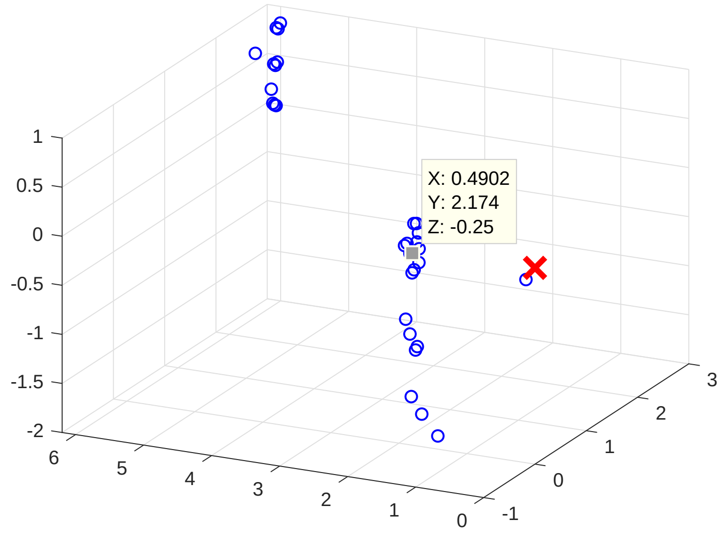

Fig. 5. The raw data from IWR1443. **X** is the position of IWR1443. **O** is the position of the object that can be detected.

3d-cartesian coordinate which is called Data points. The process of algorithm is illustrated in Fig. 6. The data point from IWR1443 is clustered, and each group is fitted in a circle. The important function of the algorithm is clustering and estimating processes.

3.1. K-Means and K Selection

K-means algorithm uses two parameters which are the initial points and group number K to cluster data. For initial points, a random function is used to locate the initial points. Actually, K depends on the experiment, but IWR1443 can detect objects depending on the obstacles in the environment. The value of K is not fixed. Many researchers have proposed K-selection [16, 17] which depends on data distribution. In this paper, we used uniform distribution to estimate K because of radar sensor uniform property. The formula is as follows:

$$f(K) = \begin{cases} 1, & \text{If } K = 1 \\ \frac{S_K}{\alpha_K S_{K-1}}, & \text{if } S_{K-1} \neq 0, \ \forall K > 1 \\ 1, & \text{if } S_{K-1} = 0, \ \forall K > 1 \end{cases} \tag{1}$$

$$\alpha_K = \begin{cases} 1 - \frac{3}{4N_d}, & \text{if } K = 2 \text{ and } N_d \geqslant 1 \\ \alpha_{K-1} + \frac{1-\alpha_{K-1}}{6}, & \text{if } K > 2 \text{ and } N_d \geqslant 1 \end{cases} \tag{2}$$

where $S_K = \sum_{i=1}^{K} I_i$, I_i is the distortion of cluster i, and N_d is the number of dimensions of data. The variable α_K is a weight of K. Since $f(K)$ increases when K is increased, we will select K when S_K is less than S_{K-1} because S_K is the summation of distortions. In this algorithm, we choose K as $arg\,min_K f(K)$.

3.2. Object Size and Position Estimation

In this paper, we assume the shape of objects is cylindrical. Therefore, the size of an object is represented by the radius of the cylinder while the position is the center of its cross-sectional circle. We can estimate circle parameters from data by the Least-squares circle fitting technique [18].

Let x_i and y_i are data points when $i = 1, 2, 3, ..., N$ and $\bar{x}$ and $\bar{y}$ are means of x_i and y_i, respectively. Define $u_i = x_i - \bar{x}$ and $v_i = y_i - \bar{y}$. From the circle equation, we find the radius and center of the circle by

$$\min \sum_{i=1}^{N} \{(u_i - u_c)^2 + (v_i - v_c)^2 - R^2\}^2, \tag{3}$$

where (u_c, v_c) is the center in uv-coordinate and R is the radius of circle.

4. Experiment and Result

4.1. Experiment Setup

To set up the experiment, three factors are required: board setup, the environment selection, and the maximum number of K. We set the board sampling time to 5 frame/sec, maximum range to 10 meters, and T_c = 200 msec. Figure 7 shows experimental environment with IWR1443 radar module. The maximum of K is ten.

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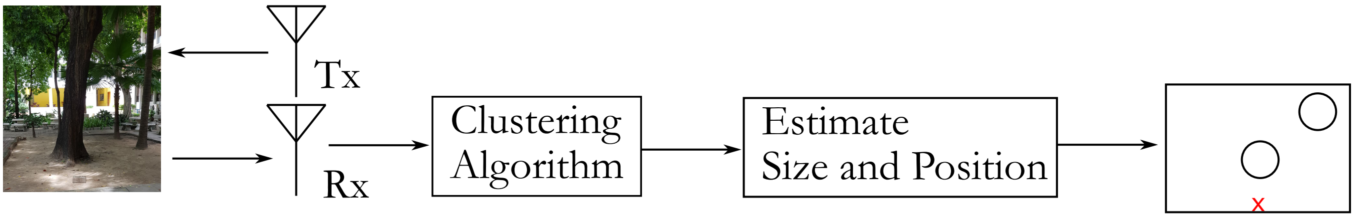

Fig. 6. Block diagram of algorithm.

Fig. 7. Experiment environment.

Figure 8 shows the flowchart of the proposed algorithm in one loop. The input is the data from IWR1443 which is collected for estimation. The algorithm can be explained in small steps below.

- *Step 1 Collect data*: IWR1443 collects the data into frame.
- *Step 2 Selection data*: We consider two problems to select the data which are the incorrect data and the insufficient information. Perhaps detected signals can be the reflection from dusts. This noise is ignored in y_i. After that we count the number of data points. If the number is less than or equal to five, we ignore this frame and repeat step 1.
- *Step 3 Clustering objects*: By using K-means algorithm, the objects are clustered as explained in 3.1.
- *Step 4 Estimation*: To avoid data insufficiency, we will calculate only groups with at least four data points. By minimizing the objective function 3, the algorithm compute radius and center for K objects.

4.2. Number of K

We used data from Fig. 5 to show the example of K selection of K-means with $N_d = 2$ in only xy-coordinate. The value of $f(K)$ is shown in Fig. 9. The minimum of $f(K)$ is $K = 2$ which is shown in Fig. 11. Comparing Figs. 10, 11, 12 and 13, we use that the most possible K which is two.

In our experiment, we collect data 900 frames to test the number of K in each frame. Figure 14 shows that the number of K in each frame of a doppler radar. IWR1443 needs some movement to detect the received signal. The amplitude of movement in our experiment is not constant. The data from radar in each frame may not detect the same object because of the doppler effect of radar.

4.3. Size and Position of the Objects

For size of objects, we show estimated radius in Fig. 15 for only $K = 1, 2, 3$. The black line shows the actual radius of tree. The position of circle is shown in the xy-coordinate. Figure 16 and 17 show estimated position. The estimated radius shows that the estimated value is less than actual with error ($|r_{\text{actual}} - r_{\text{mean}}|$) = 14.6 cm at two meters. For estimated position, most of the x-axis data are around zero, and most of the y-axis data are around two points which are two and seven meters. From Fig. 7, we observed that the back of main tree has another tree at around seven meters from IWR1443.

We used the average data to compare the range of measurements. Estimated size decreases as shown in Fig. 1. The estimated diameter is smaller than actual may be doppler radar properties (non-constant radar speed). The estimated radius is decrease, which IWR1443 collects like a camera. The object is captured by a camera that is smaller than actual, which depends on the range from the camera to the object. However, the approximate diameter of five meter is larger. It may be due to too much distance from the sensor. This result shows that this method has a limit range to detect.

We test this method with another tree in the same area with a different diameter as shown in table 1. For a diameter greater than 40 centimeters, the estimated diameter decreases with the increase of the test distance. For a diameter smaller than 40 centimeters, it can be estimated at a certain distance. Due to the smaller radius of the test, causing the radar to detect other things rather than detect the tree.

Table 1. Sample trees with range, Actual and estimated diameter.

Actual diameter (cm)	Estimation diameter (cm)			
	2	3	4	5
55	25.42	25.18	24.22	27.04
80	58.1	41.3	32.1	20.0
35	14.4	12.2	16.7	22.1
24	11.1	10.8	14.3	14.8

5. Conclusion and Future Work

The estimation of cylindrical objects based on mmWave radar system has been considered in this paper. We use K-means for clustering objects and the least square circle fitting to estimate object sizes and positions. The experiment shows that the estimated radius of objects is less than the actual value. Since the radar sensor has high position accuracy, the estimated position is close to actual value. The estimated radius is less than the actual due to the limitation of the sensor, such as the number of data points. By using this technique, we can estimate the size and the position of cylindrical objects. The advantage of this technique is that only one sensor for object detection is used.

For future work, we will use this technique to estimate the objects and improve the estimated radius accuracy and designing the collision obstacles based on only one sensor and improving the estimated radius by some mathematical technique.

Acknowledgements

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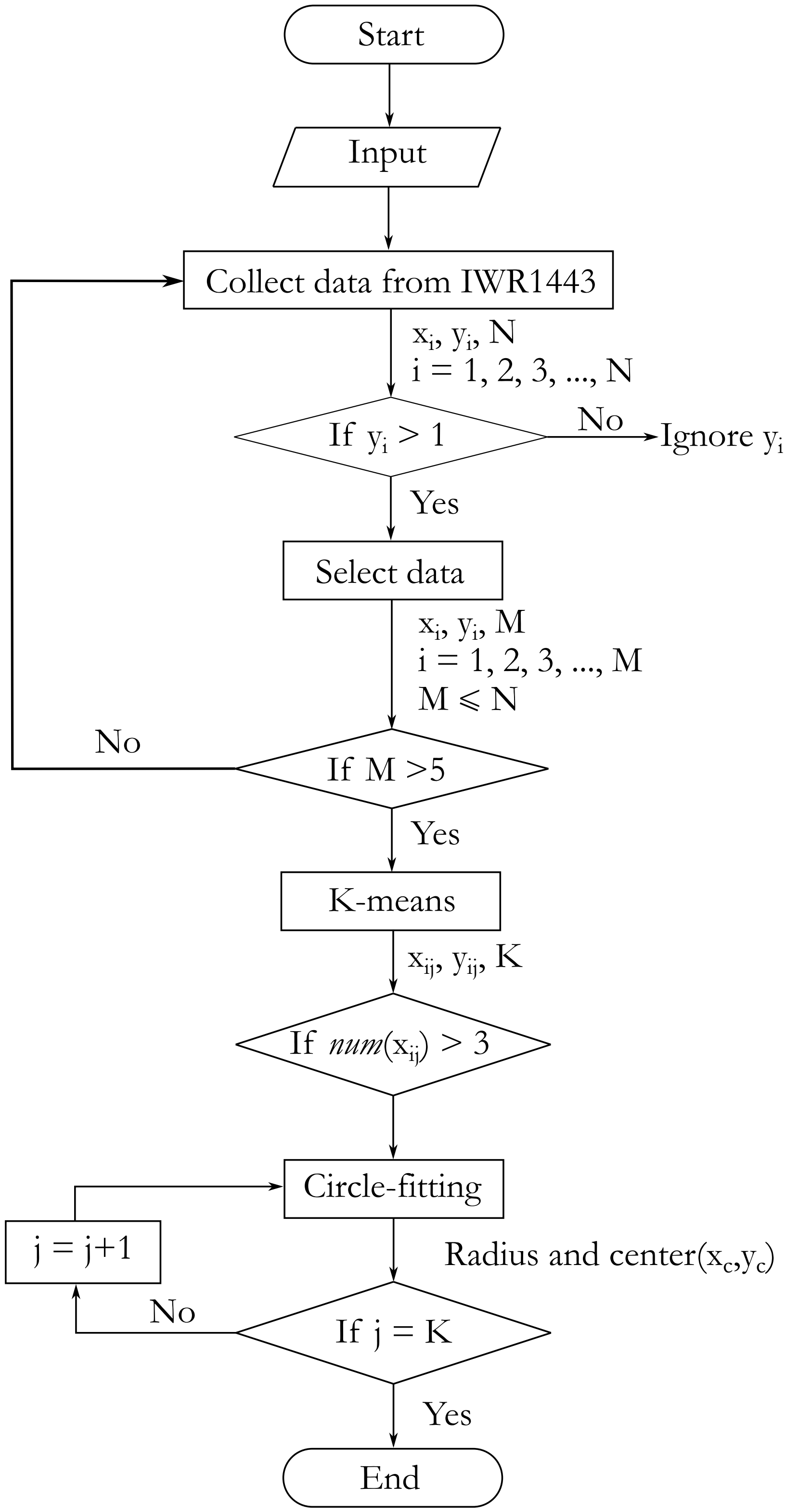

Fig. 8. Flowchart of estimation algorithm.

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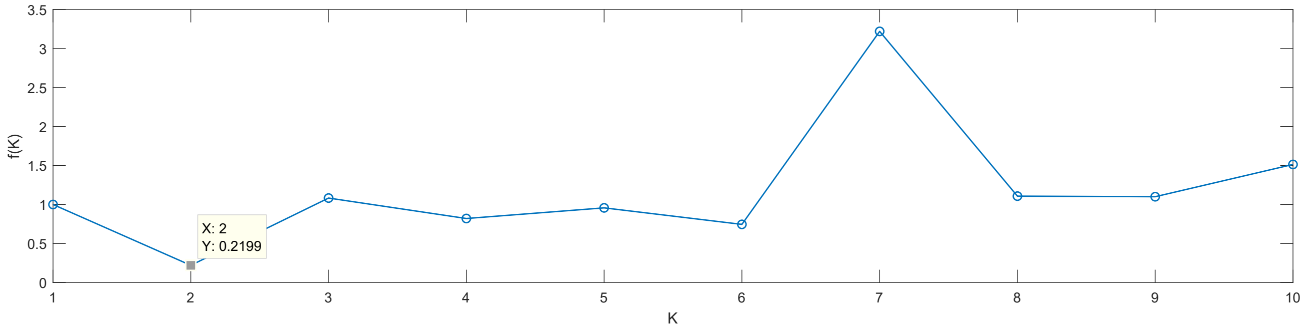

Fig. 9. $f(K)$ value with K.

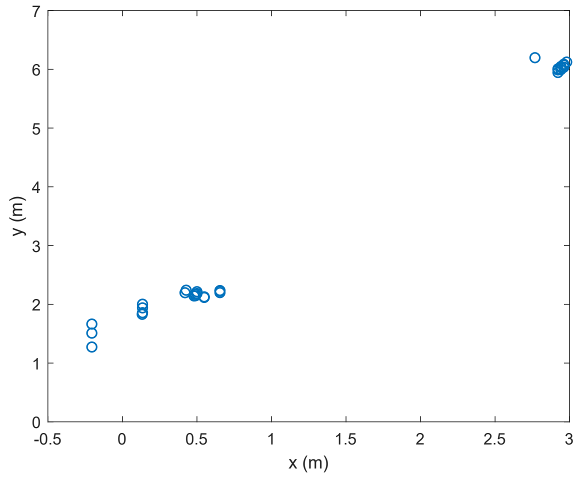

Fig. 10. Clustering of $K = 1$.

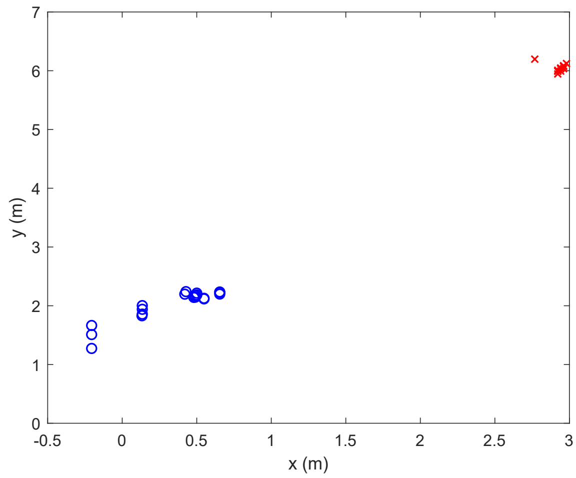

Fig. 11. Clustering of $K = 2$: ○ is a group one and × is a group two.

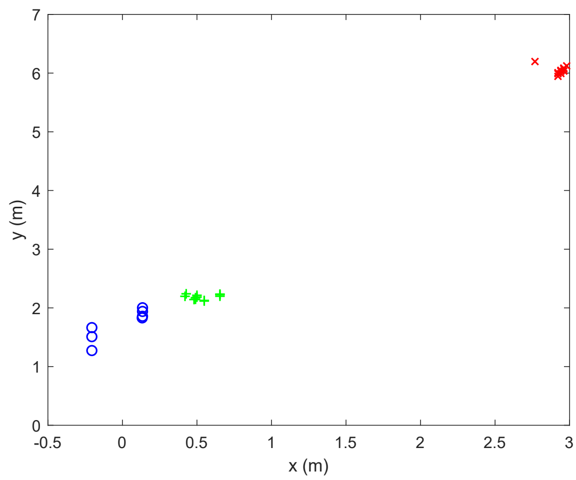

Fig. 12. Clustering of $K = 3$: ○ is a group one, × is a group two and + is a group three.

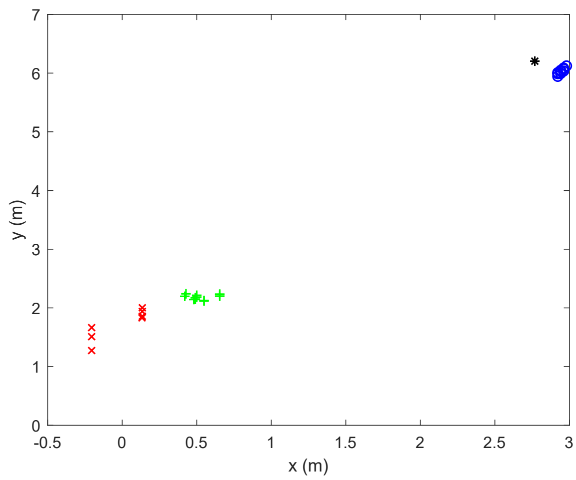

Fig. 13. Clustering of $K = 4$: ○ is a group one, × is a group two, + is a group three and ✻ is a group four.

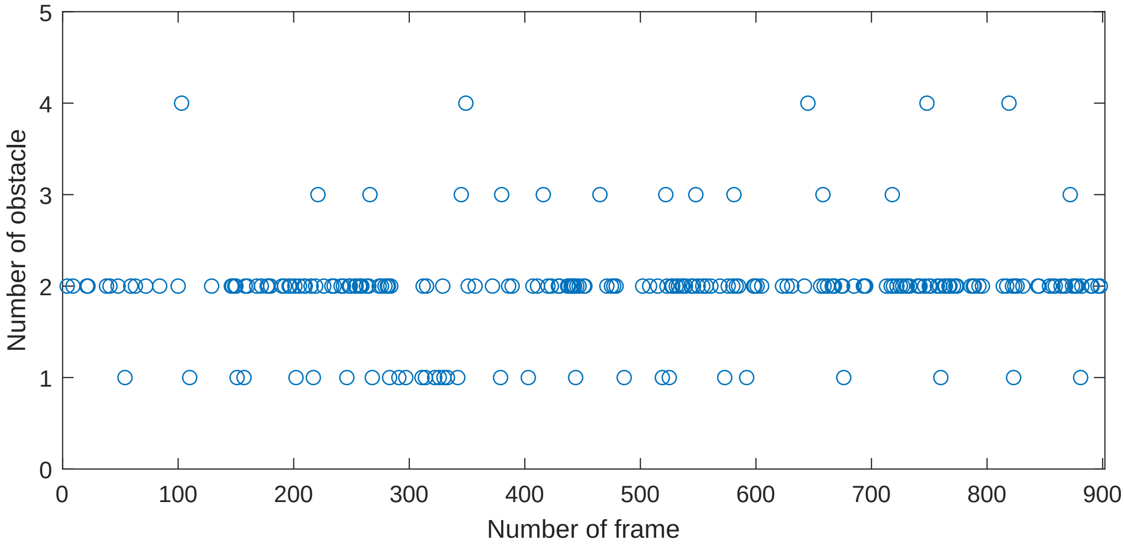

Fig. 14. Number of K with frame number.

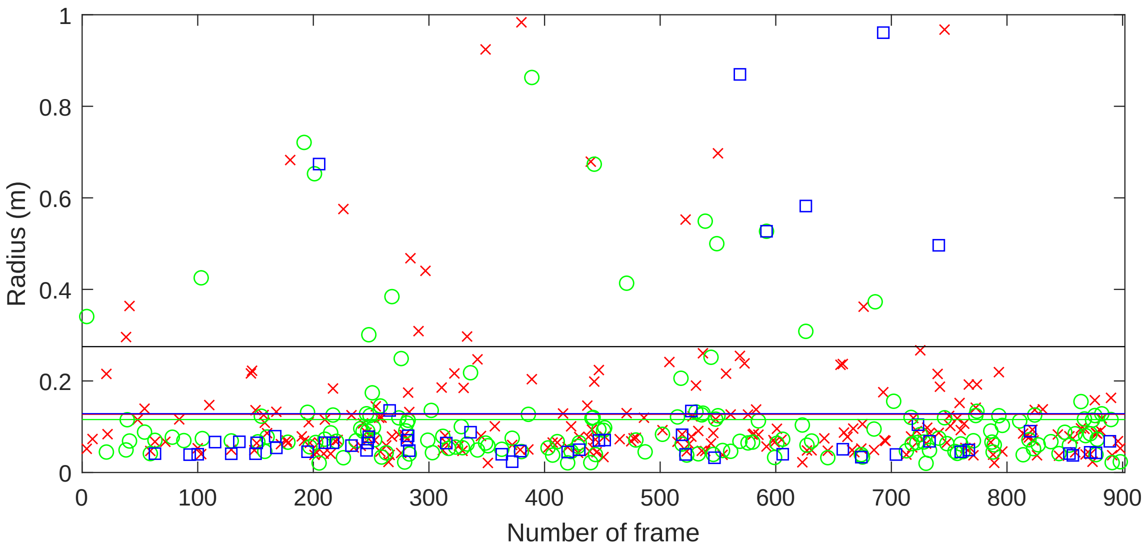

Fig. 15. Radius with frame number: Black line is actual radius of tree, Green (○) is a object number one, red (×) is a object number two, blue (□) is a object number three and color lines are the mean of each object.

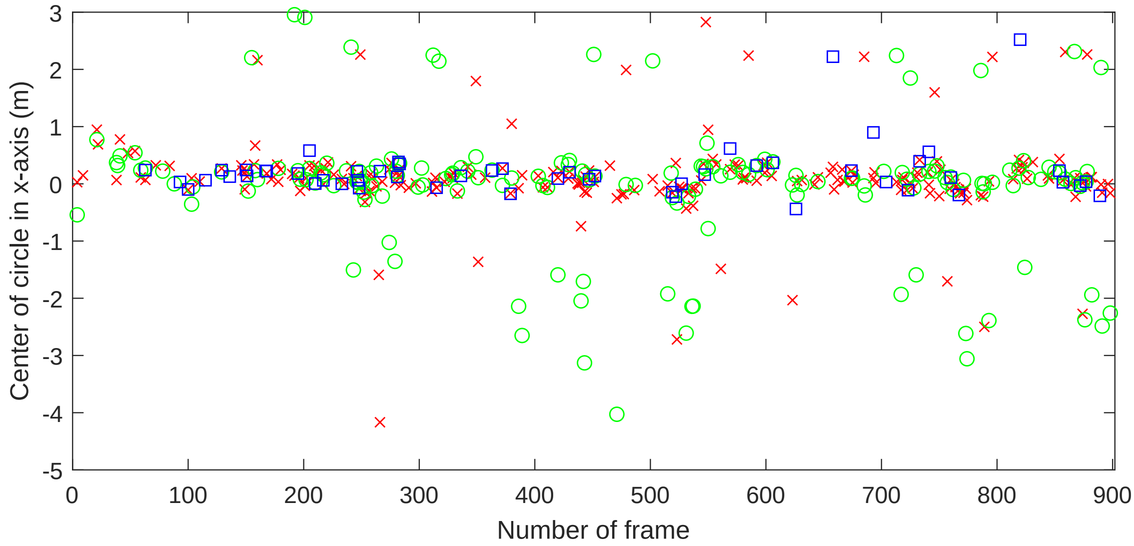

Fig. 16. Center of x with frame number: Green (○) is a object number one, red (×) is a object number two and blue (□) is a object number three.

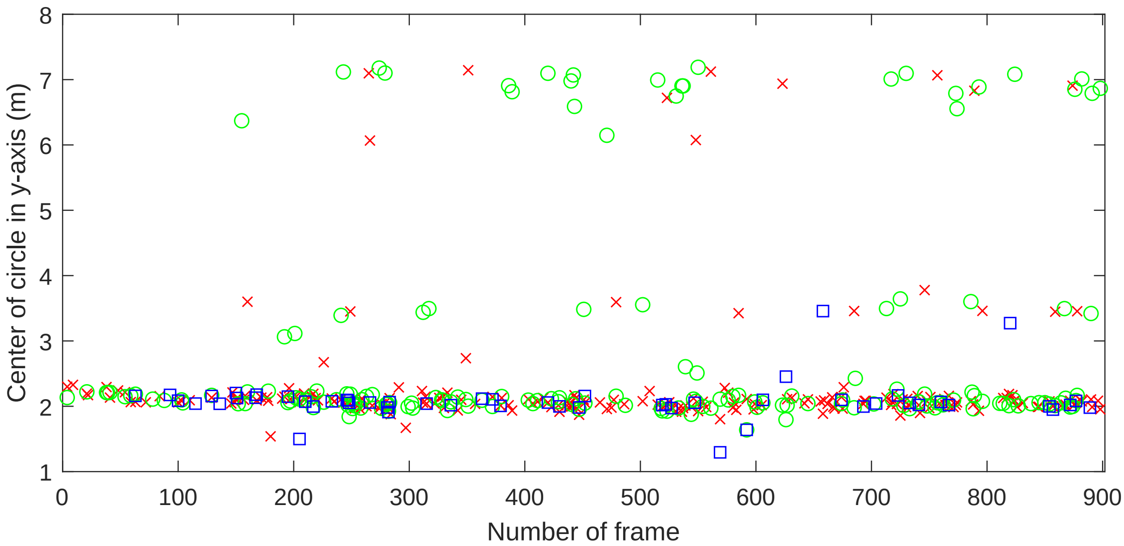

Fig. 17. Center of y with frame number: Green (○) is a object number one, red (×) is a object number two and blue (□) is a object number three.

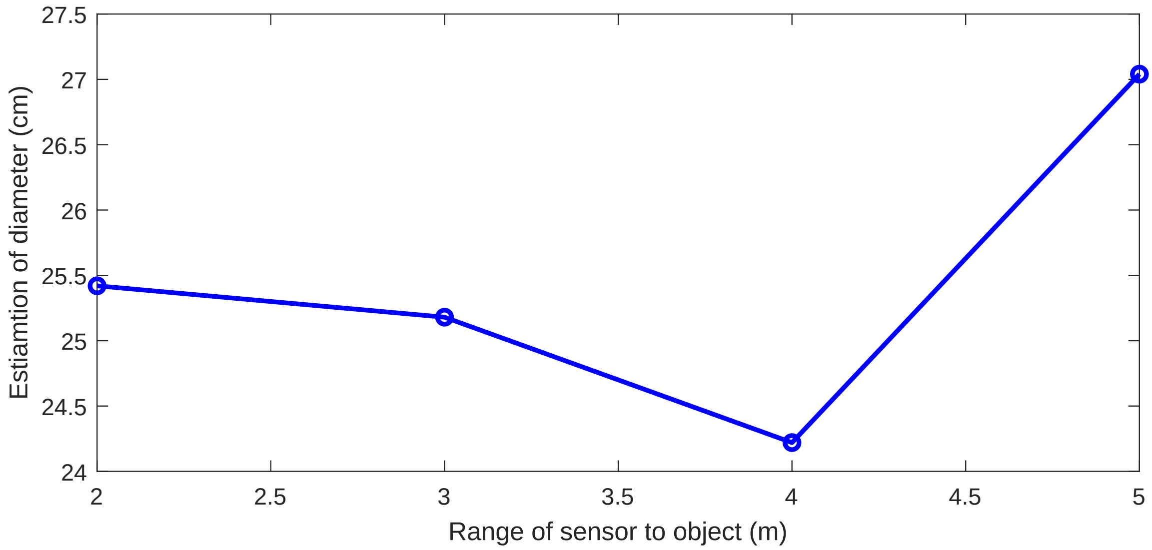

Fig. 18. estimated radius with range of sensor to object.