Multi-class Image Classification Based on Fast Stochastic Gradient Boosting

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Nowadays, image classification is one of the hottest and most difficult research domains. It involves two aspects of problem. One is image feature representation and coding, the other is the usage of classifier. For better accuracy and running efficiency of high dimension characteristics circumstance in image classification, this paper proposes a novel framework for multi-class image classification based on fast stochastic gradient boosting. We produce the image feature representation by extracting PHOW descriptor of image, then map the descriptor though additive kernels, finally classify image though fast stochastic gradient boosting. In order to further boost the running efficiency, We propose method of local parallelism and an error control mechanism for simplifying the iterating process. Experiments are tested on two data sets: Optdigits, 15-Scenes. The experiments compare decision tree, random forest, extremely random trees, stochastic gradient boosting and its fast versions. The experiment justifies that (1) stochastic gradient boosting and its extensions are apparent superior to other algorithms on overall accuracy; (2) our fast stochastic gradient boosting algorithm greatly saves time while keeping high overall accuracy.

Povzetek: Predstavljena je primerjava algoritmov za večrazredno klasifikacijo slik.

1 Introduction

With the extensive application of the Internet, search engines have become an important tool for people to obtain information, including image information which is one of the most important and interesting information. Traditional search engines on the Internet, including Google, Bing and Baidu have launched a corresponding image search function, but this kind of searching is mainly operated by the file names or related text information of the images. However, it has obvious limitations such as: file name or related information is not accurately related with the image content. So information retrieval based on image content becomes one of the hottest studies of the image retrieval. image classification is based on the image content-based information retrieval, which is based on visual information. Image classification mainly involves two aspects: One is the image feature representation and coding, on the other hand is a classifier selection.

Haralick etc. [1] first proposed a method for feature representation based on image texture features, which is considering the texture characteristics of the image feature space relations, texture and spectral information and its statistical characteristics. Later, considering rotation, affine and other factors, people gradually propose feature representation methods such as LBP [2], SIFT [3], HOG [4] and etc. Statistical represented feature coding method has been widely used, for example a typical representative of the texture histogram representation (histogram of textons) [5] and bag of words or bag of features [6] coding. In recent years, people also proposed a histogram-based pyramid encoding as PHOG (Pyramid Histogram Of Gradient) [7] and PHOW (Pyramid Histogram Of visual Word) [8]. In order to further improving the discriminative capability of feature descriptors, people propose kernel transformation such as Vedaldi's additive kernel transformation [9] can effectively enhance classification performance.

Several classifiers have been successfully used for image classification such as support vector machines, random forests and so on [10]. Haralick etc. [11] first propose method based on image characteristics, using the linear discriminant maximum and minimum decision rules to classify discrimination on the data set and aerial imagery sandstone micrographs. They obtain more than 80% accuracy rate. Ridgeway etc. [12] introduce method based on the corners with features and weighted K nearest neighbor classifier for image classification. They obtain of 93.6% accuracy rate in the 2716 image data sets, and promote performance of the method to three categories (land, forests and mountains, sunset and sunrise). Chapelle etc. [13] use histogram features and support vector machine classifier to achieve the classification performance of 89% accuracy rate on the Corel14 data set. Foody etc. [14] apply support vector machines for remote sensing image classification. They obtain 93.5% accuracy rate, better than the tree algorithm of 90.3% and discriminant analysis method of 90%

accuracy rate.

This paper presents a framework to enhance the natural image classification performance based on PHOW features representation and fast stochastic gradient, and we obtain more than 99% and 84% accuracy rate on the data set Optdigits and 15-Scenes respectively.

2 Fast stochastic gradient boosting algorithm

2.1 Analysis and comparison of algorithms based on decision tree

Traditional classification and regression trees (Classification and Regression Tree, CART) proposed by Breiman [15] is a simple and effective method, but there are many flaws [16]: 1) because decision tree is based on local optimum principle, this will led to the whole tree is not often global optimal. 2) inaccuracies and abnormal training samples have a great impact on the CART. 3) The imbalances of training sample types also affect CART performance.

Improving and enhancing the performance of classification and regression trees is a valuable question. In recent years, bagging and boosting method is the most effective ways. Bagging method [17] is an autonomous improving method, which is a random subtree building based on subsampling over all training samples to obtain samples.

Bagging method proposed by the Breiman [18] is also based on random forest, which use decision trees as a metaclassifier with independent clustering method (Bootstrap aggregation, Bagging), thus produces different training set to generate each component classifier, and finally determine the final classification results by a simple majority vote.

Extreme random tree [19] is similar to the random forest. The tree pieces are combined to form a multi-classifier, the difference with the random forest mainly involving two sides:

1) Sampling the original training samples with replacement strategy, aiming at reducing bias;

2) Splitting test threshold of each decision tree node is selected at random. Assuming split test expression is $split(x) > \theta$, where x is to be classified samples, $split$ is the test function in the random forest classifier, θ is usually based on a sample of a feature set, and in the extreme random forest classifier, θ is randomly selected.

Boosting method [20] is the method, which is starting from the basic classification tree, though iterative process, wrong classification of data give higher weights to build a new round of classification trees greater emphasising on these error detection data. Final classifier classification is based on the principle of majority voting. Despite boosting method is not accurate in some particular cases. But in most cases, it significantly enhances the classification accuracy [21].

Gradient Boosting proposed by Friedman [22] is further improvement over boosting. Their difference with the traditional approach is to improve every computing in order to reduce losses. In order to eliminate losses, it create a new model in the direction of the gradient to reduce losses so that the gradient can be descent. The big difference with conventional methods is that the new model is created from residual losses of the gradient direction of the model in order to reduce losses. Inspiring by bagging random thoughts of Breiman, Friedman introduced stochastic gradient boosting based on random sub-sampling to obtain training samples [23].

In short, bagging and boosting methods both can be called to vote or integrated approach to generate a set of sub-tree or forests, while classification is according to the sub-tree or forest in the whole set or voting on every tree. The difference is that they generate different sub-tree or forests by different ways.

2.2 Fast stochastic gradient boosting algorithm

Fast stochastic gradient boosting algorithm is shown in the Algorithm 1. where $\pi(i)_1^N$ is the random combinations of set of integers $1, 2, ..., N$, assuming sample size of random down-sampling is $\hat{N} < N$, The corresponding sample result is $(y_{\pi(i)}, x_{\pi(i)})_1^{\hat{N}}$. $F_m(x)$ is for the first m points. L is the loss function, M is the number of weak classifiers, C is class sample, R is the leaf node region, J is a terminal leaf number of nodes, ρ is the optimal weak classifier coefficient, S is the number of samples to detect the error, err and err_{min} are the exit variable, **parallel** refers parallel processing.

Algorithm inputs are training samples, outputs $\tilde{F(x)}$ are the output set of weak classifiers.

The step 1 to 17 of the algorithm is weak classifier training processes consisting of three components: The step 2 is randomized sampling. The steps 3 to 10 is weak classifier training stages. The step 11 to 16 is error detection.

The step 2 obtains training samples by randomly sampling for each weak classifier. The step 3 to 10 is weak classifiers training process by classes in turn, which contains: 1) calculating the loss, the loss for classification problems using deviance loss; 2) by calculating the value of the loss of function in the negative gradient of the current model, which was estimated as a residual;3) training a decision tree classifier based on the basic decision tree;4) updating residuals;5) calculating the optimal weak classifier coefficients; 6) generating a new weak classifiers.

The step 11 to 16 is error detection. Classification training and each error detection are simultaneously. Weak classifiers stop training when the error is less than a certain threshold.

Finally, the step 18 is the results of linear combination of weak classifiers constituting the set of training stochastic gradient boosting tree model.

Algorithm 1 Fast stochastic gradient boosting algorithm.

Input:

training data set : $T = (x_1, y_1), (x_2, y_2), ..., (x_N, y_N), x_i \in R^N, y \in Y \in R, N$ is the number of training samples.

initialization : $F_0(x) = 0, M = 100, err = 0, err_{min} = 0.0001$.

Output:

combination set of classification trees : $\hat{F}(x)$

.

for $m = 1$ to M **do**

random sampling of (**parallel**): $\pi(m)^{\hat{(N)}_1} = rand\_perm(m)_1^N$

for $k = 0$ to C **do**

calculating loss : $p_k(x) = \exp(F_k(x)) / \sum_{l=1}^{C} \exp(F_l(x)), k = 1, 2, ..., C$

calculating the gradient (**parallel**):

$$\tilde{y}_{\pi(i)k} = -\left[\frac{\partial L(\{y_{\pi(i)l}, F_l(x_{\pi(i)})\}_{l=1}^{C})}{\partial F_k x_{\pi(i)}}\right]_{\{F_l(x)=F_{l,m-1}(x)\}_1^Y} = y_{\pi(i)k} - p_{k,m-1}(x_{\pi(i)}), i = 1, 2, ..., \tilde{N}$$

basic training for weak classifiers (**parallel**): Based on the decision tree (CART).

calculating residuals (**parallel**): $\{R_{jkm}\}_{j=1}^{J} = J - terminal\_node\_tree(\{\tilde{y}_{\pi(i)k}, x_{\pi(i)}\}_1^{\tilde{N}})$

calculating the optimal weak classifier coefficients :

$$\rho_{jkm} = \arg\min \frac{C-1}{C} \frac{\sum_{x_{\pi(i)} \in R_{jkm}} \tilde{y}_{\pi(i)k}}{\sum_{x_{\pi(i)} \in R_{jkm}} \left|\tilde{y}_{\pi(i)k}\right| (1 - \left|\tilde{y}_{\pi(i)k}\right|)}, j = 1, 2, ..., J$$

generating new weak classifiers :

$$F_{km}(x) = F_{km-1}(x) + \sum_{j=1}^{J} \rho_{jkm} 1(x \in R_{jkm})$$

end for

training error detection:

sampling : $\{test(m)\}_1^S = rand\_perm\,\{m\}_1^N$

detection error (**parallel**): $err = predict(\{test(m)\}_1^S)$

if $err < err_{\min}$ **then**

exit from weak classifiers cycle

end if

end for

obtaining a combination set of classification trees :

$$\tilde{F}(x) = F_{MC}(x) = \sum_{m=1}^{M} \sum_{k=1}^{C} F_{km}(x)$$

Stochastic gradient boosting algorithm for its high accuracy rate received wide acclaim and is considered one of the most effective methods of statistical learning in classification, but its operational performance is poor, we propose two ways to improve its running performance: local parallelization and error detection shorten training times of weak classifiers.

The increasing popularity of multi-core processors to enhance the running performance of traditional algorithms provides another effective way. We propose a bottleneck module by way of parallel processing to enhance the stochastic gradient algorithm to improve running performance. First we consider parallel algorithms necessary and sufficient condition:

1) parallel algorithms have obvious advantages in large scale computing, and stochastic gradient boosting algorithm in step 2,5,6,7,13 involving the operation of the entire training samples, and general training samples exceeding thousands of pieces of data, so we consider parallel processing at these steps.

2) parallel algorithm must have a premise which is separability. Stochastic gradient boosting algorithm can not directly do paralleling at whole, because the algorithm is a additive model, each weak classifier training data is from error residuals of former process. So we can not be parallelized algorithm from the beginning of step 1,3. We can only do a local parallel processing.

Secondly, we tested the algorithm's main bottleneck module (refer to the module which has the inner loop in thousands) (see Table 1). The running count is the total count of overall algorithm (outer loop), The running time is running time of a single module running once. The running time of sampling and prediction is scale of microseconds, paralleling processing achieves few performance improvement. However calculation and residual gradient are in milliseconds. Parallel processing performance has significantly improved. The weak classifier training gain more performance improvement (10 milliseconds scale), since the whole number of cycles is up to 1000 times, thus improving overall training capability will reach 10 seconds. So parallel processing algorithms is necessary when algorithm involves huge data or are time-consuming.

In addition, the stochastic gradient algorithm to enhance the performance bottleneck lies in the number of basic classifiers. We tested the relationship between the number of classifiers and accuracy on the Optdigits data sets (see Figure 1). Classification accuracy was found to significantly increase with the increasement of the number of iteration process. The accuracy rate increase is not very obvious, even stagnation when iterations is up to 25. So, it is necessary to control the total number of iterations through the detection accuracy of the test sample in the training phase. To this end we introduce random sampling in order to optimize the training error detection methods to improve the stochastic gradient iterations through the step 11 to 16 (see Algorithm 1).

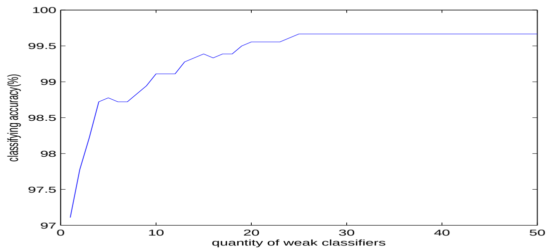


Figure 1: The relationship between classifying accuracy and quantity of weak classifiers on Optdigits data set.

3 Enhance image classification based on fast stochastic gradient boosting

This article discusses the general image classification methods and processes, we propose a fast stochastic gradient boosting to enhance image classification based the framework in Figure 2. First, we the extract image feature descriptor though PHOW features which are improved multi-scale dense SIFT descriptors, including basic steps: At first step, dense SIFT descriptors are calculated by dividing image into different scales with a fixed pixel Box (see Figure 3 line (a)). The descriptors of each grid point is calculated with four different diameter circular masks; For the second step, after extracting K-means clustering for the descriptors, a histogram is formed. At third step, we sum histogram pyramid to build space feature descriptors (see Figure 3 line (b)). Secondly, the characteristics of additive kernel transformation can generate better description of features. For finite dimensional distribution (histogram)

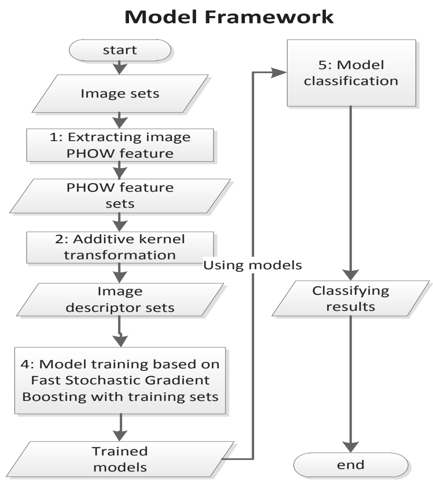


Figure 2: The framework of image classification.

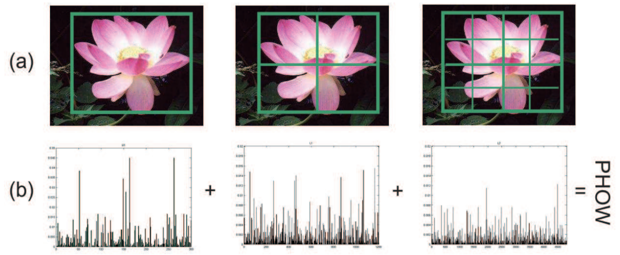


Figure 3: Image appearance representation based on PHOW.

x, y, Additive kernel is defined as :

$$K(x,y) = \sum_{b=1}^{B} k(x_b, y_b) \quad (1)$$

Here, b is a histogram of the number of each sub-grid, B is the total number of sub-grid, x_b, y_b is the distribution of every little grid, $k : \mathbb{R}_0^+ \times \mathbb{R}_0^+ \longrightarrow \mathbb{R}_0^+$ in the non-negative real number is a positive definite kernel. We proposed Vedaldi's χ^2 kernel transform for feature transformation.

Finally, We use the feature descriptors for fast stochastic gradient boosting algorithm to enhance the performance of classification model. At testing stage, we also need to extract features, then do kernel transformation of PHOW to form feature descriptor, again use a classification model to prediction. Our biggest advantage is that the entire framework is simple, good computing performance, and suitable for multi-category classification of natural images.

3.1 Experimental data sets

Optdigits data set[27] is a collection of data set standardized extracting of bit image by the U.S. National Institute of Standards and Technology handwritten Optical Character Recognition. It has 64 positive integers of feature information, the range is from 0 to 16. This data set consists of 5620 instances, belonging to 10 categories. we randomly selected 10%, 20% and 30%, 40% and 50% of total sample as the training sample, and the rest for test samples.

15-Scenes data set[28] is processed in accordance with the flow chart of our proposed framework (see Figure 2). The original 15-Scenes data set consists of 15 data categories, a total of 4485 images. We randomly select 10% and 20%, 30% and 40% and 50% of each class sample for the training sample, and the rest used to do the test samples. We use the PHOW descriptor for image features to describe each image. After kernel transformation with additive eventually, we get 36,000 dimensional feature descriptors for a single image.

3.2 Parameters

1) Maximum decision tree depth: The default value was set to 1. With the value increase, classification accuracy and running time will increase. We set maximum depth to 2, 4, 6, 8, 10, 12, 14, 16, 18 and 20 respectively. We found the highest accuracy rate when the maximum depth is 10. With similar way, we found that entropy rules of split consideration criterion get better performance.

2) The maximum depth of random random forest was similar with decision tree. The number of decision trees: we tested the value of 20, 40, 60, 80, 100, 120, 140, 160, 180 and 200 respectively. We found that the number increases, the execution time also increases, and after over the value of 100, the improvement of the accuracy rate was not obvious. So we set it to 100. The accuracy of the random forest was used to control the iteration. We tested the value of 0.0001, 0.001, 0.01 and 0.1 respectively. We found that the smaller the value was, the longer the execution time was, and after over the value of 0.001, the accuracy had no substantially change. We set it to 0.001.

3) The extreme random tree's settings was similar with random forests for consistent comparing standard.

4) With similar ways, we found that we get better performance (good balance in accuracy and running time) when the stochastic gradient enhance maximum tree depth is set to 10, cross entropy loss chosen for loss function type , 0.1 set to shrinkage factor, 0.8 set to proportional sampling under, and 100 chosen for maximum lift.

5) Similarly, in order to enhance the fast stochastic gradient boosting based on the stochastic gradient boosting, the control error was set to: 0.0001, random verification sampling ratio was set as follows: 50%.

3.3 Experimental setup

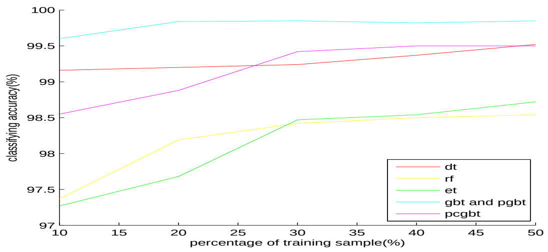
We used C++ of Microsoft visual studio 2012 to program with opencv2.4.3[24], Intel TBB[25] and darwin 1.6 platform[26]. We tested results in win7 (64) platform with hardware of Intel P6100 dual-core CPU and 6GB memory.

We converted the data set to comma delimited $M \times N$ in the form of a text file, M represented the number of (ie, the number of records) data rows, N was the number of each data attribute values. The final column was class marker.

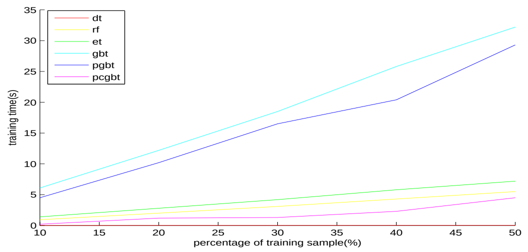
We used TBB parallel libary for parallel processing. In Algorithm 1: At steps of 2,5,7,13, We used TBB with $tbb :: parallel\_for$. At step 6 involving recursive tree, we used TBB with $tbb :: task\_list$ to achieve parallelism.

In order to better reflect the effectiveness of the proposed framework, we have two types of data sets in the test, Optdigits for low-dimensional data, 15-Scenes for high-dimensional data, and extract the sample test to verify the practicality for different circumstance.

In addition to verify the feasibility of stochastic gradient boosting algorithm and its fast versions, our experiments compared the decision tree, random forest, extreme random tree, stochastic gradient boosting , stochastic gradient boosting with error check and SVM (support vector machine). Experiment results were indicated in Table 2, 3, and Figure 4 to 7.

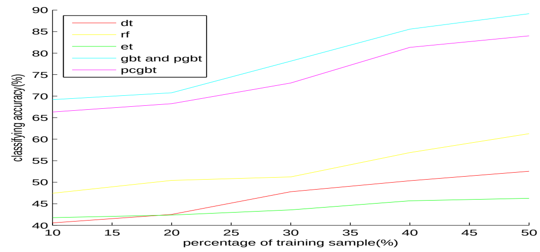


(a) Total accuracy

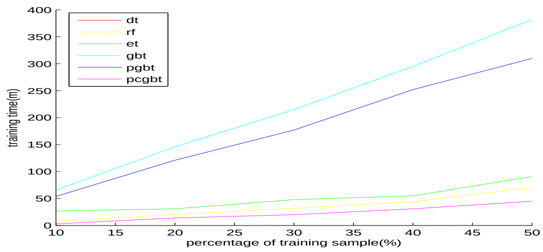


(b) Training time

Figure 4: The performances of six algorithms on Optdigits.



(a) Total accuracy



(b) Training time

Figure 5: The performances of six algorithms on 15-Scenes.

3.4 Experimental results and analysis

Table 2-3 is a averaged results tested three times under the same conditions. Where h is hours, m represents minutes, s is seconds, ms is milliseconds, such as: 1h2m3s4ms represents 1 hour, 2 minutes, 3 seconds, and 4 milliseconds. dt is a decision tree, rt is random forests, et is extreme random tree, gbt is stochastic gradient boosting, pgbt is fast stochastic gradient boosting, pcgbt is the fast stochastic gradient boosting with error check, and SVM is support vector machine.

1) With increase of the proportion of each sampling, algorithm accuracy rate increases, however the corresponding training time also increases. This indicates the adequacy of the training sample for classification accuracy is critical, but the running performance will be affected in the training. In practical applications, we should consider the two factors, and try to find the best balance between them.

2) Total accuracy comparison: As can be seen from Table 2-3 and Figure 4-5 (a), stochastic gradient boosting and fast stochastic gradient boosting have same overall accuracy. Overall accuracy on 15-Scenes data set from high to low is stochastic gradient boosting, stochastic gradient boosting with error detection, random forest, extreme random tree and decision tree. The main difference on Optdigits data set lies in that decision tree was significantly better than random forests, furthermore compared with random gradient boosting, the accuracy of our stochastic gradient boosting with error check also has a certain decline of accuracy, but is still significantly better than the decision tree and random forest.

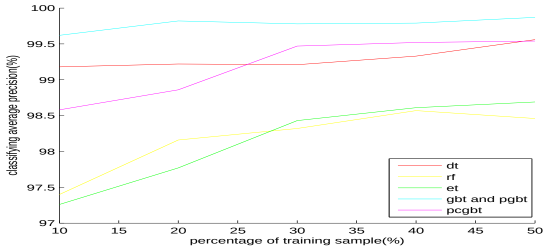
3) Running time comparison: From Table 2 to 3 and Figure 4 to 5 (b) shows that the training runtime performance in descending order is decision tree, fast stochastic gradient boosting with error detection, random forests and random forests extreme, fast stochastic gradient boosting and stochastic gradient boosting. Stochastic gradient boosting with error detection is about 10 times fast than the original stochastic gradient boosting on the data set Optdigits and 8 times on 15-Scenes data set.

4) Average recall,average precision and total accuracy comparisons: from figure 4 to 7, we can see that the cures have similar curve tendency. This shows that total accuracy basically reflect the performance of classifier on Optdigits and 15-Scenes data set respectively.

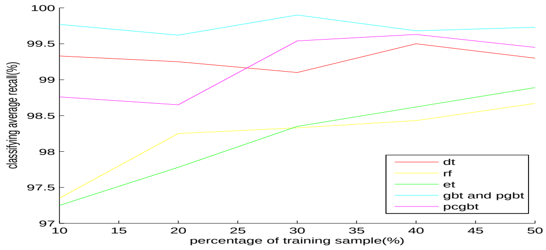
5) Comparison with support vector machine: from table 2 and table 3, we can see that the total accuracy of SVM is superior to decision tree, random forest trees and extremely random trees, however inferior to stochastic boosting tree based methods. Furthermore, on 15-Scenes data set SVM is failed when the training sampling percentages reach 40% and 50%. On the side of the training time, SVM is slower than decision tree, random forest trees and extremely random trees, but faster the stochastic boosting tree based methods.

4 Conclusions

By comparing each algorithm, we have following the experimental findings: 1) Stochastic gradient boosting is significantly better than decision tree, random forest and extreme random tree. 2) We proposed parallel stochastic gradient boosting algorithm to enhance the running performance. Experimental result of our method is significantly better than the original stochastic gradient boosting algo-

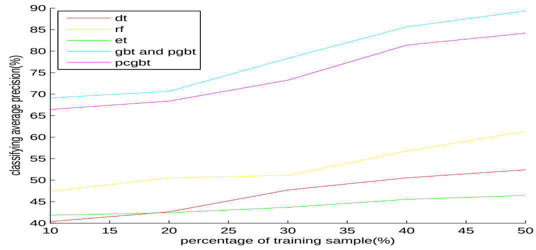


(a) Average precision

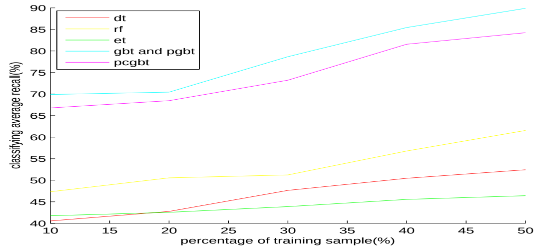


(b) Average recall

Figure 6: The performances of six algorithms on Optdigits.



(a) Average precision



(b) Average recall

Figure 7: The performances of six algorithms on 15-Scenes.

rithm. Furthermore, fast stochastic gradient boosting with error detection improves running performance to a new stage, while keeping the overall accuracy comparing to the original stochastic gradient boosting. Experiments testify that our improvement ways are effective and practical.

The main contributions of this paper are :

1) We presents a framework based on PHOW features and fast stochastic gradient boosting for natural image classification. From training sample selection, feature extracting, classifier selection to the last performance evaluation, we give a detailed analysis and commentary.

2) We analyze the running performance and bottlenecks of the stochastic gradient boosting. According to the circumstance of bottlenecks and current widely used multi-core computing, we presented modified stochastic gradient boosting to improve the performance of by local parallelism.

3) Due to reason of that increasing number of weak classifiers does not always bring better accuracy, and to further reduce the space and time of weak classifier training iterations, we introduce an error control mechanism in training phase to reduce the number of iterations of the method at the expense of a certain degree of accuracy degeneration. However, by this way we get further improvement of the running performance.

4) In this paper, a parallel realization of serial algorithm are thoroughly discussed. Taking stochastic gradient boosting as example, we proposed a well-established ideas and methods of these kind of problems, namely: 1) to detect bottlenecks, determining the optimization core; 2) the task segmentation, transforming a serial program by parallelization ideas; 3) implementation based on TBB parallel architecture.

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Modules	Sampling	calculating the gradient	weak classifier training	computing residuals	Prediction
Running count	100	1000	1000	1000	100
Serial Time	$170us$	$2.2ms$	$62ms$	$1.6ms$	$0.5ms$
Parallel Time	$150us$	$1.3ms$	$50ms$	$1.2ms$	$0.4ms$

Table 1: Serial and parallel executing time of bottleneck modules on Optdigits data set.

Accuracy (%) / Time	10 %	20 %	30 %	40 %	50 %
dt	$99.16/6.0ms$	$99.20/17.0ms$	$99.24/19.9ms$	$99.37/25.0ms$	$99.52/34.0ms$
rt	$97.37/933ms$	$98.19/2.0s$	$98.42/3.1s$	$98.50/4.3s$	$98.54/5.5s$
ert	$97.27/1.4s$	$97.68/2.8s$	$98.47/4.2s$	$98.54/5.8s$	$98.72/7.2s$
gbt	$99.60/6.1s$	$99.84/12.2s$	$99.85/18.5s$	$99.82/25.8s$	$99.85/33.2s$
pgbt	$99.60/4.5s$	$99.84/10.2s$	$99.85/16.5s$	$99.82/20.4s$	$99.85/29.3$
pcgbt	$98.55/206ms$	$98.88/1.2s$	$99.42/1.3s$	$99.50/2.3s$	$99.50/4.5s$
SVM	$98.52/406ms$	$98.60/1.8s$	$98.62/2.1s$	$98.73/3.5s$	$98.80/6.5s$

Table 2: The Comparison of accuracy and running time of six algorithms on Optdigits with different sampling.

Accuracy (%) / Time	10 %	20 %	30 %	40 %	50 %
dt	$40.56/3s$	$42.53/6s$	$47.80/10s$	$50.34/14s$	$52.56/16s$
rt	$47.44/8m$	$50.43/20m$	$51.24/32m$	$56.89/44m$	$61.28/1h11m$
ert	$41.77/27m$	$42.37/31m$	$43.58/48m$	$45.68/55m$	$46.27/1h31m$
gbt	$69.18/1h6m$	$70.77/2h26m$	$78.13/3h35m$	$85.56/4h55m$	$89.15/6h22m$
pgbt	$69.18/54m$	$70.77/2h1m$	$78.13/2h/57m$	$85.56/4h12m$	$89.15/5h10m$
pcgbt	$66.32/3m$	$68.25/14m$	$73.05/20m$	$81.33/31m$	$84.01/45m$
pcgbt	$66.32/3m$	$68.25/14m$	$73.05/20m$	$81.33/31m$	$84.01/45m$
SVM	$65.44/10m$	$67.31/34m$	$72.16/66m$	$invalid$	$invalid$

Table 3: The comparison of accuracy and running time of six algorithms on 15-Scenes with different sampling.