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Underwater Image Classification using Machine Learning Technique with SIFT Algorithm

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Abstract— **From decades, underwater exploration has increased tremendously. For data collections currently there are many instruments available (Sub bottom profiler and Remotely Operated Vehicle, Side Sonar Scan, Echo sounder with multi beam) in underwater observation and research not only provide the data about the sea surface but also provide data on objects and species. In this situation, selecting appropriate features is a very critical task. Because of less numbers of datasets in Underwater, it is so critical to distinguish the features/objects from the underwater images. To overcome this problem, Bag of Features model which is based on Machine Learning is used in this paper. From Shallow water the dataset is obtained using ROV. Making the classification of features is a quite difficult task because underwater optical images have a low light intensity; To obtain the maximum accuracy Speed Robust Features and algorithms in C are used.**

Index Terms **Speeded-Up Robust Features, Speeded-Up Robust Features, Image Classification, Underwater.**

I. INTRODUCTION

Underwater images, due to various physical phenomena such as backward and forward scattering and light absorption the quality of image is compromised. Underwater exploration has increased exponentially. Currently available instruments for data collections (Side Scan Sonar, Multi Beam echo sounder, sub bottom profiler and Remotely Operated Vehicle) in underwater research and observation not only provide the data on objects and species, but also provide data about the sea surface. Image classification is a complicated process which is influenced by multiples factors. Normally there are two steps for classification of images the first one is identification and extraction of features which is followed by image classification based on features obtained. For the most probable solutions, identification methods are used which are image based. To accomplish this will use Machine Learning. Especially, supervised learning has established itself as a prominent class label distributor with predictor features. But for underwater images, due to various physical phenomena such as backward and forward scattering and light absorption the quality of image is compromised. There are various other factors that make underwater image classification a daunting task. First, the water depth is the directly proportional to the uncertainty of the object i.e as the depth increases the object's uncertainty also increases. This uncertainty arises due to the fact that many aquatic species have the feature of themselves with the underwater environment which in turn results in certain changes in the image's background. Thus it becomes a challenging task to find a good combination of feature extractor and a classifier for a dataset where depth information is missing. Second, the costs of underwater equipment also play a major role. Third, it's a difficult task to recognize and select good features from the dataset. Nonetheless, it's a necessary precondition for object classification. And it also has numerous advantages such as minimization of computational cost and increase in accuracy. Feature Extraction is the process of segregating features from an image. It is vital to choose the features that prove to be
valuable for classification task. The chosen features must be informative, non-redundant, and must facilitate further learning steps. Therefore the bag-offeatures technique is selected for feature extraction as it is based on ordering of few local and global features.

Underwater exploration has increased exponentially. Currently available instruments for data collections (Side Scan Sonar, Multi Beam echo sounder, sub bottom profiler and Remotely Operated Vehicle) in underwater research and observation not only provide the data on objects and species, but also provide data about the sea surface. In this regard, selecting suitable features is a huge task. Due to limited datasets in Underwater, it is difficult to classify the objects/features from underwater images. In order to overcome this, machine learning based Bag of Features model is adopted in this paper. The dataset is obtained from shallow water using ROV. Since the underwater optical images have low light intensity, making the classification of features a difficult task; SURF (Speeded-Up Robust Features) and SVM (Support Vector Machines).

II. Literature Survey

Optical and sonar based systems are the two main imaging modalities used for underwater vision-based navigation [1, 2, 3]. In underwater imaging systems, recognition of man-made objects plays an important role for conducting research in domains such as oceanographic species identification, pipeline overhauling, mine detection, and naval studies, among others [4, 5, 6]. Compared with sonar imaging, optical imaging, due to its ability to capture greater details and color, has found greater applicability in underwater object detection tasks [7]. With the development of underwater optical image sensors, manmade target recognition from underwater optical images has attracted greater attention in both oceanic engineering and image processing [4, 8, 9]. Poor image quality is one of the biggest challenges in underwater optical image analysis (Fig.1). Image quality is often low due to factors such as impurities in the water, and high water density [4]. Besides, limited visibility due to the exponential attenuation of light in deep waters also further degrades image quality [7]. Very few studies have been conducted in the domain of man-made target recognition from underwater optical images. In both [10] and [11], the authors built systems to identify and recognize underwater man-made objects using color information. Hou et al. [12] proposed a detection method from features based on the color and the shape of underwater manmade objects. In [13], the authors reported a system for detecting the presence of man-made objects from unconstrained subsea videos. They extracted object contours as stable features, and then employed a Bayesian classifier to predict the presence of a man-made object in the image. Therefore, it is natural to consider the use of deep learning to recognize man-made object from underwater optical images. However, there are certain challenges which must be addressed in order to effectively use deep learning techniques for this task. For deep learning, one of the prerequisites is the availability of large-scaled labeled data, needed for the estimation of parameters during the training phase. Also, similar to traditional machine learning methods, deep learning assumes that the training and the testing samples follow a similar distribution [15] - that is, the imaging procedures for capturing the training and the testing samples should be the same or similar. In real-world scenarios, for underwater imaging, it is challenging to collect and label sufficient underwater man-made objects.

III. Related Work

Image Pre-Processing

Underwater images are degraded by scattering and absorption of light in water. The whole idea of applying enhancement technique.

Feature Extraction

The proposed system uses SURF (Speeded Up Robust Features) feature extraction algorithm. It is a local extraction algorithm capable of detecting features such as blobs and corners, but not key points about regions. Using
a pre-computed integral image with 3 integer operations, an integer approximation of the Hessian blob detector is used to locate points of interest in an object. Based on the sum of the Haar wavelet response, the feature descriptor is
calculated and can be calculated using the integral image. Since the annotation accuracy depends heavily on the representation of the feature, the use of different region / point descriptors and/or the representation of the BoW function.

Bag-of-Features

The bag of features is a new concept and is famous for its simplicity and performance. Here input image is divided into sample sets consisting of independent patches. Later visual descriptor vector is calculated for each patch. When creating the bag of features dataset, the SURF features are extracted from selected feature point locations.

IV. Proposed Approach

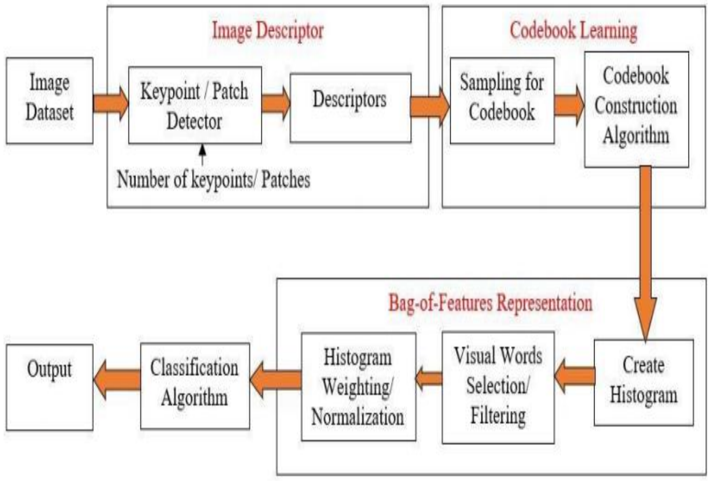


Fig. 1 Flow Diagram of Proposed System

Modules

- *Image Preprocessing*
- *Feature Extraction*
- *Codebook Learning*
- *Distance Calculation(Histogram Based)*
  - *Classification*

Methodology

Image Pre-Processing Underwater images are degraded by scattering and absorption of light in water. The whole idea of applying enhancement technique is to increase the dynamic range of the gray levels in the image being processed. This not only results in good computational analysis but also improves the performance of succeeding tasks, such as image analysis, object detection, and image segmentation. The Contrast Limited Adaptive Histogram Equalization (CLAHE) method is adopted for pre-processing. The flow diagram of the system is represented in Figure

Feature Learning First, through the K-means unsupervised learning process, the proposed system learns representative bases on unlabelled data for each model. Then the comparison between the labelled data and the representative bases is determined to derive the desired features from the labelled data. Such labelled features are fused to represent the identity and then fed to make the final identification to the classifiers. There are two main stages: object representation function and quality classification. Classification quality depends on the features extracted, classification.

Image Preprocessing:

Underwater images are degraded by scattering and absorption of light in water. Image enhancement is a pre-processing process which improves the quality and appearance of the image. The whole idea of applying enhancement technique is to increase the dynamic range of the gray levels in the image being processed.

Get the red, green, and blue values of a pixel

Use fancy math to turn those numbers into a single gray value

Replace the original red, green, and blue values with the new gray value

When describing grayscale algorithms, I'm going to focus on step 2 – using math to turn color values into a grayscale value. So, when you see a formula like this:

Gray = (Red + Green + Blue) / 3

CLAHE correction:

The Contrast Limited Adaptive Histogram Equalization (CLAHE) method is adopted for pre-processing since it is a popular method for local contrast enhancement and has been proved useful for several applications.

Feature Extraction:

It is a local extraction algorithm capable of detecting features such as blobs and corners, but not key points about regions. Using a pre-computed integral image with 3 integer operations, an integer approximation of the Hessian blob detector is used to locate points of interest in an object.

Codebook Learning:

A visual codebook is generated by using off-line k-means clustering. The word histogram is constructed by first linearly searching the codebook and finding the visual word closest to the selected feature. The codebook size is determined based on the number of feature clusters.

Distance Calculation(Histogram Based):

The word histogram is constructed by first linearly searching the codebook and finding the visual word closest to the selected feature.

Classification:

Classification of image is a huge task, and this is simplified using supervised machine learning algorithm SVM. The concept of SVM lies in the creation of hyperplane for classification. The hyperplane is nothing but a geometric line that with the help of which the classification problem is either identified as multiclass SVM or linear SVM.

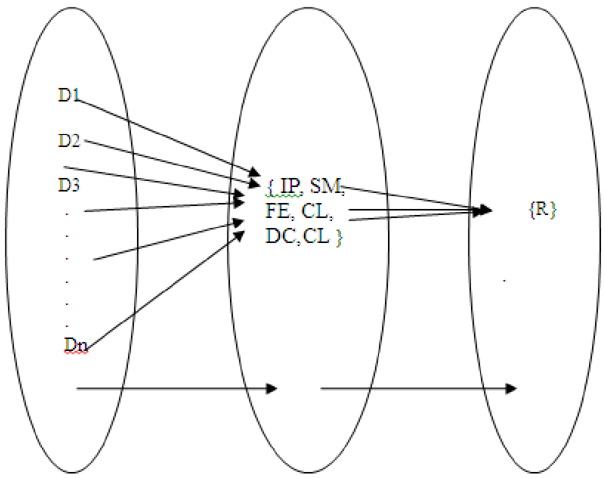
SIFT Algorithm Feature Extraction:

SIFT keypoints of objects are first extracted from a set of reference images[2] and stored in a database. An object is recognized in a new image by individually comparing each feature from the new image. From the full set of matches, subsets of keypoints that agree on the object and its location, scale, and orientation in the new image are identified to filter out good matches. The determination of consistent clusters is performed rapidly by using an efficient hash table implementation of the generalized Hough transform. Each subject to further detailed model verification and subsequently outliers are discarded. Finally the probability that a particular set of features indicates the presence of an object is compute. Object matches that pass all these tests can be identified as correct with high confidence.

Mathematical Model

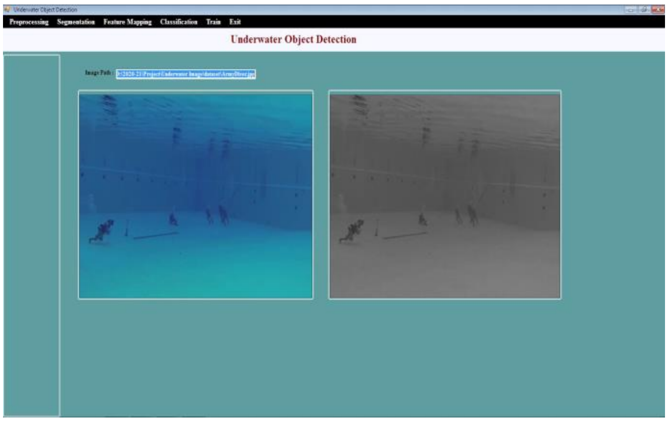
S: is a System.
D: Set of Dataset.
IP: Image Preprocessing.
SM: Segmentation.
FE: Feature Extraction(SIFT)
CL: Codebook Learning.
DC: Distance Calculation (Histogram Based).
CL: Classification

Y={ IP, SM, FE, CL, DC,CL }

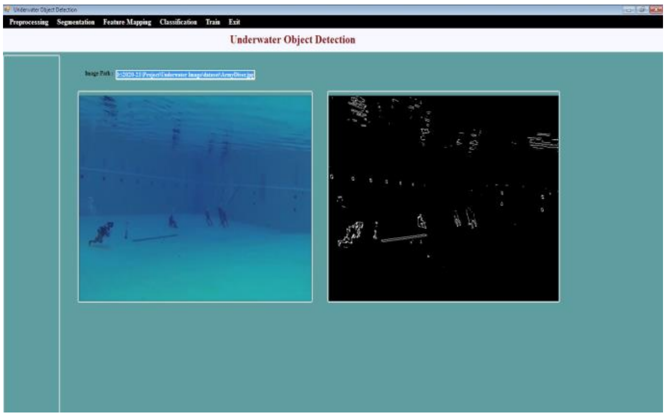


V. RESULTS

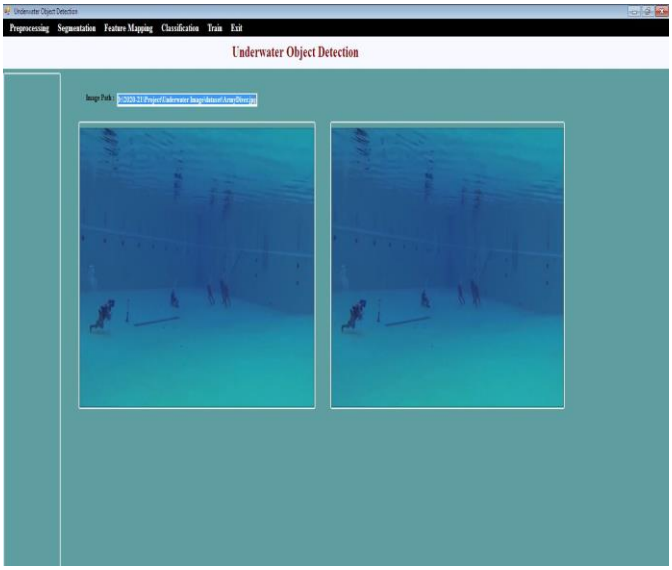
A. Grayscale



B. Cany Edge Algorithm



C. SIFT



D:Classification

VI. CONCLUSION

Our Proposed to detect the object in the image. However, to directly acquire sufficient underwater images to train the network is difficult. Thus, we synthesized the training images by emulating the imaging mechanism of the learning technique.

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