SEVAS Publishing

Computing Technology Research Journal
Compute. Tech. Res. J. (2022) 1(1):30-32

OBJECT DETECTION BASED ON SPECTRAL ANALYSIS USING SOBEL AND ROBERTS EDGE DETECTION ALGORITHM

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Received: 10th September 2022, Accepted: 3rd October 2022 and Published: 3rd October 2022

ABSTRACT

Aim: This paper proposes novel object detection (OD) approach based on a thorough examination of the image's details and its approximate density chart.
Results: Our proposed OD approach is divided into two phases. Knowledge about Spatial Distribution of Objects obtained from a density map that is used to compute initial object positions. With the aid of the original object positions estimated, a saliency map that provides entity boundaries is then used to calculate the bounding boxes with precision, which is inspired by human attention to detail. The scale variance of objects induced by uncertain perspective is a common problem in object density map estimation. A new method for estimating the prior focus for map for any image is proposed. Sobel and Roberts Edge Detection Algorithm are used in this study. The proposed approach is based on sparse defocus dictionary learning on a newly constructed dataset. The focus power is determined by the number of non-zero coefficients of the dictionary atoms.
Conclusion: The algorithm's output can capture spatial features and pick the threshold type in a variety of ways.

Keywords: Object Detection, Saliency Map, Sparse Defocus, Spatial Distribution, Sobel and Roberts Edge Detection Algorithm.

HIGHLIGHTS:

1. **Object detection based on spectral analysis using Sobel and Roberts edge detection algorithm proved to be effective when compared with existing methodologies.**

INTRODUCTION

The proposed approach is based on sparse defocus dictionary learning on a newly constructed dataset. The focus power is determined by the number of non-zero coefficients of the dictionary atoms.

Figure 1 shows the system architecture. The first step is to estimate density of the input image. Then in the next step is the object pre-localization phase. It consists of Sliding Region of Interest (ROI) window, then computing local maximum and gathering localization results. In building box estimation phase, the image goes through SLIC (Simple Linear Iterative Clustering) Segmentation [1], foreground seeds, K-means clustering and finally the bounding box is estimated and results are generated. The technologies used include Python, Numpy. Sci-learn, Eclipse IDE, Web Technologies and Bootstrap. The Sobel and Roberts edge detection algorithm are used in this study.

The basics steps involve Inputting the image and doing Density Estimation. The next step is Object Pre-localization, which involves passing a window on the image and calculating local limit at each step. This aids in comprehending the image's Region of Interest (ROI). The next step is to estimate the bounding box around every object detected in the image. SLIC is a superpixel generating algorithm that clusters pixels in the image plane based on their colour similarity and proximity. Input to this algorithm is a number of nearly equal superpixels K. At the start of the algorithm, K superpixel cluster centres Ck= [lk, ak, bk, xk, yk] are chosen at regular grid intervals S with k= [1,K]. This is how the size of the bounding box is calculated. The sudden change in pixel density help to detect edges which is done using the Sobel and Robert's Edge detection Algorithm. The last step is to process the image and provide the detection results.

The calculated density map is more useful for object localization and can better represent OSDI. The density map provides entity location, but it has no detailed information about the entity in the image field, especially the entity boundary, which is important for object detection. With the aid of pre-processing, map estimation, which provides entity boundary and is inspired by the human visual detail, is used to calculate the precise covering box. With the aid of pre-localization results, saliency map estimation, which provides entity boundary and is inspired by the human visual detail, is used to estimate the right covering box. The covering box estimation method is carried out using the superpixel point, which refers to perceptually significant patches produced by pixels. Simple linear iterative clustering yields superpixels that are compact while respecting image boundary.

For edge detection, sobel filter is used:

- It calculates the image strength gradient at each pixel within the image.
- It defines the direction of the most important transition from light to dark, as well as the rate of change in that direction.
- When the filter is applied to a pixel in a constant-intensity field, the output is a zero vector.
- When you add it to a pixel on an edge, you get a vector that points from darker to lighter values around the edge.

1. Two 3 x 3 kernels are used in the Sobel filter. One for changes in the horizontal axis and the other for changes in the vertical axis.
2. To measure the approximations of the derivatives, the two kernels are convolved with the original picture.
3. To compute x and y, we place the necessary kernel (window) over the input image, compute one pixel's value, and then shift one pixel to the right.
4. We step down to the beginning of the next row until the end of the row is hit.

Some advantages of proposed system are:

1. An image's spatial features are captured.
2. It's one of the most precise learning algorithms on the market. It generates a highly accurate classifier for many data sets.
3. It performs better when the number of dimensions exceeds the number of available samples.
4. The ability to choose the threshold type in a variety of ways.

After 1 epcoh of training our model is able to predicting the points as shown in Figure 2.

RESULTS

The Algorithm is one of the most precise learning algorithms, which generates a highly accurate classifier for many datasets. It performs better when the number of dimensions exceeds the number of available samples. The Algorithm is able to capture spatial features and it has the ability to choose the threshold type in a variety of ways. After training our model and predicting the values, the mean square root error of the model is 1533.91. The mean absolute error comes out to be 1337.67. This result is obtained after 1 epoch of training.

CONCLUSION

We propose a method for detecting small objects that takes both the image and the predicted density map into consideration.

REFERENCES

1. https://doi.org/10.1016/j.neucom.2017.05.096

FIGURES

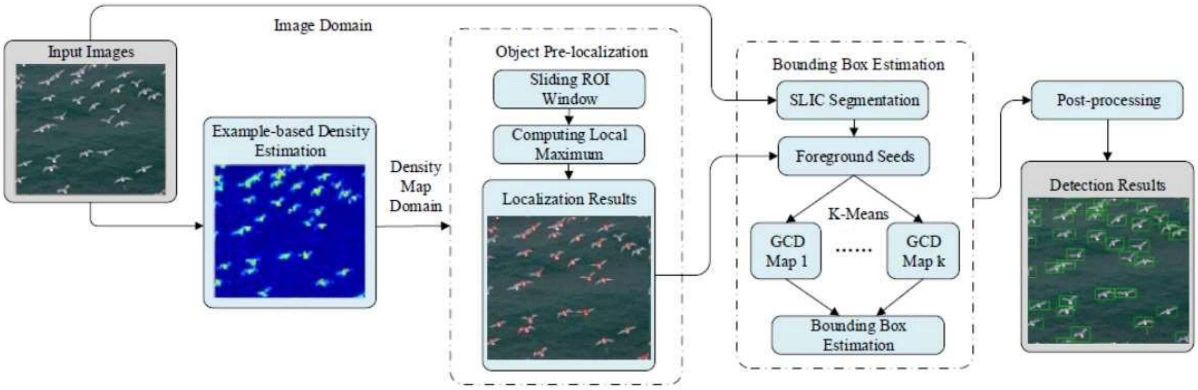

Figure 1: Proposed Architecture Diagram

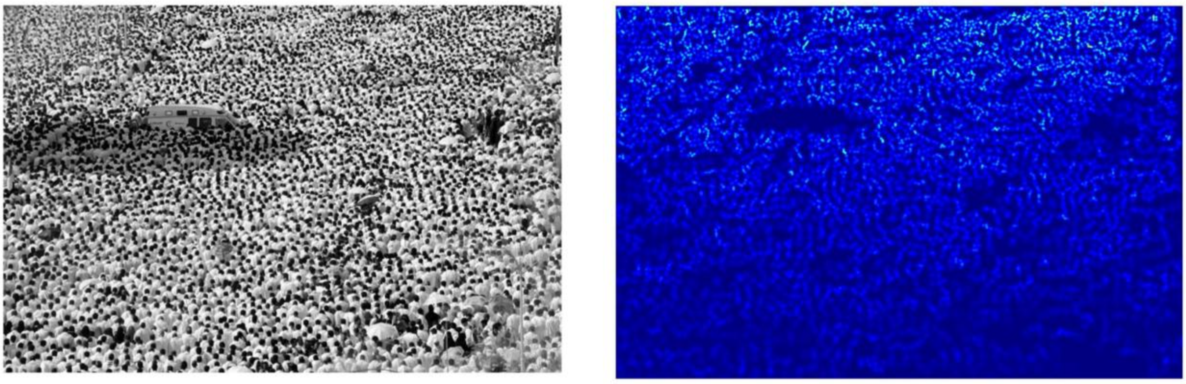

Figure 2: Image Detection Results