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Fish Image Recognition Using Benefit Based Partial Classification

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Abstract: *Live fish recognition is one in every of the foremost crucial parts of fisheries survey applications wherever large quantity of knowledge square measure chop-chop non heritable. Totally different from general eventualities, challenges to underwater image recognition square measure announce by poor image quality, uncontrolled objects and settings, similarly as problem in effort representative samples. Also, most existing feature extraction techniques square measure hindered from automation owing to involving human management. Toward this finish, we tend to propose associate degree underwater fish recognition framework that consists of a totally unsupervised feature learning technique associate degree an error-resilient classifier. Object components square measure initialized supported prominence and relaxation labeling to match object components properly. A non-rigid half model is then learned supported fitness, separation and discrimination criteria. For the classifier, associate degree unsupervised cluster approach generates a binary category hierarchy, wherever every node could be a classifier. To use data from ambiguous pictures, the notion of partial classification is introduced to assign coarse labels by optimizing the "benefit" of indecision created by the classifier. Experiments show that the projected framework achieves high accuracy on each public and collected underwater fish pictures with high uncertainty and sophistication imbalance.*

Keywords: Unsupervised Learning, Underwater Image, Recognition

I IINTRODUCTION

Object recognition may be a method for distinguishing a selected object in an exceedingly digital image or video. Visual perception algorithms think about matching, learning, or pattern recognition algorithm victimization appearance-based or feature-based techniques [1]. Common techniques embody edges, gradients, bar chart of bound Gradients, Harr wavelets, and linear binary patterns. Visual perception is helpful in applications like video stabilization, automatic vehicle parking systems, and cell count in bio-imaging.
The fish detection strategy includes 3 primary steps [2]. First, the presence of fish is recognized and also the initial locations area unit determined victimization segmentation of a frame distinction from associate averaged background image. A Haar like detector is then used to estimate the snout and tail locations, from that the initial position and orientation of every fish within the image may be derived [3]. Later, a form previous model is made by PCA employing a set of coaching samples. The extent sets curve is then initialised and evolved to find the fish boundary.

The ultimate aim of this paper is to develop a general approach to the automated mensuration of fish in underwater environments. The main focus of this work are going to be on Recognition of fish using feature learning. In context of this thesis, automated detection methodologies comprise two steps: identification and subsequent delineation of the fish outline

II RELATED WORK

Clausius Entropy is used in detection and tracking of multiple moving objects [4].In this method entropy difference with adaptive threshold is used to detect the moving object in static environment. The result is then used to track the movement of the object using the fast level set method. Fast level set method combines the Fast Marching Method and the Smart Narrow Band. This technique detect moving object in indoor and outdoor video sequence. The drawback is clutter formation in outdoor images and in complex scenes.

An image-based fish species recognition method [5] measures a number of fish features, as seen by a camera perpendicular to a conveyor belt. The specific features here are the widths and heights at various locations along the fish, which are then used as input values to a neural network. The number of species considered here is only six.

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An automatic color equalization model based on a color correction method they apply their method to an underwater fish image to segment fish regions. Their project focuses on developing an information system for aquariums. They calculate various features, including geometric, color, texture, and motion features. A feature reduction process is also applied to eliminate useless or redundant features. [6] proposed a method in which the minimization is per-formed in a sequential manner by the fusion move algorithm that uses the QPBO min-cut algorithm. Multi-shape GCs are proven to be more beneficial than single-shape GCs. Further, a quadratic Bayes classifier is used to classify selected fish into one of the learned species. In their experiments, they collected 12 fish species and 1,346 samples.

Recognizing isolated patterns of fish [7] propose a new algorithm for detecting the movement of fish. In this an input fish image is first cropped to remove the ventral part of the pattern of interest, and then, a color histogram is calculated. From this histogram, three features (i.e., standard deviation, homogeneity, and energy) are extracted from the gray-level cooccurrence matrix (GLCM) [8]; further, two features of median and variance values are directly calculated. The multilayer feed forward neural network model with a back-propagation classifier is then employed for the classification task. The number of species in their research is 20.

Hierarchical classification method for live fish recognition in an unrestricted natural environment recorded by underwater cameras [9]. In this method, the Grabcut algorithm is first employed to segment fish from the background. Next, their method extracts 66 features, which consist of a combination of color, shape, and texture features from different parts of the fish. Their method also reduces the number of feature dimensions via forward sequential feature selection. The number of species in their research is ten, with 3,179 fish images.

III PROPOSED WORK

An underwater fish recognition framework that consists of a fully unsupervised feature learning technique and an error-resilient classifier [10]. Object parts are initialized based on saliency and relaxation labeling to match object parts correctly. A non-rigid part model is then learned based on fitness, separation and discrimination criteria. For the classifier, an unsupervised clustering approach generates a binary class hierarchy, where each node is a classifier. To exploit information from ambiguous images, the notion of partial classification is introduced to assign coarse labels by optimizing the “benefit” of indecision made by the classifier.

The proposed hierarchical partial classification reduces misclassification by avoid making guesses with low confidence and thus enhances the recognition performance in practical datasets. Moreover, the extent of conservativeness of the proposed classifier is highly adaptive since the indecision region is optimized based on the distribution of data. This makes the proposed classifier intelligent and fully automatic that requires no manual interference by the user.

An underwater fish recognition framework that consists of a totally unsupervised feature learning technique Associate an error-resilient classifier. Object elements square measure initialized supported strikingness and relaxation labeling to match object elements properly. A non-rigid half model is then learned supported fitness, separation and discrimination criteria. For the classifier, unsupervised clump approach generates a binary category hierarchy, wherever every node may be a classifier. To take advantage of info from ambiguous pictures, the notion of partial classification is introduced to assign coarse labels by optimizing the “benefit” of indecision created by the classifier.

The projected class-conscious partial classification reduces misclassification by avoid creating guesses with low confidence and therefore enhances the popularity performance in sensible datasets. Moreover, the extent of conservativeness of the projected classifier is very accommodative since the indecision region is optimized supported the distribution of knowledge. This makes the projected classifier intelligent and absolutely automatic that needs no manual interference by the user.

In many cases, the performance of unsupervised learning algorithms depends highly on how well the variables are initialized. For the proposed non-rigid part model, one can decide the number of parts to be learned by the part model. This factor not only affects

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the power of discrimination but also gives different dimensionality of feature descriptors that represent fish species characteristics. The modules are listed below:

- Part Initialization
- Part Localization
- Part Model Discovery
- Hierarchical classifier

Part Initialization

The effectiveness of alternating optimization guarantees only the convergence to local optima. To ensure a good solution can be obtained, we propose a systematic approach to initialize the part model. Note that most details that distinguish fine-grained categories match those parts which are prominent to humans' perception, such as the beak of a bird, the petals of a flower, or the tail fin of a fish. A saliency operator works perfectly for this purpose.

Part Localization

In this step, the part features P and sizes S are given. By updating X , we localize the sub-region that corresponds to each part in each image.

Unsupervised Part Model Discovery

In the proposed unsupervised part discovery algorithm, each iteration consists of three steps. The algorithm first updates the locations X (part localization) with the remaining variables fixed, then updates the sizes S (part size fitting) with the remaining variables fixed, and finally updates the part features P (part model learning) with the remaining variables fixed. For each training image the part locations and sizes are initialized based on the saliency detection and relaxation labeling procedure. The appearance for each part is initialized by the average value of the corresponding block over the training set.

Unsupervised Construction of Class Hierarchy

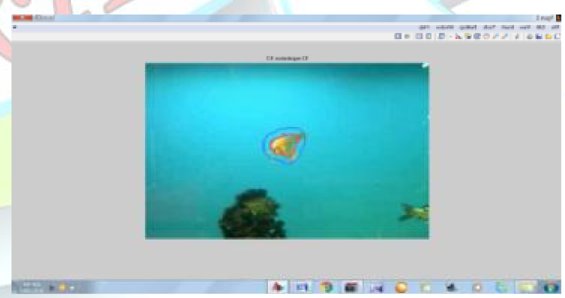
The class hierarchy follows a binary tree structure, i.e., each node separates data into two categories. The arrangement of class grouping is learned by an unsupervised recursive clustering procedure as follows. The EM algorithm for mixture of Gaussians (MoG) is applied to separate all data into two clusters, which can be viewed as "positive" and "negative" data respectively.

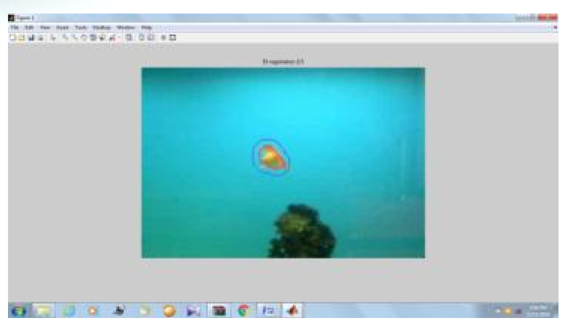
V SIMULATION AND RESULTS

Initial Frame

Part Localization

Fish Recognition





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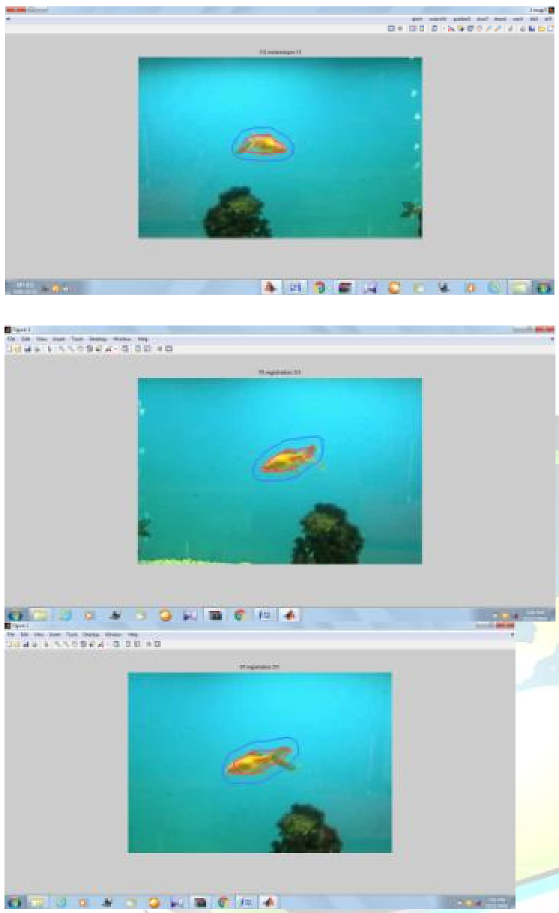

The fish are recognition based on the features specified by the user. The specified features are detected by the part discovery module and construct the class hierarchy for tracking the fish. The proposed algorithm tracks both the background and foreground for the specified feature for a given image. There are 99 frames are used for tracking the fish image. The frames are segmented and registered according to the features of an image.

CONCLUSION

The proposed algorithm assists by unsupervised learning algorithms with non-rigid part model. The non-rigid part model successfully finds discriminative parts by assuming saliency and relaxation labeling. Fitness, separation and discrimination of parts are considered for finding meaningful representations of fish body parts in a fully unsupervised fashion. On the other hand, data uncertainty and class imbalance are two of the most common issues in practical classification applications. The results shows that the proposed algorithm efficiently classify the feature of the fish and track the fish significantly.

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