ISSN: 2348 - 2117

International Journal of Engineering Technology and Computer Research (IJETCR)
Available Online at www.ijetcr.org
Volume 4; Issue 4; July-August; 2016; Page No. 50-57

CLASSIFICATION OF SPORTS IMAGES USING NAIVE BAYESIAN CLASSIFIER

VIJAY KUMAR GUGULOTHU[1], Prof. Dr S K MOHAN RAO[2]

[1]Senior lecturer, Department of Computer Engineering, Government Polytechnic, Siddipet, Telangana State-India.

gvijay21@hotmail.com

[2]Department of Computer Engineering, Siddartha Institute of Engineering & Technology

Ibrahimpatnam Mandal –Ranaga Reddy District-Telangana State-India.

Abstract
For an efficient image data mining accurately finding and classification of various images are required. Therefore there is a need for an image classification method which can be wild applicable to image data mining tasks. In this paper we propose a Bayesian method for classifying the sports images. The proposed method is based on the Bayesian framework and employees four color features to exploit the properties of images.

Key Words: Mining efficiency, Image data mining, Color Coherence Vector, Color coherence vector, Bayesin theorem.

1. Introduction

Efficiently finding and retrieving various kinds of images from the raw images in a large image database is essential for the domain of image data mining. The first problem is the inadequacy of flexibility. It is possible to achieve high classification performance for only limited domains. But it is quite difficult to accurately classify a wide variety of objects. A troublesome preprocessing is often required depending on the classification tasks. The second problem is the lack of diversity of the features used to classify the objects. Since an object has various features such as contour, color and texture, integrating multiple features is required to fully describe and discriminate the real world objects. The third problem is the difficulty in finding the appropriate features to precisely discriminate the objects. However, it is difficult to determine the appropriate features because it determined be should depending on the object. To solve this problem, the following two viewpoints are important. The first is collaborated: each visual learner should be trained taking the learning process of the other learners into consideration. The second is selectivity. Because of the complementary nature of the collaborative learning framework, each visual nature of the collaborative learning framework, each visual learner is specialized in discriminating a kind of objects.

The fourth problem is the mining efficiency. Since an image consists of a large number of pixels, the amount of information (or the number of dimensions) or an image is quite large. Moreover, in the image data mining tasks, the images should be found and retrieved from large image databases. Hence, the computational complexity should be reduced. For the efficient image classification, we propose two types of image classification methods as the visual learners. The first is the appearance-based classification method. It utilizes the contours represented by a set of fragmented lines. They are combined into a meaningful structure. The second is the region-based classification method. It utilizes the local distribution of pixel intensity values. A feature vector is generated by transforming the distribution using polar Fourier transform. These visual learning methods provide simpler but more informative features than raw image data and thus the classification process becomes more efficient. **Fayyad et al. [1996]** describes advances in knowledge discovery data mining. **Greg pass ET al. [1996]** have comprising the images using color coherence vectors. **Vasconcelos et al.[1997]** describes reorientation for efficiently video compression and retrieval. **Alejandro et al.[1999]** have used the model basic classification of visual information for content based retrieval. **Theogevers et at. [2000]** describe the classification of image on internet by visual and textual information.

Xuzaho et al. [2008] describes automatic resource management in visualized data centers using fuzzy logic based approaches. **Brain et al. [2009]** have approached the integrated resource management for visualized data centers. In this paper we propose a Bayesian method for classifying the sports images. The proposed method is based on the Bayesian framework and employees four color features to exploit the properties of images.

2. METHODOLOGY

Sports images can be distinguished exclusively since the differences between same sports images are noticeable. For instance, images of water sports such as swimming and windsurfing have a large blue region by water, while image classifier uses four low-level features to classify the sports images. Each feature represents color or shape characteristic of images. These classifiers assume that each framing image belongs to one of the classes. The four low-Level features used to depict an image are color Histogram, Color Coherence Vector, Edge Direction Histogram and Edge Direction Coherence Vector. We describe their features briefly from the viewpoint of sports image classifier as illustrated in Fig 1.

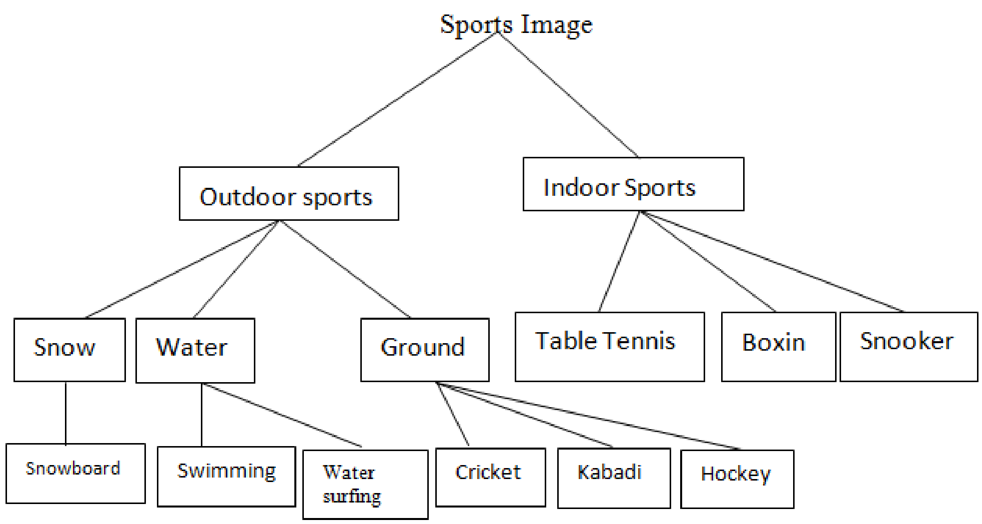


Figure 1: Viewpoint of Sports Image Classifier

3. BAYESIAN FRAMEWORK

The Naïve Bayesian classification or simple Bayesian classifier, it works as follows:

- Let 'D' be the training set of tuples and their associated labels. Let each tuple is represented by an n-dimensional attribute Vector 'X'=[x_1,x_2,………x_n] showing 'n' measurements mode on the tuples from 'n' attributes respectively A_1, A_2,………A_n.
- Let us assume that there are 'm' classes. C_1, C_2,…….C_m. Given that 'X' the classifier will predict that X belongs to the class having the highest posterior probability, condition m_x. i.e, the Naïve Bayesian classifier predicts that tuple X € C_i, iff

  $P(C_i |X) > P(C_i | X)$ for $i<=j<=m, j\neq i$

  Now, $P(C_i | X)$ we maximize, so the class for which $P(C_i | X)$ is maximized is called maximum posterior hypothesis.

Fore there By Bayesin theorem $P(C_i \mid X) = \dfrac{P(X \mid C_i)\, P(C_i)}{P(X)}$

- $P(C_i \mid X)$. $P(C_i)$ need to be maximized because P(X) is constant. If we do not know the value of class prior probabilities, we assume that classes are equally likely $P(C_1)=P(C_2)=\ldots\ldots\ldots=P(C_m)$.

Fore there we would maximize P(X | Ci). Otherwise we maximize.

P(X | Ci).P(Ci) Where $P(Ci)=| C_{i.D} | \; | D |$

Here, $|C_{i.D}|$ is the number of training tuples of class C_i in D.

- Given data sets with many attributes, it is very extremely computationally expensive to calculate $P(X \mid C_i)$. In order to avoid this, the Naïve assumption class conditional independence is made i.e. the values of the attributes is independent of one another; give the class label of the tuples.

$$P(x \mid Ci) = {}^{n}\Pi_{k=1} P(x_k \mid Ci)$$

$$= P(x_i \mid Ci),\ P(x_2 \mid Ci), \ldots\ldots\ldots\ldots P(x_n \mid Ci)$$

Now, we can easily estimate the probability $P|C_i)$, $P(x_2| C_{i,}$ …………$P(x_n \mid Ci)$ from the training tuples.

For tuple x, here x_k refers to the value of attribute $A_{k.}$ We observe that for each value of the attribute whether it is a categorical or continuous valued.

For example, we compute P(x | Ci), the following steps are involved.

I.If A_k is categorical, then $P(x_k \mid Ci)/|Ci \mid P|$

Where $P(x_k \mid Ci)$ is the number of tuples of class Ci, in having the value X_k for $A_{k.}$

Where, |Ci, D| is the number of tuples of class Ci, in D.

II.If A_k , is continuous valued, then

A_k is continuous valued, a continuous value is assumed by Gaussian distribution with a mean in and standard deviation σ, defined by

$$g(x,\mu_1) = \frac{1}{\sqrt{2\text{II}6}} \quad e \quad - \frac{(x-\mu)^2}{26^2}$$

Where $P(x_k \mid Ci) = g(x_k, \mu_{ci}, \sigma_{ci})$

We have to compute μ_c and $\sigma_{c.}$ Where μ_c is the mean and standard deviation is σ_c

$P(C_i |X)$. $P(C_i)$ is evaluated for each class Ci, In order to predict the class label of

X. The classifier predicts that the class label of tuple X is the class Ci if and only if

$P(C_i|X) . P(C_i) > P(X | Ci)P(Ci)$ for <= j<=m, j≠i, PCX | C_i). PC C_i) is maximum

Color histogram is a compact summary of an image in color dimension. In the Bayesian sports image classification, a value of color histogram identifies the characteristic of each sports image in color dimension. Color histograms are frequently used to compare images. Their use in multimedia applications includes scene break detection and objects identification. For a given image *I*, its color histogram is H_I. An image database can be queried to find the most similar image to *I*, and can return the image *I'* with the most similar color histogram H_I. Typically, color histograms are compared using the sum of squared differences, called as L_2-distance, or the sum of absolute value of differences, called as L_1- distance. So the most similar image to *I* would be the image *I'* minimizing the L_2-distance or L_1-distance. Equation of L_1-distance and L_2-distance are as follows.

$$||H_1 - H_1|| = £^{n2} (H_1| I] - H0_{1-[I]})^2$$

$$| H_I - H_I | = £^{n2} | H_I I] - H_I (I) |$$

Where *M* is the number of pixels that an image has. We assumed that all images have the same number of pixels for the ease of explanation. *H(h1, h2, ..., hn)* is a vector, in which each component *hj* is the number of pixels of color *j* in the image, *n* is the number of distinct (discredited) colors. Color coherence vector is the degree to which pixels of that color are members of large similar colored regions. We refer to these regions as coherent regions. Our coherence measure classifies pixels as either coherent or incoherent. Coherent pixels are a part of some sizable contiguous region, while incoherent pixels are not. A color; coherence vector (CCV) represents this classification for each color in the image. CCVs prevent coherent pixels in one image from matching incoherent pixels in another. This allows distinctions that cannot be made with color histograms. In the Bayesian sports image classification, CCVs help to find a sports image class having similar characteristic with input images in color dimension. At first, we blur the image slightly by replacing pixel values with the average value in a small local neighborhood [currently including the 8 adjacent pixels]. This eliminates small variations between neighboring pixels. Then we discrete the color space, such that there are only *n* distinct colors in the image. The next step is to classify the pixels within a given color bucket as either coherent or incoherent. A coherent pixel is a part of a large group of pixels of the same color, while an incoherent pixel is not. We determine The pixel groups by computing connected components. We classify pixels as either coherent or incoherent depending on the size in pixels of its connected component(*C*). A pixel is coherent if the size of its connected component exceeds a fixed value *T [*e.g. 1% of number of pixels], otherwise, the pixel is incoherent. Color coherent vector and equation for distance measure of image *Ia* and I_b using the weighted Euclidean distance are as follows.

$$[(a_1, b_1) \text{-----------} (a_n, b_n)]$$

$$\frac{£^{n2}}{} \quad \sqrt{\frac{(a_j - a^I j)^2 (bj - b^I j)^2}{}}$$

j=I 2n

where *aj* is [number of coherent pixels of the *j*'s discretized color) / (total number of pixels in the image]. *bj* is [number of incoherent pixels of the *j*'s discretized color) / (total number of pixels in the image].

Edge direction histogram (EDH) represents the global information of shape in an image. The edge direction information can be obtained by using the canny edge detector. In the Bayesian sports image classification, the EDH identifies the characteristic of each sports image in shape dimension. At first, we calculate Gaussian filter $Si_{,j}$ then compute the gradient along x-direction, Pi_{j}, and compute the gradient along y-direction, *Qi,j*. Next, we compute the magnitude of the gradient to obtain an edge image, *Mi,j*, using *Si,j* and *Pi,j*.

Finally, we compute edge direction histogram as follow:

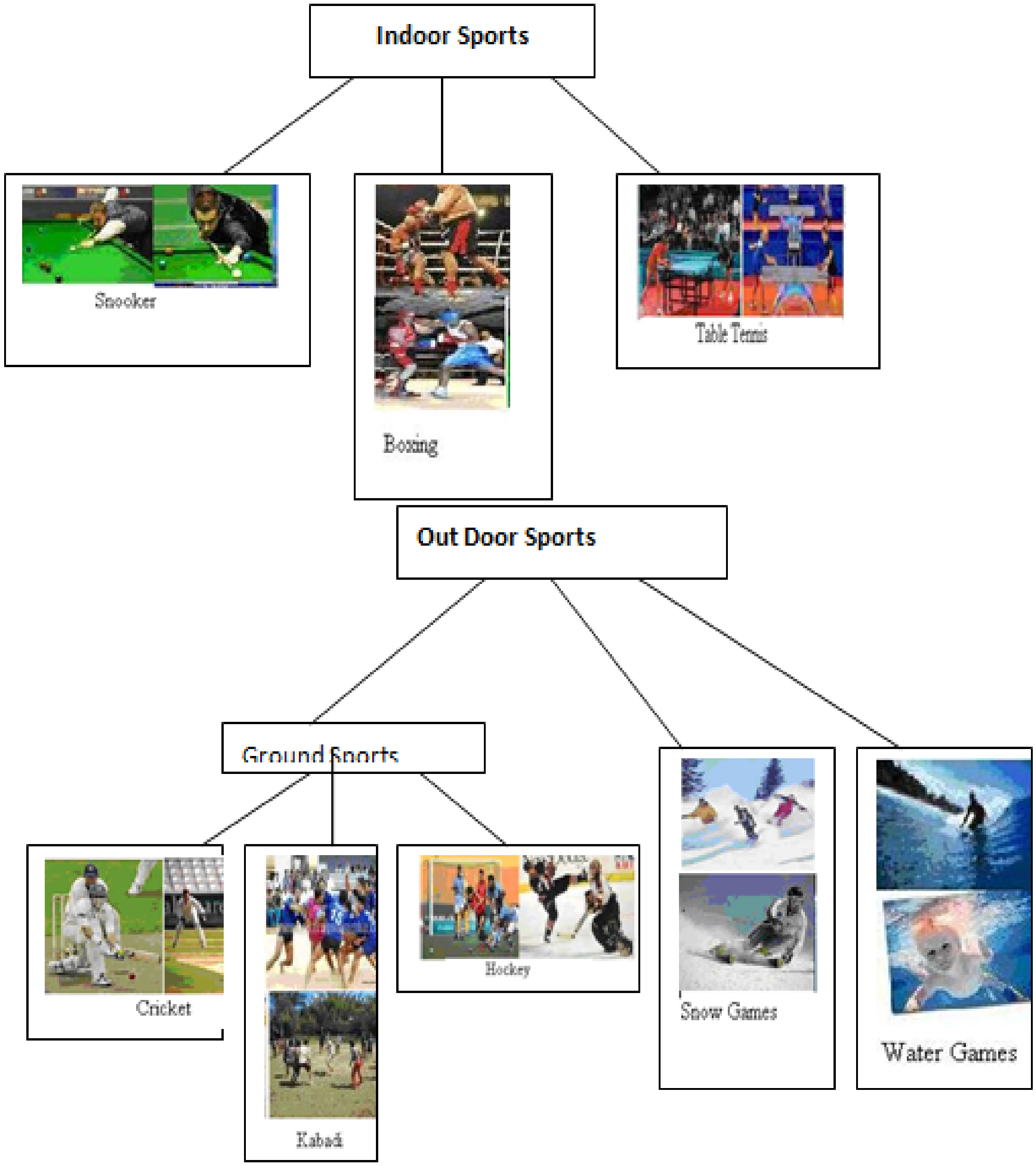
$$\text{Ø} = \text{Tan}^{-1} \left(\frac{Q_i, j}{P_i, j} \right)$$

An edge direction coherence vector (EDCV) stores the number of coherent versus non-coherent edge pixels with the same directions (within a quantization of 5o). A threshold on the size of every connected component of edges in a given direction is used to decide whether the region is coherent or not. Thus this feature is geared towards discriminating structured edges from arbitrary edge distributions when the edge direction histograms are matched. The EDCV helps the classifier to find sports image class having similar characteristic with input images in shape domain. The shape characteristic of images in the same sports

class is similar by its background [i.e. ring or form of ground] or pose of player (i.e. shooting pose or almost fixed camera angle). There are several differences between Bayesian classifier of textual data and that of image data. Images usually have various and complex attributes, which means image data, may be represented in high-dimension space. In addition, most of these attributes have continuous values. Accordingly, the Bayesian sports image classifier should reflect such characteristics of image data.

4. EXPERIMENTAL RESULTS

For experiments, we used a sports image database composed of several sports classes such as Snooker, Boxing, Table Tennis, Cricket, Kabadi, Hockey, baseball, Snooker, Swimming. We gather such sports images from Internet. Each sports class contains about 60 images. The total number of sports images in the database is 532.



First, we classified images using the proposed sports image classifier employing each single image feature. Image sets is classified into indoor/outdoor categories. Then images, belonging to the indoor category, are further divided into three categories, which are Snooker, boxing and Table tennis. Images of water sports are classified into swimming images and windsurfing images. Images of snow sports are classified into ski images and snowboard images. Finally, images of ground sports are classified into Cricket, Kabadi and Hockey categories. Secondly, the proposed sports image classifier uses the combinations of image features and performs classification. Accuracy of each classification is shown in Table 1 and Table 2.

Table 1: Accuracy of classification using each single image feature

	CH	CW	EDH	EDCV
Indoor / Out door	312/532= 58.8	316/532=59.3	322/532=60.5	331/532=62.2
Water/Snow/Ground	278/416=66.8	279/416=67.06	283/416=68.02	292/416=70.19
Snow	82/99=82.08	84/99=74.07	87/99=87.08	87/99=87.08
Swim/Water surfing	73/99=73.09	74/99=74.07	75/99=75.07	78/99=78.07
Cricket /Kabadi / Hockey	110/170=64.7	117/170=68.08	121/170=71.01	132/170=77.06
Table Tennis/ Snooker /Boxing	92/156=58.09	903/156=66.02	103/156=66.02	107/156=68.05

Table 2: Accuracy of classification using combinations of image features.

	CH & EDH	CH & EDCV	CCV&EDH	CCV&EDCV
Indoor / Out door	361/532=67.08	372/532=69.09	381/532=71.06	387/532=72.07
Water/Snow/Ground	282/416=67.07	284/416=68.02	289/416=69.4	292/416=70.19
Snow	86/99=86.08	87/99=87.08	87/99=87.08	89/99=89.08
Swim/Water surfing	76/99=76.07	78/99=78.07	82/99=82.08	84/99=84.08
Cricket /Kabadi / Hockey	114/170=67.05	118/170=69.04	122/170=71.07	127/180=74.07
Table Tennis/Snooker /Boxing	94/156=60.25	96/156=61.05	105/156=67.03	112/156=71.07

The classification using combinations of features is more accurate than the classification using a single feature. In the classification employing a single feature, the most effective feature is dependent on characteristic of the image. For example, classifications of sports images, which is dependent on color features such as water/ snow/ground classification, has the best accuracy when it uses color features such as CH or CCV. By the contrast, sports image classification that is not based on color features such as swimming/windsurfing classification shows better accuracy when it uses edge features such as EDH or EDCV instead of color features.

5. Conclusion:

In this paper we have presented collectively a set of comprehensive sports images using Bayesian estimating method in this paper by image data set has been collected from sports images are more suitable for all types of analysis because of its high quality and less noise. The informing is more for these images. These images are less smooth noise characteristic was identified while measuring the textual future. In future statistical movements based on common descriptive of future are measured and based spastically movement quality measuring also analyzed.

6. REFERENCES

1. U.M. Fayyad, G. Piatetsky-Shapiro, P. Smyth, R. Uthurusamy: Advances in Knowledge Discovery and Data Mining. AAAI/MIT Press, (1996).
2. Maria Luiza Antoniek Osmar R. Zaiane, Alexandru Coman: Application of Data Mining Techniques for Medical Image Classification. In Proc. The 2nd Int. workshop Multimedia Data Mining (MDM/KDD), San Francisco, USA, August 26 (2001).
3. M. Datcu, K. Seidel: Image information mining: exploration of image content in large archives. IEEE Conf. On Aerospace, Vol. 3, (2000).
4. Ji Zhang, Wynne Hsu, Mong Li Lee: Image Mining: Issues, Frameworks and Techniques. In Proc. The 2nd Int. workshop Multimedia Data Mining

(MDM/KDD), San Francisco, USA, August 26 (2001).

5. L. Bruzzone, D.F. Prieto: Unsupervised retraining of a maximum likelihood classifier for the analysis of multitemporal remote sensing image. IEEE Transactions on Geoscience and Resmote Sensing, Vol. 39, February (2001).
6. Alejandro Jaimes, Shih-Fu Chang: Model-Based Classification of Visual Information for Content-Based Retrieval. Storage and Retrieval for Image and Video Databases VII,IS&T/SPIE99, San Jose, CA, January (1999).
7. Theo Gevers et. al. Classification of Image on Internet by Visual and Textual Information. Internet Imaging, SPIE, San Jose, January (2000.).
8. N. Vasconcelos, A. Lippman: Library-based coding: A representation for efficient video compression and retrieval. Data Compression Conf.'97, Snowbird, UT, (1997).
9. Jiawei Han, Micheline Kamber: Data Mining: concepts and techniques, Morgan Kaufmann press, p.296-303, (2001).
10. A.K. Jain, A. Vailaya: Image retrieval using color and shape, Pattern Recognition. 29(8):1233-1244, (1996).
11. J. Canny: A computational approach to edge detection. IEEE Transactions on Pattern Analysis and Machine Intelligence, PAMI-8(6):679-698, (1986).
12. Greg Pass, Ramin Zabih, J. Miller: Comparing images using color coherence vectors. In Proc. ACM Multimedia, 65-73, Boston, MA, November (1996).
13. Brain J wat sow et al [2009], 1000 islands an integrated approach to resource management for visualized data ceters. Cluster computers 12, 45-57
14. Xw J Zalo et al. [2008], Automactic resource management is visualized data centers using Fuzzy logic based approaches. Cluster computers 11, 213-227.