

A Novel Fusion Method for Semantic Concept Classification in Video

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Abstract—Semantic concept classification is a critical task for content-based video retrieval. Traditional methods of machine learning focus on increasing the accuracy of classifiers or models, and face the problems of inducing new data errors and algorithm complexity. Recent researches show that fusion strategies of ensemble learning have appeared promising for improving the classification performance, so some researchers begin to focus on the ensemble of multi-classifiers. The most widely known method of ensemble learning is the Adaboost algorithm. However, when comes to the video data, it encounters severe difficulties, such as visual feature diversity, sparse concepts, etc. In this paper, we proposed a novel fusion method based on the CACE (Combined Adaboost Classifier Ensembles) algorithm. We categorize the visual features by different granularities and define a pair-wise feature diversity measurement, then we construct the simple classifiers based on the feature diversity, and use modified Adaboost to fusion the classifier results. The CACE algorithm in our method makes it outperform the standard Adaboost algorithm as well as many other fusion methods. Experimental results on TRECVID 2007 show that our method is an effective and relatively robust fusion method.

Index Terms-Fusion; classifiers ensemble; Adaboost; semantic concept classification

I. INTRODUCTION

Content-based video retrieval though has been extensively studied for many years, there are still difficulties lying in how to cross the gap between semantic concepts and low level features. To solve this problem, approaches are proposed to learn semantic concepts using machine learning to establish a mapping between the learned concepts and

low-level features, which have provided good results in recent TRECVID benchmarks [1].

These semantic concepts cover a wide range of topics that can be roughly categorized as objects, scenes and events. The main idea of semantic concept classification is to treat it as a statistical learning problem. For each video shot, the associated concepts can be detected using multiple unimodal classifiers or multimodal classifiers [2] based on visual, audio and text/speech features. Using an annotated corpus and different learning algorithms, these concepts can be learnt.

However, new issues are arising on the combination (fusion) of several features, modalities and/or intermediate concepts to obtain a better accuracy of concept classification. Using a generic framework, usual approaches based on fusion propose either to combine feature data on a concatenated vector before achieving classification, called early fusion, or to perform several classification and then to merge confidence scores or ranks using classifier combination methods, called late fusion [3].

Early fusion methods are not practical for such a large number of features in video due to the high dimensionality of any combined representation. Late fusion methods, can potentially support adaptive fusion strategies, and have been widely accepted.

Previous theoretical and empirical researches have shown that it is promising to fusion classification based on ensemble learning. The ensemble classifiers are often more effective than single classifiers. To construct an ensemble classifier, there are two key issues: the first is on which features do the classifier construct, the second is how to select weak classifiers to generate ensembles classifier. Adaboost is the most popular method for ensembles and has been proved to be more robust than many other fusion methods on the TRECVID. However, the standard Adaboost seems not as effective as expected when used in TRECVID.

In this paper, we proposed a novel fusion method based on the Combined Adaboost Classifier Ensembles algorithm.

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We category the visual features by different granularities and define a pair-wise feature diversity measurement, and then we construct the simple classifiers based on the feature diversity, and use modified Adaboost to fusion the classifier results. Both feature diversity measurement and constructing weak classifiers based on feature diversity, which gives more flexibility to fusion make our CACE algorithm a more effective fusion method than the standard Adaboost [4], and other fusion methods.

The organization of this paper is as follows. First, we introduce fusion for semantic concept classification and Adaboost for classifiers ensemble in section 2. Then we discuss the feature diversity and present a process of Combined Adaboost Classification Ensemble algorithm in section 3. We discuss the experimental setup in which we evaluate our method and present results in section 4. Finally in section 5 we summary our conclusions.

II. RELATED WORK

A. Fusion for Semantic Concept Classification

Currently concept classification approaches usually comprise three components: low-level feature extraction, classification training and fusion. As an indispensable phase, fusion has received considerable attention in the past few years.

As noted above, there are two general fusion strategies within the machine learning trend to video semantic analysis, namely: early fusion and late fusion. They are different in the way they integrate the results from feature extraction on the various modalities.

The common basic framework for concept classification which relies on information fusion can be depicted as follows: build weak classifiers independently using different low-level features and take the weighted result as the final output. Various low-level features are extracted such as visual features, audio features, textual features, and so on. Support Vector Machines (SVM) is often used to build weak classifiers for different features. Then the fusion of these weak classifiers is made.

According to the process of algorithms, fusion can be divided into two types, non-heuristic and heuristic. Non-heuristic algorithms does not need the training process, through a simple calculation they can get the results, such as Max, Min, Average, and Product, etc. Non-heuristic algorithms are simple but not efficient enough. Heuristic algorithms include some parameters, and require special data sets for training. Such algorithms are OWA (Ordered Weighted Average [5], WA (Weighted Average) [6], Adaboost, and so on. In the field of semantic concept classification, there are a lot of fusion methods which have been applied. Recent researchers have provided successful tools for semantic concept classification and video retrieval problems, such as IBM, Microsoft and Tsinghua [1]. Nevertheless, it is still far away from finding a robust and effective fusion method yet.

B. Adaboost for Classifiers Ensembles

The method of combining the class predictions from multiple classifiers is known as ensemble learning. By the inspiration of ensemble learning, more and more ensemble classifiers have been introduced in the field of pattern recognition, such as face recognition, image annotation. Since the ensemble classifiers often have been shown to be more effective than single classifiers, ensemble learning model is adopted as a fusion framework which has been used to aggregate weak classifiers efficiently and effectively for semantic concept classification.

The most widely known method of ensemble learning is Adaboost. It has been proved to be a more robust algorithm than many other ones. However, when it comes to the video data, the standard Adaboost seems not as effective as expected in TRECVID. To conquer the ineffectiveness of the standard Adaboost, several improvements have been made on the original algorithm, but still can not really solve the problems. Since the video data have a large number of diverse features, and the features is invariant to kinds of variances, it hard to find a unified scheme that can deal with the problems and avoid curse of dimensionality as well.

III. THE FRAMEWORK

First we show the categories of visual features. Then we construct the weak classifiers based on the diversity measurements. Finally we further expatiate our CACE algorithm and its implementation.

A. Features

We distinguish the features because the effectiveness of ensemble classifiers relies on the features that construct the base classifier. Different features of the base classifiers will lead to different fusion results.

In order to solve the first key issue of classifier ensemble, we categorize the features by the hierarchical granularity they are extracted, namely global, grid, and keypoint. The diversity of feature comes from the different granularity, feature types and feature extraction methods. While the global features capture holistic statistical properties of one image, the grid-based features focus on characterizing variations in a specific area of the same image, and the keypoint-based features account for the fine details in the image [7].

The global granularity is the coarsest granularity, including color histogram (CH), color correlogram (CC) Co-occurrence texture (CT), and Edge Histogram (EH).

- CH- global color represented as a 166-dimensional histogram in HSV color space;
- CC- global color and structure represented as a 166-dimensional single-banded auto-correlogram in HSV space using 8 radii depths;
- CT- global texture represented as a normalized 96-dimensional vector of entropy, energy, contrast, and homogeneity extracted from the image gray-scale co-occurrence matrix at 24 orientations;

- EH- global edge histograms with 8-edge direction bins and 8-edge magnitude bins, 64-dimensional based on a Sobel filter.

The Grid Granularity, which is of the middle granularity, contains two kinds of layout features extracted from a grid partition. They are Color moment (CM) and Wavelet Texture (WT).

- CM- localized color extracted from a 5*5 grid and represented by the first 3 moments for each grid region in Lab color space as a normalized 225-dimensional vector;
- WT- localized texture extracted from a 3*3 grid and represented by the normalized 108-dimensional vector of the normalized variances in 12Haar wavelet sub-bands for each grid region.

The Keypoint granularity describes the characteristics of regions around the keypoints. We use the SIFT descriptor [8].

- SIFT- weighted and interpolated histogram of the gradient orientations and locations in a patch surrounding the keypoint, and the keypoint detector we use is Difference of Gaussian (DoG). It uses 4*4 location and 8 orientation bins, and 128 in total.

B. Diversity Measures

So as to measure off the visual features, we need a formal definition to characterize the diversity among them, so called feature diversity. We define the feature diversity based on the classification results of single features. Among a set of single feature classifiers, basically, there are two kinds of diversity measure methods, pairwise and non-pairwise.

Pairwise measures consider a pair of classifiers at a time. Non-pairwise measures consider all the classifiers together and calculate directly one diversity value for the ensemble.

Here we use a pair-wise feature diversity measurement between each two features as the correlation between their outputs. Consider two single feature classifiers C_i and C_j , the output of them is shown in TABLE I.

TABLE I. A PAIR OF CLASSIFIERS RELATIONSHIP TABLE.

	C_i correct(1)	C_i wrong(0)
C_j correct(1)	p^{11}	p^{10}
C_j wrong(0)	p^{01}	p^{00}

where, p^{00} = Classifier i is incorrect, Classifier j is incorrect
 p^{01} = Classifier i is incorrect, Classifier j is correct
 p^{10} = Classifier i is correct, Classifier j is incorrect
 p^{11} = Classifier i is correct, Classifier j is correct

Entropy is the best-known measure of uncertainty [9], and the definition of it is as following:

$$H(x) = -\sum p \log_2 p \tag{1}$$

In which p means the probability of a given symbol.

An entropy-based pair-wise diversity measure can be noted as follows

$$\frac{2}{L(L-1)} \sum_{i=1}^{L-1} \sum_{j=i+1}^L -(p^{00} \log p^{00} + p^{01} \log p^{01} + p^{10} \log p^{10} + p^{11} \log p^{11}) \tag{2}$$

Since we are concerned with finding more positive instances than negative ones, we use the top ranked outputs of each classifier. We define the top k ranked result lists of single feature classifiers C_i and C_j as τ_i^k, τ_j^k , and the feature diversity is defined as

$$Diversity(\tau_i^k, \tau_j^k) = \tag{3}$$

$$\frac{2}{L(L-1)} \sum_{i=1}^{L-1} \sum_{j=i+1}^L -(p_k^{00} \log p_k^{00} + p_k^{01} \log p_k^{01} + p_k^{10} \log p_k^{10} + p_k^{11} \log p_k^{11})$$

The larger $Diversity()$ between the two classifiers results, the larger the diversity between the two features.

C. Combined Adaboost Classifiers Ensemble

Our Combined Adaboost Classifier Ensemble algorithm is composed of two stages. The first stage, we use the process *Build-Classifier-Ensemble()* to get the weak classifiers based on the feature diversity. The diversity among the combination of classifiers is defined as: if one classifier has some errors, then for combination, we look for classifiers which have errors on different objects [10].

In the second stage, we use AP-based Adaboost [11] to combine the results of each weak classifier. The whole process of our algorithm is shown in Figure 1.

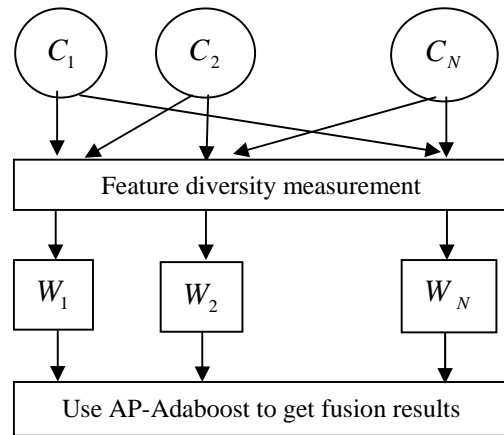


Figure 1. Combined Adaboost Classifiers Ensemble

The process of building weak classifiers can be described in TABLE II as follows.

TABLE II. THE PROCESS OF BUILDING-CLASSIFIER-ENSEMBLE ().

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Process: Build-Classifier-Ensemble ()
Input dataset  $D, S$ . The types of feature is  $N$ 
For each instance in  $D$ 
    Training the classifier  $C_i$  [ $i=1.. N$ ] of each feature.
For  $i=1$  to  $N$ 
    For  $j=1$  to  $N$ 
        Diversity measurement (classifier  $C_i$ , classifier  $C_j$ )
    End For
End For
 $S' \leftarrow \Phi, D_{new} \leftarrow \Phi, W \leftarrow \Phi$ 
For  $i=1$  to  $N$ 
    Select the classifier  $C_k$  ( $k \in N$ ) of maximum diversity.
    For each instance  $I_x$  in  $D, S$ 
        Use classifier classifier  $C_k$  to make prediction.
        If predict ( $I_x$ ) below  $\sigma$  and  $I_x \in D$ ,
             $\sigma$  is the value of experience
             $D' \leftarrow D - \{I_x\}$ 
        Else If predict ( $I_x$ ) to be positive and  $I_x \in S$ 
             $S' \leftarrow \{I_x\}$ 
        End If
    End For
     $D_{new} \leftarrow D' + S'$ 
    Build Weakclassifier  $W_i$  by training the instance of  $D_{new}$ 
End For
 $W \leftarrow W \cup \{W_i\}$ 
    
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We modify the standard Adaboost for Video data in TRECVID based on average precision (AP). AP emphasizes the return of more relevant shots earlier and is the average of precisions computed at successive recall points. Let R be the number of true relevant documents in a set of size S . At any given index j let R_j be the number of relevant documents in the top j documents. Let $I_j = 1$ if the j^{th} document is relevant and 0 otherwise. Assuming $R < S$, the non-interpolated AP is then defined as

$$\frac{1}{R} \sum_{j=1}^S \frac{R_j}{j} * I_j \tag{4}$$

The process of AP-Adaboost training and testing can be described as follow.

Input a dataset of n training instances with label $\{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, $x_i \in X, y_i \in Y = \{0,1\}$. $y_i = 0$ and $y_i = 1$ represent negative and positive instances. There are m positive instances and l negative ones of the dataset.

Suppose there are T weak classifiers W_1, W_2, \dots, W_T . Initialize the weight of each instance (x_i, y_i) as

$$\begin{cases} w_i^1 = \frac{1}{m} & y_i = 1 \\ w_i^1 = 0 & y_i = 0 \end{cases} \quad i = 1, 2, \dots, n \tag{5}$$

We normalize the weights of each instance in T

$$w_i^j \leftarrow \frac{w_i^{j-1}}{\sum_{j=1}^n w_j^{j-1}} \quad i, j = 1, 2, \dots, n \tag{6}$$

According to the prediction of instances, sort each weak classifier W_g in descending. Then initialize the number of positive instances $NumPositive_g$ and the precision of W_g precision _{g} .

$$\begin{cases} NumPositive_g = 0 \\ precision_g = 0 \end{cases} \tag{7}$$

If x is a positive instance, then

$$\begin{cases} NumPositive_g = NumPositive_g + 1 \\ precision_g = precision_g + \frac{NumPositive_g}{r} * w_g^j(x_r) \end{cases} \tag{8}$$

Choose the weak classifier with the maximum precision as the classifier chosen in this run which has the best performance, as W_t

The error rate of W_t is

$$\varepsilon_t = 1 - precision_t \tag{9}$$

Accordingly, we update instances weights

$$w_i^{t+1} = w_i^t \beta_t^{\varepsilon_i}, i = 1, 2, \dots, n \tag{10}$$

Where $\varepsilon_i = |W_t(x_i) - y_i|, \beta_t = \frac{1 + \varepsilon_t}{1 - \varepsilon_t}$

So, the weight of weak classifier W_t is

$$\alpha_t = \log\left(1 + \frac{1}{\beta_t}\right) \tag{11}$$

Then normalize the weights of weak classifiers

$$\alpha_t \leftarrow \frac{\alpha_t}{\sum_{j=1}^T \alpha_j} \quad t = 1, 2, \dots, T \tag{12}$$

Finally, the strong classifier is the sum of T weak classifiers selected which allow repetition as follows

$$W(x) = \sum_{t=1}^T \alpha_t W_t(x) \tag{13}$$

We use weighted AP as the criteria of weak classifier selection in each run. See (8), and instance weight as a weighted factor. If an instance is of the greater weight and the higher ranking, it makes greater contribution to the accuracy of weak classifier. In order to ensure the algorithm logically correct, there are some modifications in the formula of ε, β and α respectively, see (9) and (10).

IV. EXPERIMENTS

A. Data Sets

We carried out the experiments and evaluated the performance of our method on TRECVID 2007 datasets. TRECVID2007 is a popular and huge video dataset for semantic video retrieval. The development data of it were comprised of 110 lens and 30.6 GB, the test data 109 lens and 29.2 GB.

In TRECVID2007 dataset, the development collection contained 21,532 reference shots and test collection contained 18,142 reference shots. In the experiments, we used the 20 semantic concepts which were selected in TRECVID 2007 evaluation. The class labels of development collection were provided by LSCOM and MCG-ICT-CAS [12] team. We adopt one key frame per shot for experiments.

We first randomly divided the development collection into three parts in accordance with the ratio of 3:2:1, and each set be denoted as D_{train} , D_{fusion} and D_{test} . We used

D_{train} to train the classifiers of each feature, and built the weak classifiers based on the feature diversity and SVM prediction in D_{test} . D_{fusion} was used for Adaboost training.

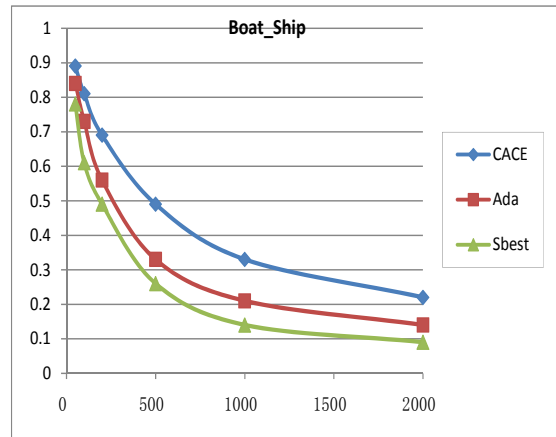
We practiced our algorithm in the test collection. Figure 2 shows the key frames of the 20 semantic concepts.



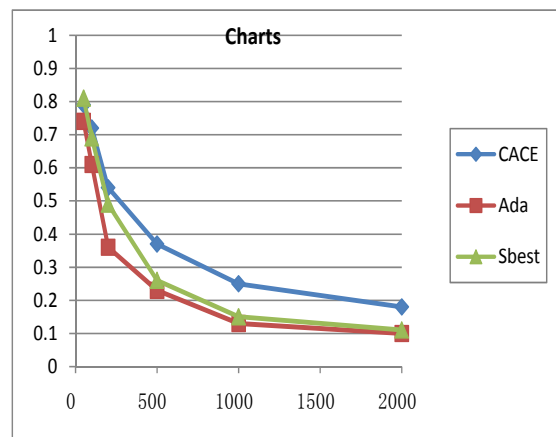
Figure 2. Key frames examples of 20 concepts in TRECVID 2007 evaluation

B. Experiment Results

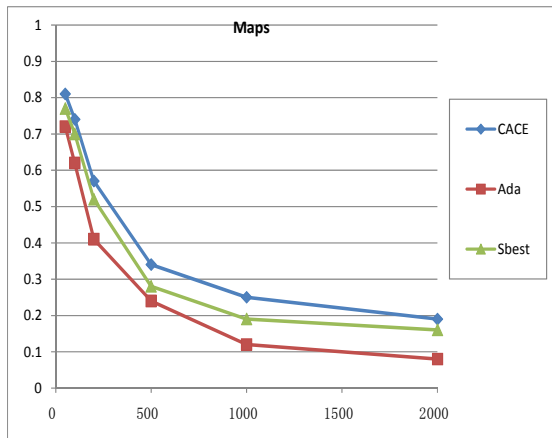
In our experiment, we compared our CACE algorithm with the standard Adaboost (Ada), and the best result of single visual classifiers (Sbest). Figure.3 shows the result of several concepts on the test collection. There are Boat_Ship, Charts, Maps, Computer_TV-screen, Weather, and Waterscape_Waterfront. The AP (ordinate) is computed over the top k ranked results, where k is equal to 50, 100, 200, 500, 1000, and 2000(Abscissa). As seen in the figure, the CACE algorithm outperformed Ada and Sbest.



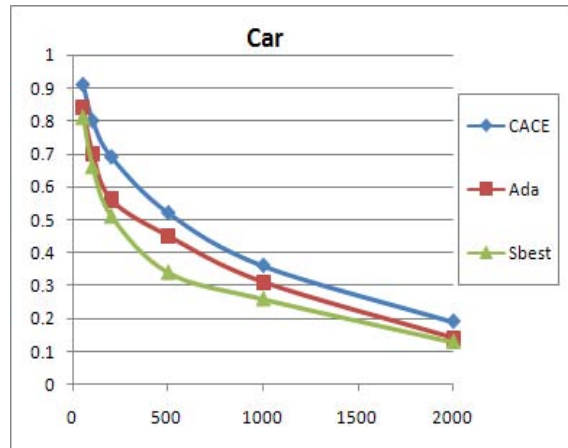
(a)Boat_Ship



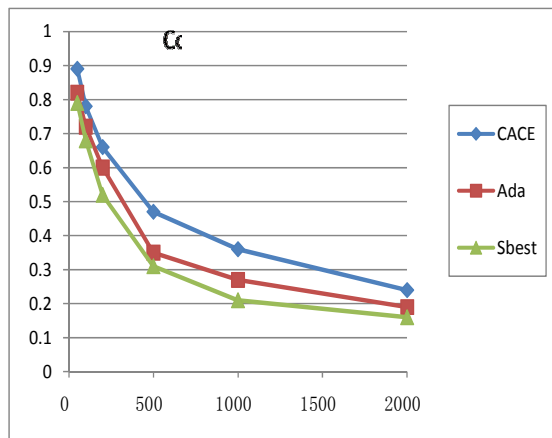
(b)Charts



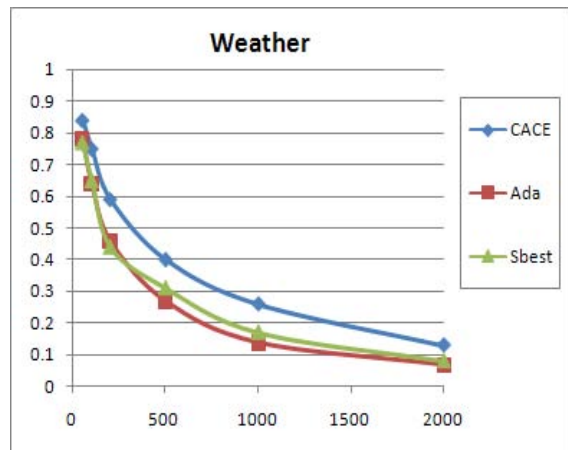
(c)Maps



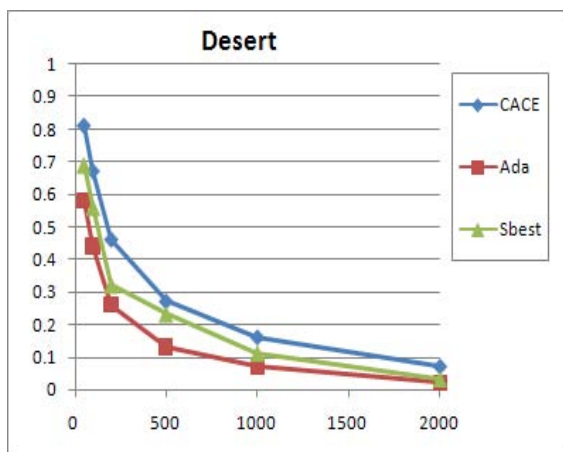
(f)Car



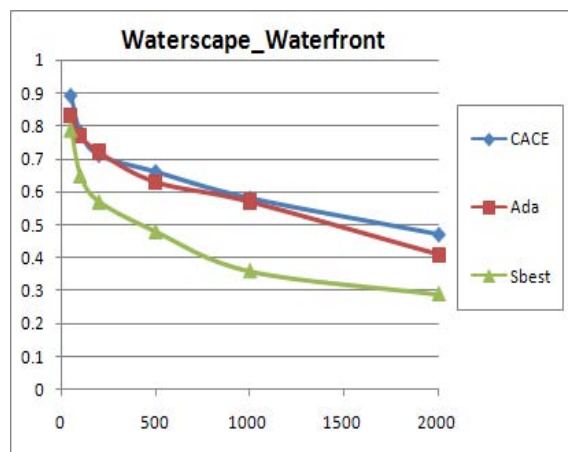
(d)Computer_TV-screen



(g)Weather



(e)Desert



(h)Waterscape_Waterfront

Figure 3. Comparative experiments of CACE, standard Adaboost and the best single classifier result on several concepts

With CACE algorithm, we have conducted experiments on 20 semantic concepts of TRECVID 2007 datasets by comparing it with the standard Adaboost and the best single classifier. 12 of them achieved higher average precision. There are Weather, Desert, Waterscape_Waterfront, Animal, Car, Boat_Ship, and so on. In addition, some of the 20 concepts equaled to best of three. See Table 3 for details.

TABLE IV. EXPERIMENT RESULTS OF COMPARIN CACE, STANDARD ADABOOST AND THE BEST SINGLE CLASSIFIER ON 20 CONCEPTS

Concept	Sbest	Ada	CACE
Sports	0.1512	0.2104	0.2081
Weather	0.0799	0.0791	0.0912
Office	0.1242	0.2784	0.2503
Meeting	0.1307	0.1387	0.1362
Desert	0.0691	0.0213	0.0725
Mountain	0.1727	0.1636	0.1562
Waterscape_Waterfront	0.1924	0.4106	0.4891
Police_Security	0.0112	0.0021	0.0024
Military	0.0965	0.0710	0.1022
Animal	0.3277	0.3411	0.3578
Computer-TV_screen	0.1782	0.2060	0.2279
Flag_US	0.0041	0.0078	0.3605
Airplane	0.1122	0.0856	0.0972
Car	0.1522	0.1591	0.1823
Truck	0.0101	0.0059	0.0063
Boat_Ship	0.1011	0.1371	0.2183
People_Marching	0.1083	0.1089	0.1081

Concept	Sbest	Ada	CACE
Sports	0.1512	0.2104	0.2081
Explosion-Fire	0.0039	0.0156	0.0301
Maps	0.1673	0.0592	0.1923
Charts	0.1106	0.1082	0.1799
MAP	0.1152	0.1305	0.1734

On the whole, CACE provided a 4.29% gain to the standard Adaboost and gain to the best classifier in mean AP (MAP).

Finally, we compared six fusion methods with CACE including Max, Min, Average, WA, OWA and Standard Adaboost in 20 concepts. Figure 4 shows our experimental results. During the experimenting process, we looked for the most effective fusion method for each concept and found the CACE a relative robust and effective method. The statistic is listed in Table 4, best results of 9 out of 20 concepts which is 45% come from our CACE algorithm. It is obvious that CACE outperforms the other six fusion methods.

TABLE V. STATISTIC RESULT ABOUT SIX FUSION METHODS AND CACE ON 20 SEMANTIC CONCEPTS

Line	Fusion	Counts of Best	Percent
Line1	MAX	0	0
Line2	MIN	0	0
Line3	AVG	1	5%
Line4	WA	2	10%
Line5	OWA	5	25%
Line6	Adaboost	3	15%
Line7	CACE	9	45%

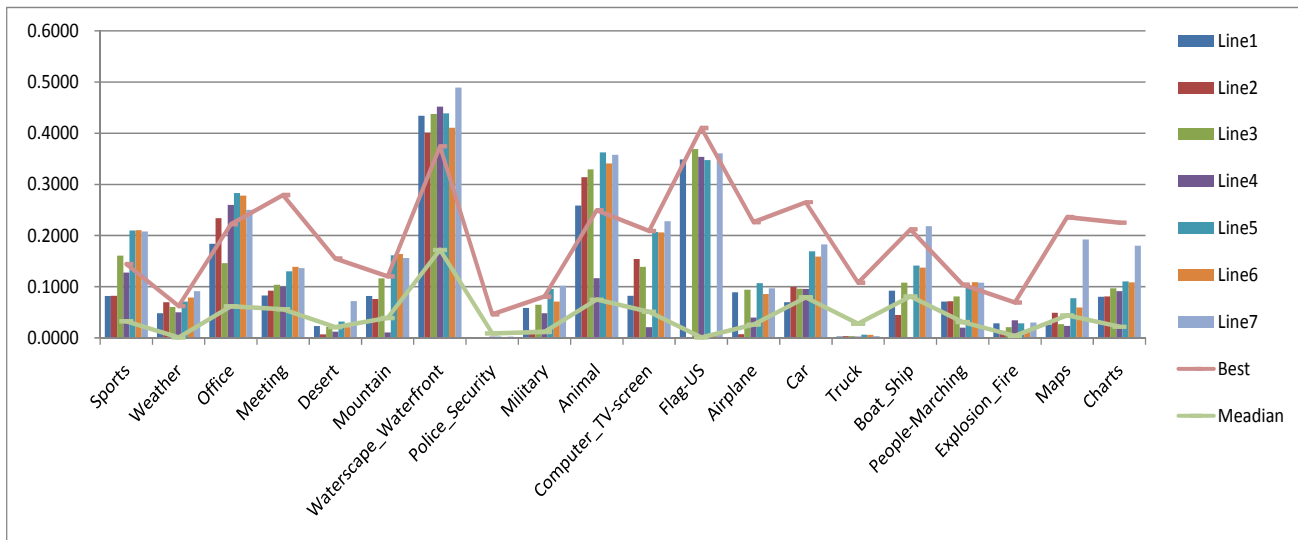


Figure 4. MAP Performance of our experiments for each concept vs. median and best performance of all submitted run of TRECVID 2007 evaluation

V. CONCLUSIONS

To sum up, this paper focuses on ensemble learning methods for semantic visual concepts classification and proposes CACE fusion algorithm. CACE algorithm is an effective and relatively robust fusion method which outperforms the standard Adaboost and many other current methods. The CACE differs from previous fusion methods in that it relies on the diversity measurement. The CACE constructs the simple classifiers based on the feature diversity, and uses AP-based Adaboost to fusion the classifier results. Our current experiments indicate that CACE either outperforms other fusion methods or is comparable to them.

However, there are still a few concepts that the classification accuracy of them cannot be improved by the CACE algorithm. In our opinion, the main reason lies in both of the limit of diversity measurement and the imbalance data problem. It also needs further study on how to further enhance the classification accuracy of more concepts, as well as to provide more diversity in the visual features of the measurement. They are left as topics for future research.

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