NO REFERENCE UNDERWATER IMAGE QUALITY ENHANCEMENT USING ACTIVE INFERENCE FOR DEEP-SEA DEBRIS DETECTION

IT7712- MINI PROJECT

A Project Report

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BONAFIDE CERTIFICATE

Certified that this creative and innovative project report **"NO REFERENCE UNDERWATER IMAGE QUALITY ENHANCEMENT USING ACTIVE INFERENCE FOR DEEP-SEA DEBRIS DETECTION"** is a bonafide work of "**ABINAYA M N (2018506004), DIVYA DARSHINI KANNAN (2018506029), KAMALNATH K N (2018506044)"** who carried out this project work under my supervision.

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CHAPTER 1
INTRODUCTION

MARINE environment has always been getting more and more attention all over the world. Debris is everywhere from the shallow seas to the open seas, from the coast to seabed. In most cases, these man-made marine trashes will eventually sink to the bottom of the sea. The deep sea is a veritable marine rubbish repository. Deep-sea debris causes more serious water pollution and greater damage to the ecological environment than garbage on the sea surface and beach. Submersibles could solve this problem by surveying and picking up submerged marine debris from the seabed with the help of a debris detection system. However, without an excellent classifier, a satisfying detection system is impossible. Consequently, an accurate deep-sea debris classification algorithm is not only essential for the detection system, but also contributes to further scientific research on deep-sea debris and marine ecological protection

Currently, it is common to use image quality assessment approaches to evaluate underwater image quality before debris detection. It can make underwater images differently by either applying image enhancement methods to improve image quality, so that detection algorithm become efficient. Therefore, it is necessary to assess underwater image quality before the debris detection process.

In water medium, image quality tends to be impaired by water density, light attenuation and scattering effect and it suffer from poor visibility due to the medium, which causes scattering and absorption of light so image quality is affected. For these distorted images No Reference Image Quality Assessment(NR-

IQA) is performed so that image enhancement of underwater images can be done. The goal of NR-IQA is to predict the quality of an image as perceived by human observers(subjective perception)without the need of perfect undistorted source images.

CHAPTER 2

COMPREHENSIVE ANALYSIS OF RELATED WORK

2.1 LITERATURE SURVEY

Jupo Ma, et al., [1] This paper presents a novel BIQA metric by mimicking the active inference process of IGM. This paper Implemented an active inference module based on the generative adversarial network (GAN) to predict the primary content in which the semantic similarity and the structural dissimilarity are both considered during the optimization. With the help of primary content obtained and the comprehensive quality degradation measurement from the multi-stream CNN, their method achieves competitive performance on five popular IQA databases- LIVE, CSIQ, TID2013, LIVE-MD, LIVE-CH. WGAN-GP is adopted to stabilize the adversarial training. Multi-stream CNN-based quality evaluator which can measure image quality from multiple aspects is proposed. But NR IQA has been done, enhancement step remains. AIGQA model is applied on images taken only in air medium.

Hongtao Yang al, et al., [2] This Proposed a blind image quality assessment based on generative adversarial network (BIQA-GAN) with its advantages of self-generating samples and self-feedback training to improve network performance. Three different BIQA-GAN models are designed according to the target domain of the generator. Natural distorted images are authentically distorted images, this is the first time that GAN related method applied to the natural distorted image quality assessment, but now other efficient GANs have came to exist

Kai Hu , et al [3] This paper proposes to add the natural image quality evaluation (NIQE) index to GAN to provide generated images with higher contrast and make them more in line with the perception of the human eye, and at the same time, grant generated images a better effect than the truth images set by the existing dataset. The real-time performance of the algorithm was analyzed to verify that the algorithm could be used in engineering. but only standard GAN is used

Michael Fulton1, et al [4] In this paper, they examine the problem of detecting debris, particularly plastic debris, in an underwater environment. In this paper, they applied and evaluated four deep-learning based object detectors to the problem of finding marine debris, particularly plastic. They have created unique comprehensive marine plastic database and kept it public/open-source for research purposes.But Image quality assessment and enhancement were not considered in their scope.YOLOv2 has been used although significant improvements have been done in YOLO models now.

Bing Xue, et al, [5] This study is to determine whether deep convolutional neural networks can distinguish the differences of debris and natural deep-sea environment. Five common convolutional neural networks (CNNs) frameworks are also employed to implement the classification process.But Image quality assessment and enhancement are not considered in their scope.

2.2 RESEARCH GAP IDENTIFIED

- Primary Content detection[1] using Active Inference(IGM constraints) were not applied on images obtained in water/underwater medium in the base paper, which presents different challenges as opposed to air medium images
- After performing Image quality assessment [1] using GAN and CNN, Image quality enhancement step was lacking in the base paper.
- In deep sea debris detection , since the images [5] are distorted it needs the quality enhancement and then model to be trained for detecting the debris but quality enhancement of underwater images is lacking

CHAPTER 3

MOTIVATION OF THE PROJECT

- Immediate need for solutions to environmental problems highlighted in IPCC 2021 REPORT
- Ocean contamination by man-made activities causes marine life degradation
- Marine life ingesting microplastic debris
- No reference Image Quality Assesssment is efficient in many real time applications
- Implementing Active inference and obtaining primary content makes assessment and enhancement of the distorted images efficient and easier for the real time applications

CHAPTER 4

APPLICATIONS OF THE PROJECT

Assessment of image quality and enhancement gives possibility of better detection, especially in light-distorted images captured in deep-sea/water mediums, that present high light scattering and high light absorption.

Marine/Deep-sea debris detection aids automated underwater systems in extracting such debris from depths, which is one of the needs of the hour as highlighted by scientific reports that have announced "code-red" for humanity

CHAPTER 5

PROBLEM STATEMENT

To detect deep-sea/marine debris using deep learning techniques after assessment and enhancement of the quality of underwater images using Active Inference technique employed using a GAN-CNN-GAN *sandwich* model.

CHAPTER 6

SCOPE OF THE PROJECT

In light-distorted images captured in deep-sea/water mediums, that present high light scattering and high light absorption, assessment of image quality & enhancement gives possibility of better debris detection.

Marine/Deep-sea debris detection aids Automated Underwater Vehicular Systems(AUV) in debris removal, which is of urgent environmental importance as presented in global sustainable models

CHAPTER 7

PROPOSED WORK

Image quality assessment:

Generative Adversarial Network

First input dataset is fed into GAN. Generally, GAN consists of two subnetworks: a generator G to generate samples and a discriminator D to distinguish the real samples from the generated samples. Through the adversarial training, the generator is expected to generate more ‘realistic’ samples to fool the discriminator. Various GAN models have been developed and achieved great success in many image generation tasks, such as image synthesis, image super-resolution, image style transfer and image enhancement, which demonstrate the standout performance of GAN in generating realistic semantics and high-quality details. In our work, the objective function of **WGAN-GP** is adopted to stabilize the adversarial training.

Active Inference Module(Obtaining Primary Content)

Two IGM-inspired constraints are proposed in the objective function of G to make the predicted primary content more consistent with IGM.

Semantics Similarity Constraint:

The main semantics of the input image and its primary content should be highly consistent. So IGM tries to find the semantics similarity between the input image and its primary content

Structure Dissimilarity Constraint:

To give the best explanation of an input image, IGM also tries to avoid the disorderly information between the input distorted image and its primary content

Multi-Stream CNN(Quality Evaluator)

On the basis of the primary content, a multi-stream CNN-based quality evaluator which can measure image quality from multiple aspects is proposed. Existing CNN-based methods commonly only take the distorted image as input, which makes it difficult to learn effective features for multifaceted quality analysis. By incorporating the characteristics of the three aspects, a multi-stream quality evaluator is built .The primary content ,the distortion map,and the structural degradation map are fed into the subnetwork-2, subnetwork-3, subnetwork-4 respectively to extract features from different aspects. Besides, the distorted image Id is also fed into the subnetwork-1 to extract information about the original input scene. Then the features from the four subnetworks are concatenated together and transported into the fusion network to predict the quality score.

Image quality enhancement:

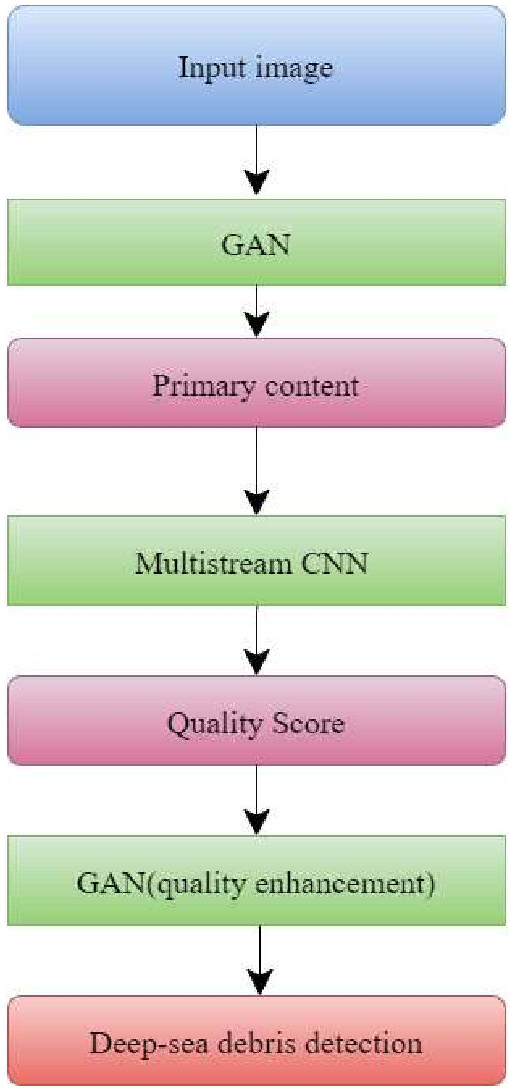
Generative Adversarial Networks

For image enhancement we use Unsupervised Image enhancement generative adversarial network (UEGAN), which learns the corresponding image-to-image mapping from a set of images with desired characteristics in an unsupervised manner, rather than learning on a large number of paired images. It is based on single deep GAN which embeds the modulation and attention mechanisms to capture richer global and local features. In enhancing the image 2 losses are considered (1) fidelity loss, (2) quality loss.

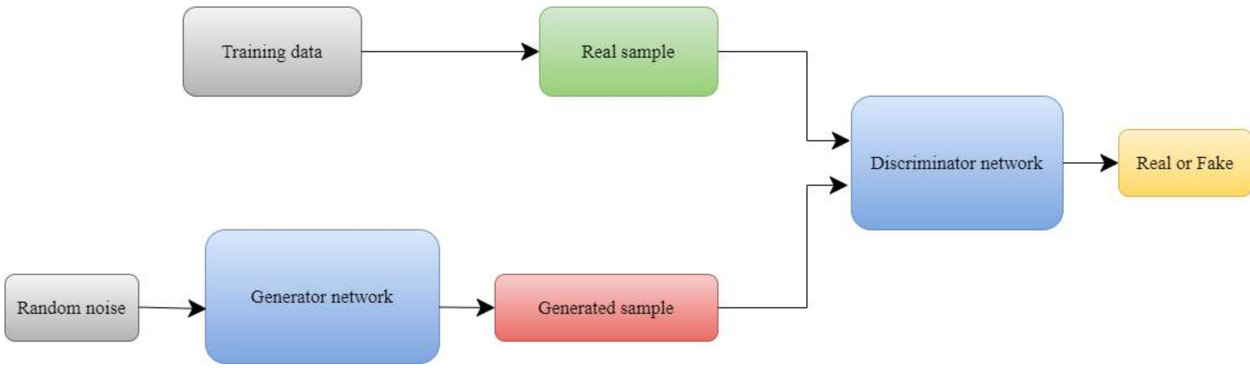
Marine/Deep-Sea Debris Detection:

With the newly enhanced image, we perform debris detection using deep learning techniques

7.1 ARCHITECTURE DIAGRAM OF PROPOSED WORK



GAN- ARCHITECTURE DIAGRAM:



7.2 EXPECTED OUTCOMES/RESULTS

- Proposed the Image Assessment and Enhancement Sandwich Model
- Established the assessment and enhancement of underwater image quality using Active Inference
- Deep-Sea Debris Detection Model
- Detection of deep-sea marine debris on newly enhanced image.

CHAPTER 8

PROJECT BASELINE REQUIREMENTS

8.1 HARDWARE REQUIREMENTS

- Intel i5 processor or higher.
- 8 GB RAM or higher.

8.2 SOFTWARE REQUIREMENTS

- Windows 10 or higher
- Python 3.5.x or higher
- Google Colab/Kaggle Jupyter notebook
- TensorFlow 1.8x
- Pytorch
- NumPy Stack (NumPy, Pandas, SciPy, Matplotlib)

8.3 DATASET

The TrashCan [6] dataset is comprised of annotated images (7,212 images currently) which contain observations of trash, ROVs, and a wide variety of undersea flora and fauna. The annotations in this dataset take the format of instance segmentation annotations: bitmaps containing a mask marking which pixels in the image contain each object. The imagery in TrashCan is sourced from the J-EDI (JAMSTEC E-Library of Deep-sea Images) dataset, curated by the Japan Agency of Marine Earth Science and Technology (JAMSTEC). This dataset contains videos from ROVs operated by JAMSTEC since 1982, largely in the sea of Japan.

CHAPTER 9

IMPLEMENTATION OF THE PROPOSED WORK

PRELIMINARY RESULTS:

Comparative results for standard GAN vs WGAN

GAN:

```
reshape_2 (Reshape)          (None, 28, 28, 1)         0
=================================================================
Total params: 1,493,520
Trainable params: 1,489,936
Non-trainable params: 3,584
_________________________________________________________________
0 [D loss: 0.927131, acc.: 31.25%] [G loss: 0.803602]
1 [D loss: 0.383937, acc.: 89.06%] [G loss: 0.748535]
2 [D loss: 0.352623, acc.: 81.25%] [G loss: 0.816699]
3 [D loss: 0.330376, acc.: 90.62%] [G loss: 0.826817]
```

```
9975 [D loss: 0.744054, acc.: 53.12%] [G loss: 0.978629]
9976 [D loss: 0.705545, acc.: 57.81%] [G loss: 1.042471]
9977 [D loss: 0.641256, acc.: 65.62%] [G loss: 0.894654]
9978 [D loss: 0.584786, acc.: 68.75%] [G loss: 0.933539]
9979 [D loss: 0.651454, acc.: 56.25%] [G loss: 0.897742]
9980 [D loss: 0.598377, acc.: 71.88%] [G loss: 1.003853]
9981 [D loss: 0.711726, acc.: 51.56%] [G loss: 0.917319]
9982 [D loss: 0.609751, acc.: 68.75%] [G loss: 1.023377]
9983 [D loss: 0.660293, acc.: 59.38%] [G loss: 0.946922]
9984 [D loss: 0.642686, acc.: 65.62%] [G loss: 0.940280]
9985 [D loss: 0.619865, acc.: 65.62%] [G loss: 1.021310]
9986 [D loss: 0.621439, acc.: 60.94%] [G loss: 0.965273]
9987 [D loss: 0.602460, acc.: 73.44%] [G loss: 0.940870]
9988 [D loss: 0.614636, acc.: 67.19%] [G loss: 0.951511]
9989 [D loss: 0.595025, acc.: 68.75%] [G loss: 0.992106]
9990 [D loss: 0.642508, acc.: 64.06%] [G loss: 1.068656]
9991 [D loss: 0.596207, acc.: 71.88%] [G loss: 0.956265]
9992 [D loss: 0.602738, acc.: 64.06%] [G loss: 0.909192]
9993 [D loss: 0.623157, acc.: 60.94%] [G loss: 0.966151]
9994 [D loss: 0.611336, acc.: 71.88%] [G loss: 0.974965]
9995 [D loss: 0.675141, acc.: 60.94%] [G loss: 0.965197]
9996 [D loss: 0.636095, acc.: 68.75%] [G loss: 0.985253]
9997 [D loss: 0.687537, acc.: 56.25%] [G loss: 1.022756]
9998 [D loss: 0.601049, acc.: 64.06%] [G loss: 1.003551]
9999 [D loss: 0.602870, acc.: 62.50%] [G loss: 0.903529]
```

WGAN:

```
Total params: 1,028,673
Trainable params: 1,028,289
Non-trainable params: 384
__________________________________________________
0 [D loss: 0.999914] [G loss: 1.000165]
1 [D loss: 0.999920] [G loss: 1.000168]
2 [D loss: 0.999927] [G loss: 1.000184]
3 [D loss: 0.999923] [G loss: 1.000180]
4 [D loss: 0.999922] [G loss: 1.000188]
5 [D loss: 0.999924] [G loss: 1.000190]
6 [D loss: 0.999922] [G loss: 1.000186]
7 [D loss: 0.999924] [G loss: 1.000179]
8 [D loss: 0.999927] [G loss: 1.000178]
9 [D loss: 0.999933] [G loss: 1.000172]
10 [D loss: 0.999933] [G loss: 1.000171]
11 [D loss: 0.999925] [G loss: 1.000169]
12 [D loss: 0.999925] [G loss: 1.000166]
13 [D loss: 0.999928] [G loss: 1.000169]
14 [D loss: 0.999932] [G loss: 1.000169]
15 [D loss: 0.999935] [G loss: 1.000159]
16 [D loss: 0.999932] [G loss: 1.000145]
```

```
3977 [D loss: 0.999964] [G loss: 1.000047]
3978 [D loss: 0.999973] [G loss: 1.000056]
3979 [D loss: 0.999963] [G loss: 1.000044]
3980 [D loss: 0.999967] [G loss: 1.000043]
3981 [D loss: 0.999966] [G loss: 1.000068]
3982 [D loss: 0.999962] [G loss: 1.000054]
3983 [D loss: 0.999972] [G loss: 1.000051]
3984 [D loss: 0.999966] [G loss: 1.000050]
3985 [D loss: 0.999969] [G loss: 1.000051]
3986 [D loss: 0.999973] [G loss: 1.000052]
3987 [D loss: 0.999973] [G loss: 1.000061]
3988 [D loss: 0.999969] [G loss: 1.000060]
3989 [D loss: 0.999966] [G loss: 1.000069]
3990 [D loss: 0.999962] [G loss: 1.000058]
3991 [D loss: 0.999972] [G loss: 1.000051]
3992 [D loss: 0.999966] [G loss: 1.000061]
3993 [D loss: 0.999979] [G loss: 1.000057]
3994 [D loss: 0.999973] [G loss: 1.000066]
3995 [D loss: 0.999964] [G loss: 1.000056]
3996 [D loss: 0.999974] [G loss: 1.000053]
3997 [D loss: 0.999970] [G loss: 1.000076]
3998 [D loss: 0.999962] [G loss: 1.000061]
3999 [D loss: 0.999981] [G loss: 1.000054]
```

CHAPTER 10

TENTATIVE WORK PLAN

S.No	Review	Work Plan
1	First Review	Obtaining dataset
		Preliminary Outputs
2	Second Review	Training the GAN Model to obtain the Primary content
3	Third Review	Image quality assessment of underwater images
		Finding the quality score using multi-stream CNN
	Work to be continued	Enhancing the image quality using GAN Deep sea debris detection

CHAPTER 11

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