IMAGE CONTENTS ANNOTATIONS WITH THE ENSEMBLE OF ONE-CLASS SUPPORT VECTOR MACHINES

Bogusław Cyganek[1] and Kazimierz Wiatr[2]
[1]*AGH University of Science and Technology, Al. Mickiewicza 30, 30-059, Kraków, Poland*
[2]*Academic Computer Center Cyfronet AGH, Ul. Nawojki 11, 30-950, Kraków, Poland*

Keywords: Image indexing, Clustering, One-class SVM, Ensemble of classifiers.

Abstract: The paper presents a system for automatic image indexing based on color information. The main idea is to build a model which represents contents of a reference image in a form of an ensemble of properly trained classifiers. A reference image is first k-means segmented starting from the characteristic colors. Then, each partition is encoded by the one-class SVM. This way an ensemble of classifiers is obtained. During operation, a test image is classified by the ensemble which responds with a measure of similarity between the reference and test images. The experimental results show good performance of image indexing based on their characteristic colors.

1 INTRODUCTION

Automatic indexing of images finds broad interest among researchers (Müller, 2010); (Hermes, 2005). It is driven by demands of development of powerful search tools which allow very fast retrieval of visual information from data repositories or the Internet. The paper presents a system of automatic image indexing based on color information. The main idea is to construct a model of an image, or its region, in a form of an ensemble of classifiers which with their structure convey information on image contents. On the other hand, such ensemble should have some generalization properties, so similar images can be recognized by it as well. Also important is to assure that the system does not require excessive memory and allows sufficiently fast performance for search within large data repositories. The mentioned image model can be conceived in many different ways. In the presented method an ensemble of the one-class support vector machines (OC-SVM) is proposed due to their good generalization properties and fast response time. However, prior to building the ensemble of OC-SVMs, the reference image is segmented with the k-means methods with starting mean points set to the characteristic RGB colors. This way a number of segmented partitions is obtained. Then, each of these partitions is encoded by the OC-SVM. The experimental results show good performance of the method when compared with other methods that are based exclusively on color information. A similar idea of prior clustering of arbitrary datasets was presented in (Cyganek, 2010). In this paper we present its version suitable for the purpose of image indexing based on color information.

The rest of the paper is organized as follows. In section 2 we describe an architecture of the system, the segmentation method, as well as the ensembles of the OC-SVMs. Section 3 presents the experimental results. The paper ends with conclusions and biography.

2 SYSTEM DESCRIPTION

In this section we present and discuss the basic stages of training and operation of the proposed system. However, the system in the proposed shape can be seen as a kind of color based prefiltering of similar image in a repository. Thus, it can constitute a module in a cascade of filters for image search. Then, other methods can be used to obtain further information on image contents or on correlation among images. For this purpose the sparse methods are very suitable, e.g. the ones which are based on sparse color invariants (Koen, 2010). In the final application all different match measures can be gathered and used to select the most similar images. Nevertheless, very important aspect of this search is

Cyganek B. and Wiatr K..
IMAGE CONTENTS ANNOTATIONS WITH THE ENSEMBLE OF ONE-CLASS SUPPORT VECTOR MACHINES.
DOI: 10.5220/0003684002770282
In *Proceedings of the International Conference on Neural Computation Theory and Applications* (NCTA-2011), pages 277-282
ISBN: 978-989-8425-84-3

to assure that this way reported images are similar in human sense, since it often happens that although images bare some resemblance in terms of a qualitative measure, it is not perceived as similar for users of that system.

2.1 Operation of the System

General architecture of the system is depicted in Figure 1. After training, the system represents a color contents of a training image in a form of an ensemble of OC-SVMs and a prototype signature vector representing relative numbers of points in each of the OC-SVM (Kuncheva, 2004).

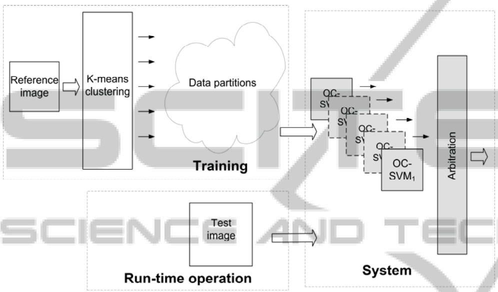


Figure 1: Architecture of the system. It is built during training from a reference image to represent its color distribution. During run-time operation the system returns a similarity measure to the reference image.

The system is trained as follows:

1. Do the k-means clustering, with eight starting RGB points (in the RGB space).

2. In each of the obtained clusters build an ensemble of OC-SVMs.

The initial clusters obtained in the first step are checked and the ones which contain only small amount of points are rejected. On the other hand, the clusters which are countless can be further split by means of the method proposed by Cyganek (Cyganek, 2010). Thus, in effect a number of OC-SVMs encodes boundaries of sub-spaces of color space of a given reference image or its region. Also a kind of a prototype signature of an image is obtained in a form of a vector of numbers of pixels which are classified by each of the member of the ensemble.

During operation the system classifies each pixel of the test image, and a number of accepted pixels by each member of the reference ensemble is counted. Also counted is a number of pixels which were not accepted by either member of the ensemble. These counters are then used to compute a correspondence measure between the two images. For this purpose the weighted Bhattacharyya measure is used. The closest images are reported.

2.2 Image Segmentation

There are many methods of data segmentation depending on a type of data and chosen features (Duda, 2001); (Filippone, 2008). In the area of image segmentation proper segmentation methods allow selection of characteristic objects depending on their specific features. However, their choice is not a trivial one and there is a continuous research in autonomous image segmentation (Kruse, 2007). In the light of the presented method we were interested in a method that works for broad group of different images and which does not require specific settings. Considering these the k-means method was selected which requires specification of a number of expected clusters as well as their initial mean values.

The method operates as follows. For a set $\{\mathbf{x}_i\}$ of training points the k-means algorithm starts with selection of the initial number of clusters D_i . Then each mean value $\boldsymbol{\mu}_i$ is selected. After initialization the algorithm proceeds iteratively by assigning each point $\mathbf{x}_i$ to the closest mean $\boldsymbol{\mu}_m$ in a cluster $D(i)$, as follows

$$D(i) = \arg\min_{1 \le m \le M} \left\| \mathbf{x}_i - \boldsymbol{\mu}_m \right\|_L , \tag{1}$$

where $\|.\|_L$ is the Euclidean distance, and M is the number of clusters. Then each mean value is recomputed in accordance

$$\boldsymbol{\mu}_m = \frac{1}{\# D_m} \sum_{\mathbf{x}_i \in D_m} \mathbf{x}_i . \tag{2}$$

The above steps (1) and (2) are repeated until convergence state is reached, i.e. there are no changes in values of the means.

In the presented system the chosen initial mean points must be the same for all images. Therefore the most distant ones in the RGB space are used. For this purpose the corner points of the RGB cube are selected, i.e. [0,0,0], [1,0,0], [1,1,0], [0,1,0], and [0,1,0], [1,0,1], [1,1,1], [0,1,1], as depicted in Figure 2.

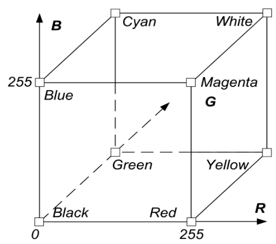


Figure 2: Characteristic RGB color points set as initial means for the k-means clustering.

A qualitative insight into the k-means clustering can be gained by analyzing the total sums of distances:

$$S_m = \sum_{\mathbf{x} \in D_m} \left\| \mathbf{x} - \boldsymbol{\mu}_m \right\|^2 \text{, and } S_t = \sum_{m=1}^{M} S_m \ . \qquad (3)$$

which should be as minimal as possible since k-means does not guarantee the globally optimal solution (Duda, 2001). However, in practice the algorithm converges very fast.

2.3 Modeling of Image Partitions with the OC-SVMs

The SVM binary classifiers were introduced by Vapnik et al. (Vapnik, 1995). They allow two class data classification in the so called feature space. Thanks to this the superior classification results, as well as generalization properties, were obtained. An important factor is also fast operation of the SVM classifiers which depends mostly on the number of necessary support vectors. The special one-class version of SVM allows description of data belonging to only one class, whereas all other points are treated as outliers. Formulation of the OC-SVM is due to Tax et al., who formulated an optimization problem for construction of the tightest hypersphere around the data points (Tax, 2004). In their work the method was named support vector data description. An alternative formulation was presented by Schölkopf et al. (Schölkopf, 2002). In their approach, instead of a hypersphere, a hyperplane is used which separates the one-class data from the origin of the coordinate system. In this section we briefly outline the latter approach.

Given a set of data points $\{\mathbf{x}_i\}$ the one-class SVM problem can be stated as computation of a hyperplane $\mathbf{w}$ that separates $\{\mathbf{x}_i\}$ with *the maximal margin* from the origin. This hyperplane can be represented as follows:

$$\left\langle \mathbf{w}, \mathbf{x} \right\rangle - \rho = 0 \qquad (4)$$

where $\langle \mathbf{w}, \mathbf{x} \rangle$ denotes an inner product between vectors $\mathbf{w}$ and $\mathbf{x}$ (Schölkopf, 2002). This is depicted in Figure 3.

Additionally to account for the outliers in the data set $\{\mathbf{x}_i\}$ the slack variables are introduced. In effect the following convex optimization problem has to be solved:

$$\min_{\mathbf{w}, \xi_1 \ldots \xi_N, \rho} \left[\frac{1}{2} \left\| \mathbf{w} \right\|^2 + \frac{1}{\nu N} \sum_{n=1}^{N} \xi_n - \rho \right], \text{ with}$$
$$\underset{1 \le n \le N}{\forall} \quad \left\langle \mathbf{w}, \mathbf{x}_n \right\rangle \ge \rho - \xi_n, \quad \xi_n \ge 0. \qquad (5)$$

In the above ξ_n denote the slack variables, N is a number of points in $\{\mathbf{x}_i\}$, and ν is a parameter that controls allowable number of outliers.

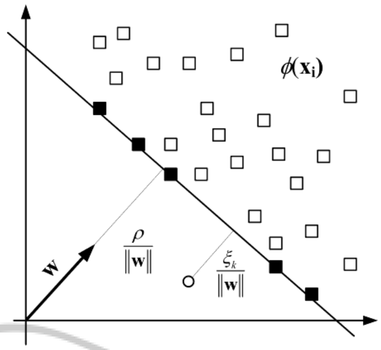


Figure 3: A hyperplane that separates a single class of points in the feature space Φ. Support vectors (SV) are on the hyperplane. Outliers are on the second side of the hyperplane and are controlled by the slack variables ξ.

The problem (5) can be solved by means of the Lagrange multipliers (Fletcher, 2003)(Bertsekas, 1996). Its dual Wolfe representation is:

$$\min_{\alpha_1 \ldots \alpha_N} \left[\sum_{n=1}^{N} \sum_{m=1}^{N} \alpha_n \alpha_m \left\langle \mathbf{x}_n, \mathbf{x}_m \right\rangle \right], \text{ with}$$
$$\underset{1 \le n \le N}{\forall} \quad 0 \le \alpha_n \le \frac{1}{\nu N} \text{, and } \sum_{n=1}^{N} \alpha_n = 1 . \qquad (6)$$

In the above α_n denote the Lagrange multipliers. There are few ways to solve (6), one possibility is to employ the SMO algorithm (Gestel, 2004)(Hsu, 2003). The solution can be represented introducing a series of N values of α_n (some of which can be 0), each associated with a single data point. The points for which their corresponding α_n>0 lie on the hyperplane $\mathbf{w}$ and are called the support vectors (SV). Now, the hyperplane $\mathbf{w}$ can be expressed as an α-weighted sum of the SVs.

$$\mathbf{w} = \sum_{n \in SVs} \alpha_n \mathbf{x}_n \ , \qquad (7)$$

since for all other points than SVs it holds that α_i=0. Now, taking any support vector $\mathbf{x}_m$ a distance of the hyperplane $\mathbf{w}$ to the origin can be computed as follows

$$\rho = \left\langle \mathbf{w}, \mathbf{x}_m \right\rangle = \sum_{n \in SVs} \alpha_n \left\langle \mathbf{x}_n, \mathbf{x}_m \right\rangle . \qquad (8)$$

The above derivations can be extended into the feature domain substituting each $\mathbf{x}$ for a point generated by a certain mapping function $\Phi(\mathbf{x})$. However, we easily notice that the formulation of the decision hyperplane (8) involves exclusively inner products between vectors. In the feature space this transforms into a kernel computation, as follows (Shawe-Taylor, 2004); (Schölkopf, 2002); (Hsu, 2003):

$$K\left(\mathbf{x}_i,\mathbf{x}_j\right)=\Phi^T\left(\mathbf{x}_i\right)\Phi\left(\mathbf{x}_j\right), \quad (9)$$

which is a scalar value. In our experiments we used the Gaussian kernel:

$$K_G\left(\mathbf{x}_i,\mathbf{x}_j\right)=e^{-\gamma\left\|\mathbf{x}_i-\mathbf{x}_j\right\|^2}, \quad (10)$$

where the parameter γ controls its spread. For this type of kernel it can be shown that the above derivation is equivalent to the hypersphere formulation presented by Tax *et al.* (Tax, 2001) (Tax, 2004).

Taking above into consideration a distance of a test point $\mathbf{x}_x$ to the hyperplane in the feature space can be expressed as $K(\mathbf{w},\mathbf{x}_x)$ which, if greater than ρ, indicates that a point belongs to the class. That is, a point $\mathbf{x}_x$ is classified if the following holds

$$\sum_{n\in SVs}\alpha_n\left\langle\mathbf{x}_n,\mathbf{x}_x\right\rangle \geq \underbrace{\sum_{n\in SVs}\alpha_n\left\langle\mathbf{x}_n,\mathbf{x}_m\right\rangle}_{\upsilon}. \quad (11)$$

A value on the right side of the condition (11) can be precomputed to a scalar υ to speed up response of the system. Finally, it is worth mentioning that a hardware implementation of the classifier operating in accordance with equation (11) was created which allows real time image processing. This was possible due to relatively small number of support vectors selected during cross-checked training. Their number in our experiments did not exceed 20.

2.4 Measuring Correlation of Images

A relative distance of color distributions between the reference and test images is computed with the Bhattacharyya measure, defined as follows (Bhattacharyya, 1943); (Aherne, 1998):

$$D_B=\sum_{i=1}^{M}\sqrt{t_i r_i}, \quad (12)$$

where t_i and r_i are the normalized ratios of numbers of pixels classified by the i-th OC-SVM classifier, taken out of the total number of M classifiers belonging to the ensemble. However, apart from the pixels which were accepted by one of the members of the ensemble, in the test image there can be pixels which do not appear in the reference image, for which the ensemble was constructed. To account for these pixels a ratio h of a number of pixels rejected by the ensemble to the total number of pixels in the test image is computed. Then, the final match measure is obtained based on the following formula

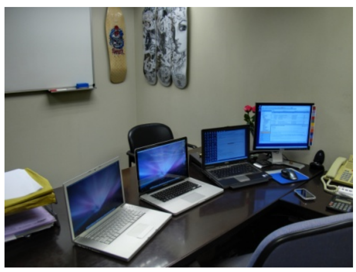
$$D=\left(1-h\right)D_B. \quad (13)$$

A value D can take on values from the range of [0,1] with D close to 0 meaning no match at all, whereas values of D close to 1 mean a perfect match in terms of the model expressed by an ensemble of OC-SVMs.

3 EXPERIMENTAL RESULTS

In order to analyze properties of the presented method a small subset of the Flickr database was used, which consists of about 350 images. The corresponding website of this database contains numerous images with the accompanying user-generated keywords (Flickr, 2011). Based on some subjective measures these are divided into semantic categories, such as cars, offices, faces, flowers and other. Examples of some test images from the three categories are presented in Table 1.

Table 1: Examples of test images from the three categories (from top down) - cars, flowers, and office.



In our experiments the result of searching for the similar images is considered correct if within the five most similar images either majority of them belong to the same category. Otherwise an answer is checked by an operator and is accepted if the responded image visually bears a similar distribution of dominating colors of the reference one. Although the first criterion is easily measurable, the second is subjective. However, the tests were performed by three persons independently. The obtained results are presented in Table 2.

The results show comparatively good performance of the method since the achieved accuracy is in the range of 82-89%. Usually, worse results were obtained for more complicated scenes. On the other hand, if an image consisted of few objects with dominating color (such as in the categories cars and faces), in majority of cases the method was capable of selecting visually similar instances.

Table 2: Results for image classification to different categories.

Image category	Accuracy
Cars	89 %
Flowers	87 %
Office	82 %
Faces	85 %

Very useful feature of the method is that it is invariant to geometric deformations, as well as to slight variations of illumination. This was measured by artificially generated affinely transformed versions of the reference images, for which deformation parameters were randomly selected from the predefined range. These were random rotations of maximally ±25°, horizontal and vertical changes of scale ±12%, as well as translation of ±25 pixels. To such deformed image additive noise was added in the range of 10%. The algorithms for generation of these deformations are described in the book (Cyganek, 2009). The obtained results of these tests show accuracy of 98-100%. The invariance to the geometric deformations is mostly due to measuring boundaries of dominating color distributions, while to the variations of illumination comes from the generalizing properties of the OC-SVM classifiers.

4 CONCLUSIONS

The paper presents a simple but capable method of the prototype encoding in a form of a set of ensembles of OC-SVM classifiers. Such an encoding allows fast examination of a database and selection of images similar in their color distributions. However, thanks to the boundary descriptors of the OC-SVMs the output ensembles consume much less memory than the original images or 3D histograms. They also allow fast comparison of the test pixels coming from the other images. The experimental results show acceptable accuracy for three different groups of test images.

Further research will be devoted to development of methods that consider other characteristic features of the images such as spatial position of color pixels and texture. As alluded to previously, the presented method should be connected with one of the search methods that utilize invariant features of the images. Future research should be also focused on development of methods which allow responses which agree with similarity in the sense of human visual perception, as well as on human-computer interfaces which allow easy formulations of queries for search of visual information. For the latter, the combination of different approaches seems to be the most versatile, due to numerous categories of scenes in the repositories. Also important is development of parallel algorithms which allow faster operation for very large databases.

ACKNOWLEDGEMENTS

This research was supported from the Polish funds for scientific research in the year 2011 under the *Synat* project.

REFERENCES

Aherne, F. J., Thacker, N. A., Rockett, P. I., 1998. The Bhattacharyya Metric as an Absolute Similarity Measure for Frequency Coded Data. *Kybernetika*, Vol. 34, No. 4, pp. 363-368.

Bertsekas, D. P., 1996. Constraint Optimization and Lagrange Multiplier Methods. *Athena Scientific*.

Bhattacharyya, A., 1943. On a Measure of Divergence Between Two Statistical Populations Defined by their Probability Distributions. Bull. *Calcutta Mathematic Society*, Vol. 35, pp. 99-110.

Cyganek, B., Siebert, J. P., 2009. An Introduction to 3D Computer Vision Techniques and Algorithms, *Wiley*.

Cyganek, B., 2010. Image Segmentation with a Hybrid Ensemble of One-Class Support Vector Machines. *HAIS 2010, Part I, Lecture Notes in Artificial Intelligence* 6076, Springer, pp. 256–263.

Duda, R. O., Hart, P. E., Stork, D. G., 2001. Pattern Classification. *Wiley*.

Filippone, M., Camastra, F., Masullia, F., Rovetta, S., 2008. A survey of kernel and spectral methods for clustering. *Pattern Recognition 41*, pp. 176-190.

Fletcher, R., 2003. Practical Methods of Optimization, 2nd edition. *Wiley*.

Flickr, 2011. http://www.flickr.com/

Gestel, T. V., Suykens, J. A. K., Baesens, B., Viaene, S., Vanthienen, J., Dedene, G., De Moor, B., Vandewalle, J., 2004. Benchmarking least squares support vector machine classifiers. *Machine Learning*, Vol. 54, No. 1, pp. 5-32.

Hermes, T., Miene, A., Herzog, O., 2005. Graphical Search for Images by Picture-Finder. Multimedia Tools and Applications. *Special Issue on Multimedia Retrieval Algorithmics*, Vol. 27, No. 2, pp. 229-250.

Hsu, C-W., Chang, C-C., Lin, C-J., 2003. A Practical Guide to Support Vector Classification. *Department of Computer Science and Information Engineering, National Taiwan University*, (www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf)

Koen, E. A. van de Sande, Gevers, T., Snoek, C. G. M., 2010. Evaluating Color Descriptors for Object and Scene Recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 32, No. 9, pp. 1582-1596.

Kruse, R., Döring, C., Lesot, M-J., 2007. Fundamentals of Fuzzy Clustering, in Advances in Fuzzy Clustering and its Applications, ed. de Oliveira, J.,V., Pedrycz, W., *Wiley*, pp. 3-30.

Kuncheva, L. I., 2004. Combining Pattern Classifiers. *Wiley*.

Müller, H., Clough, P., Deselaers, T., Caputo, B., 2010. ImageCLEF. Experimental Evaluation in Visual Information Retrieval. *Springer*.

Schölkopf, B., Smola, A. J., 2002. Learning with Kernels, MIT Press.

Shawe-Taylor, J., Cristianini, N., 2004. Kernel Methods for Pattern Analysis. *Cambridge University Press*.

Tax, D. M. J., 2001. One-class classification. PhD thesis, *TU Delft University*.

Tax, D., Duin, R., 2004. Support Vector Data Description, *Machine Learning 54*, pp.45-66.

Vapnik V. N., 1995. The Nature of Statistical Learning Theory, *Springer*.