Incremental New Actions Learning System with Limited Cost and Storage

Che-Wei Chang
Graduate Institute of Electronics Engineering
National Taiwan University
Taipei, Taiwan

Liang-Gee Chen , Fellow, IEEE
Graduate Institute of Electronics Engineering
National Taiwan University
Taipei, Taiwan

Abstract—In the future robotic applications, robot requires the ability not only to recognize human actions but also to learn incrementally and quickly. Therefore, we proposed an incremental action learning system for this future requirement. The proposed system can continuously learn new actions quickly with robust performance and less effort.

Keywords—Action recognition, Incremental learning, new class learning, Nearest class mean classification, representative data selection

I. Introduction

Human activities recognition has become an active research area, because the ability to recognize human action is important to facilitate interaction between humans and robots. Many applications such as handicapped people monitoring and household intelligent robot become popular. However, the knowledge and environment in the real-world are complicated and ever-changing. Robots are supposed to be equipped with incremental learning ability and can adapt itself to any new environment.

The most obvious difference between incremental learning and traditional learning is the streaming training data. Retraining the system each time for the new data seem to be wasteful.

Generally speaking, incremental learning system refer to two learning abilities [1]. 1. Examples-incremental learning. The learned model can continuously be updated with new training data. 2. Class-Incremental Learning. The model can continuously learn the new class. That means the system can recognize new activities incrementally without retraining the whole system.

We focus on the new class learning. Some incremental learning methods [2] are improved from cluster-based ML algorithm. Marko Ristin propose NCM Forest [3] for large-scale incremental image recognition. The core concept is to update part of the forest nodes and leaves without retraining the whole forest. Some transfer learning methods [4] [5] are also proposed to exploit prior knowledge to help us learn the new class. Bo-Feng Zhang even exploit SVM to build incremental learning system by learning additional one vs rest SVM [6] (C-IL).

There are still lots of challenges for incremental learning. First of all, all the incremental learning model still have the limited recognition performance with more class it had learned. Additionally, with the extension of the system, it will require increasing memory storage and more learning time. Consequently, it's still hard to utilize the incremental learning system in many large-scale and real-world applications.

In the remainder of the paper, we will detail the incremental learning method we use and the technique to deal with these issues. Then we will illustrate the whole system we propose for the incremental learning system.

II. Incremental Learning Algorithm

A. Nearest mean classifer (NCM + SGD)

For the learning system, we follow the concept of NCM [2]. Nearest mean classifier will learn the centroids for each class and recognize the data by finding out the nearest class's centroid.

$$C_n = Argmin\, d(x\,, u_n) \tag{1}$$

$$\mu_n = \frac{1}{N_c} \sum_{y_i=n} X_i \tag{2}$$

The Mahalanobis distance is induced by to W to lower dimension space (3). Class probabilities $p\ (y|\ x)$ are obtained based on multi-class logistic regression. For each time the new class is coming, we have to learn weight matrix W for the new data. To learn all classes separately, stochastic gradient decent technique is induced to maximize the log-likelihood (4) for each sample.

$$d_w(x - x') = (x - x')^T W^T\, W(x - x') \tag{3}$$

$$L = \frac{1}{N} \sum_{i=1}^{N} \ln p(y_i \mid x_i) \tag{4}$$

$$p(c \mid x) = \frac{exp\left(-\frac{1}{2} d_w(x, \mu_c)\right)}{\sum_{c'=1}^{C} exp\left(-\frac{1}{2} d_w(x, \mu_{c'})\right)} \tag{5}$$

$$W := W - \alpha . \Delta L \tag{6}$$

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B. Representative data selection (GMM)

To reduce the increasing memory issues, we select the representative data for each class rather than store all the data we learned. We use Gaussian Mixture Model to determined representative data. GMM will calculate the posterior probabilities for each point, which indicate the probability belonging to each cluster.

We regard the data with higher posterior probability as the representative data and apply the representative data to the learning process. The system can largely reduce memory storage and the learning computation as new data continuously stream in.

III. EXPERIMENT

To examine the robustness and efficiency of the incremental learning algorithm, we use the ImageNet dataset and represent each image with bag of visual words computing from dense-SIFT descriptor. Each classes contains 1000 training images. We implement our system on a 3.40GHZ CPU and let the incremental learning system to learn from 5 original classes to 15 classes. We compare the re-learning time and accuracy performance with SVM, which is one of the most prevailing machine learning technique in many visual applications. We also compare the our method with C-ID[6], NCM with Similarity-Embedded Hashing. The result is demonstrated in Fig. 1.

Result show that our learning system (NCM+SGD+GMM) can achieve competitive performance with average 3%~6% worse than retraining SVM, but can largely save the re-learning time and save 75 % memory usage. In addition, comparing with other incremental learning technique, it seem to be more robust according to the average accuracy decay rate (– 2.06 %) when learning each new class.

IV. LEARNING SYSTEM

The whole system we proposed is show in Fig. 2. When unseen action are detected by unknown detector. We have to tell the system a semantic label and start the incremental learning process.

To mimic real-world learning scenario, we use streaming video dataset and compute the HON4D descriptor [7]. The system has already trained 10 actions previously. After 8 new action are learned, it can still achieve average 80 % accuracy.

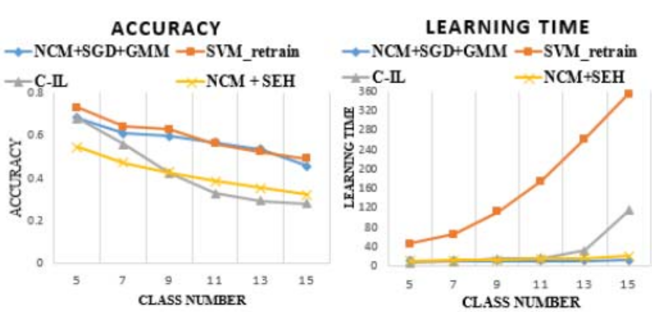

Fig. 1. (a) show learning time when learning each N+1 class (b) show the accuracy performance when learn each N+1 class

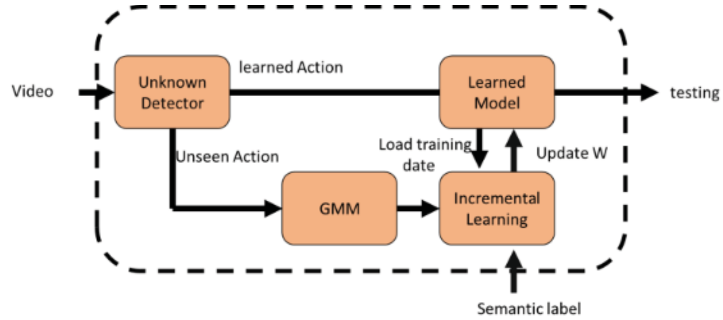

Fig. 2. Detail of the proposed incremental action learning system

TABLE I

class order	*11th*	*12th*	*13th*	*14th*	*15th*	*16th*	*17th*	*18th*
action	*Hand clap*	*Hand wave*	*Side-boxing*	*Forward kick*	*Side kick*	*joggin g*	*Tennis swing*	*Tennis serve*
accuracy (%)	75.3	76.3	78.65	79.2	80.2	81.43	80.95	81.65
learning time (s)	131	138	131	132	135	135	138	137

I. DISCUSSION AND CONCLUSION

In this paper, we consider future machine learning scenario. In traditional machine learning scenario, SVM, Deep learning and some other mature ML techniques already provide fantastic performance. However, retraining time and memory issues need to be considered in incremental learning scenario. We apply the characteristic of NCM and representative data selection technique to reduce the incremental learning cost. The action learning system we proposed can scale up with limited cost and memory usage.

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