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Data augmentation by combining feature selection and color features for image classification

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ABSTRACT

Image classification is an essential task in computer vision with various applications such as bio-medicine, industrial inspection. In some specific cases, a huge training data is required to have a better model. However, it is true that full label data is costly to obtain. Many basic pre-processing methods are applied for generating new images by translation, rotation, flipping, cropping, and adding noise. This could lead to degrade the performance. In this paper, we propose a method for data augmentation based on color features information combining with feature selection. This combination allows improving the classification accuracy. The proposed approach is evaluated on several texture datasets by using local binary patterns features.

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1. INTRODUCTION

Image classification has a huge application in different fields such as in agriculture [1], textile industry [2], trading market [3], medical image [4], hyperspectral imaging [5]. Generally, this task requires a lot of labeled training data for building good model and achieving better performance. The lack of training data mayaffect to the performance of different computer vision tasks. Indeed, the annotation process is costly to obtain. Different studies consider this problem in a semi-supervised learning, or few shot learning context [6]–[8]. Data augmentation is proposed to tackle those issues and enhance the prediction performance. Chaitanya *et al.* [9] propose a method to generate new image by combining intensity transformations and deformation by incorporating label information. Gómez-Ríos *et al.* [10] apply different basic images transformation to generate new coral texture images such as random shift, rotation, zoom, flipping for training into a neural network. Chen *et al.* [11] using pre-annotation information to label generated image by generative adversarial network for training image segmentation problem. Hao *et al.* [12] apply five images transformation on magnetic resonance imaging (MRI) images to create new images. These data augmentation techniques are applied independently to each color component and being trained by a deep neural network. Jain *et al.* [13] apply data augmentation for tackle the problem of imbalance and small dataset. Shawky *et al.* [14] generate remote sensing images for each imbalance class and carry out the classification by using convolutional neural network-multilayer perceptron (CNN-MLP) pretrained model.

Instead of using any pre-processing methods such as translation, compression, flipping for creating synthesis images, Duong and Hoang [15] recently applied color space transformation for generating and extracting local binary pattern (LBP) color features. They only used one training image for each class and then generate new image by transforming that image into another color space. We observe that the generation process can produce misinformation and irrelevant features, so it could lead to degrade the performance. Moreover, feature selection approach allows preserving the meaning and relevant features or eliminating noisy features. To prevent the curse of dimensionality phenomena given by adding color features information, we propose to incorporate feature selection into that scheme. The rest of this paper is organized as. Section 2 introduces related background of the proposed approach. Subsection 2.1 presents how to extract color local features based on LBP descriptor and subsection 2.2 introduces the feature selection method applied in this research. Section 3 illustrates the combination of data augmentation method and feature selection for image classification. Then, section 4 present the experimental results and the conclusion is given in section 5.

2. RELATED BACKGROUND

This section briefly reviews local image descriptor and feature selection method applied in this paper. LBP extracts color local image features. Feature selection (FS) extracts the useful features. These techniques were explained as:

2.1. Local binary patterns

To extract local image features, various descriptors have been introduced [16], [17]. Among them, LBP is a popular texture image descriptor because of its simplicity to implement and low computing complexity. It is widely applied in many fields such as medical imagery [18], hyperspectral imaging [19], face recognition [20]. The original LBP operator is generalized by investigating the intensity values of central pixel value in a circular neighborhood. The radius values R is used to define the circular neighborhood and P neighbors around the central pixel. Mathematically, the $\text{LBP}_{P,R}$ code is calculated by comparing the gray value g_c of the central pixel with the gray values $\{g_i\}_{i=0}^{P-1}$ of its P neighbors, according to the (1):

$$LBP_{P,R} = \sum_{i=o}^{P-1} \zeta(g_i - g_c) \times 2^i \tag{1}$$

where the threshold function $\zeta(h)$ is calculated as (2):

$$\zeta(h) = \begin{cases} 1 & if \quad h \geq 0 \\ 0 & otherwise \end{cases} \tag{2}$$

To extract color LBP features, many works [21], [22] have been proposed to consider the interaction between pixel from different color components. In this work, we follow [15] to extract extend opponent color LBP (OCLBP), each image is then characterized by 9 LBP histograms.

2.2. Feature selection

Feature selection (FS) is a technique that allows to eliminate noisy and redundant features while preserving a subset of useful features. FS can be divided into different sub-methods according to learning contexts or evaluation methods. Meethongjan *et al.* [23] considered LBP histogram to characterize texture image and applied feature selection methods for vehicle logo classification. In this paper, we apply ranking method based on a well-known Fisher score for selecting the most useful features extracted from color LBP histograms in supervised learning context.

Given data matrix X=[$\mathrm{x}_1, \dots, \mathrm{x}_i, \dots \mathrm{x}_N$], where $\mathrm{x}_i \in R^{D\times N}$, each image is given by a predefined class label y_i, $\{\mathrm{x}_i, y_i\}, y_i \in \{1, \dots, c, \dots C\}$ where C is the number of classes and N_c denotes the number of images of each class c. Let μ^r denotes the mean of all images on the r^{th} feature, μ^{rc} and $(\sigma^{rc})^2$ the mean and variance of class c corresponding to the r^{th} feature, respectively. The Fisher score of the r^{th} feature is computes by (3):

$$Fisher^r = \frac{\sum_{c=1}^{C} N_c(\mu^{rc} - \mu^r)^2}{\sum_{c=1}^{C} N_c(\sigma^{rc})^2} \tag{3}$$

where, the numerator is the between-class variance considering the r^{th} feature and the denominator is the within-class variance considering the r^{th} feature. The features are then ranked in the ascending order to select the relevant ones according to their score value.

3. PROPOSED METHOD

In this paper, we consider the problem of image classification in one shot learning context. The training set of each dataset only consists of one image of each class. From the first chosen color space, the data augmentation process is applied for generating new synthesis images via color space transformation. Next, thecolor LBP features of the new training dataset are extracted before feature selection step. The subset of learningfeatures chosen by Fisher score is then applied in the classification stage with the same procedure. Figure 1 illustrates the proposed scheme in the two stages.

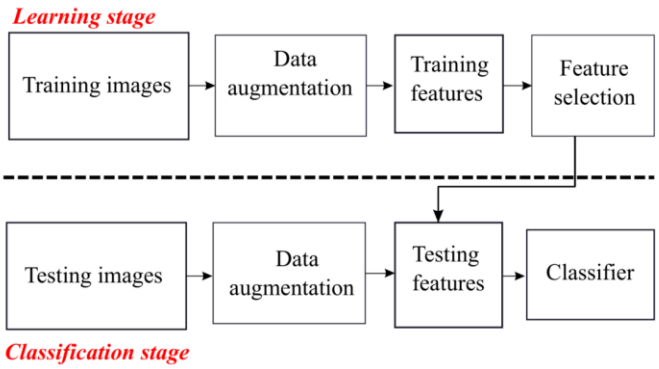


Figure 1. Illustration of the proposed process

4. EXPERIMENTAL RESULTS

To evaluate the proposed method, we use three texture image datasets such as Outex-13 [24], USP-tex [25], and Stex [15] in Figure 2. These datasets have the test suites for evaluating in supervised learning context. We randomly choose one image for training from the original training dataset. This image is then transformed into different color space to expand the size of learning images. Each image is characterized by a vector of color LBP with 2,304 features. Fisher score is applied to rank and select the most useful and relevant featuresaccording to filter strategy. The 1-NN classifier is applied to classify the testing set by using accuracy metric. It is worth to note keep that we keep the original testing suite to compare the results in [15].

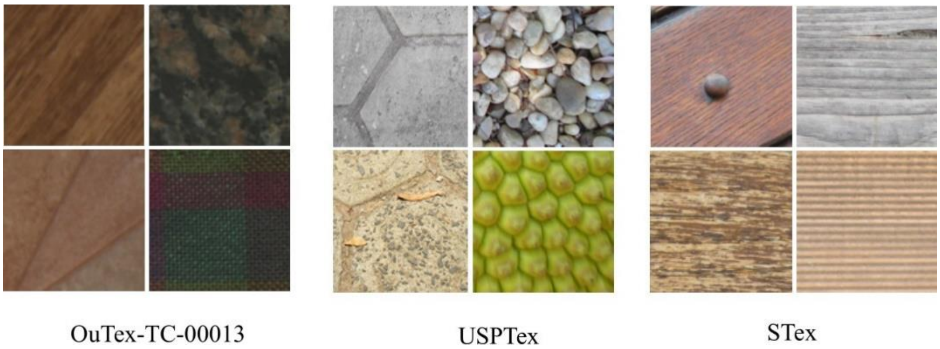


Figure 2. Datasets used for experiment

Table 1 shows the classification performance on the three datasets. The first column indicates the name of dataset. The three considered color space corresponding to space 1 (RGB), space 2 (HSV), and space 3 (ISH), respectively. For each column, there exists three sub-columns stand for three different experimentstrategies:

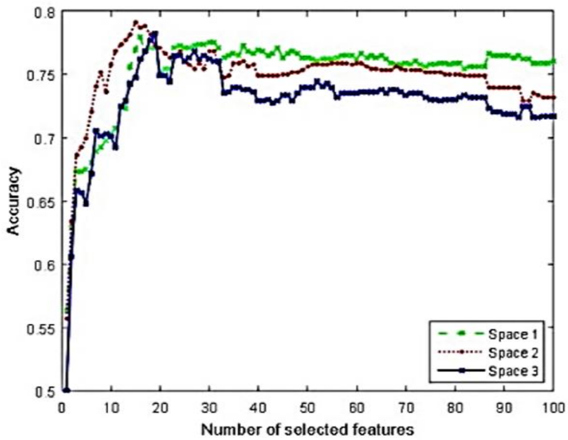
– Without Augm: The training data consists of one image of each class.
– With Augm: The training data contains one image per class where two new images are generating by data augmentation.
– Combine: The combination of data augmentation and Fisher score are considered.

Table 1. Experimental results on the three datasets

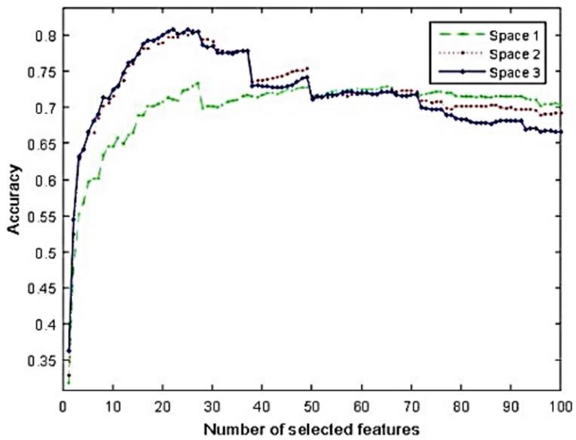
Experiment strategies	Space 1			Space 2			Space 3		
	Without Augm	With Augm	Combine	Without Augm	With Augm	Combine	Without Augm	With Augm	Combine
Outex	0.7647	0.7583	**0.7794**	0.6932	0.7066	**0.7912**	0.7096	0.7098	**0.7824**
USPtex	0.7022	0.6994	**0.7339**	0.6194	0.6768	**0.8063**	0.6115	0.6640	**0.8080**
Stex	0.6585	0.6698	**0.6707**	0.6008	0.6184	**0.7912**	0.6164	0.6692	**0.7849**

We observe the data augmentation slightly improve the classification performance in some cases. For example, when no data augmentation is applied with space 2, the accuracy is achieved at 0.6932 for Outex and it can reach to 0.7066 for using data augmentation techniques. Globally, the combination of data augmentation and Fisher score clearly improves the performance for all datasets and color spaces considered. For Outex-13 dataset, the proposed method enhances nearly 3% of accuracy for space 1, 9% for space 2, and 8% for space 3.

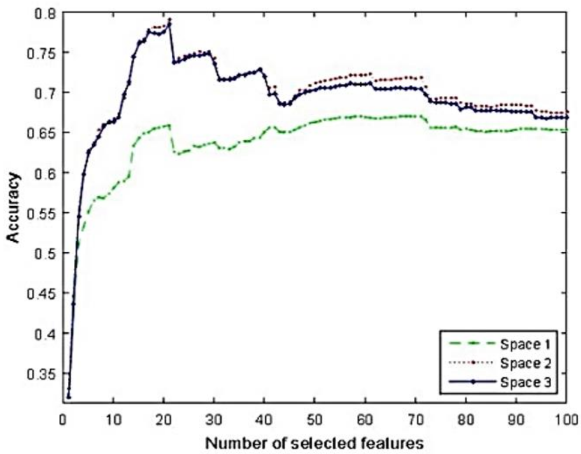
Figure 3 shows the efficiency of Fisher score, the number of selected features corresponding the percentage from 1 to 100 for each dataset. Figure 3(a) present the comparison of the three considered color spaces, we observe that the highest accuracy is obtained with 20% of features in used. We can get the similar observation for USPtex and Stex in Figures 3(b) and 3(c). The data augmentation techniques by color space transformation produce highly noisy features, so Fisher score allows ranking and selecting the most relevant features. This experimental result shows the efficiency of the proposed approach compared with those obtained in [15] by the same data augmentation method.



(a)



(b)



(c)

Figure 3. The classification results of three datasets (a) Outex, (b) USPtex, and (c) Stex by using fisher score under three different color spaces

5. CONCLUSION

In this paper, we propose a method for enhancing the data augmentation method via color space transformation for image classification. After the generation of new synthesis image and feature extraction, the feature selection is applied for selecting and ranking the most relevant attributes by using Fisher score in supervised learning context. The experimental results show the efficiency of the proposed approach on three color image databases. The future of this work is now extended to learning and selecting the suitable color space and feature extraction for the augmentation process.

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