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An Artificial Immune System Classification for Recognition of Categorized Objects from Noisy Web Image Collection

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***Abstract*— The segmentation and recognition of categorized objects addresses the problem of recognition of a single category of object across a collection of images, where categorized objects are referred to objects within the same category. Web image collections are noisy, which are not in the same category. To overcome this limitation, introduces "an artificial immune system classification for recognition of categorized objects from noisy web image collection". The unique feature of this multi-class classifier based on immune system principles is that the embedded property of local feature selection. Training an automatic object segmentation algorithm that operates directly on a collection of images, and an object category recognition algorithm, 'An artificial immune system for classification with local feature selection' that identifies which images contain the target object. The amount of data needed for classification was reduced by up to 99%. The classifier has good performance compared with both other immune inspired classifiers and other classifiers in normally.**

Key Words:* *Image segmentation, object recognition, segmentation of categorized objects, auto-context model, artificial immune system classification.

I. INTRODUCTION

Object recognition is the task of finding and identifying objects in an image or video sequence. Humans recognize a mess of objects in images with very little effort, despite the actual fact that the image of the objects could vary somewhat in different viewpoints, in many different sizes and scales or even when they are translated or rotated. Objects will even be recognized once they are partially obstructed from view. Algorithmic description of this task for implementation on machines has been very difficult. The object recognition problem can be defined as a labeling problem based on models of known objects. Formally, given an image containing one or more objects of interest (and background) and a set of labels corresponding to a set of models known to the system, the system should assign correct labels to regions, or a set of regions, within the image. The object recognition problem is closely tied to the segmentation problem. Without at least a partial recognition of objects, segmentation can't be done, and without segmentation, object recognition is not possible.

When fed with a collection of images in the same object category, it is helpful to leverage the high level information across the full image collection to at the same time extract a foreground object from all images, rather than segmenting the images independently through modeling only one single image. Such a problem is referred to as the segmentation of categorized objects.

Nevertheless, most methods of segmentation of categorized objects were built on the belief that all images of the given collection contain the target object, that renders them unable to handle situations where the given collection of images contain noisy images which don't contain the target category of object. Such noisy image collection is also gathered, e.g., by performing a text query using one of the main stream image search engines like Google and BING image search. This motivated us to create an automatic program to jointly cleanse and extract the categorized objects from noisy Web image collections.

The objective is to achieve a system to conjointly extract and recognize categorized objects from noisy Web image collections. The proposed method concurrently learns an object segmentation model, which automatically extract the target categorized object from a collection of images, and an object category recognition model, which operates on either the segmented object regions, or the whole image. A good object category model helps remove outliers images from the noisy Web image collection. On the other hand, a good object segmentation model largely removes the cluttered background and in turn can help learn better object category model.

The input to our training framework is a collection of noisy Web images (e.g., "Apple fruit" obtained by Google image search), the highest hierarchic initial dozens of images are first selected to be put in the categorized image collection, which will grow along the co-training process. The first dozens of images from the text query rarely contain any outlier/noisy images, hence they provide a good initialization of a clean categorized image collection. Starting from this initial categorized image collection, learn an object segmentation model by interleaving the learning of an auto-context model [3] inside an iterative energy based segmentation algorithm using graph cut (i.e., min-cut/max-flow) [8]. The learned object segmentation model will

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automatically segment the target categorized objects and learned efficient object category classifier categorize objects from all images in the categorized image collection. Motivation is to build the enabling technologies to automatically extract and recognize categorized objects from a noisy Web image collection. Key contributions is uses an efficient classification algorithm that is An Artificial Immune System for Classification with Local Feature Selection [9].

II. RELATED WORK

There is considerable previous work on Joint segmentation and recognition of categorized objects from noisy web image collection [6]. The algorithm automatically identifies the set of true positives in the noisy Web image collection, and simultaneously extracts the target objects from all the identified images. They collect the web images and initialize the categorized image collection with these images. Then jointly extract the categorized objects from the categorized image collection, learn an object segmentation model with an embedded auto-context model from all these images, and learn an object category model based on all segmented images, by progressively expanding the categorized image collection with images from the candidate Web image collection. The fast HIKSVM proposed in [5] is used to train the object category classifier. The accuracy of the segmentation method [6] is lower than [8], and this may be explained by the fact that [8] has strong ability of encouraging segmentation of images along boundaries of homogeneous color/texture. So incorporate such constraints in the proposed framework.

III. PROPOSED SYSTEM

Web image collections are noisy, which are not in the same category, such as those image collections gathered by a text query from modern image search engines. We use an artificial immune system for recognition of categorized objects from noisy web image collection. The unique feature of this multi-class classifier based on immune system principles is the embedded property of local feature selection. This is achieved by first training an automatic object segmentation algorithm that operates directly on a collection of images, and an object category recognition algorithm, 'An artificial immune system for classification with local feature selection' [9] that identifies which images contain the target object. This method of feature selection was inspired by the binding of an antibody to an antigen, which occurs between amino acid residues forming an epitope and a paratope. Antibodies binding (recognizing) with most antigens (instances) create an immune memory set. This set can be reduced during an optional apoptosis process. Local feature selection and apoptosis result in data-reduction capabilities. The amount of data required for classification was reduced by up to 99%.

1. Filtering the Noisy Web Image Collection

The noisy Web images obtained through an Internet search often contain some illustration images, such as pencil, drawing, sketch, tattoo, symbol images, etc., and most of them are characterized by a keyword in the accompanying captions or a distinctive intensity distribution. Thus, we leverage both text-based and visual-based image filtering to remove the corresponding illustration images.

For the text-based filtering, directly reject the images whose accompanying captions contain the following stemmed keywords, i.e., “draw”, “sketch”, “tattoo”, “graph”, “plot”, “symbol”, “map”, “chart”, “paint”, “abstract”, “origami” and “watercolor”.

For the visual-based filtering, use the intensity histogram to reject the drawing and symbolic images, as they are characterized by a distinctive intensity distribution. There is a wide difference in the histograms of a natural image and a drawing image.

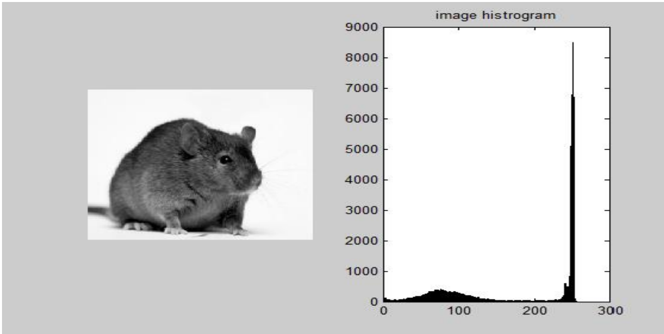

Fig. 1. Intensity histogram of a n image.

2. Segmentation of Categorized Objects

For an efficient segmentation use segmentation method in [8], has strong ability of encouraging segmentation of images along boundaries of homogeneous color/texture. The contextual information in all images of the image collection can be used for the segmentation of each image.

3. Auto-context Model

Contextual dependency is one major visual cue in segmentation. To better determine how fit a pixel belongs to foreground or background by including a large amount of contextual information, an auto-context model has been developed for automatic object extraction from images [3]. We use an auto-context model originally proposed by Tu [2] and later extended by Wang et al. [3] for automatic object extraction from images. The auto-context model builds a multi-layer Boosting classifier on image features and context features surrounding a pixel to predict if this pixel is associated with the target concept, where subsequent layer is working on the probability maps from the previous layer. The auto-context model is trained on all images of the categorized image collection in the automatic process of segmentation of categorized objects.

4. Categorized Images Recognition

A bag-of-words model is used as the object category model to recognize categorized images while rejecting the outlier/noisy images. In the training process of the object category model we first compute the SIFT descriptors on a regular grid across each categorized image, and each noisy image. The SIFT descriptors computed on the image collection and the rejected image set are then clustered into visual words by using k-means, and the visual words to form a visual word vocabulary. We then compute the histogram of visual words from each image. Each histogram can be regarded as a representation for the corresponding image/object/background. Finally, an object category classifier is trained on the histograms for the target category using an artificial immune system for classification with local feature selection [9].

5. An Artificial Immune System for Classification with Local Feature Selection

It is a multiclass classifier based on immune system principles. The unique feature of this classifier is the embedded property of local feature selection. This method of feature selection was inspired by the binding of an antibody to an antigen, which occurs between amino acid residues forming an epitope and a paratope. Only certain selected residues (so-called energetic residues) take part in the binding. Antibody receptors are formed during the clonal selection process. Antibodies binding (recognizing) with most antigens (instances) create an immune memory set. This set can be reduced during an optional apoptosis process. Local feature selection and apoptosis result in data-reduction capabilities. The amount of data required for classification was reduced by up to 99%. The classifier has only two user-settable parameters controlling the global-local properties of the feature space searching. The comparative tests were performed using k-NN, support vector machines, and random forest classifiers. The obtained results indicate good performance of the proposed classifier in comparison with both other immune inspired classifiers and other classifiers in general.

IV. EXPERIMENTAL RESULTS

The accuracy of boost classifier and the artificial immune system classifier is given below.

Table 1. Accuracy, recall and precision of artificial immune system classifier and boost classifier

	Boost classifier	Artificial immune system classifier
Accuracy	88.7640	94.6667
Recall	0.8883	0.9467
Precision	0.8879	0.9467

Proposed system recognizes the categorized images and using the artificial immune system classification we get more accurate target category images. Below given the graphical view of comparison of accuracy, precision and recall with our artificial immune system classification with local feature selection.

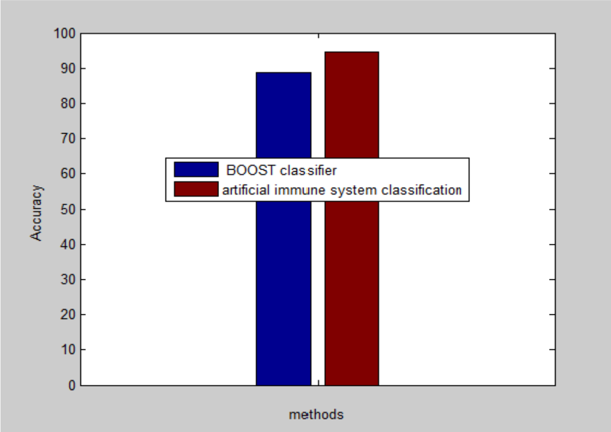

Fig. 2. Comparison of accuracy between the boost classifiers and the Artificial Immune system classification with local feature selection

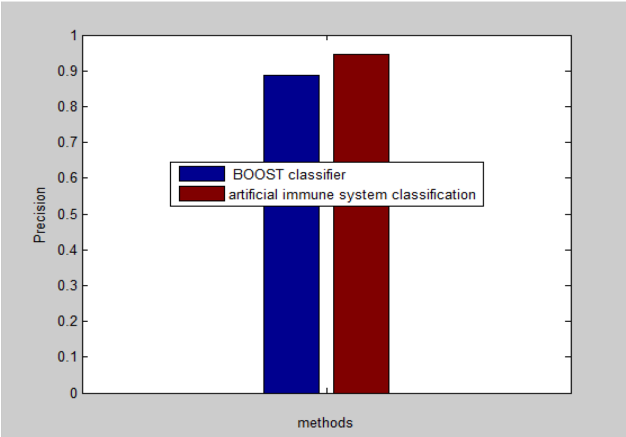

Fig. 3. Comparison of precision between the boost classifiers and the Artificial Immune system classification with local feature selection

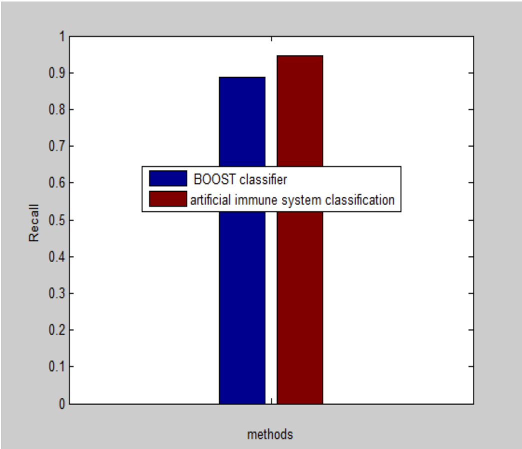

Fig. 4. Comparison of recall between the boost classifiers and the Artificial Immune system classification with local feature selection

V. CONCLUSION

Propose an artificial immune system classification for recognition of categorized objects from noisy web image collection for automatically extracting and recognizing categorized objects from noisy Web image collections. Which automatically extracting and recognizing categorized objects from noisy Web image collections. Proposed system recognizes the categorized images and using the artificial immune system classification get more accurate target category images.

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