# CLASSIFICATION AND INDEXING OF PAINTINGS BASED ON ART MOVEMENTS

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## ABSTRACT

This paper outlines the automatic extraction of features of paintings' art movements such as classicism, impressionism and cubism; and introduces a system developed for the classification and indexing of paintings based on their art movements. A six dimensional feature set is proposed for the representation of content and it is shown that the feature set enables to highlight art movements efficiently. In the classifier design, statistical pattern recognition approach is exploited and Bayesian, k-NN and SVM classifiers are employed. A classification accuracy of over 90% is achieved with very small false alarm ratios while the lowest performance is obtained by the k-NN. System also offers a quick query based database search by indexing the paintings with their six dimensional feature vectors, and provides an applicable program for museums and exhibition centres.

## 1. INTRODUCTION

Recently, the studies for digitizing the paintings and storing them in databases are becoming widespread. Automatic identification of art movements for digital paintings and, in addition to their extracted features, automatic labelling of paintings with their proper art movements for indexing and storing processes are significant improvements in the construction of online museums. Several researches are undertaken, especially, in European countries regarding these topics [1,2]. These researches are focused on the identification of painters or painting styles, and offer several studies that can be exploited for artistic paintings. We developed our classifiers taking these previous studies into account and employing additional features in order to construct an integrated classification and indexing system.

Philosophical approaches, common understandings and technical possibilities of an era determined the features of its paintings. For example, in "classicism" movement, born in Italy and widely accepted between 1400-1600, realism, harmony and simplicity were determining factors that reflect the Roman and Greek philosophy. Painters of classicism preferred dark colours in their paintings and tried to draw the objects as real as possible because of the lack of technologies like photograph cameras. On the other hand, "impressionism", born in France in late 19.century, is focused on natural paintings and light-colour changes [3]. Bright colours and smooth transitions that hide the sharp edges are some of the determining features of impressionist art movement. "Cubism" movement that emerged in the beginning of 20.century generated paintings reflecting different perspectives and involving analytic, visual-based features. The ratio of dark and bright colours used in the paintings has no determining power for cubist movement. However, the distinctive edges and, consequently, the high contrast are some of the determining features of this art movement.

Explanations, given above, outline the visual information of the paintings that belong to specific art movements. The design of an automatic painting classifier requires the mathematical modelling of these visual clarities as determining features. In this paper, the features that distinguish the art movements of classicism, impressionism and cubism are defined, and the implementation of statistical painting classifiers is described.

## 2. FEATURE EXTRACTION AND INDEXING

In this study, it has been shown that the art movements of paintings can be indexed by exploiting six different features. Let $\mu_i$, *i*.th individual entity of the six dimensional feature vector is defined as below for $i$=1,2,..,6;

$\mu_1$ : Percentage of dark colours.
$\mu_2$ : Gradient coefficient calculated from the gradient map of the painting image.
$\mu_3$ : Number of local and global maxima in the luminance histogram.
$\mu_4$ : Colour range that the peak point of the luminance histogram corresponds.
$\mu_5$ : After the partition of the painting image into identical blocks, the deviation of average grey level acquired within each block from the average grey level acquired within entire image.
$\mu_6$ : "Skew," the deviation of grey level distribution from Gauss distribution.

The mathematical formulations of the features are as follows:

The luminance component of a colour image defined in RGB space is computed by Eq.(1).

$$Y = 0{,}299\ R + 0{,}587\ G + 0{,}114\ B. \qquad (1)$$

There is a very high relation between the luminance component and grey level image. In the research, the luminance component is represented with 8 bits (256 grey level) and the pixels whose luminance value corresponds to [0,64] range are considered as dark pixels.

$$\mu_1 = \frac{\text{Number of dark pixels in the painting image}}{\text{Number of all image pixels}}.$$

$$\mu_2 = \text{Normalized}\left(\sum_{i=1}^{r}\sum_{j=1}^{c}\sqrt{(f_{ij})_x^2 + (f_{ij})_y^2}\right),$$

where $r$ and $c$ are the row and column numbers of the image respectively, and $(f_{ij})_x$ and $(f_{ij})_y$ are the first order derivation of the image's ($ij$) pixels in $x$ and $y$ directions respectively.

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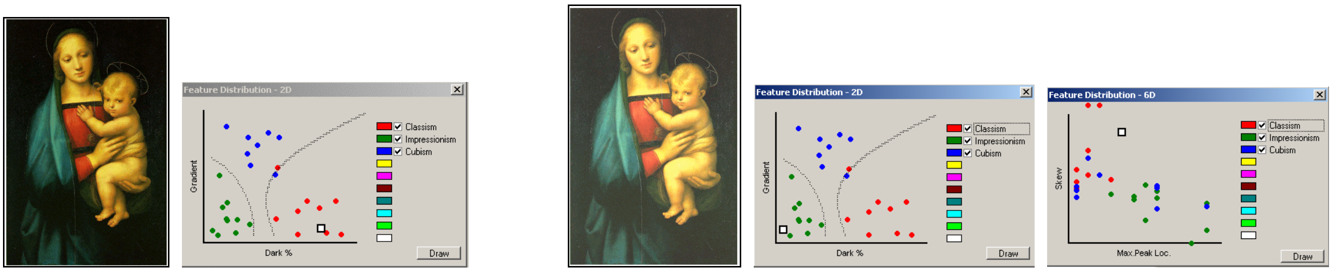
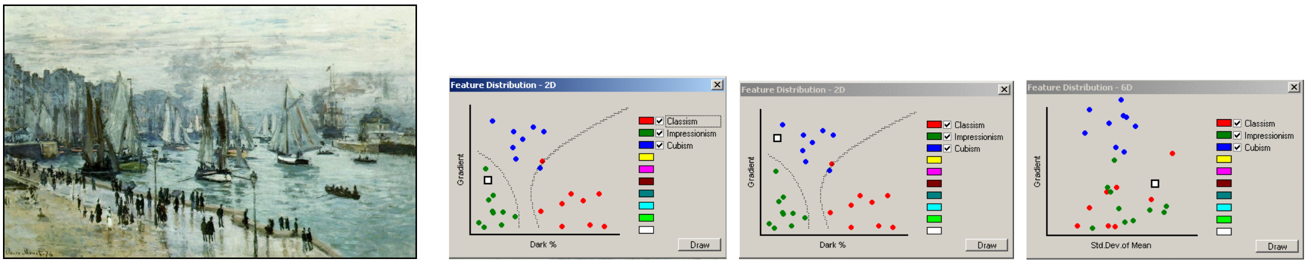



(a) (b) (c) (d) (e)

Figure 1 - a) Rafael's "Granduca" painting that belongs to "classicism" movement. b) Classification result of the painting in (a) whose 2 dimensional feature vector is classified as classicism (the classified vector is pointed by a small square). c) The bright "Granduca" which is obtained after changing the lighting condition of the original image in (a). d) The misclassification (impressionism) of the painting in (c) using 2 dimensional vectors. e) Correct classification result (classicism) obtained with the effect of "skew" feature, after using 6 dimensional feature space.




(a) (b) (c) (d)

Figure 2 - a) Monet's "Le Havre" painting that belongs to "Impressionism" movement. b) Classification result of the painting in (a) whose 2 dimensional feature vector is classified as impressionism (the classified vector is pointed by a small square). c) Classification result of the painting in (a) after the painting's resolution is reduced by ½. 2 dimensional feature vector is misclassified as cubism. d) Correct classification result (impressionism) of the ruined painting after upgrading to 6 dimensional feature space.

Especially, the "classicism" movement can be classified quite accurately by using these two features: $\mu_1$ and $\mu_2$. However, these features, alone, are insufficient for classification of other art movements. Additionally, changing lighting conditions and the resolution of the painting images may cause false classification. For example, Rafael's "Granduca" painting (Figure 1 a) belongs to the "classicism" movement and can be correctly classified with $\mu_1 = [\mu_1 \;\; \mu_2]^t$ feature vector (Figure 1 b). However, when the lighting conditions change, classification gives incorrect results (Figure 1 c). Similarly, "Le Havre" painting (Figure 2 a) created by a representative painter of impressionist movement, Monet, can be classified correctly using two dimensional feature vector (Figure 2 b). On the other hand, when the resolution of the painting image is reduced by 50 percent, two dimensional space is not sufficient for classification (Figure 2 b). In order to solve such problems, additional features are defined in the system:

$$\mu_3 = \text{number}\left(\left|H(i)\right| > thr\right),$$

where *thr* is the threshold value determined to correspond the amplitude of the histogram to a maximum.

$$\mu_4 = \max_i |H(i)|, \qquad i = 0, 1,.., 255,$$

where *H(i)* is the value of the histogram for $i^{th}$ grey level.

The classification performance of paintings that belong to impressionism movement is augmented by the inclusion of these two features. Main reason of this augmentation is that impressionist paintings generate one maxima in the bright regions of the luminance histogram. For classicist paintings, maximum point occurs in dark regions and for cubist paintings, more than one maximum point occurs in variable regions of the histogram. On the other hand, following features are included to preserve the system performance against changing lighting conditions and resolution differences:

$$\mu_5 = \sum_{i=1}^{9} (mean_i - mean),$$

where *mean* represents the luminance value of the $i^{th}$ block. *mean* is the average luminance value of the entire image and calculated by the Eq. (2).

$$mean = \frac{\sum_{i=1}^{r}\sum_{j=1}^{c} f_{ij}}{rc}. \tag{2}$$

In the computation of $\mu_5$, paintings in the training set are partitioned into 9 identical sub-blocks each of which preserves the original painting's aspect ratio. For each sub-block, average colour value is calculated in grey level. The deviation of these 9 values from the average colour value calculated for entire image gives out the $\mu_5$, "Std. Deviation of Mean" feature. While, in impressionist or classicist paintings, this feature gives high values because of local brightness or semantic colour changes (*human face, sky…etc*), it does not exceed a specific value for cubist paintings since each sub-block does not demonstrate a big deviation from the overall average value.

As $\mu_5$ is the criterion for deviation of average grey levels of sub-blocks from the entire image, its value is not affected by resolution changes. When the resolution of "Le Havre" painting in Figure 2 a) is reduced, the effect of edges, and consequently the effect of $\mu_2$ feature increases. This causes the false classification of the painting as "cubism" (Figure 2 c). Same painting is accurately classified as "impressionism" when $\mu_5$ feature is included (Figure 2 d). In this example, feature vector is extracted as equals to, $\mu = [6.655\ 48.660\ 1\ 10\ 13.520\ -0.033]^t$ . The sixth feature, $\mu_6$, the criterion for deviation grey level distribution of the image from Gauss is defined as follows:

$$\mu_6 = skew = \frac{\sum_{i=1}^{r}\sum_{j=1}^{c}\left(\frac{f_{ij} - mean}{\sigma}\right)^3}{rc},$$

where $\sigma$ is defined in Eq.(3).

$$\sigma = \frac{\sqrt{\sum_{i=1}^{r}\sum_{j=1}^{c}\left(f_{ij} - mean\right)^2}}{rc-1}. \quad (3)$$

The colour distribution of Rafael's "Granduca" painting in Figure 1 c) completely changes because of the variation in the lighting condition. This effect causes the classification of this actually "classicist" painting as "impressionist" (Figure 1 d). However, the deviation of grey level distribution from Gauss is not affected with this artefact and the painting is correctly classified with the help of the $\mu_6$ feature (Figure 1 e).

"Skew" attribute preserves its value, even when the brightness is harshly increased, and it helps to successfully model the condition in classicist movements where colour distribution displays a different characteristic than that of the Gaussian distribution. Paintings of cubist movement, generally, demonstrate a characteristic that matches the Gaussian distribution. However, in impressionism, the distribution slightly loses this property and it disappears considerably in the classicist movement.

## 3. CLASSIFIER DESIGN

In this study, statistical pattern classification approach is used and the classification of artistic paintings movements is performed using three different classifiers: Bayesian parametric classifier, k-NN classifier and Support Vector Machines (SVMs).

### 3.1 Bayesian Classifier

In the statistical pattern recognition approach, it can be assumed that the feature vectors of classicist, impressionist and cubist movements fit to the Gaussian distribution in $d$ dimensional feature space. By this approach, the classification problem can be reduced to the estimation of parameters that determine the Gaussian distribution (mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$) using "Maximum Likelihood (ML)" parameter estimation method.

In Bayesian approach, mean vector $\boldsymbol{\mu}$ and covariance matrix $\boldsymbol{\Sigma}$ defined in $d$ dimensional decision space; and $p(\boldsymbol{x})$, the probability distribution of features of a painting, $\boldsymbol{x}$, that belongs to a particular art movement are formulated in Eq.(4) and Eq.(5), respectively.

$$\mu = \begin{bmatrix} \mu_1 \\ \vdots \\ \mu_d \end{bmatrix}, \quad \Sigma = \begin{bmatrix} \sigma_{11} & \dots & \sigma_{1d} \\ \vdots & & \vdots \\ \sigma_{d1} & \dots & \sigma_{dd} \end{bmatrix}. \quad (4)$$

$$p(x) = \frac{1}{(2\pi)^{d/2}\left|\Sigma^{1/2}\right|}\exp\left[\frac{-1}{2}(x\text{-}\mu x)^t\,\Sigma^{-1}\,(x\text{-}\mu)\right]. \quad (5)$$

The estimated mean vector and covariance matrices using ML method are formulated as in Eq.(6) .

$$\hat{\mu} = \frac{1}{n}\sum_{k=1}^{n} x_k\,, \qquad \hat{\Sigma} = \frac{1}{n}\sum_{k=1}^{n}(x_k - \hat{\mu})(x_k - \hat{\mu})^t\,. \quad (6)$$

In this notation, $\boldsymbol{x}_k$ represents a training sample that belongs to a particular art movement, and $n$ represents the total number of training samples that are used to estimate the parameters of this particular art movement. Discriminant function for $i^{th}$ art movement is calculated by using estimated parameters as in Eq.(7).

$$g_i(x) = \frac{-1}{2}(x-\mu_i)^t\,\Sigma_i^{-1}(x-\mu_i) - \frac{d}{2}\ln 2\pi - \frac{1}{2}\ln|\Sigma| + \ln P(w_i)\,. \quad (7)$$

In the mathematical equation given above, $\boldsymbol{x}$ represents the $d$ dimensional feature vector of the painting that will be classified. $P(w_i)$, is the prior probability of paintings that belong to $i^{th}$ art movement. In this study, prior probabilities are considered equal for all of the three art movements. Bayesian classifier classifies a painting by taking the maximum discriminant function of the class, and decision rule is stated as follows:

*If* for every $i \neq j$, $g_i(\mathbf{x}) > g_j(\mathbf{x})$, *then* assign the $\mathbf{x}$ vector to $i^{th}$ class.

### 3.2 Support Vector Machines

Support Vector Machines (SVMs) have been shown to have equivalent or significantly better performances than comparative classification methods [4].

Given $n$ observations described by a feature vector $\boldsymbol{x}_i \in R^d$, $i=1,\dots,n$, and the associated class label $y_i \in \{classic, impressionist, cubic\}$, the hyperplane that separates the data satisfies: $\mathbf{w}\,\boldsymbol{x} + b = 0$ where $\mathbf{w}$ is the weight vector and normal to the hyperplane, $b$ is the margin, and $|b|/|\mathbf{w}|$ is the perpendicular distance from the hyperplane to the origin. The parameters $\mathbf{w}$ and $b$ are determined by training the SVM. The optimization of the margin can be achieved by using Lagrange multipliers function described by Eq.(8)

$$f(x) = \sum_{i=1}^{n}\lambda_i y_i K(x, x_i) + b\,. \quad (8)$$

where $\lambda_i$'s are the Lagrange multipliers and $K(\boldsymbol{x},\boldsymbol{x}_i)$ is the Kernel function specified by the user. Obviously, for the linear case $K(\boldsymbol{x},\boldsymbol{x}_i) = \boldsymbol{x}^T\boldsymbol{x}_i$ . Note that Eq.(8) is a function of the observation $\boldsymbol{x}$, and can be interpreted as the distance of the $\boldsymbol{x}$ from the separating hyperplane, or decision surface.

In this work, since the RBF is a generalized type of a linear kernel, and it has the advantage of non-linear mapping into a higher dimensional space, a non-linear Gaussian RBF kernel is used thus $K(\boldsymbol{x},\boldsymbol{x}_i) = \exp(-\gamma\,\|\,\boldsymbol{x} - \boldsymbol{x}_i\,\|^2)$ , $\gamma>0$. To obtain a feasible solution for non-separable data and to manage the tradeoff between the margin and misclassification, the optimization constraints are relaxed and a cost parameter $C \geq 0$ is defined, thus the optimal value of C for the RBF are determined by the grid search method under the constraint $0< \lambda_i <C$.

## 4. RESULTS

The classification system, designed within the research, enables the selection of different feature sets and provides the performance comparison of these different sets individually. With the help of this functionality, experiments are implemented with variable feature vectors and optimised feature set is obtained consequently.

Table 1. Robustness to changes in brightness, contrast and size in 4 and 6 dimensional feature spaces.

| **Art Mov.** | 6D Feature Set | | | 4D Feature Set | | |
|---|---|---|---|---|---|---|
| | **Bayes** | **k-NN** | **SVM** | **Bayes** | **k-NN** | **SVM** |
| **Classis.** | 93 | 80 | 87 | 83 | 80 | 83 |
| **Cubism** | 98 | 91 | 91 | 95 | 91 | 91 |
| **Impr.** | 84 | 74 | 94 | 78 | 74 | 84 |
| **Overall** | 91.66 | 81.66 | 90.66 | 85 | 81.66 | 86 |

A training set is constructed with the 27 original paintings [5] that belong to classic, cubic or impressionist movements, 9 from each class. The six features are extracted for every image in each movement. In order to observe efficiency of the proposed feature set and robustness to changes in the illumination and resolution, a test set is created with lighting effects and resolution changes on the original paintings. Note that non of the training samples is used in the test set including 107 paintings ( 31 classic, 34 cubic, 42 impressionist).

In the SVM classification implementation phase, LIBSVM software package [6] was used. This package provides efficient multi-class Support Vector Classification and Regression results. Experiments were conducted to evaluate the classification performance in 6 and 4 dimensional feature spaces. The data sets were scaled to the range [0,1]. Since the RBF function is used both in parameter selection and classification, $K(\boldsymbol{x},\boldsymbol{x}_i) = \exp(-\gamma \parallel \boldsymbol{x} - \boldsymbol{x}_i \parallel^2)$ , $\gamma > 0$. The best values of the parameters $\gamma$ and C for the RBF are determined by the grid search method. A grid search has been implemented on $C = 2^{-5}, 2^{-3}, \ldots 2^{-15}$ and $\gamma = 2^{-15}, 2^{-13}, \ldots 2^{3}$. After 5 fold cross-validation in the grid search method, the C and $\gamma$ values were determined as 1000 and 10, respectively. The stopping criterion is selected as 0.0001. After selecting the appropriate parameters, the scaled training data set is used to generate the SVM model and the corresponding support vectors. The SVM model is then used in the classification process of the testing data set.

The classification results that are implemented with 107 paintings apart from the training set are given in Table 1. For each of the three movements, an overall classification performance over 80% is achieved in 4 dimensional feature space while in 6 D it increases to 90% for SVM and Bayesian classifiers. The experiments are also implemented with k-NN classifier (k=7) but it has been observed that the obtained performance results were not as successful as other classifiers. Classification results obtained by using SVM shows that the overall performance of SVMs overcomes the Bayesian as well as the k-NN classifier in 4 dimensional feature space, while the Bayesian classifier is slightly better than SVM in 6 D. In 6 dimensional feature space, the false alarm ratio is less then 10% which is very low, except k-NN.

System, developed within this research, also enables the user to run queries and search for a given painting in the database. All painting data stored in the database are in XML format, which is also the base language of MPEG-7. After the classification, user can add the classified painting into the database or look through the paintings in the database and review or delete the existing records. When the user runs a query, if the input painting is available in the database, system retrieves the painting together with its details like the name of the painter, art movement, creation year, etc. If the painting is not available, system returns the best matching record. In Figure 3, the classification and query system developed within this study, also named "Art Historian", is given together with a classification result run for six dimensional feature set. The query sample painting is impressionist Monet's "Umbrella" and it can be classified correctly even with 2 dimensional space.

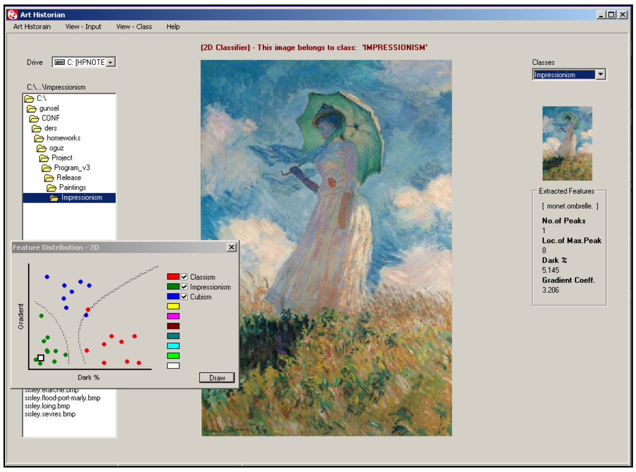



Figure 3. Result of a query implemented in "Art Historian".

It is concluded that all of the classifier's performance has been improved significantly, by using six dimensional feature vectors. The proposed six features are adequate to represent content of paintings resulting in a successful classification and indexing in terms of art movements. The developed system is robust to changes in illumination as well as resolution.

## REFERENCES


[1] F. Nack, M. Windhouwer, L. Hardman, E. Pauwels, M. Huijberts, "The Role of High-level and Low-level Features in Style-based Retrieval and Generation of Multimedia Presentations", *Future Directions for Intelligent Systems and Information Sciences*, Part II (edited by N. Kasabov), Springer-Verlag 2000, ISBN 3790812765.

[2] H.Jaap van den Herik and Eric O. Postma, "Discovering the visual signature of painters" *The New Review of Hypermedia and Multimedia*, Volume 7, 2001.

[3] S. Tansug, "*History of Artistic Paintings*", Remzi Printhouse, Istanbul Turkey, 1996, ISBN 9741402212.

[4] C.J. Burges, "A Tutorial on Support Vector Machines for Pattern Recognition," *Data Mining Knowledge Discovery*, vol.2, pp.121-167, 1998.

[5] Web Museum-Paris, *http://www.ibiblio.org/wm.*

[6] Chih-Chung Chang and Chih-Jen Lin, LIBSVM : a library for support vector machines, 2001. Software available at http://www.csie.ntu.edu.tw/~cjlin/libsvm.