



Survey on Deep Learning for Classifying and Collecting Different Types of Floating Garbage on Water Surface using Robots

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ABSTRACT: We all know water is an integral part of our life. About 60%-80% of all marine debris is composed of plastic (Rios et al. 2007) and Ocean Conservancy's Trash Free Seas Alliance estimates that year. This paper proposes the surveys related to many models for collecting the debris it includes Fast R-CNN for object detection, Deep neural network for garbage recognition, YOLO, and YOLOv3, new approaches are used for object detection. This survey collectively helps to create a model that can clean the water surface with more accuracy and speed. There are many challenges arising during the object detection, object tracking, object disposal on water surface as compared to the land garbage collection procedure. Due to unstable surface there fluctuation in the distance between the object similarly its become very much difficult to recognize the plastic bottles or bags due to number of different types of plastic bottles are present in the water bodies.

KEYWORDS: Deep neural network ,RCNN ,YOLO, YOLOv3, Garbage recognition, Garbage detection, Garbage collection robot, Fast R-CNN, Faster R-CNN.

Motivation

Plastics that act as pollutants are categorized into micro-, meso-, or macro debris, based on size. To collect the plastic from the surface of water needs a very advance and intelligent robot. Different models give easy size detection it can also predict the distance of the plastic garbage from that machine. The limitations get arise due to the unstable surface as the garbage is floating the estimation of the garbage becomes difficult. So to overcome this problem we use the advance and new approaches for garbage detection.

I. INTRODUCTION

The oceans and rivers cover 71% of the earth's surface and provide a home for billions of aquatic organisms. Plastic pollution affects land, waterways, and oceans. 1.1 to 8.8 million tones of plastic enter the oceans particularly marine animals can be harmed by mechanical effects, problems related to the ingestion of plastic waste. Due to increase of plastics in the marine environment are increasing concern because of their effects on the oceans, wildlife, and, humans. In Arctic sea ice, at the sea surface, and on the sea floor plastic debris are getting collected. Fragmentation into particles is taking place due weathering of plastic small fishes may ingest . Its small size also leads this debris untraceable to its source and becomes difficult to remove from open ocean , suggesting that the most effective mitigation strategies must reduce inputs Our goal is to create and super fast robot and with a high level of accuracy. We will come to know about many techniques used for object detection and object collection. YOLOv3 for high speed and object detection accuracy. Deep learning for recognition accuracy and convolutional neural network for object detection and classification. Fast R-CNN increases accuracy and speed to accelerate the training time. Faster R-CNN is used for real-time object detection with region proposal network. Dynamic conditions that arises on the surface to water becomes a challenge for the robot to the garbage that is floating itself. YOLO (you look only once) its predicts the object present and where they lie and it is extremely fast.



II. LITERATURE SURVEY

Sr no	Published year	Published by	Research Topic	Dataset	Research Gap
1.	2019	J. Sun, Z. Pu, and J. Yi	“Conditional disturbance negation based active disturbance rejection control for hypersonic vehicles”	Flexible air-breathing hypersonic vehicles dynamic model	1. Even though there are number of merits hypersonic vehicles still there is challenge due to high complexity of air-breathing hypersonic vehicle dynamics.
2.	2018	J. Redmon and A. Farhadi,	YOLOv3: An incremental improvement	Open Images Dataset	1. work on Anchor box x,y offset predictions. 2. Work on linear x,y prediction instead of logistic.
3.	August 2018	J. Bai, S. Lian, Z. Liu, K. Wang, and D. Liu	Deep learning based robot for automatically picking up garbage on the grass	Segnet , Resnet	1. The time cost of the pickup is expected to be smaller. 2. Recognition accuracy of the garbage is less
4.	June 2016	J. Redmon, S. K. Divvala, R. B. Girshick,	You only look once: Unified, real-time object detection	PASCAL VOC	1. YOLO can predict more accurately bounding boxes and detections.
5.	Dec 2015	and A. R. Girshick Farhadi	Fast R-CNN	MS COCO dataset	1. Not having the advanced techniques that allows dense boxes to perform
6.	Dec 2015	S. Ren, K. He, R. Girshick, and J. Sun.	Faster R-CNN: Towards realtime object detection with region proposal networks	PASCAL VOC 2007	1. More accuracy, Efficiency is required in Faster R-CNN for realtime object detection.
7.	February 2015	J.R Jambecketa l	“Plastic waste inputs from land into the ocean”.	-	1. Consumption of plastic is increasing day by day we need machines which will provide management of these waste.
8.	May 2015	J. Redmon and A. Angelova	Real-time grasp detection using convolutional neural networks	Cornell Grasping Dataset	1. unable to quantitatively evaluate the model in this respect because no current dataset has an appropriate evaluation for multiple grasps in an image.
9.	2015	I. Lenz, H. Lee, and A. Saxena	“Deep learning for detecting robotic grasps”	RGBD data using deep learning approach.	1. Many robotics problem needs the use of perceptual information so this approach should have been used.
10.	March 2014	S. Watanasohn and S. Ouitrakul	“Garbage collection robot on the beach using wireless communications”	-	1. Bluetooth and adhoc connections are required for the navigation of the robot. 2. The robot is not able to detect the garbage by its own. 3. The range to control the robot is very limited.

Table no.1 Literature Survey.



III. LIVE SURVEY

2.1] Economic Floating Waste Detection for Surface Cleaning Robot [11]

Task of removing waste out of water surface can be operated by using autonomous surface cleaning robots. Based on the concept of refraction and reflection of laser ray, the proposed laser-based technique is applied on floating waste detection. The economic waste detector is constructed and installed on the robot. Five equation of motion ie DOF are formulated for calculation and estimation of waste position deciding distance measured by the laser and also the robot motion caused by wind force as well as water surface tension.[11]

2.2] Clean Water AI [12]

Water safety becomes difficult when there is vast distribution of a municipal water system. Contamination by bacteria or dangerous particles is often difficult to detect before health issues occur. AI is able to detect water contamination level as well as issues, using trained models to recognize harmful particles and bacteria. Devices that monitor water for problems will help to detect impurity check as quickly as possible. Clean Water AI trains a neural network model, then deploys it to edge devices that classify and detect harmful bacteria and particles.[12] Cities can install IoT devices across water sources to monitor quality in real time.

2.3] Fluid robotics uses robots to manage and maintain urban water infrastructure [13]

There is inefficient water distribution and waste water treatment it is due to leaks and illegal taps. Only 20% of waste water is collected and treated rest water pollutes lakes, groundwater, rivers etc. the company develops multi-sensor robots to inspect pipes, tunnels. Due to this there is better pipeline assessment. This technology not only removes dirty human waste but also it gives less effort in data interpretation.

2.4] Water cleaning boat [14]

Motor powered propeller are used to run the water cleaning boat which uses air thrust to move boat forward.[14] A hand which is a robot used for grabbing and turning at the front side of boat. This robotic hand collects the waste from the surface and collect in the basket behind. [14]

2.5] Fred robot[15]

Large, unmanned, semiautonomous ocean-faring robot which is FRED. It gets the energy from renewable source. It is designed to clean harmful floating debris from water bodies such lake, river and oceans etc. [15]

2.6] Mr trash wheel [15][16]

Floating debris are removed using rotating fork and it then place the debris onto the conveyor belt which move it into the garbage collector. Internet is being used to control the water wheel remotely.

2.7] Trash hunter [17]

The trash hunter technology is used in the lakes, rivers, and other waterways for cleanup of debris and floating garbage. The trash hunter has twin catamaran hulls that can easily collect floating debris and manmade garbage



IV. ACCURACY AND EFFICIENCY SURVEY

Sr no	Published year	Published by	Research Topic	Efficiency	Outcomes
1	2019	J. Sun, Z. Pu, and J. Yi	“Conditional disturbance negation based active disturbance rejection control for hypersonic vehicles”	1. Robustness of the proposed control scheme is stronger against various disturbance and better tracking performances.	1. There are various uncertainties and disturbances in conditional disturbance negation based active disturbance rejection control scheme for velocity and altitude similarly tracking control of flexible air-breathing hypersonic vehicles.
2.	2018	J. Redmon and A. Farhadi,	“YOLOv3: An incremental improvement”	1. At 320×320 YOLOv3 runs in 22 ms at 28.2 mAP, as accurate as SSD . 2. It three times faster than the SSD.	1. YOLOv3 is a good detector, fast, accurate. It is not accurate as COCO average AP between .5 and .95 IOU metric.
3.	August 2018	J. Bai, S. Lian, Z. Liu, K. Wang, and D. Liu	“Deep learning based robot for automatically picking up garbage on the grass.”	1. The robot can perceive the range of 60° with about 10 m. 2. 42 minutes to pick all 20 garbage up	1. robot system for cleaning the garbage on the grass automatically 2. Based on the powerful deep neural networks, the proposed robot can recognize and pick up the garbage without any human assistance.
4.	June 2016	J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi	“You only look once: Unified, real-time object detection”	1. The Fast R-CNN model achieves a mAP of 71.8% on the VOC 2007 test set. When combined with YOLO, its mAP 75.0%. 2. The accuracy increases by 3.2% compared to Fast CNN.	1. The YOLO design enable send-to-end training and real-time speeds while maintaining high average precision.
5.	Dec 2015	R. Girshick	Fast R-CNN	1. Accuracy and speed of Fast R-CNN increases and accelerates R-CNN by 10 to 100 times at test time. 2. Training time is also reduced by 3 times due to faster proposal feature extraction.	1. It provide a clean and fast update to R-CNN and SPPnet. 2. Detector quality is improved by the sparse object proposals which was time consuming but has become practical with Fast R-CNN
6.	Dec 2015	S. Ren, K. He, R. Girshick, and J. Sun.	Faster R-CNN: Towards realtime object detection with region proposal networks	1. Region proposal Networks and Fast R-CNN achieves mAP of 59.9% using up to 300 proposals	1. Region Proposal Networks (RPNs) gives efficient and accurate region proposal generation 2. RPNs enables deep learning based object detection system to run at 5-17Fps.
7.	February 2015	J.R Jambeck et al	“Plastic waste inputs from land into the ocean”.	-	1. Plastic accumulation increasing day by there is need of perfect machine or robot.



8.	May 2015	J. Redmon and A. Angelova	“Real-time grasp detection using convolutional neural network”	1.It achieves around 85 percent accuracy in both image-wise and object-wise splits. 2.the direct regression model runs in 76 milliseconds per batch, with a batch size of 128 images	1.A fast, accurate system for predicting robotic grasps of objects in RGB-D images. 2. Grasp detection and object classification can be combined without sacrificing accuracy or performance
9.	2015	I. Lenz, H. Lee, and A. Saxena	“Deep learning for detecting robotic grasps”	1.The recognition performance is increased with deep learning methods by 9%.	1.Algorithm used was able to recognize and learn features which can relate strongly to graspable cases and non graspable cases
10.	March 2014	S.Watana sohn and S. Ouitrakul	“Garbage collection robot on the beach using wireless communications”	1. The distance that the camera can transmit the clearly image is the range 0 – 15 meters. 2.The delay time of transmitted image is 0.5 and 2 seconds in the range of 15 and 25 meters respectively	1. The robot can move with an average speed of 0.5 m/s on the sand via wireless communication and collect the large garbage with side 12.5 x 49 cm.

Table.2. Accuracy and efficiency survey

V. CONCLUSION AND FUTURE WORK

The above survey conducted results that we can use various deep learning methods and object detection methods to improve the working mechanism of the machines or robots in more efficient and precise way. The drawbacks of the robot movement in various parameters can be overcome so that there will be smooth movement on any surface like water, land, grass and air. We can also conclude that the comparison between the techniques may lead to better understanding of the model or algorithm that should be used. It will give the outcomes as per the requirement and speed, efficiency gets increased. It will also lead to decrease in cost of the machines and robots.

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