Low-Cost Quadcopter Indoor Positioning System Based on Image Processing and Neural Networks

I. Hatem, M. Jamal, Y. Murhij and Z. Ali

Abstract Quadcopter positioning in indoor environments is considered a major problem because of the difficulty of estimating a reliable position. Moreover, the positioning system is expected to work in real-time and to be accurate and cost-effective. In this paper, a combination of image processing techniques and neural networks is proposed to obtain the quadcopter position along the X, Y and Z coordinates. Three neural networks were used, one for each dimension. The proposed neural network based technique estimates the quadcopter target position along X, Y, and Z from two image points extracted from images captured by two low-cost IP cameras. The offered positioning system has been implemented on a locally designed and assembled quadcopter. Hovering experiments on the quadcopter have been performed in an indoor lab based environment. The results show that combining image processing techniques with neural network-based method achieves a low-cost accurate positioning system within a precision of a few centimeters with a frequency of 16 Hz.

Keywords Image processing · Indoor quadcopter positioning · Neural networks

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1 Introduction

Currently, the most commonly used positioning technique in quadcopters is the global navigation satellite systems (GNSS). However, global navigation satellite systems are generally not suitable to establish indoor locations since microwaves are attenuated and scattered by roofs, walls and similar barriers [1, 2]. In order to make positioning data available, indoor positioning system can be used. Most common indoor positioning systems are wireless-based, laser-based or vision-based technologies. Wireless and laser based technologies provide sufficient accuracy and enough low latency for stable vehicle control but they need further development work. Passive systems like motion capture systems are very popular choices for indoor environments. They can provide increased accuracy at the expense of overpriced equipment and installations. However, technologies used in indoor positioning system depend on the type of application. For an autonomous quadcopter project, as in our application, a positioning system is needed to track the location of the quadcopter accurately inside a lab area. This system need to be real-time, cost-effective and have a precision of a few centimeters for the X, Y and Z axes. To accomplish this, we implemented a real-time 3D positioning system based on visual features and three trained neural networks using two low-cost IP cameras.

2 Related Work

Previous work on quadcopter positioning can be categorized into three different research areas. One area focuses on vision technology such as stereo vision, another area focuses on wireless technologies and Ultra-wideband range measurements, and the rest focuses on monocular Simultaneous Localization and Mapping (SLAM). In 2012, a stereo vision sensor was introduced as an indoor positioning system for UAVs by Mustafah et al. [3]. The system utilizes two video cameras for stereo vision and a set of fast algorithms to obtain position information in real-time. The conducted experiment showed that the system could provide a reliable accuracy in real-time. In 2016, Guo et al. [4] introduced a localization system for quadcopters by using measurements from ultra-wideband range. In this system, an ultra-wideband module on the quadcopter communicates with fixed modules at known positions to obtain a distance. This distance is fed to a localization algorithm after calibration and outlier detection process. Extended Kalman filter (EKF) was used in this algorithm to sustain initialized trilateration. Recently, a localization using a monocular SLAM framework was introduced by Shree et al. (2017) [5]. Indoor localization and mapping new areas were combined and run together in a framework of SLAM. Onboard cameras and a cascaded position controller along with a Luenberger observer (which can combine

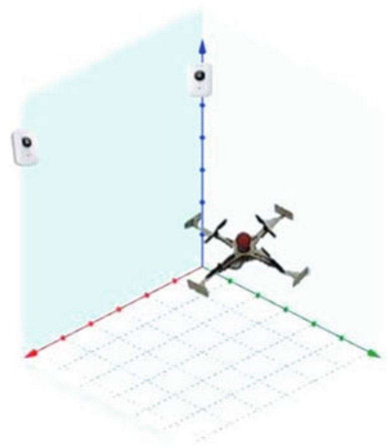

Fig. 1 3D representation of the positioning system

the data of inertial sensors and vision based position to generate a complete velocity feedback for the system) have been used. Sensor data fusion using EKF have been performed for scale estimation.

3 Materials and Methods

The proposed positioning system consisted of two IP cameras of type TP-Link connected to a Core-i3 notebook computer. The quadcopter dimensions were 40 * 40 cm. The IP cameras were positioned on a wall on height of 2.8 m: one in the corner horizontally aligned with the other camera on a distance of 4 m (Fig. 1). The work was implemented by using C++ on CodeBlocks IDE, Opencv image processing library and MATLAB.

4 Detecting the Object of Interest

Because of its distinctive color and invariant-direction shape, the colored ball on the quadcopter easily allowed the system to detect its position. First, video frames were grabbed from each camera and converted from RGB color model into HSV color model (Figs. 2 and 3). To reduce the variation in edge pixels due to light density changes, a Gaussian filter with a suitable mask was used to blur the resulting image and enhance the edges of the target object. Next, the resulting image was thresholded to segment the object of interest (the red ball). To eliminate unwanted small areas in the resulting image, morphological operations were applied including erosion, dilation and connected components [6] (Figs. 4 and 5). The object coordinates in

Fig. 2 Original camera frame

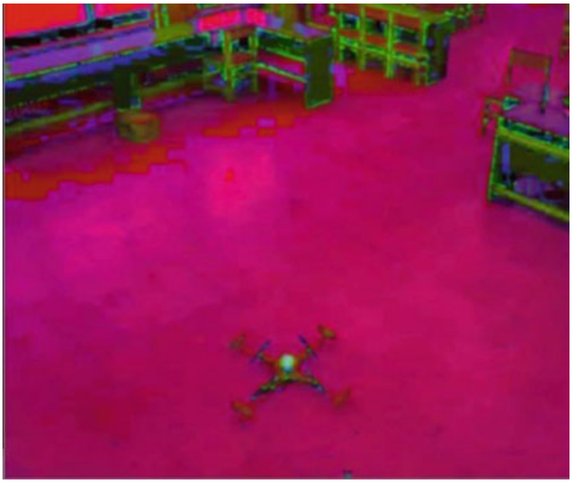

Fig. 3 Frame after converting to HSV

the image were determined by the center of mass of the segmented image through Eq. (1).

$$\{x, y\} = \{M_{10}/M_{00}, M_{01}/M_{00}\} \tag{1}$$

$$\text{where}: \quad M_{ij} = \sum_x \sum_y \left(I\,(x, y)\,.x^i.y^i\right) \tag{2}$$

where $I\,(x, y)$ is pixel intensity at position x, y.

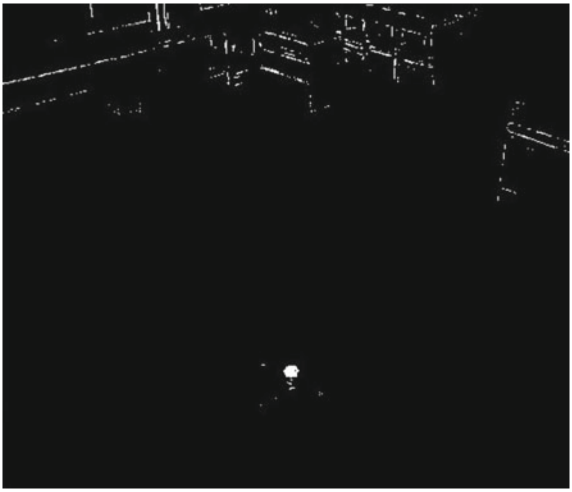

Fig. 4 Segmented image

Fig. 5 Final image after morphological operations

5 Building a 3D Positioning Neural Networks System Using Information from Two IP Cameras

To build the positioning system, three neural networks were developed, for X, Y and Z. Each network has four inputs: x_1, y_1, x_2, y_2 which are the pixel coordinates of object center in the image frames grabbed from the first and the second camera, respectively. Every neural network was a feed-forward network and had one hidden

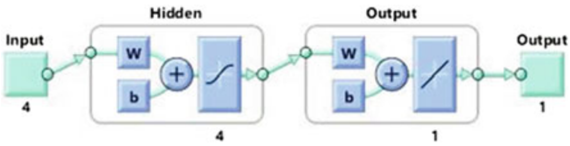

Fig. 6 Neural network structure (Matlab)

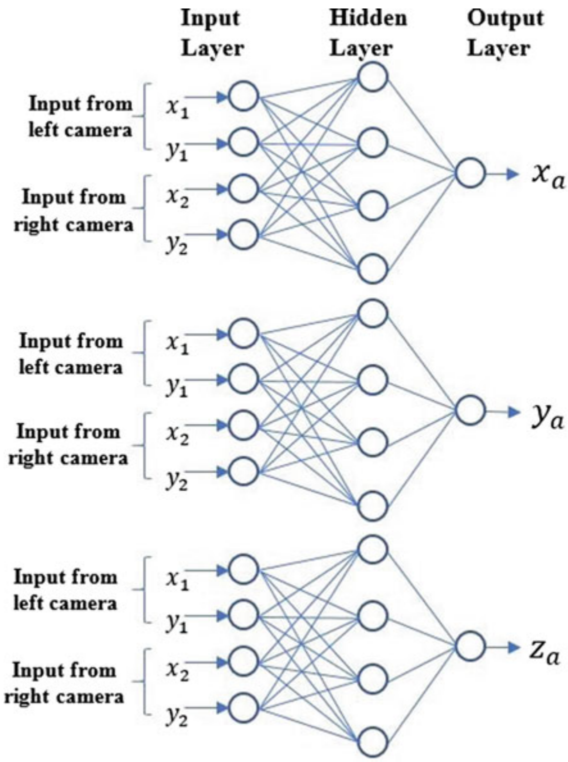

Fig. 7 System structure

layer. The hidden layer had four neurons. See Figs. 6 and 7. Neurons used in the hidden layer had *Tan-sig* activation function with the Eq. (3).

$$a = 2/\left(1 + e^{-2n}\right) - 1; \tag{3}$$

where n is the input of the neuron.

Each network had one output: the estimated position along one of the three Cartesian axes X, Y and Z in our virtual 3D system. Networks had been trained using *Levenberg Marquardt Algorithm* [7, 8]. More than one hundred distributed data samples were taken manually by measuring the real distance of the object along a virtual 3D space constructed in the workspace.

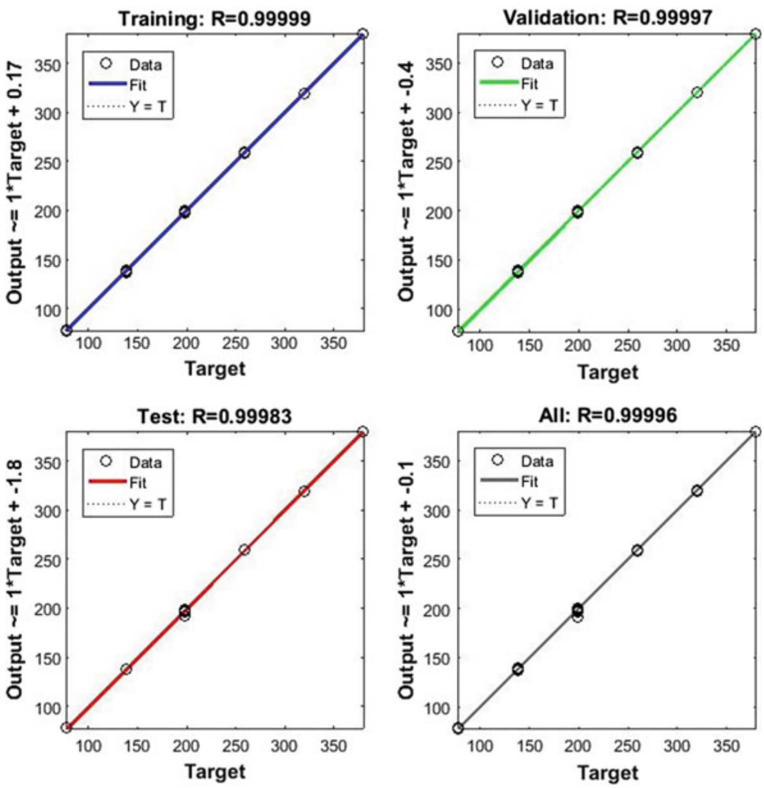

Fig. 8 Regression related to X axis neural network

Neural networks were trained on 80% of samples and validated on 10% samples and tested on the remaining 10% of the samples. Matlab software was used to construct and train the neural networks based system to get the appropriate weights and offsets for each neuron. The training regressions are shown in Figs. 8, 9 and 10. The positioning system performances on X, Y and Z axes on the training data are shown in Figs. (11-a, 12-a, 13-a) which show the current and set position of the quadcopter. Figures (11-b, 12-b, 13-b) show the error in position in tested data.

6 Implementation and Results

Testing this positioning system in a real-time application of quadcopter on new data sets showed a similar precision to the training results and proved the validity of using this indoor positioning method. Figure 14 shows the real quadcopter trajectory versus the output of the positioning system. Figures 15, 16 and 17 represent

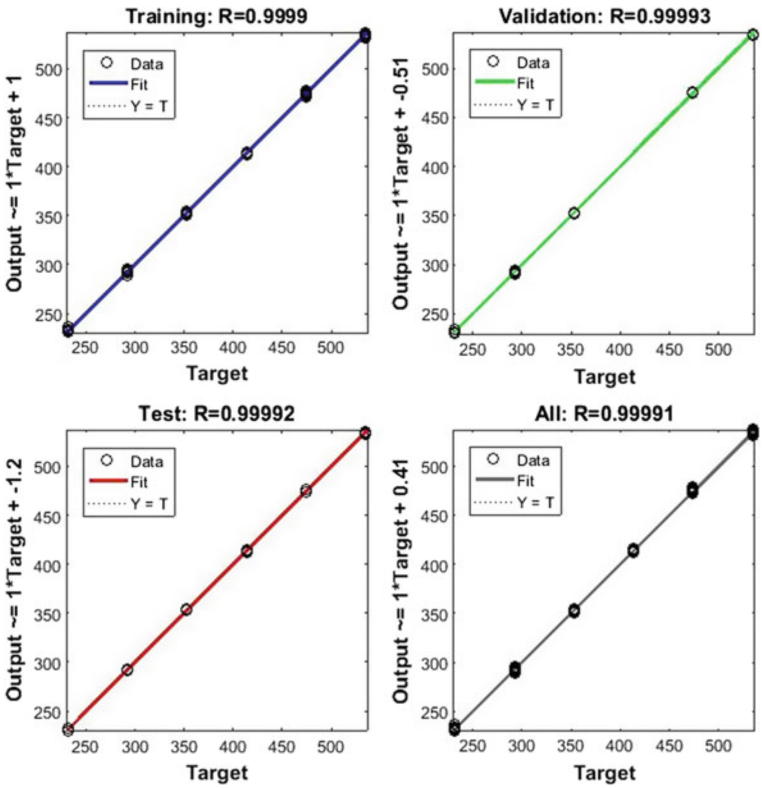

Fig. 9 Regression related to Y axis neural network

projections on X-Y plan [X = constant], X-Y plan [Y=constant] and Y-Z plan, respectively. Results show that the system has approximate precisions of ±1 cm on X axis positioning neural network and ±4 cm on Y axis positioning neural network and ±3 cm on Z axis positioning neural network with a frequency of 16 Hz. Flying tests have been applied and showed that these specifications were satisfying to control the quadcopter in real time.

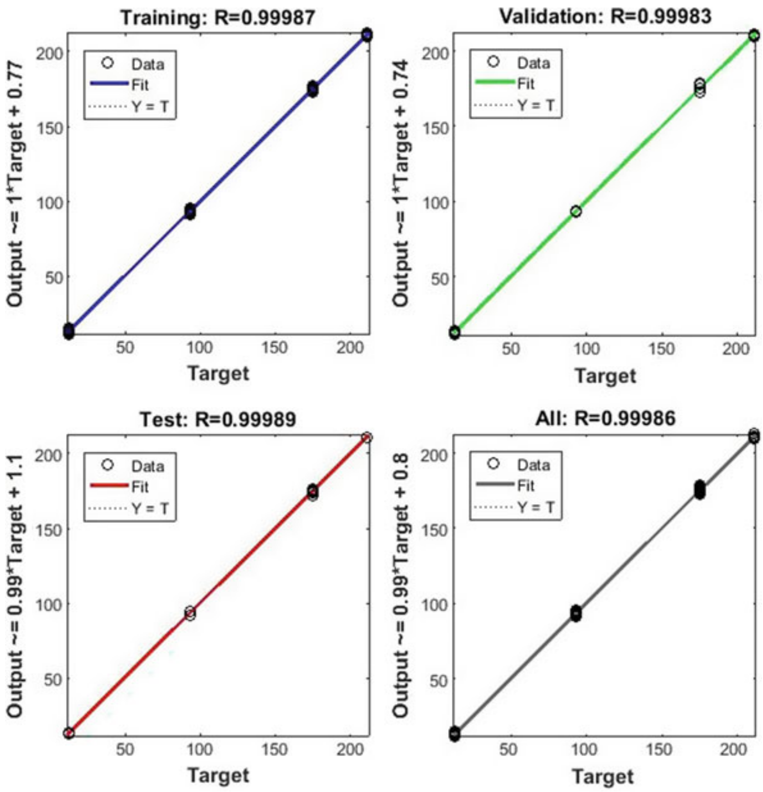

Fig. 10 Regression related to Z axis neural network

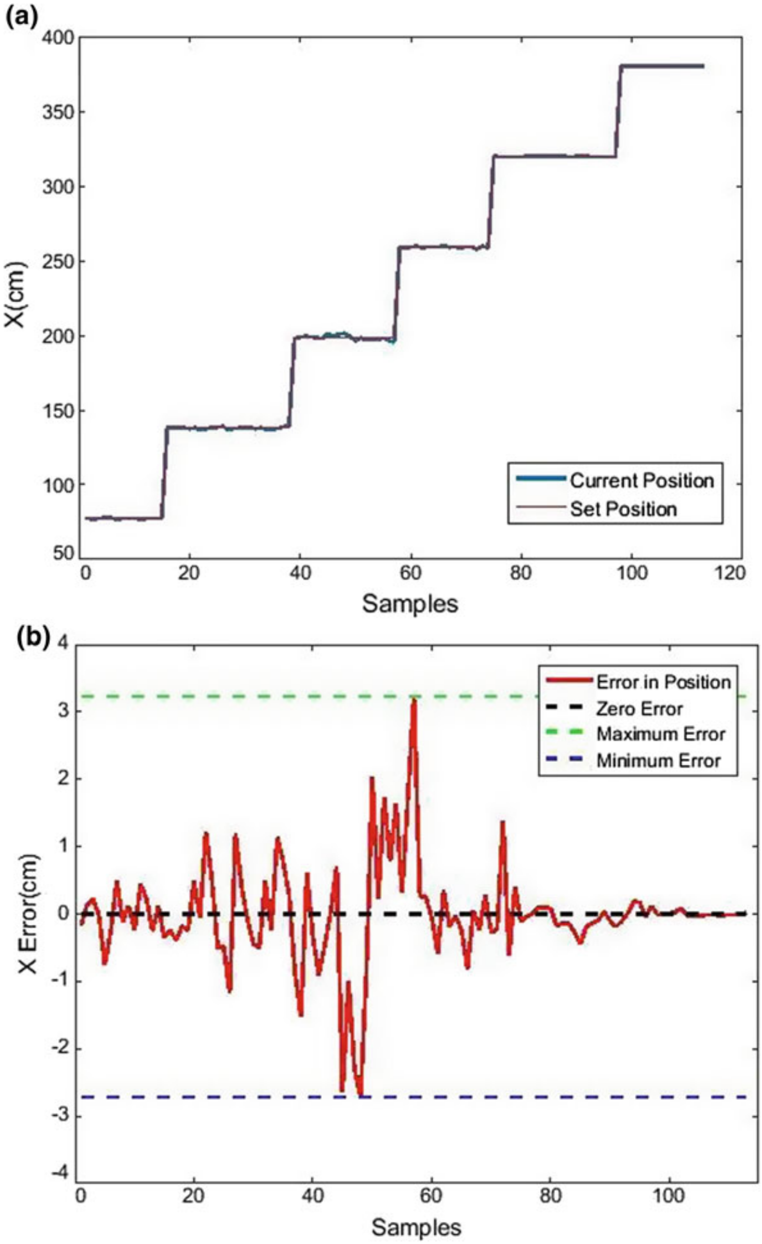

Fig. 11 **a** Current position versus set position along X-axis (cm)—**b** Error in position along X-axis (cm)

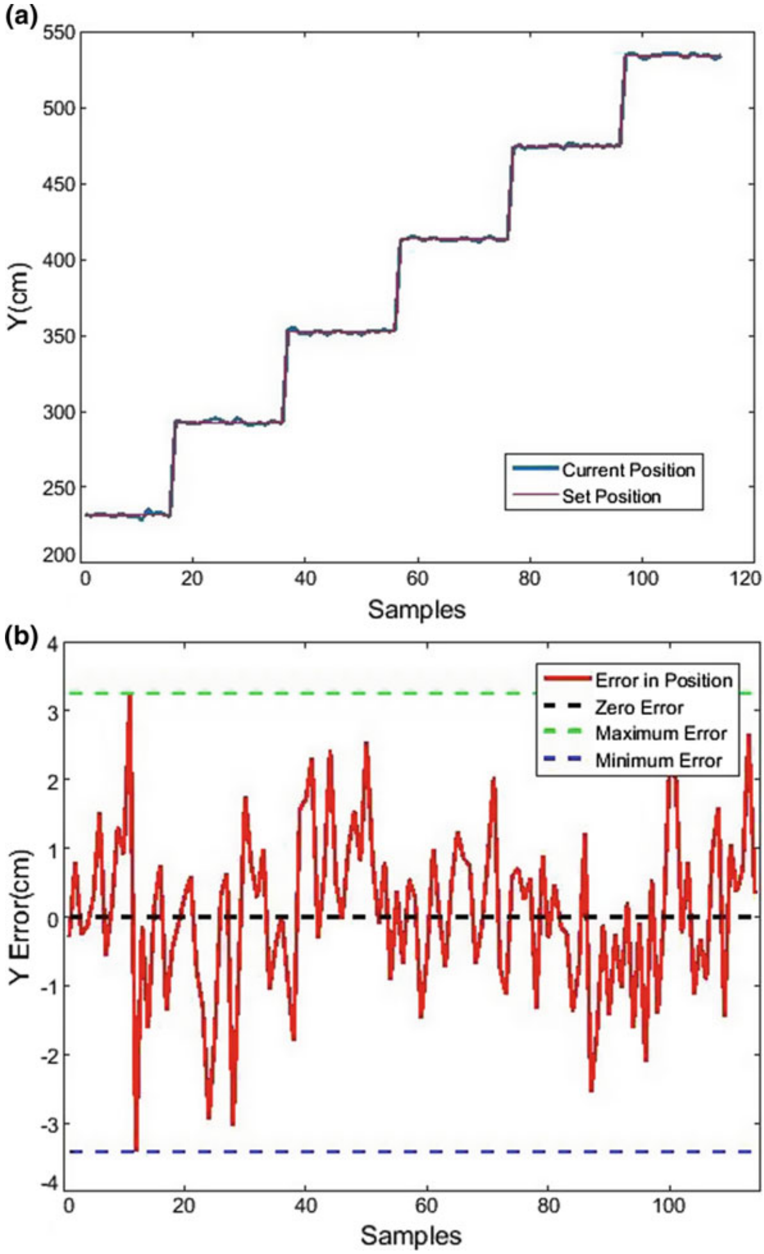

Fig. 12 **a** Current position versus set position along Y-axis (cm)—**b** Error in position along Y-axis (cm)

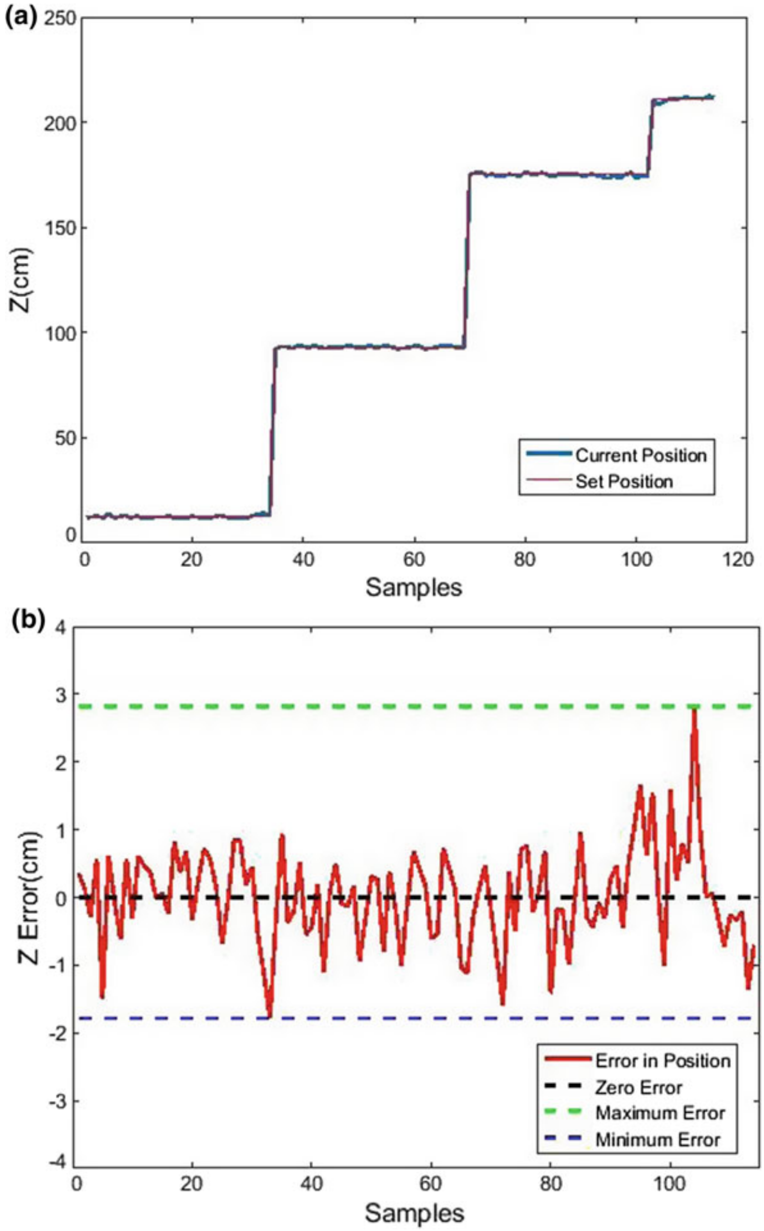

Fig. 13 **a** Current position versus set position along Z-axis (cm)—**b** Error in position along Z-axis (cm)

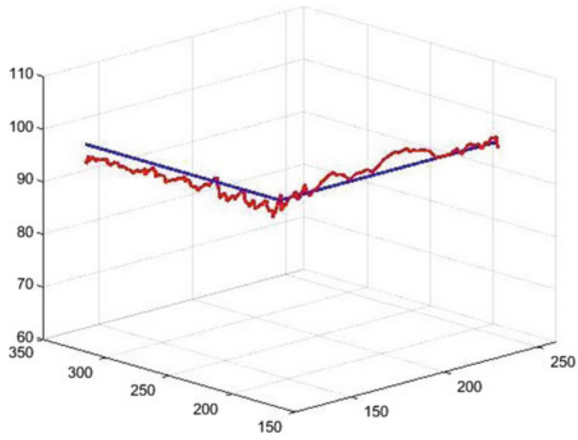

Fig. 14 Simple 3D flight trajectory

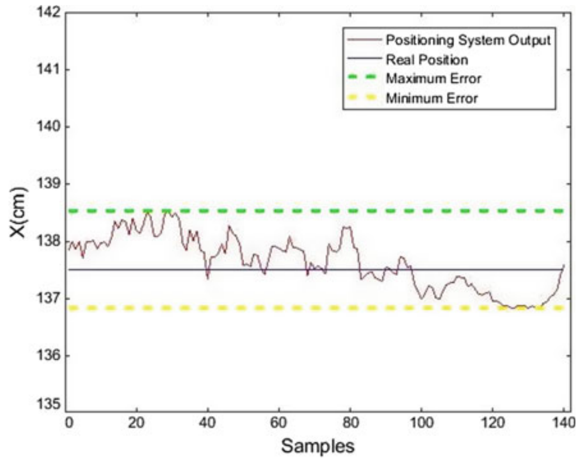

Fig. 15 X-Y plan projection [X = const]

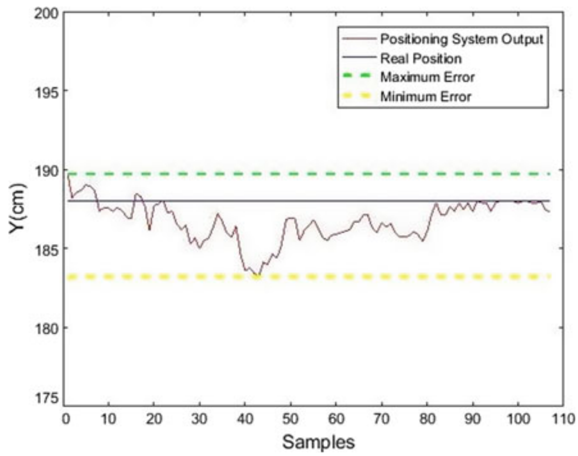

Fig. 16 X-Y plan projection [Y = const]

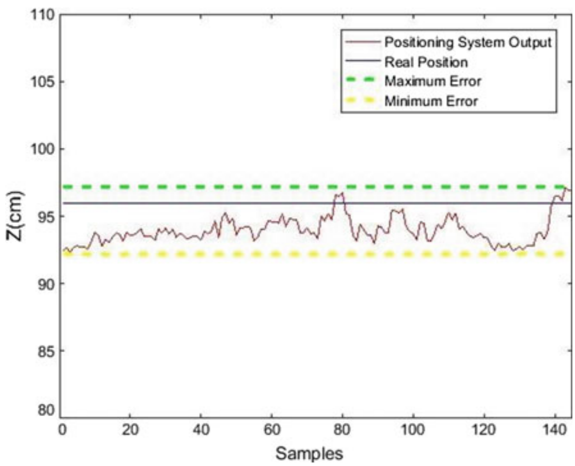

Fig. 17 Y-Z plan projection

7 Conclusions

This study has demonstrated the validity of the proposed neural-network and image-processing based technique to estimate the real-time 3D position of a flying quadcopter. First, image processing techniques to detect the object were introduced. Then, the network structure, network training and training results were explained in detail. Finally, the positioning system performances on X, Y and Z axes for a flight test of the quadcopter were presented. Results demonstrates that the proposed positioning system is a low-cost good-precision positioning system with a precision of few centimeters capable of controlling the position of the quadcopter in real time.

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