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Machine Learning to Design Full-reference Image Quality Assessment Algorithm

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Abstract

A crucial step in image compression is the evaluation of its performance, and more precisely, available ways to measure the quality of compressed images. In this paper, based on a learned classification process in order to respect human observers, a method namely Machine Learning-based Image Quality Measure (MLIQM) is proposed, which classifies the quality using multi-Support Vector Machine (SVM) classification according to the quality scale recommended by the ITU. Then, the classification process is performed to provide the final quality class of the considered image. Finally, once a quality class is associated to the considered image, a specific SVM regression is performed to score its quality. Obtained results are compared with the one obtained applying classical Full-Reference Image Quality Assessment (FR-IQA) algorithms to judge the efficiency of the proposed method.

Keywords*: FR-IQA algorithm, classification, SVM, SVM regression*

1. Introduction

Terabytes of pictures bytes transmitted on the Internet will surely increase the burden of network communication. In order to reduce the number of bytes transmitted, the appropriate image compression has been referred to in schedule. Image compression will result in image distortion sometimes, and hinder human subjective recognition. In this context, the image quality evaluation comes into being [1, 2].

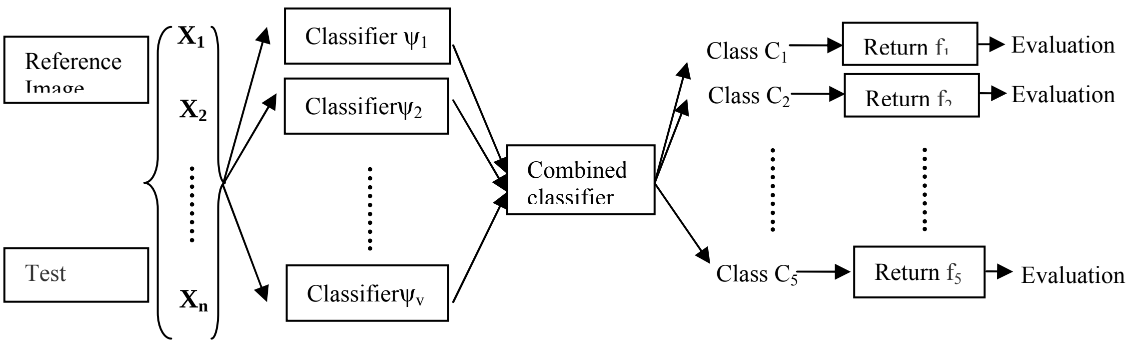

Figure 1. Image Quality Evaluation of the Total Process based on Machine Learning

Typically, there are 3 image evaluation algorithms: (1) Full-reference image quality assessment algorithm (FR-IQA), (2) Half reference image quality assessment algorithm (RR-IQA), (3) No reference image quality assessment algorithm (NR-IQA). This article proposed a new FR-IQA (MLIQM) algorithm by the machine learning expert system to simulate human judgment thinking. The algorithm is based on the classification process of the SVM approach, and finally arrived at the assessed value of a test image quality. In the classification process, the selection of the feature vector is essential. Figure 1 show the image quality evaluation based on

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machine learning process. Eigenvectors calculated by the reference image and test image, x_i, i=1,2,.....n. The classifier Ψ_i is a binary classifier, i=1, 2……10. c_i is a reflection of the class of the test image quality, i=1, 2, ……5. These five quality classes corresponding to the ITU [1] standards: excellent, better, good, poor, poorer. Finally we may obtain a final appraisal quality score value through the SVM regression technology.

2. Full-reference Feature Selection

It is to obtain the difference between the measured standard image and the degraded image using a feature set to measure the distortion of image quality degradation. The standard is set on the basis of the image definition domain (such as color space), the frequency domain (such as Fourier Transform, DCT) and spatio-temporal frequency space (such as wavelet transform).

2.1. The Space Standards

Space standards can measure the brightness distortion, distortion and structure comparison between the test image and reference image. Due to the image in the image space with a vector representation, any image can be seen by the reference image with a distorted view of the change vector.

(1)The brightness distortion between original image I and its degenerated image J can be defined as:

$$l(I,J)=\frac{2u_I u_J+C_1}{u_I^2+u_J^2+C_1} \tag{1}$$

In which u_I, u_J represent the average brightness strength of the image I, J respectively. C1 is a non-zero constant, which can be used to prevent the denominator is zero when $u_I^2+u_J^2=0$. Generally, $C_1=(K_1L)^2$, the theoretical range of the image pixels is $K_1=0.01$.

(2) The contrast gradient comparison defines as:

$$c(I,J)=\frac{2\sigma_I\sigma_J+C_2}{\sigma_I^2+\sigma_J^2+C_2} \tag{2}$$

C2 is a negative constant. Generally, $C_2=(K_2L)^2, K_2=0.03$. σ_I,σ_J represent the standard deviation of the image I, J respectively.

(3)The structure comparison is defined as:

$$s(I,J)=\frac{2\sigma_{I,J}+C_2}{2\sigma_I\sigma_J+C_2} \tag{3}$$

in which $\sigma_{IJ}=1/(N-1)\sum_{i=1}^{N}(I_i-u_i)(J_i-u_J)$.

3. SVM Classification and Regression

Establishment of a support vector machine is based on VC dimension theory of statistical learning and Structural risk minimization principle (St-ructural Risk Minimiza-tion, SRM). It has given dual attention to the experience risk and the believing scope and then has constructed a function into a function subset sequence. It can make the actual risk minimization if compromised consideration between the empirical risk and confidence interval in a subset [3-5].

3.1. Linearly Separable Situation

For a given set of training samples: (x_i, y_i) , $i = 1,2,3......n$. The i-th input sample $x_i \in R^m$; The i-th output sample $y_i \in \{-1,+1\}$,And the classified equation is:

$$f(x) = w \cdot x + b = 0 \tag{4}$$

To find the optimal classification line able to separate the different classes, the classification intervals simultaneously achieve maximum to make two types of samples meet $|f(x)| \geq 1$, When satisfies the above formula from the optimal classification line recent sample point, classification interval is equal to $\frac{2}{\|w\|^2}$. Seeking classification interval maximum which is equivalent to the following optimization problem:

$\min G(w) = \|w\|^2$

Support vector is such a sample point which satisfies $y_i[(w \cdot x_i) + b] - 1 = 0$ and $y_i[(w \cdot x_i) + b] - 1 \geq 0 \quad i = 1,2,3......n$ .As shown in Figure 2. Introduction of Lagrangian function for quadratic programming:

$$L(w,a,b) = \|w\|^2 - \sum_{i=1}^{n} a_i\{y_i[(w \cdot x_i) + b] - 1\} \tag{5}$$

$a = (a_1, a_2, ...a_n)$ is Lagrange multiplier, Carries on separately to w, b asks to lead transforms as the formula $\min G(w) = \|w\|^2$ antithesis question:

$$\max(a) = \sum_{i=1}^{n} a_i - \frac{1}{2} \sum_{i=1, j=1}^{n} a_i a_j y_i y_j (x_i \cdot x_j) \tag{6}$$

The constraint condition is $\sum_{i=1}^{n} y_i a_i = 0, a_i \geq 0, i = 1,2,3......n$. If there is the optimal solution a_i^* ,then $w^* = \sum_{i=1}^{n} a_i^* y_i x_i$, and the Optimal hyperplane is:

$$F(x) = \operatorname{sgn}\{(w^* \cdot x) + b^*\} = \operatorname{sgn}\{\sum_{i=1}^{n} a_i^* y_i (x_i \cdot x) + b^*\} \tag{7}$$

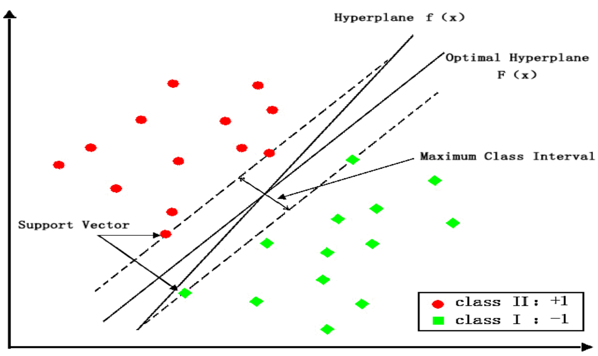

Figure 2. SVM Classification Diagram

3.2. Linearly Inseparable Situation

The **linearly inseparable** basic thought is using the nuclear function to map the low-dimensional input space to the high-dimensional feature space through the non-linear mapping function, and it can transform the linearly inseparable problem in input space into the linearly separable problems in feature space. As shown in Figure 3, needing to introduce relaxation factor ξ_i （$\xi_i \geq 0$） and penalty factor C, then objective function requires the following minimum values:

$$\Phi（w,\xi） = \| w \|^2 + C\sum_{i=1}^{n} \xi_i \tag{8}$$

The constraint condition is $y_i[(w \cdot x_i) + b] \geq 1 - \xi_i, i = 1,2,3 \ldots \ldots n, 0 \leq a_i \leq C$.

For nonlinear sampling points with a non-linear function Φ mapping the sample room into a high-dimensional feature space (As shown in Figure 4), linear classification in the feature space. Then the $(x_i \cdot x)$ in the formula $F(x) = \mathrm{sgn}\{\sum_{i=1}^{n} a_i^* y_i (x_i \cdot x) + b^*\}$ can be $(\Phi(x_i) \cdot \Phi(x))$ to replace. The kernel RBF kernel function is $K(x_i \cdot x) = \exp\{-\frac{|x_i - x|^2}{\sigma^2}\}$, and the Optimal hyperplane is:

$$F(x) = \mathrm{sgn}\{\sum_{i=1}^{n} a_i^* y_i K(x_i \cdot x) + b^*\} \tag{9}$$

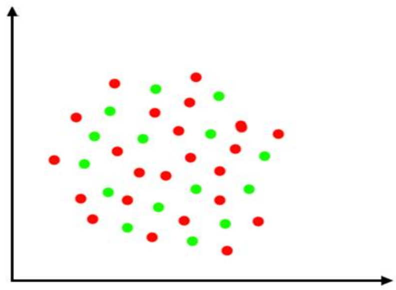

Figure 3. Low-dimensional Space of Linearly Inseparable

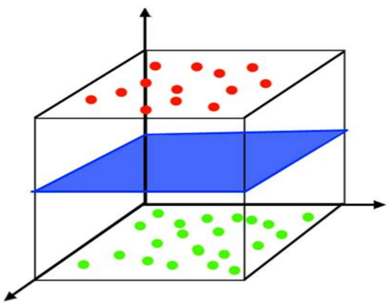

Figure 4. Higher Dimentional Space of Linear Separable

3.3. Selection of SVM Model

Selection of kernel function is essential for the design of a machine learning expert. Radial basis function (RBF) is often chosen as the SVM kernel function, because it is ideal for the similarity measure between two objects. In this paper, a common one-on-one decomposition method generates 10 binary classification [6, 7] as shown in Table1, which produces a total of five quality categories (excellent, better, good, poor, poorer). It is divided according to the ITU specified standard. The support vector machine gives a binary decision function:

$$h(x) = sign(f(x)) \tag{10}$$

in which $f(x) = \sum_{i=1}^{m} y_i a_i^* K(x, x_i) + b^*$. $K(x, x_i)$ is inner product function, determined on the basis of the kernel function. By regarding the formula $h(x)$ as the SVM decision function, the results of the i-th binary classification can be drawn. Then all the binary classifiers come together and eventually come to the final quality assessment results.

Table 1. Binary Classification

CLASS	*T5.4*	*T5.3*	*T5.2*	*T5.1*	*T4.3*	*T4.2*	*T4.1*	*T3.2*	*T3.1*	*T2.1*
5	1	1	1	1						
4	-1				1	1	1			
3		-1			-1			1	1	
2			-1			-1		-1		1
1				-1			-1		-1	-1

3.4. Joint Classifier

The binary classification is the first step in the combined classification. Each binary classifier can be seen as a precision signal source. The signal source is seen as the input of the joint classifier [8, 9]. The final accuracy of the classification results is built on the basis of the accuracy of each binary classifier. This accuracy can be expressed with the posterior probability. Posterior probability will not be provided directly by the SVM. It is obtained through the SVM output computation and it is a type of conditional probability, $p(y=1 \mid f) = 1/(1+\exp(Ef+F))$. In which SVM represents the output value of uncalibrated. Parameter E, F can use the maximum likelihood estimation of the training set $(f_i, \ y_i)$ to determine, which is obtained by the negative logarithm likelihood function minimum of the training data, $\min -\sum_i t_i \log(p_i) + (1-t_i)\log(1-p_i)$. In which $t_i = (y_i+1)/2$ is a new target probability of training set $(f_i, \ y_i)$, $p_i = 1/(1+\exp(Ef_i+F))$.

3.5. Regression of SVM

Because SVM cannot present the picture quality result directly, we use the support vector regression (v-svr) to solve this problem.

Define the damage function of low sensitivity.

$$|y - f(x)| = \begin{cases} 0 \cdots\cdots\cdots\cdots \; when \; |y - f(x)| - \xi \le 0 \\ |y - f(x)| - \xi \ldots\ldots\ldots \; other \end{cases}, \quad f(x,w) = w^T z + b \tag{11}$$

According to the 1 function to minimize the gap with training data as much as possible, $z = \Phi(x)$ is the projection of x in the high-dimensional space. Training set is $s = \{(x_i, y_i)\}_{i=(1,\ldots,m)}, x_i \in R^n$, $y_i \in \{-1,1\}$.

Minimize of $\|w\|: \min \frac{1}{2}\|w\|^2 + C(\sum_{i=1}^{m}(\xi_i + \xi_i^*))$. For any $i = (1....m)$, have $-\varepsilon - \xi_i \le y_i - f_i \le \varepsilon + \xi_i^*; \xi_i^*, \xi_i \ge 0$, $f_i = f(x_i, w)$ and C is constant. Through the training of non-zero parameters $\xi_i', \xi_i^{*\prime}$ the difference between y_i, f_i can be reflected accurately.

4. Experiment

Image involved in the experiment comes from LIVE image database. The experiment creates two sets. One is the training set TRC1, the other is the test set TEC2. Figure 5 is the predictive value and the value of the correlation coefficient SROCC of the subjective DMOS. The experiment chooses one original image from the LIVE image database, using JP2K, JPEG, white noise, Gaussian blur and fast fading means to deal with separately, and the distorted image after processing is evaluated with five kinds of algorithms that is MLIQM, MSSSIM, VIF, VSNR, PSNR successively. Judging from the experimental results, MLIQM algorithm has the big superiority compared with other algorithms. It is a kind of successful algorithms of IQA algorithm performance improvements.

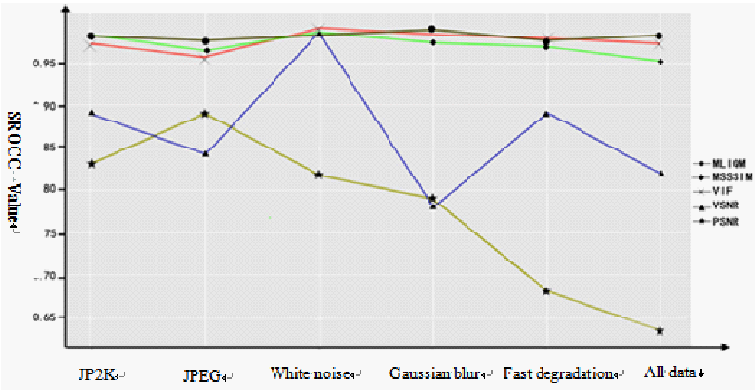

Figure 5. Coefficient between the predictive Value and Subjective DMOS (SROCC value)

5. Conclusion

This paper proposes a new FR-IQA algorithm (MLIQM). Factors that affect the algorithm are a selection of feature vectors, a selection of the kernel function. Therefore it is crucial to choose what kind of feature vectors and kernel function for the algorithm. In the classification process, these feature vectors are selected from the characteristics of the HVS characteristics and reference images. The kernel function is chosen as the radial basis kernel function. Compared with the other experimental results of image quality assessment algorithm, this algorithm can give better results and improves the correlation coefficient reflecting human subjective judgment meaningfully.

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