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Classification of Product Images in Different Color Models with Customized Kernel for Support Vector Machine

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***Abstract* — Support Vector Machine (SVM) is widely recognized as a potent data mining technique for solving supervised learning problems. The technique has practical applications in many domains such as e-commerce product classification. However, data sets of large sizes in this application domain often present a negative repercussion for SVM coverage because its training complexity is highly dependent on input size. Moreover, a single kernel may not adequately produce an optimal division between product classes, thereby inhibiting its performance. The literature recommends using multiple kernels to achieve flexibility in the applications of SVM. In addition, color features of product images have been found to improve classification performance of a learning technique, but choosing the right color model is particularly challenging because different color models have varying properties. In this paper, we propose color image classification framework that integrates linear and radial basis function (LaRBF) kernels for SVM. Experiments were performed in five different color models to validate the performance of SVM based LaRBF in classifying 100 classes of e-commerce product images obtained from the PI 100 Microsoft corpus. Classification accuracy of 83.5% was realized with the LaRBF in RGB color model, which is an improvement over an existing method.**

Keywords - color; gradient; histogram; image; kernel; product; vector

I. INTRODUCTION

The era of e-commerce has transformed the way retail business is done and brought consumers much closer to desired products. E-commerce is playing a key role in the global economic growth and this is why it is important to evolve methods to manage the surge of products in this domain [1]. One of the most important processing tasks in e-commerce is the classification of product images [2], which involves associating products to appropriate classes. Product classification helps to realize an efficient indexing and retrieval of e-commerce products. It is also useful in advanced technology for in-store shopping such as shopping recommendation assistant system [3].

Image preprocessing, feature extraction and feature classification are essential phases of image analysis required for the classification of product images [4]. The pre-processing of a product image prior to image classification is essential in order to improve quality of image data, improve the computed result, prepare an input product image for classification and speed up the processing time. Commonly used image pre-processing methods include image resizing, image segmentation, noise and background removal.

Color is one of the most important features usually extracted for product image classification [5]. The efficacy of color feature resides in its unique properties of being insensitive to size, zooming and orientation invariance under varying illumination conditions. Colors are usually specified in different color models with each having advantages, limitations and areas of useful applications [5]. Previous studies have considered the use of color features in different color models to improve classification accuracy. Examples of color models commonly employed for product image classification are RGB, oRGB, XYZ, CMYK, YIQ, YUV, YCBCR and HSV [6].

Many machine learning classifiers amongst which Support Vector Machine (SVM) is widely recognized have been extensively applied for e-commerce product image classification [1, 5, 7, 8]. However, the huge data sets in the e-commerce application domain often inhibit the performance of a single kernel for SVM [9, 10]. Moreover, it has been emphasized that the performance of classifiers can be affected for a large number of classes [11]. The recent developments in the application of SVM have emphasized the need to consider multiple kernel transformation (MLT) to provide good performance with greater flexibility for high dimensional data sets [10]. In [9] for instance, a multiple kernels PRBF based on Polynomial (P) kernel and Gaussian Radial Basis Function (RBF) kernel was used to take advantage of their respective strengths.

Previous studies have shown that the number of classes considered product image classification is highly limited in scope, usually between 3 to 50 classes were used in comparison to the available number of product classes in real life e-commerce databases [8, 12]. In addition, no universal color model can be used to obtain high classification accuracy of product image data sets acquired from different application domains. Consequently, the motivation for the study at hand is the need to develop product image classification systems that can classify hundreds of product classes with an acceptable level of accuracy. The first paramount objective of this study is to extract color features of 100 image classes obtained from the PI100 database using the histogram of oriented gradient (HOG) algorithm in five different color models, which are RGB, oRGB, XYZ, HSV and YUV. The HOG algorithm [13] has been widely reported in the literature to be effective for image feature extraction. The second important objective of this study is to

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develop a customized kernel based on the linear kernel and the RBF kernel to improve the classification of e-commerce product images using SVM. The linear kernel and RBF kernel have been previously used in isolation for SVM based classifications [10].

II. MATERIALS AND METHODS

Fig. 1 shows the block diagram of the product image classification system with dataset, image preprocessing, feature extraction and data classifier as components.

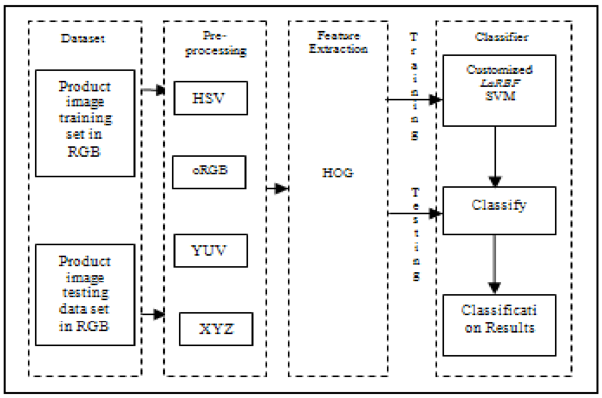

Figure 1. Block diagram of product image classification with customized *LaRBF* kernel for SVM

A. Data sets

The product image utilized for this study was obtained from PI 100 product image corpus [14]. The PI 100 corpus contains 10000 low resolutions (100×100) images that are grouped into 100 classes. Each image contains the dominant object in relatively stable forms, exactly the way product images normally appear on e-commerce website, such as Amazon.com, Kaymu.com, eBay, Jumai.com, Web.com, and Volusion. We chose this database because it contains colored product images of good qualities and it is widely used for product classification studies [8, 12]. Overall, 100 classes of images with each class having 20 color images were extracted in this study. This culminates in a total data set of 2000 color images. Fig. 2 shows a sample of selected images to be Baby shoe, Jacket, Cowboy hat, Can and Briefcase product image classes.

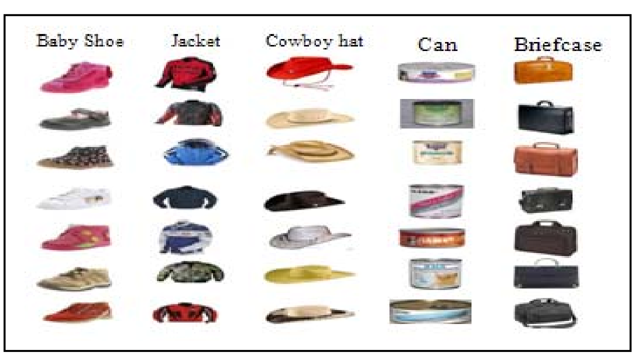

Figure 2. Sample of e-commerce product images from PI 100

B. Image Preprocessing

At the preprocessing phase, an input image is first tested to determine if the dimension is equal to 100 x 100 pixels, otherwise, the image size is adjusted to this dimension. Thereafter, an input color image, which is in the RGB color model by default is transmitted to the subsequent block or converted into any of the selected color models such as the oRGB, XYZ, HSV and YUV. These color models are briefly described as follows.

RGB (Red, Green and Blue) is the most commonly used color model and other color models are usually derived from it by means of linear or nonlinear transformations. However, RGB image is sensitive to luminance, surface orientation and other photographic conditions. The opponent color model (oRGB) [6] is an invertible transform of RGB and it is primarily based on the three fundamental psychological opponent axes, which are white-black, red-green and yellow-blue. This color model has three axes, which are *L*, C_1 and C_2 channels. The L channel contains the luminance (luma) information and its values are between [0, 1]. The C_1 and C_2 channels contain the chromatic (chroma) or color information. The values of C_1 and C_2 lie within [-1, 1] and [-0.8660, 0.8660] respectively. The oRGB color model works efficiently in computer graphics and computational applications. This color model has been shown to give better performance in several image processing tasks [6]. The transformations from RGB color model to other color models have been presented.

C. Feature Extraction

The Histogram of Oriented Gradient (HOG) algorithm was selected for feature extraction in this study (Fig. 1). The idea of HOG is based on the observation that local object appearance and shape often can be well characterized by the distribution of local intensity gradients. For each pixel in an image, HOG computes the gradient magnitude at different orientation and then builds a histogram representation of the entire image. HOG is one of the most powerful feature descriptors in the image processing literature.

In this study, we followed the same principle applied in Dalal et al [13] to compute the HOG features from the pre-processed color images in each channel of the selected color models. Each product image is divided into smaller rectangular block of 9 x 9 pixels and each block is further divided into 9 cells of 3 x 3 pixels. We used gradient orientation of 9 bins ranging from 0^0 - 180^0. Finally, we combined all the gradient orientation histograms in the three color channels to form a feature vector of size 243 (9 bins x (3 x 3) pixels x 3 channels) for one product image.

D. *Feature Classification*

The SVM is a widely used supervised learning algorithm for solving diverse classification problems [8, 15, 16]. It has been successfully employed in various application domains such as biometrics and bioinformatics [17], text categorization [7] and product image classification [8]. The classifier discriminates image samples of different classes by trying to find a separating hyperplane with the maximum margin in the input space [18]. In a binary classification task, given a training data set $\{(x_i, y_i)\}_{i=1,...,N}$ of N instances consisting of an image feature $x_i \in x$ and class labels $y_i \in \{-1,1\}$ [15], a linear decision surface can be defined as:

$$w.x + b = 0 \tag{1}$$

The training of SVM is to find $w \in R^N$ and b that maximize the margin between the two classes. The decision surface of an SVM can be obtained by solving a constrained optimization problem that can be stated as:

$$\min_w \frac{1}{2}\|w\|^2$$

Subject to the constraint:

$$y_i(wx_i + b) \geq 1 \tag{2}$$

The optimization problem does not have a solution if the data points are not linearly separable. To handle nonlinearly separable problems, which is the case in this study, the modified SVM introduces a slack variable $\xi \geq 0$ and the modified optimization problem can be stated as:

$$\min_{w,\xi} \frac{1}{2}\|w\|^2 + C\sum_i \xi_i$$

Subject to:

$$y_i(w.x_i + b) \geq 1 - \xi_i, i = 1,..., N \tag{3}$$

where $C > 0$ is a regularization parameter controlling the penalty for a misclassification. Since the objective function $\|w\|^2$ is convex, minimizing it under the linear constraint in Equation (3) can be achieved using the Lagrange multipliers [15]. If we denote the *N* non negative Lagrange multipliers associated with the linear constraint in Equation (3) by $\alpha = (\alpha_1,...,\alpha_N)$, the optimization problem leads to maximizing:

$$w(\alpha) = \left\{\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{j-1}^{N}\alpha_i\alpha_j y_i y_j x_i x_j\right\} \tag{4}$$

with $\alpha_i \geq 0$ and under the constraint:

$$\sum_{i=1}^{N} y_i\alpha_i = 0.$$

Once the vector $\alpha = (\alpha_i,...,\alpha_N)$,which is a solution of the maximization problem in Equation (4) is obtained, the optimal separating hyperplane can be represented as:

$$w = \sum_{i=1}^{N}\alpha_i y_i x_i \tag{5}$$

The hyperplane decision function can be defined as:

$$f(x) = \text{sgn}\left(\sum_{i=1}^{N}\alpha_i y_i x_i x + b\right) \tag{6}$$

The non-zero training feature vectors α_i are called the support vectors. In addition, complex nonlinear boundaries are introduced in the original input space by SVM using kernels. A kernel must satisfy the condition of Mercer [19]. Examples of the SVM kernels that satisfy the condition of Mercer are linear, polynomial, radial basis function, quadratic and Cauchy. With these kernels, Equation (6) becomes:

$$f(x) = \text{sgn}\left(\sum_{i=1}^{N}\alpha_i y_i K(x_i x) + b\right) \tag{7}$$

E. Proposed LaRBF Kernel

The choice of kernels often determines the performance of SVM. Based on the shortcomings of a single kernel for SVM [20, 11, 9], literature has suggested multiple kernels to improve classification performance [7, 10]. Although, multiple kernels have been used in SVM for classification in e-commerce [7, 8, 10, 12, 20], they are mostly applied to a limited number of classes, which are far from the practical reality in this application domain.

Different approaches for combining kernels for SVM can be appositely grouped into: linear, non-linear and data-dependent [18]. The linear combination approach is the simplest of all and it is further categorized into weighted sum and unweighted sum or simply an additive combination. The unweighted sum linear combination approach has very low computational cost [18], which is the reason for using it in this study to realize the LaRBF kernel. The *LaRBF* kernel possesses the intrinsic benefits of each component kernel. These include the RBF high classification accuracy and the intrinsic high speed performance in linear kernel [10]. The linear kernel is represented as:

$$K_{Linear}(x, y) = x.y \tag{8}$$

The RBF kernel is represented as:

$$K_{RBF}(x, y) = \exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right) \tag{9}$$

The proposed *LaRBF* multiple kernel for SVM is consequently obtained from Equations (8) and (9) as:

$$LaRBF = K_{Linear}(x, y) + K_{RBF}(x, y) \tag{10}$$

where σ is a bandwidth parameter of the RBF kernel. The *LaRBF* multiple kernel is an admissible Mercer's kernel because both of its linear and RBF constituent kernels satisfy the condition of Mercer. This is premised on the fact that linear combination of Mercer's kernels is also Mercer compliant [19]. This new kernel applies to the classification of product images in this study and it is experimentally compared with four other kernels as detailed in the subsequent section.

F. Experiments

All the experiments in this paper were performed on a PC with Intel Core i5-2540MCPU @2.60GHz speed with 4.00GB RAM and 64-bit Windows 7 operating system. To carry out the necessary experiments, the pre-processing procedure, which involves the transformation of the RGB color model to the selected color models, was implemented in the MATLAB R2012a programming environment. Similarly, this programming platform was used to implement all the algorithms discussed in this paper, such as the HOG algorithm for feature extraction and the proposed *LaRBF* for SVM. We utilized the One-Against-All (1AA) strategy to extend the SVM to the case of the multiple class classification task in this study. In addition, 10-fold cross validation was used to train each of the SVM configurations and for the RBF kernel for SVM, the bandwidth parameter is $\sigma = 2^3$.

Five different experiments were performed in this study to determine the performance of product image classification using the extracted HOG features in the RGB, oRGB, XYZ, HSV and YUV color models respectively. One experiment is performed for each color model and for each experiment, we compared three single kernels, which are linear, polynomial and radial basis function as well as two multiple kernels, which are the PRBF [7] and the proposed *LaRBF*. Moreover, five experimental trials were carried out for each kernel of the SVM and the average classification accuracy was thereafter computed.

III. RESULTS AND DISCUSSION

The HOG features for the first experiment were extracted in the RGB color model. The results of the five different trials for each of the kernels in the first experiment are shown in Table I. As shown in the Table, the highest average accuracy of 83.5% is obtained with the proposed *LaRBF* kernel. This accuracy is better than what was obtained from linear and RBF kernels, which are the single kernel components of the *LaRBF*. The accuracy of the proposed *LaRBF* is also better than PRBF multiple kernel. The lower accuracy of the PRBF multiple kernel, is as a result of the poor performance of a single polynomial kernel, which is one of its components. This result shows the superiority of *LaRBF* in the RGB color model.

TABLE I: CLASSIFICATION RESULTS OF SVM KERNELS IN RGB COLOR MODEL

SVM Kernels in RGB Color Model		Classification Accuracy (%)					
		Trial					Mean
S/N	Kernel	1	2	3	4	5	
1	Linear	80.0	80.5	81.5	81.0	79.5	80.8
2	Polynomial	54.5	57.5	56.5	58.0	59.0	57.1
3	RBF	83.5	80.0	80.5	82.5	85.5	82.3
4	PRBF	78.5	79.0	79.0	80.5	82.5	79.5
5	LaRBF	84.5	84.0	83.5	82.5	83.0	83.5

In the second experiment, the HOG features were extracted in the oRGB color model. The result of this experiment is shown in Table II. As shown in the Table, the highest average accuracy of 82.5% was obtained with the proposed *LaRBF* kernel. Similar to the result in the first experiment, the proposed *LaRBF* kernel gives a better classification accuracy than when linear kernel, RBF kernel and PRBF multiple kernel were used. However, the classification accuracy of the proposed *LaRBF* kernel is better in the RGB color model in the first experiment than the oRGB color model in the second experiment.

TABLE II: RESULTS OF SVM KERNELS CLASSIFICATION IN ORGB COLOR MODEL

SVM Kernels in oRGB Color Model		Classification Accuracy (%)					
		Trial					Mean
S/N	Kernel	1	2	3	4	5	
1	Linear	83.0	80.0	83.5	81.0	83.0	82.1
2	Polynomial	61.5	57.0	56.0	55.5	60.5	58.1
3	RBF	82.5	83.0	80.5	81.0	85.0	81.8
4	PRBF	77.5	78.0	80.5	82.5	83.0	80.3
5	LaRBF	83.5	82.5	84.5	82.5	79.5	82.5

The HOG features for the third experiment were extracted in the HSV color model. The result of the experiment is shown in Table III. The highest accuracy of 72.7% was obtained using the proposed *LaRBF* kernel. This result is better than the linear kernel (70.3%), RBF kernel (67.2%) and the PRBF multiple kernel (70.3%). However, the average accuracy obtained in the HSV color model in this experiment is poorer than the result in the first and the second experiment in which RGB and oRGB color models were utilized respectively.

TABLE III: CLASSIFICATION RESULTS OF SVM KERNELS IN HSV COLOR MODEL

SVM Kernels in HSV Model		Classification Accuracy (%)					
		Trial					Mean
S/N	Kernel	1	2	3	4	5	
1	Linear	71.0	73.5	69.5	69.5	68.0	70.3
2	Polynomial	38.5	39.5	39.0	38.0	40.0	39.0
3	RBF	67.0	68.0	68.5	67.0	65.5	67.2
4	PRBF	67.0	69.0	69.5	72.0	74.0	70.3
5	LaRBF	73.5	75.0	72.5	72.0	70.0	72.7

In the fourth experiment, the feature extraction was done in the XYZ color model. The results of this experiment are shown in Table IV. As shown in the Table. The highest accuracy of 80.5% was obtained with the proposed LaRBF kernel. Similar to the results in the three previous experiments, the proposed LaRBF kernel outperformed the linear (80.0%) and RBF (78.8%) kernel. It also outperformed the PRBF multiple kernel. Meanwhile, the LaRBF accuracy in the XYZ color model in the current experiment is poor compared to its accuracy in the RGB and oRGB color models. The accuracy of the LaRBF kernel is however better in the XYZ color model than in the HSV color model.

TABLE IV: CLASSIFICATION RESULTS OF SVM KERNELS IN XYZ COLOR MODEL

SVM Kernels in XYZ Color Model		Classification Accuracy (%)					
		Trial					Mean
S/N	Kernel	1	2	3	4	5	
1	Linear	78.0	79.5	81.5	81.0	80.0	80.0
2	Polynomial	42.0	39.5	44.0	41.5	38.0	41.0
3	RBF	79.5	76.5	78.5	80.5	79.0	78.8
4	PRBF	77.0	78.0	79.0	80.0	82.0	79.2
5	LaRBF	80.5	82.5	79.5	79.0	81.0	80.5

In the fifth experiment, which is the last in this study, the HOG features were extracted in the YUV color model. The results of this experiment are shown in Table V. As shown in the Table, the proposed *LaRBF* kernel outperforms all the other kernels. This result is similar to the results obtained in the four previous experiments. The average accuracy of 80.5% for *LaRBF* in the YUV color model is the same as was obtained using the XYZ color model in the fourth experiment. The classification accuracy of the *LaRBF* kernel in the YUV color model is better than was obtained for HSV in the third experiment. However, the results in the first and second experiments in the RGB and oRGB color models are better than the result obtained for the YUV color model.

TABLE V: CLASSIFICATION RESULTS OF SVM KERNELS IN YUV COLOR MODEL

SVM Kernels in YUV Color Model		Classification Accuracy (%)					
		Trial					Mean
S/N	Kernel	1	2	3	4	5	
1	Linear	79.5	74.5	78.0	80.5	79.0	78.3
2	Polynomial	37.0	39.0	41.0	37.5	42.0	39.3
3	RBF	74.5	71.0	69.0	72.0	70.0	71.4
4	PRBF	78.0	79.0	80.5	81.0	81.5	80.0
5	LaRBF	79.5	80.0	82.0	80.0	81.0	80.5

The results of the five experiments, which are summarized and plotted in Fig. 3, show that the proposed multiple kernels *LaRBF*-SVM gave the best average classification accuracy of 83.5% in the RGB color model. This is followed by the average accuracy obtained for the oRGB color model. It can also be observed that all the kernels considered in this study (except the polynomial kernel) gave their highest accuracies in the RGB color model.

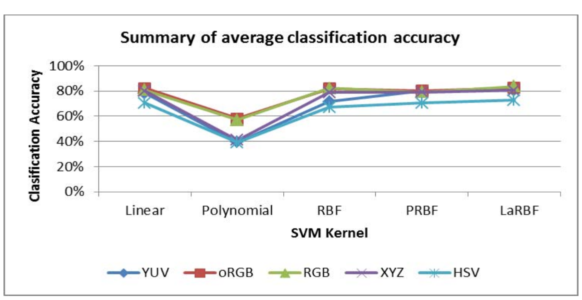

Figure 3. Summary of average classification accuracy

The results of this study show that *LaRBF* kernel consistently outperformed the linear and RBF kernels used in isolation. This perfectly agrees with the literature result that multiple kernel SVM usually give better performance than single kernel SVM [20, 10]. The results obtained in this study also show that the proposed multiple kernel *LaRBF* outperformed a similar multiple kernel PRBF in all the experiments. Although the author in [9] achieved 92.5% accuracy for a data set of 26 classes using the PRBF multiple kernel, it did not achieve such level of accuracy in our experimental results. This is because of the large size of our data set, which contains 100 classes and the poor performance of the polynomial kernel, which has been reported to have poor capability for high dimensional data set. The experimental results in this study provide a strong validation of the efficacy of the proposed *LaRBF* multiple kernels. So far, we have been able to achieve the two overarching objectives of this study, which are to use the HOG algorithm to extract a set of color features from 100 classes of images in the PI 100 corpus and to develop a multiple kernel from the linear kernel and RBF kernel to improve the accuracy of product image classification.

IV. CONCLUSION

In this paper, we proposed customized LaRBF kernel based on linear and RBF kernels. The HOG features extracted in five different color models were used to train an SVM that utilizes four existing kernels and the proposed *LaRBF* kernel. Experimental results show that the proposed LaRBF kernel based SVM gave the best average accuracy in the RGB color model. This result is highly promising for designing practical applications of product image classification, recommendation and other e-commerce systems. We hope to improve the performance obtained in this study in the future by incorporating color image segmentation at the pre-processing phase.

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