An Efficient Dual Dimensionality Reduction Scheme of Features for Image Classification

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Abstract: The statistical property of Bag of Word (BoW) model and spatial property of Spatial Pyramid Matching (SPM) are usually used to improve distinguishing ability of features by adding redundant information for image classification. But the increasing of the image feature dimension will cause "curse of dimensionality" problem. To address this issue, a dual dimensionality reduction scheme that combines Locality Preserving Projection (LPP) with the Principal Component Analysis (PCA) has been proposed in the paper. Firstly, LPP has been used to reduce the feature dimensions of each SPM and each dimensionality reduced feature vector is cascaded into a global vector. After that, the dimension of the global vector is reduced by PCA. The experimental results on four standard image classification databases show that, compared with the benchmark ScSPM(Sparse coding based Spatial Pyramid Matching), when the dimension of image features is reduced to only 5% of that of the baseline scheme, the classification performance of the dual dimensionality reduction scheme proposed in this paper still can be improved about 5%.

1 INTRODUCTION

Image classification is the basic research problem in the field of computer vision, artificial intelligence and machine learning (Xie et al., 2014). With the rapidly increasing number of images, however, the traditional classification scheme has not been applicable any more. Various image classification schemes have been proposed. The representative scheme is the Bag of Word (BoW) model based on sparse representation proposed by Yang et al., (2009). In the scheme, the local feature is firstly extracts from the image; next the over-complete base (dictionary) is obtained by dictionary learning method; then the linear combination of a few dictionary atoms are used to represent the image; finally, SVM (Support Vector Machine) classifier is adopted for classification and recognition. The greater the dictionary atom number is, the sparser the image representation is, and the stronger the characterization ability is.

The BoW model mainly uses statistics information of local features of image, tends to ignore the spatial information of image. Therefore, Spatial Pyramid Matching (SPM) has been introduced by Lazebnik et al., (2006). For a three layers of SPM (1 + 4 + 16 = 21), if the dictionary number is 1024, then the final feature dimension of each image is 1024×21. With the increasing number of images, the matrix size is more and more big, and the calculation is more complicated, leading to huge computation and memory pressure for subsequent analysis, so-called the "curse of dimensionality" problem (Bellman, 1961).

Dimensionality reduction technique can effectively overcome the problem of "curse of dimensionality". The DPL (Projective Dictionary Pair Learning) algorithm was proposed by Gu et al., (2014), in which the advantages of analysis dictionary and synthesis dictionary were combined, and used in the objective function. The algorithm improved the distinguishing performance of features by increasing the type of dictionary. Object Bank algorithm was proposed Li et al., (2010), in which 177 object filters were used to extract high-level semantic feature for each image by the sliding window method, and SPM and max pooling to representation feature, with each image being represented as a 44604-D vector. PCA technique was been reduced dimensionality Literature (Gu et al., 2014; Li et al., 2010), in which centralized dimensionality reduction scheme was used, with the

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spatial information of features being ignored, did not highlight the advantages of SPM.

A dual dimensionality reduction scheme in which feature dimension is reduced on the premise of reserving image spatial information has been proposed in this paper. Different from the centralized dimensionality reduction scheme in Literature (Gu et al., 2014; Li et al., 2010), the scheme adopts the Spatial Pyramid Matching (SPM) and Locality Preserving Projection technique (Niyogi, 2004) to reduce feature dimension in each subspace, which is called subspace dimensionality reduction scheme, in order to reserve spatial information of the image. Each subspace vector is cascaded into a global vector; after that, the dimension of the global vector is reduced by the Principal Component Analysis, in order to reserve the principle component of the vector and obtain more compact image representation vector. Experimental results show that, when the feature dimension is reduced to 5% of the ScSPM (Yang et al., 2009) by the dimensionality reduction scheme proposed in this paper, the accuracy of image classification is still slightly increased, which proves the effectiveness of the scheme.

2 DUAL DIMENSIONALITY REDUCTION SCHEME

In the field of image classification, the suitable combination of BoW model and SPM (Zhang et al., 2014; Zhang et al., 2014; Lei et al., 2015; Wang et al., 2014; Yan et al., 2015; Yang et al., 2015) is used to improve distinguishing ability of image representation by adding redundant information. However, it leads to the image representation dimension being increased dramatically, and brings huge calculation and memory pressure of subsequent image classification. Therefore, many researchers adopt dimensionality reduction technique to solve the “curse of dimensionality” problem. With both of speed and efficiency being taken into considered, the Dual Dimensionality Reduction Scheme (DDRS) has been proposed in this paper, on the basis of which an image classification scheme has been also proposed. The block diagram is shown in figure 1.

2.1 Image Representation

Dense SIFT feature (Lazebnik et al., 2006) has been extracted for each image in this paper. The sample region is 16×16 pixel patches and the step size is 6 pixels (Yang et al., 2009).

Suppose that X is the set of M column-wise D-dimension feature vectors from an image, $X = \left[x_1, x_2, \cdots x_M\right] \in \mathbb{R}^{D\times M}$. In a visual dictionary $\mathrm{V} \in \mathbb{R}^{\mathrm{D}\times\mathrm{N}}$, each element is called visual word; N is the number of visual word. $U = \left[u_1, u_2, \cdots, u_M\right] \in \mathbb{R}^{N\times M}$ is the reconstitu-tion sparse coefficients. The goal of sparse coding is to approximate the input vector X by a linear combination of the dictionary:

$$\begin{aligned} &\min_{U,V} \sum_{m=1}^{M} \left\| x_m - u_m V \right\|^2 + \beta \left\| u_m \right\|_1 \\ &s.t.\ \left\| v_n \right\|^2 \le 1,\ \ \forall n = 1, 2, ..., N \end{aligned} \tag{1}$$

This is a non-convex problem. If a variable can be fixed, it becomes a convex optimization problem. So method of fixing a variable is used to attain the visual dictionary and sparse coefficients. Firstly, sparse coefficients are fixed and Eq. (2) is obtained.

$$\min_{U,V} \sum_{m=1}^{M} \left\| x_m - U \times V \right\|^2 \tag{2}$$

This optimization can be solved efficiently by the Lagrange dual as used in Yang et al., (2009) to get the visual dictionary. Then, the visual dictionary is fixed and Eq. (3) is obtained.

$$\min_{U,V} \sum_{m=1}^{M} \left\| x_m - u_m V \right\|^2 + \beta \left\| u_m \right\|_1 \tag{3}$$

In order to solve this optimization, sparse coefficients can be obtained by feature-sign search algorithm. The visual dictionary with smallest reconstruction error is gotten by multiple iterations. At last, the visual histogram is generated with by combining SPM and the max pooling algorithm.

2.2 Dual Dimensionality Reduction Scheme

In this paper, the dual dimensionality reduction scheme diagram is shown in figure 2. This scheme is divided into two layers: in the first layer, LPP is adopted to reduce dimension of corresponding feature in each subspace of SPM, respectively; then, each subspace vector is cascaded into a global vector; in the second layer PCA is used to reduce dimensionality, to further remove redundancy between feature vectors and obtain the final image representation vector in the lower dimension.

Two important parameters have been involved in LPP: Maximum dimension (dmax) and Principal

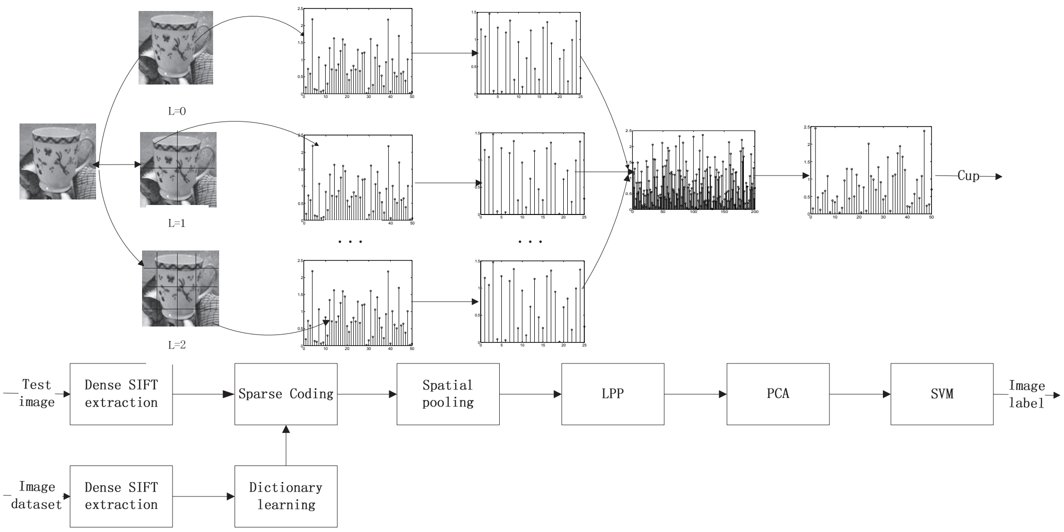


Figure 1: A typical example and the flowchart of the proposed dual dimensionality reduction based image classification method.

Component Analysis ratio (PCAratio), the number of K-Nearest Neighbour (KNN) is fixed as 20. The Maximum dimension indicates how many dimension vectors have been retained to be, while the Principal Component Analysis ratio refers to the proportion of the proposed principal component accounted in the total of contracted dimension in a vector. These two parameters are related. When the parameter dmax is larger than the value of the PCAratio, the PCAratio becomes the priority, vice versa.

3 EXPERIMENT RESULTS AND ANALYSIS

The comparison of classification accuracies has been made between the ScSPM scheme and the dual dimensionality reductions scheme on Butterfly (Li et al., 2004), Scene-15 (Lazebnik et al., 2006), Caltech-101 (Lazebnik et al., 2004) and Caltech-256 (Griffin et al., 2007) dataset.

The Butterfly-7 dataset contains 619 images of 7different species of butterflies. In these species, the minimum number of images is 42 while the maximum number is 134. This dataset is characterized with variety in resolutions, small difference between species and large difference in species.30 images per category have been selected and used as training set, and others as testing set.

The Scene-15 dataset contains15 scenes: thirteen scenes are provided by Li et al., (2004) and two scenes (industrial and store) are added, which totally is composed of 4485 images. Each category has 200 to 400 images, Where 100 images per category are selected randomly for training and others or testing.

The Caltech-101 dataset contains 9144images of 101 categories and one kind of background. Each category has 31 to 800 images. Image categories include animal, plant, face, etc. The objects in the same category are in large difference. 30 images per category are randomly picked up for training, and the rest for testing.

The Caltech-256 dataset contains 29,780 images of 256 categories and one kind of background with much higher object location variability and higher intra-class variability compares with Caltech-101 (Yang et al., 2009). Each category has at least 80 images. In our experiments, we take 60 images for training and use the rest for testing.

3.1 Influence of Different Parameters

Two important parameters have been involved in LPP: Maximum dimension (dmax) and Principal Component Analysis (PCAratio). We analyse the influence of these two parameters by image classification accuracy on three datasets of Butterfly-7, Scene-15, Caltech-101, experimental results are shown in figure 3~5. Figure (a) indicates that how dmax affects the classification accuracy on three datasets when PCAratio is fixed, while Figure (b) indicates, how PCAratio affects the classification accuracy when dmaxis fixed. It can be known from figure3~5 that, with the increase of image dimension, the classification accuracy on three datasets increase first, and then decline, which indicates that not the higher the image representation

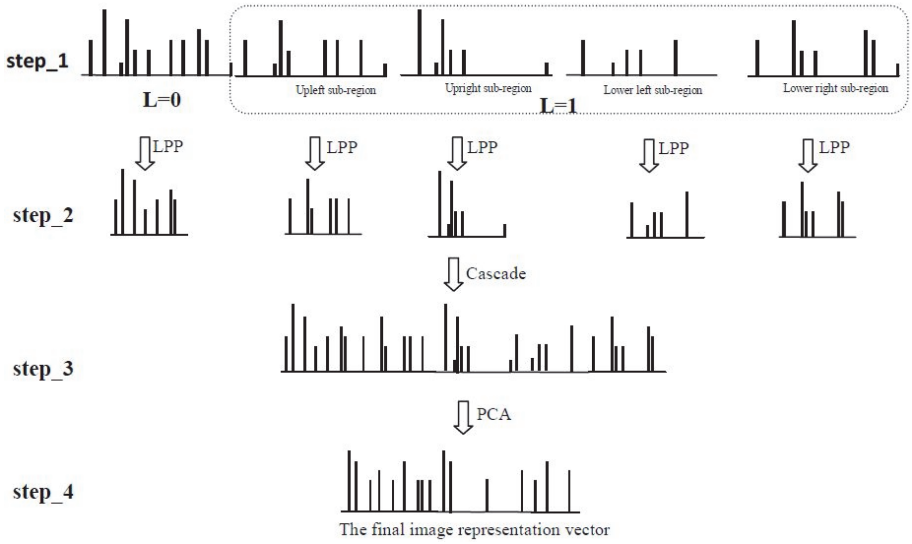
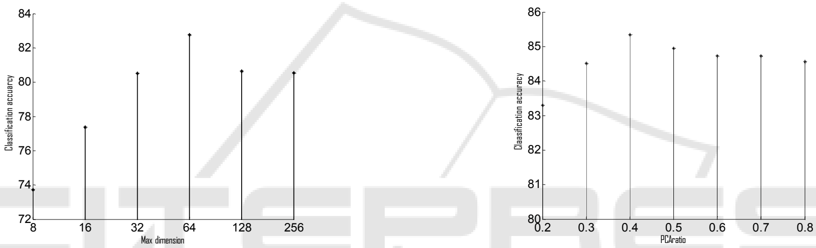
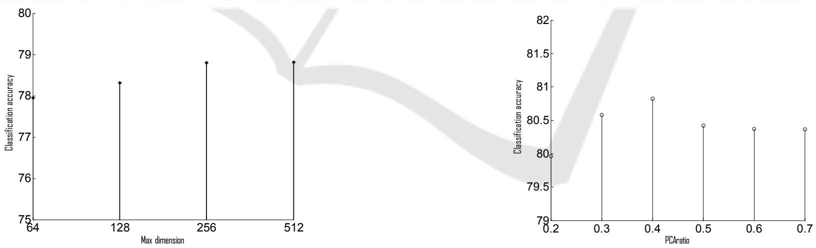


Figure 2: The diagram of Dual dimension reduction scheme.



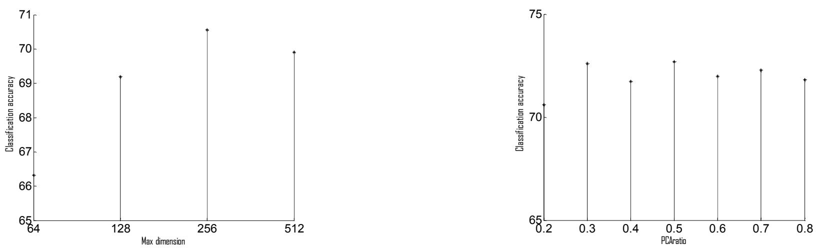
(a) (b)

Figure 3: The dmax and PCAratio parameters effect on image classification accuracy in Butterfly-7 dataset.



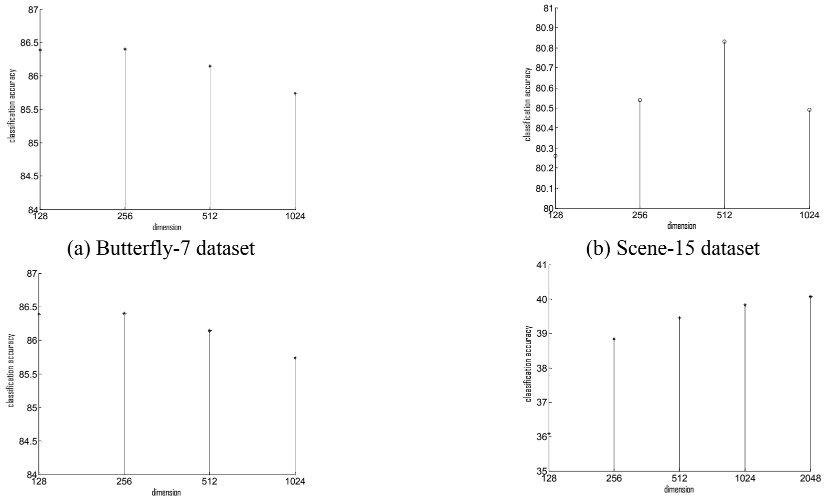
(a) (b)

Figure 4: The dmax and PCAratio parameters effect on image classification accuracy in Scene-15 dataset.



(a) (b)

Figure 5: The dmax and PCAratio parameters effect on image classification accuracy in Caltech-101 dataset.



(a) Butterfly-7 dataset (b) Scene-15 dataset

(c) Caltech-101 dataset (d) Caltech-256 dataset

Figure 6: The Dim parameters effect on image classification accuracy in four datasets.

dimension is, the better the classification accuracy is. Similarly, the principal component analysis ratios begin to decline after reaching peak. The parameter combinations of four databases are shown in table 1.

The parameter of PCA is mainly dimension (Dim); this parameter also has direct impact on the classification accuracy. The following is analysis influence of different Dim values for classification accuracy; the specific results are shown in figure 6.

Table 1: Combination of parameters in four datasets.

dataset	dmax	PCAratio	Image representation	KNN
Butterfly-7	64	0.4	1344×619	20
Scene-15	256	0.4	2794×4485	
Caltech-101	256	0.3	2876×9144	
Caltech-256	256	0.3	2876×30607	

According to the change trend of figure 6, it can be seen that with the increase of the dimension, the classification accuracy does not increase accordingly. When it reaches a certain value, it begin to drop; this shows that the high dimension do not improving the characterization ability of feature. In this paper, final dimensions of image representation are determined on Buterfly-7, Scene-15, Caltech-101 and Caltech-256 datasets to 256, 512, 1024, and 2048, respectively.

3.2 Comparison of Image Classification Scheme

3.2.1 Caltech-101 Dataset

Image representation dimension is set as 1024 in Caltech-101 dataset, 1/21(1024/(21 × 1024)) of ScSPM. Table 2 shows the classification accuracy of different image classification schemes on Caltech - 101 dataset. It can be seen that the classification accuracy of the proposed scheme has drastically improved, increasing nearly 10%, compared with the kernel Spatial Pyramid Matching (KSPM) (Lazebnik, 2006) and kernel Codebook Spatial Pyramid Matching (KCSPM) (Van Gemert et al., 2008). Compared with ScSPM, locality-constrained coding (LLC) (Wang et al., 2010) and IMFSC (Luo et al., 2014) based on Combing Multi-feature and Sparse Coding scheme, it has different degrees of increase.

Table 2: The classification accuracy on Caltech-101 dataset.

Scheme	Acc.
KSPM	64.4±0.80
KCSPM	64.14±1.18
ScSPM	73.2±0.54
LLC	73.44
IMFSC	73.55
DDSR	74.10

3.2.2 Caltech-256 Dataset

In this paper, the feature dimension of the Caltech - 256 dataset is set as 2048, 2/21 of benchmark scheme. Table 3 shows the classification accuracy the different classification schemes on the dataset. It can be seen that the proposed scheme is slightly higher than the Laplace sparse coding LScSPM (Gao et al., 2010) and benchmark scheme. Dictionary number of locality-constrained coding algorithm LLC (Wang et al., 2010) is 4096, image vector dimension is 21×4096, data quantity is 42 times over ours, if the dictionary number is set as 1024, its classification accuracy is 37.79±0.42% (Gao et al., 2013), classification accuracy of our proposed scheme is 3.18% higher than LLC algorithm.

Table 3: The classification accuracy on Caltech-256 dataset.

Scheme	Acc.
ScSPM	40.14
LLC	47.68
LScSPM	40.43
DDSR	40.97

3.2.3 Butterfly-7 Dataset

In this paper, the image representation dimension of the Butterfly-7 dataset is set as 256, 1/84 of ScSPM. Butterfly dataset is different from Caltech dataset, it belongs to fine-grained recognition. The inter-class difference among sample data is small, the inner-class difference is big, and so its classification is more difficult. Table 4 shows the classification accuracy of different classification methods on Butterfly-7 dataset. It can be seen from the table that, the classification accuracy of the scheme provided in this paper is higher than that of ScSPM and LLC.

Table 4: The classification accuracy on Butterfly- 7 dataset.

Scheme	Acc.
ScSPM	81.30±1.57
LLC	87.54
DDSR	89.92

3.2.4 Secne-15 Dataset

The image representation dimension of Secne-15 dataset is set as 512, 1/42 of benchmark scheme. The classification accuracy of different algorithms on Secne-15 dataset is given in table 5, of which OB (Li et al., 2010) scheme based on object bank, WSR-EC (Zhang et al., 2013) based on weak attributes of object combining template classifier. As can be seen from the table, the classification accuracy of the proposed scheme is 4.91% higher than KCSPM scheme, and slightly higher than the other scheme.

Table 5: The classification accuracy on Scene-15 dataset.

Scheme	Acc.
KSPM	81.40±0.50
KCSPM	76.67±0.39
WSR-EC	81.54±0.59
OB	80.9
ScSPM	80.28±0.93
DDSR	81.58

4 CONCLUSIONS

In order to solve the problem that image represent-tation dimension is over high, the dual dimensiona-lity reduction scheme has been proposed in this paper, being designed to reduce image representation dimension, and reverse the distinguishing ability of image representation at the same time. In four standard dataset of Butterfly - 7, Scene - 15, Caltech - 101 and Caltech-256, compared with the benchmark scheme, experimental results show that, on condition that the image representation dimension is reduced to 5% of the original dimension, the image classification accuracy of the dual dimensionality reduction scheme is still improved more than 3% average.

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