DOI: doi.org/10.58797/cser.010204

YOLOv3 Algorithm to Measure Free Fall Time and Gravity Acceleration

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Abstract

Computer vision methods as an alternative to sensors in modern measurements are feasible in physics experiments due to their speed, accuracy, and low cost. The You Only Look Once (YOLO) algorithm is widely used in computer vision because it detects object positions quickly and accurately. This research uses YOLO version 3 (YOLOv3) to compute an object's falling time and gravitational acceleration. Two steps are performed in this study: first, the detection of predefined objects using YOLOv3, and second, the use of trained YOLOv3 to track the object's coordinate. According to the object tracking results, the object's falling time can be measured based on the object tracking results. The gravitational acceleration is calculated using the time data after the fall time of the object is measured. The measurement result of the fall time of the object will be compared with the data from the sensor. The result of the gravitational acceleration calculation is measured for its relative error against the value of 9.78150 m/s^2, which is the value of gravitational acceleration in Jakarta city. The results show that YOLOv3 can accurately detect objects and measure free-fall motion, with a time measurement error of only 1.1 milliseconds compared to sensor measurements. The error obtained from the measurement of the Earth's gravity is 0.634%.

Keywords: computer vision, object tracking, YOLOv3, gravitational acceleration

Received: 28 June 2023
Revised: 23 December 2023
Accepted: 28 December 2023
Published: 31 December 2023
Assigned: 31 December 2023

Current Steam and Education Research
e-ISSN: 3025-8529

INTRODUCTION

Free fall is an object's motion phenomenon affected only by the earth's gravitational force (Schlegel et al., 2019). Free fall measurements include time to fall, distance to fall, velocity of the target, and gravitational acceleration (Haidul et al., 2021). These measurements must provide accurate data to support a more reliable decision-making process. Some examples of industries that use free fall calculations for decision-making regard rescue using lifeboats (Qiu et al., 2020), testing hydrodynamic performance (Liu et al., 2021), testing free-fall cone penetration test systems (Liu et al., 2021), analyzing orange fall motion in the food industry (Gharagani et al., 2018), and geotechnical investigations. Furthermore, using accurate measuring instruments to calculate the free fall motion is essential to achieve the best results.

One of the methods for free-fall motion measurement is using (You Only Look Once) YOLOv3 technology as an intermediary for the camera. YOLOv3 is an object recognition model that enables real-time object recognition and tracking (Jiang et al., 2021). The research conducted by Redmon et al. (2016) concluded that YOLOv3 has the same accuracy in detecting objects as the SSD algorithm but is three times faster. Furthermore, YOLOv3 shows better accuracy and speed than YOLOv2 and the basic version of YOLO (Ji et al., 2023). The study conducted by Shin Ji et al. on detecting small objects reveals that YOLOv3 exhibits a faster object detection speed (59 FPS) compared to YOLOv4 (43.41 FPS) and YOLOv5 (22 FPS) when utilizing the same GPU. Moreover, the average precision (mAP) shows a relatively minor distinction, with YOLOv3 achieving 72%, YOLOv4 obtaining 75%, and YOLOv5 attaining 78% (Ji et al, 2023). Therefore, YOLOv3 is suitable for calculating free-falling motion because it can recognize objects of different sizes. Furthermore, this model offers optimal speed for efficient data processing.

In this research, the YOLOv3 is used to detect the ball and sensors. After the detection of these objects, the fall time of the ball will be measured using the program. Based on the ball's fall time, programming can calculate gravity acceleration. The results of measuring the falling time of the ball in this study will be compared with the results of measuring the falling time using the sensor (specifications of the sensor are available on the website: https://www.pudak-scientific.com/detail_products.php).

LITERATURE REVIEW

Free Fall Motion

Free fall is a type of straight motion occurring in an object under the influence of Earth's gravitational acceleration(Haidul *et al*, 2021). Equation 1 and 2 gives the position equation for a vertically falling object.

$$y = y_0 + v_0 t + \frac{1}{2} g t^2 \tag{1}$$

$$v = v_0 + g t \tag{2}$$

Where y is the distance traveled (in meters), y_0 is the initial position (in meters), v is the recent velocity (in meters per second), v_0 is the initial speed (in meters per second), g is the earth's gravity acceleration (in meters per second squared), and t is the time (second).

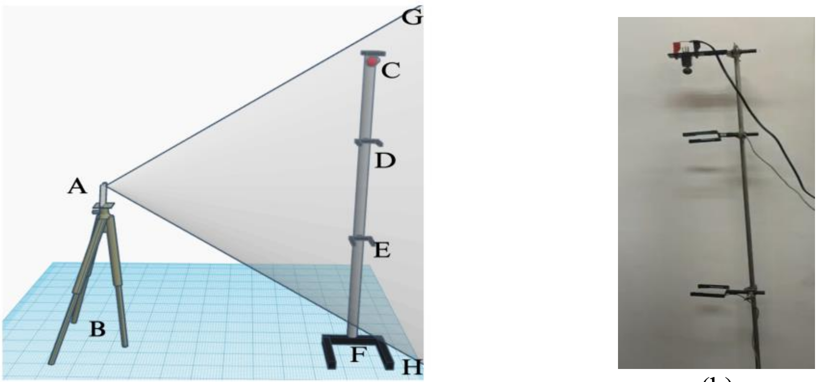
You Only Look Once Version 3 (YOLOv3)

YOLOv3 is a deep learning architecture for object detection in digital images. The YOLOv3 architecture comprises one input layer, 102 hidden layers, and three output layers [8]. The YOLO input layer is responsible for processing and resizing the labeled image (Redmon *et al, 2018)*. The hidden layer consists of several components: A convolution layer, a skip connection, a convolution-based downsampling layer, and an upsampling layer. YOLOv3 has three output layers, which allows YOLOv3 to recognize objects of different sizes. In addition, YOLOv3 reduces the high computational cost by using a fully convolutional architecture, which does not include a fully connected layer.

The YOLOv3 output tensor has dimensions N x N x (B x 5 + C), where N is the number of cells in the grid, B is the number of bounding boxes predicted by each cell, 5 is the number of bounding box attributes (x, y coordinates, width, height, and confidence score), and C is the number of classes to be detected. For each class to be detected, a class probability is predicted in addition to the bounding box attributes. The class probability is the probability that the object within the bounding box is a member of that class. The next step is to filter using a confidence score threshold after all predictions have been made for each cell in the output tensor. Bounding boxes with confidence below a threshold are ignored. A non-maximum suppression procedure is also performed to overcome the overlap between adjacent bounding boxes. This procedure selects the highest confidence bounding box from the overlapping ones and removes the others (Zhang et al., 2020).

METHOD

Experiment Setup



(a) (b)

Figure 1. (a) Experimental setup used for measuring the motion of a falling ball. (b) One of the frames was taken during the data acquisition. It consists of a stand, a ball, and two sensors.

Figure 1 displays the experimental setup of this study. First, a tripod with a height of 52 cm (AB) was used to support the camera. The function of the tripod was to keep the camera stable during the experiment. First, a tripod with a height of 52 cm (AB) was used to support the camera. The function of the tripod was to keep the camera stable during the experiment. This is followed by a 115 cm high stand (CF), which fulfills two essential functions. First, it provides a location for two sensors. The first sensor is located at point D, while the second is at point E. The distance between the two sensors is 30 cm. The stand is also used to determine the ball's starting point before it is dropped, which is shown as point C. The distance between point C and the first sensor (D) is 20 cm. The distance from the camera to the stand was also set to 80cm (BF) to adjust the height. This ensures that the object captured by the camera is not too small or too large in the picture. The main objective of this research is to measure the acceleration of gravity by the time of fall of the ball between the two sensors that have 30 cm between them.

Datasets

The data is categorized into training and evaluation data for the YOLOv3 model and experimental videos depicting free-fall motion that align with Figure 1. The YOLOv3 model utilized a dataset comprising 1700 images, explicitly focusing on detecting two objects of interest: balls and sensors. The data collection process encompassed capturing diverse variations in object sizes, viewing angles, backgrounds, and lighting conditions. The dataset was meticulously annotated and subsequently divided into training and testing data, following an 80:20 ratio. The deliberate selection of this ratio aimed to enrich the variability within the training data, facilitating an enhanced understanding of the detected objects by the model. Additionally, experimental videos were employed to calculate the gravitational acceleration using the YOLOv3 model. The videos were recorded at a frame rate of 120 FPS, enabling precise and detailed capture of the moving objects.

Training and evaluation of the YOLOv3 model

The model was configured with parameters such as batch size (128), subdivisions (64), learning rate (0.001), and maximum iterations (2000) to optimize its accuracy and computational resources. The architecture consisted of input, convolution, downsampling, shortcut layers, upsampling, and three output layers. The goal was to detect falling balls and calculate their free-fall motion accurately. Training data is used in the model training process, while test data is used in the evaluation process. The evaluation matrix used is the Mean Average Precision (mAP).

Time measurement & gravity acceleration calculation

After creating the YOLOv3 model to detect balls and sensors, four additional steps have been taken: 1) object tracking to determine the coordinates of the ball and the two sensors, 2) establishing conditions to start timing when the ball passes the first sensor and stop timing when the ball passes the second sensor, 3) measuring the time taken for the ball to fall and pass the two sensors, 4) calculating the acceleration due to gravity using equations (1) and (2). The fall time measurement results are compared to the sensor measurement results to calculate the relative error. The result of the gravitational acceleration calculation based on the fall time is compared with Earth's gravitational acceleration in Jakarta city, which has a value of 9.78150 m/s^2.

RESULTS AND DISCUSSION

In this study, the YOLOv3 model achieved an mAP value of 90.92%. This result shows the model can detect the balls and sensors in the environment. The model is supported by good acquisition data, including digital images with different background variations, viewing angles, object sizes, and lighting conditions. Additionally, the model is supported with configurations that match the architecture and data. There are 1800 iterations in the training process with the configuration performed.

The ball drop time and video were measured using the trained YOLOv3 model. The settings were as shown in Figure 1. The tracking results show that the coordinate of the center point of the upper sensor relative to the y-axis is 750 pixels. In comparison, the coordinate of the center point of the lower sensor relative to the y-axis is 1181 pixels. In addition, the ball's movement concerning the y-axis can be observed in Figure 2. According to object tracking results, the measured ball drop times differ between the YOLOv3 at 118.3ms and the sensor at 117.2ms. Therefore, there is a relative error of 0.938%. The result of the calculation of the gravitational acceleration of the Earth based on the fall time using the program is 9.7831 m/s^2. On the other hand, the measurement with the sensor gives a value of 9.89 m/s^2. Therefore, the relative error of the program method on the importance of 9.71850 is 0.634%, while the relative error of the sensor method on the value is 1.845%.

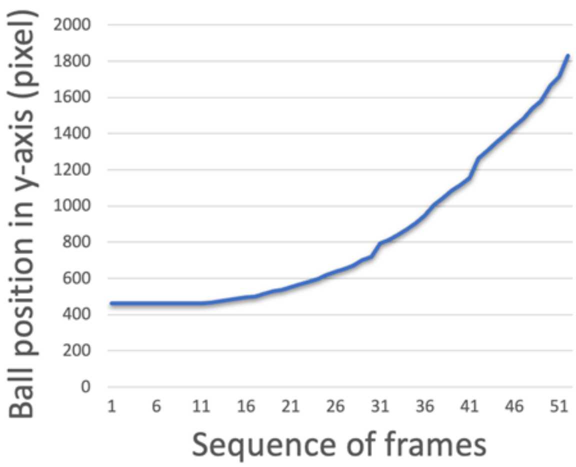


Figure 2. Graph of ball movement on the y-axis in the frame sequence.

CONCLUSION

The calculation results with the YOLOv3 model show high accuracy in estimating the earth's gravitational acceleration. The calculation of the Earth's gravitational acceleration is highly dependent on the measurement of the fall time, which in turn depends on the detection results of the object that is the focus of the research. Furthermore, the YOLOv3 model used is supported by a good quality of acquiring, annotating, and configuring the YOOv3 model.

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