

Bubble detection

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Abstract

Keywords: Distributed sensing, network pruning

1 Comparison of bubble detectors and size distribution estimators

General

Bubble(circular objects) detection algorithms can be divided into two approaches, geometry-based and appearance-based.

Geometry-based approaches detect parameterized circular objects in the image edge map.

Drawbacks: Sensitive to noise, high false positive rate.

Appearance-based approaches using sliding window combining with a classifier like boosting based, Hog based and CNN classifier

Drawbacks: need large amount of training data.

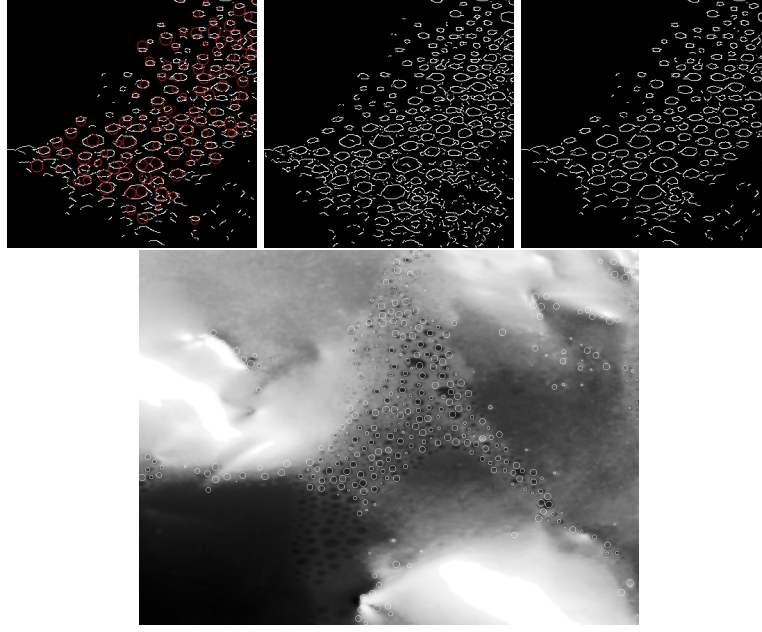
Estimation of bubble size

2 results of conventional techniques

The results of conventional image processing methods are as follows:

As we can see from the results, bubbles with round extracted edges can be detected. However, the false positive rate and false negative rate are relatively high. The problems of Hough circle detection can be listed as follows:

1. High false positive rate because Hough circle detection tends to detect the arcs that can fit in a circular model.
2. Due to the different angle of view, the extracted edges of some bubbles look more like ellipses rather than a perfect circle. The circular bounding box can not perfectly mark out a bubble



3. The reflection of the surface will cause much false positive detection.

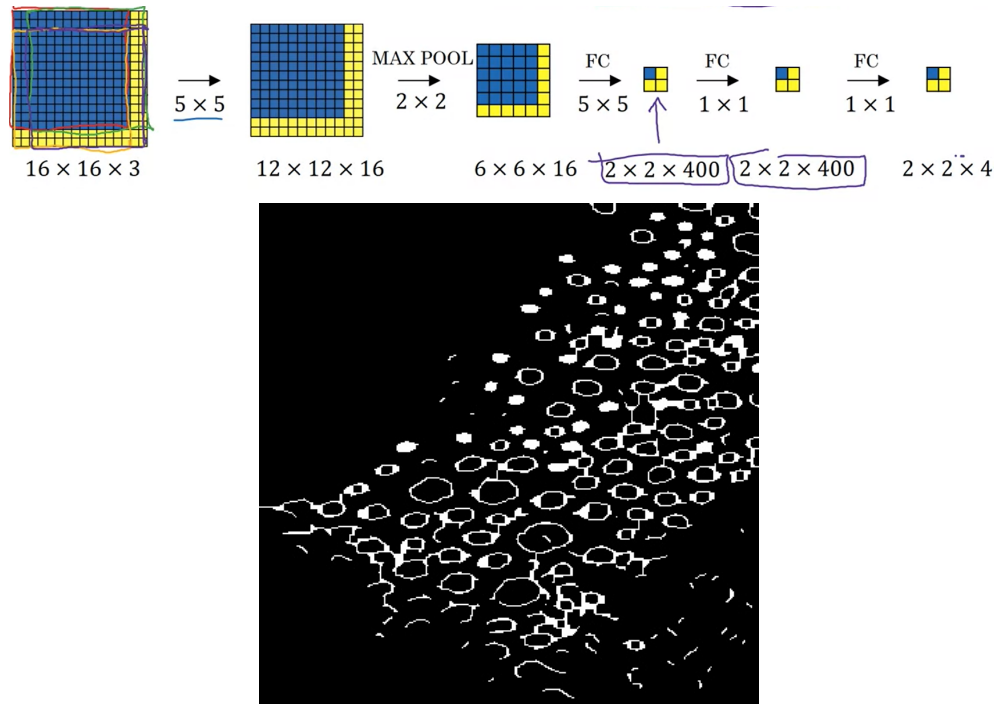
3 related work

Jarmo Ilonen and etc has compared the performance of different bubble detection methods, which includes circular Hough transform (CHT) method, Concentric Circular Arrangements (CCA), boosting based method and CNN method. And the results show that CNN method outperforms other methods.

They established a dataset, which contains 120 images (72 for training, 48 for testing, 20 images for each rotor speed). Each image is 1482×1482 pixel. During training, they extract each bubble using a 28×28 image patch and label it as positive examples. They also implement data augmentation like shifting and scaling. In this way, the training data contained 148,860 positive and 317,732 negative examples.

During bubble detection, they use sliding window of different scales as the input of CNN model to detect whether there is a bubble in the window. For lowest scale, the window size is 28×28 . Since only square bounding boxes can be obtained in this way. The author integrates the results of each window to form a detection image (detection probability map) under a certain scale. After that, they implement connected component analysis on the detection image. They first threshold the detection image into binary image. They reject the areas that do not meet the following requirements:

1. area is larger than t_a
2. the proportion of the pixels in the convex hull that are one is larger than t_s
3. the ratio of minor and major axis is larger than t_m

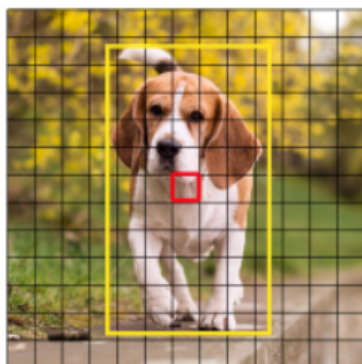


4 YOLO

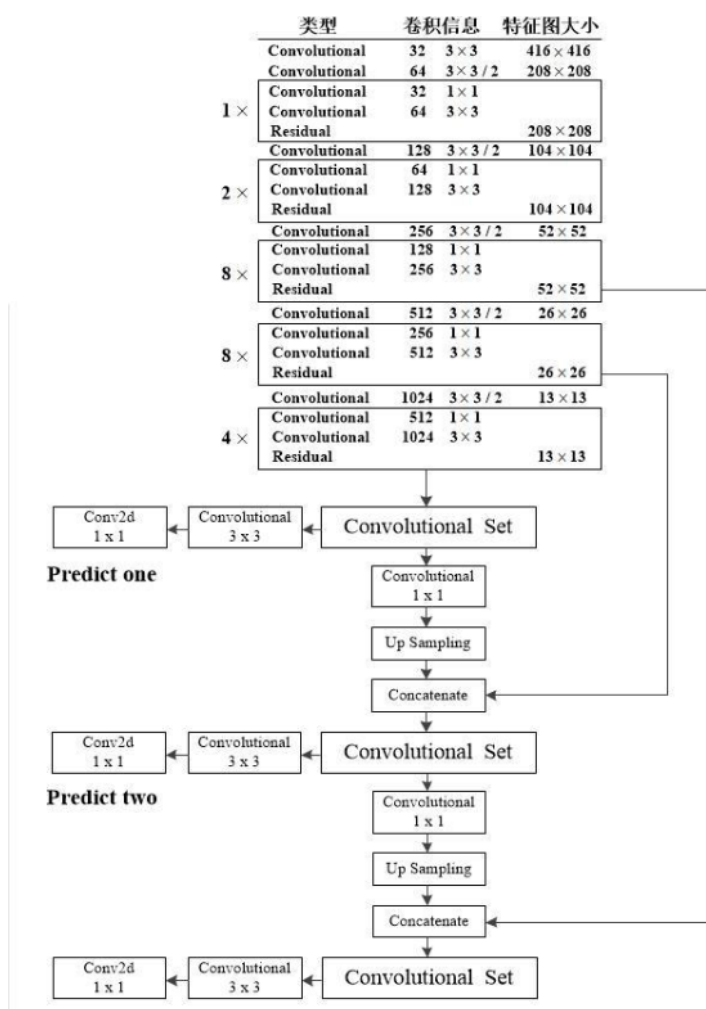
YOLO is a one stage object detection algorithm. The basic idea of yolo algorithm is also sliding windows. First, the image is split into multiple grids. As shown in the image, 13 by 13 grid is used. The final output of yolo is a $13 * 13 * (B*(5+C))$ tensor. It means each grid corresponds to a pixel in final $13 * 13$ feature map. The dimension of each pixel is $(B*(5+C))$. If we assume only one bounding box is detected in one grid and we only want to detect 3 classes, the final output can be written as $[P, bx, by, bw, bh, c1, c2, c3]$. During training phase, only the grid that the center of the GT box falls into are responsible for detecting the object. In other words, the grid which contains the centroids of the GT bounding box is labeled as $[1, bx, by, bw, bh, c1, c2, c3]$

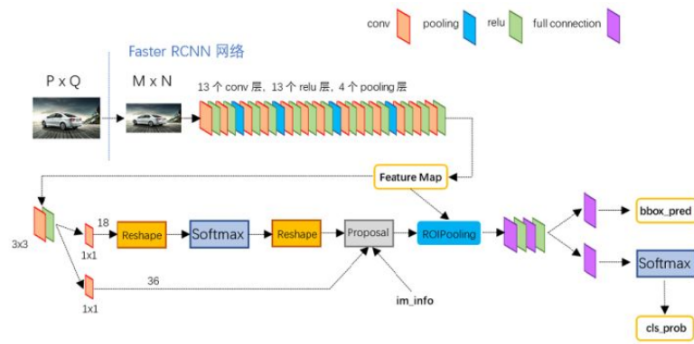
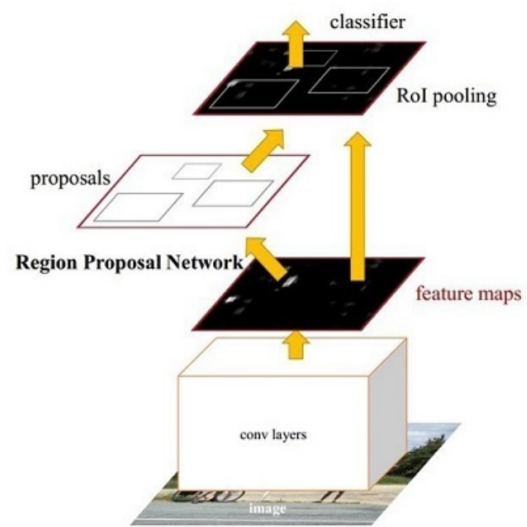
5 faster rcnn

The basic idea of faster rcnn is to using the RPN(region proposal network) to find the region of interest and use the region of interest as the input of CNN network to obtain the classification results. The basic structure of faster rcnn are shown in the follow figure. First, input the image to a convolutional layer to extract the features of the image. The features are used to obtained the bounding box proposal in the original image. Using the bounding box proposal and the features we can select the feature map inside the bounding box proposal and input them into the fully connected layer the detect which object is.



13 x 13





6 System

Considering that we cannot obtain enough data and labelling the exact shape of each bubble is difficult.

I tend to construct the algorithm as follows:

1. Using sliding windows to generate small images and manually label them as bubble or no bubble.
2. Build a convolutional model that can output detection map of different scales using the data above
3. Extracts the bounding box of bubble based on the detection image.