Analysis of Influence of Image Contents on Facial Muscle Activity for Image Quality Assessment

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Summary
In this paper, we have conducted an analysis of the influence of image contents on facial muscle activity for image quality assessment of JPEG coded image, using multiple regression analysis. In previous studies, we have successfully established a relationship between facial muscle activity and the subjective assessment score of image quality, by using Facial Electromyography (fEMG). Measurements were taken through fEMG and compared to subjective assessments conducted through questionnaires. We measured six relevant facial muscles in our experiments. With this paper, we are advancing the model a step further, by introducing a new set of variables, which focus on the contents represented in the images, and the different features represented, compared to the previous general look at all images as equal input sets. For this purpose, we have used the entropy information in order to differentiate image contents and improve the image quality prediction model.
Keywords:
Image quality assessment, Subjective assessment, Biological information, Facial electromyography, image entropy.

1. Introduction

In our previous research [1], we have successfully established a relation between the activity of facial muscles and perceived image degradation caused by JPEG coding. This crucial relationship previously unknown, has set a premise for further improvement of a robust model for image quality prediction. Previously, we have used a subjective image quality assessment test to obtain results from subjects observing images on a screen. We have also employed the use biometric technology of Facial Electromyography [9] for observing the same subjects' facial muscle movements, while observing same images. The comparison of the two results provided evidence of strong correlation between subjective assessment and facial muscle activity.
With this paper we are advancing the model a step further, by introducing a new set of variables - Image Entropy, which focuses on the contents represented in the images, and the different features represented, compared to the previous general look at all images as equal input sets.
In previous work, we identified that facial muscle activity increases when subjects were observing lower quality of image. We argue that this tendency relates to the observer judging image quality by focusing on the degradation parts of coded images. Therefore, for improving the prediction performance of previously proposed model, we must take into account the image features related to the coarse-fine information of spatial frequency characteristics [5]. The key to improving the model performance is finding the appropriate methodology for factoring in the image features related to muscle activity. One of the important features is the entropy of image, the value of which is strongly connected with image content. If an image contains a lot of detail information, its entropy value is very close to 8 bits/pixel (for a monochrome image). On the other hand, if the image contains mostly flat areas, then the entropy value is much lower than 8 bit/pixel. This feature is useful for expressing image contents.

2. Image Entropy

Image entropy is a quantity used to describe the amount of information which must be coded by a compression algorithm. Low entropy images, i.e. containing plain color areas, have very little contrast and large number of pixels with the same or similar DN values [2]. An image that is completely flat will have therefore an entropy of zero and can be compressed to a relatively small size. On the other hand, high entropy images having a lot of variation in content contain a lot of contrast between adjacent pixels, and as a result cannot be compressed as much as low entropy images.
The formula for calculating image entropy is given in Equation 1:

$$\text{Entropy} = -\sum_{i} P_j \, Log_2 \, P_j \tag{1}$$

In the above expression, Pj is the probability of i-th gray lever for monochrome still image (8 bits/pixel) converted from color image (24 bits/pixel). Therefore, the maximum value of the entropy for gray level image is 8 bits/pixel [3]. A high entropy value represents the presence of maximum information, containing high-detail areas. An image with

Manuscript received December 5, 2014
Manuscript revised December 20, 2014

very low entropy value represents coded noise with tiling based on the block size and false contours (like Images 8, 9 and 11 in Fig.2) .

In Figures 1 and 2, we can see the test images used in the experiment. In this study, we have added the additional variables of Entropy and Δentropy.

Image 1
QS:30
Entropy = 7.748
Δentropy = 0.008

Image 2
QS:30
Entropy = 7.416
Δentropy = 0.220

Image 3
QS:30
Entropy = 7.233
Δentropy = 0.347

Image 4
QS:30
Entropy = 7.412
Δentropy = 0.081

Image 5
QS:30
Entropy = 6.922
Δentropy = 0.628

Image 6
QS:30
Entropy = 7.328
Δentropy = 0.019

Figure 1. Test images at QS 30.

Entropy was calculated by converting images to grayscale, which allows us to quantify image contents, as explained above. For the purpose of obtaining Δentropy, we have also calculated Original Entropy, using the “perfect” images and deducted Entropy from Original Entropy, as detailed in Table 1. Δentropy represents the difference between the original image and the coded image, and serves a good indicator for image content analysis in our calculations.

Image 7
QS:5
Entropy = 7.106
Δentropy = 0.650

Image 8
QS:5
Entropy = 5.746
Δentropy = 1.890

Image 9
QS:5
Entropy = 5.898
Δentropy = 1.682

Image 10
QS:5
Entropy = 5.406
Δentropy = 2.087

Image 11
QS:5
Entropy = 4.390
Δentropy = 3.159

Image 12
QS:5
Entropy = 6.591
Δentropy = 0.756

Figure 2. Test images at QS 5.

From Table 1, it can be observed that Δentropy of images 8-11 is fairly high, compared with the others, because these images contain large flat areas like the background (see Fig. 2). As a result, the degradations of these images (like blocking artifacts and contours [13]) are more visible than in other images. This explains why it is easy to judge the quality assessment by 5-grade scale without looking or seeking the degradation parts specifically.

Table 1. Test Images Entropy Results

Image	Entropy	Δentropy	Original Entropy
1 (QS:30)	7.748	0.008	7.756
2 (QS:30)	7.416	0.220	7.636
3 (QS:30)	7.233	0.347	7.580
4 (QS:30)	7.412	0.081	7.493
5 (QS:30)	6.922	0.628	7.550
6 (QS:30)	7.328	0.019	7.347
7 (QS:5)	7.106	0.650	7.756
8 (QS:5)	5.746	1.890	7.636
9 (QS:5)	5.898	1.682	7.580
10 (QS:5)	5.406	2.087	7.493
11 (QS:5)	4.390	3.159	7.550
12 (QS:5)	6.591	0.756	7.347

3. IEMG of Muscle Activity

We have analyzed the fEMG using integrated electromyogram (IEMG). IEMG is the integral value of full-wave rectification over a certain time range (as shown in Fig. 3). In order to compare waveform values, we converted waveform values to quantifiable values [9]. IEMG represents the amount of total muscle activity for a certain period (between the red lines in Fig. 3).

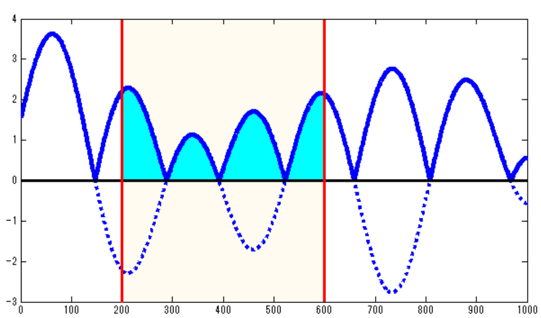

Fig. 3. IEMG

By comparing the amount of muscle activity, all measured waves were cleared of AC noise by band-stop filtering [25].

Next, we calculated IEMG using full-wave rectification for 10 seconds during MVC. For normalization of MVC for all muscle points, we defined M_{IEMG} as 100% of IEMG. M_{IEMG} has the maximum value of IEMG from 3 trials of MVC measurement testing for all muscle points.

In the subjective assessment experiment, we obtained the f_{EMG} for each testing session. Then we calculated IEMG for all image assessment results. We also calculated P_{IEMG} which is the percentage of IEMG for all image assessment results, by comparing IEMG with M_{IEMG}., and we identify the amount of muscle activity in Equation 2:

$$P_{IEMG} = \frac{IEMG}{M_{IMEG}} \times 100 \qquad (2)$$

4. Regression Analysis

4.1 Stepwise Regression Analysis

In our previous study [1], regression analysis [10] was conducted on an individual basis for each subject from the point of view of Quality of Experience (QoE). We did not need or attempt to average or deduct statistical models from our experiment, but rather identify specific relations between facial muscle activity and the sensation of image quality degradation.
In the regression analysis the independent variables used were the amount of muscle activity of M1 to M6, while the depended variables were the subjective score values, based on the Rec. ITU-R BT.500-11 Five-grade Quality Impairment Scale [30]:

5 : Imperceptible

4 : Perceptible, but not annoying

3 : Slightly annoying

2 : Annoying

1 : Very annoying.

The results of the step-wise regression analysis are detailed in Table 2.

Table 2. Results of step-wise regression analysis

Subject	Entry Variable	Coefficient of Correlation
A1	M1	0.58
A2	M2	0.85
A3	M4	0.76
A4	M1	0.68

A5	M3	0.85
A6	M4	0.64
A7	M5	0.82
A8	M3	0.86

The estimated regression equations are shown in Equations 3 to 10:

$$\text{Prediction A1} = -0.25 \times \text{M1} + 8.27 \quad (3)$$
$$\text{Prediction A2} = -0.17 \times \text{M2} + 8.78 \quad (4)$$
$$\text{Prediction A3} = -0.20 \times \text{M4} + 6.68 \quad (5)$$
$$\text{Prediction A4} = -0.64 \times \text{M1} + 10.41 \quad (6)$$
$$\text{Prediction A5} = -0.09 \times \text{M3} + 5.49 \quad (7)$$
$$\text{Prediction A6} = -0.20 \times \text{M4} + 6.15 \quad (8)$$
$$\text{Prediction A7} = -0.13 \times \text{M5} + 6.59 \quad (9)$$
$$\text{Prediction A8} = -0.14 \times \text{M3} + 6.27 \quad (10)$$

Through the stepwise regression analysis we established a definite relation between subjective scores and biometric information obtained through Facial Electromyography.

4.2 Multiple Regression Analysis

In order to factor in the additional variables of Image Entropy, we have conducted a multiple regression analysis [3] using 3 sets of variables (muscle activity, entropy and Δentropy), in order to established the most suitable pattern for quality prediction. The results are indicated as Multiple R, Adjusted R (obtained as the square root of Adjusted R Squared) and Maximum (Prediction) Error.
As in the case of regression analysis, the subjective scores for each image served as the dependent variables.
The first analysis was conducted using only muscle activity data (M1-M6) as independent variables. The results are detailed in Table 3.

Table 3. Results of Multiple Regression using only Muscle Data

Subject	**Multiple R**	**Adjusted R**	**Max Error**
A1	0.579	0.518	2.827
A2	0.854	0.838	2.016
A3	0.740	0.709	2.538
A4	0.677	0.635	1.370
A5	0.847	0.831	1.575
A6	0.636	0.588	1.768
A7	0.817	0.796	1.546
A8	0.857	0.842	1.305

The second analysis was conducted using muscle data, plus Entropy, as independent variables. The results are detailed in Table 4.

Table 4. Results of Multiple Regression using Muscle Data and Entropy

Subject	**Multiple R**	**Adjusted R**	**Max Error**
A1	0.813	0.765	1.886
A2	0.870	0.839	1.606
A3	0.881	0.853	1.190
A4	0.851	0.814	1.516
A5	0.856	0.820	1.451
A6	0.818	0.771	1.906
A7	0.923	0.905	1.095
A8	0.892	0.867	1.030

The third analysis was conducted using muscle data, plus Entropy, plus Δentropy as independent variables. The results are detailed in Table 5.

Table 5. Results of Multiple Regression using Muscle Data, Entropy and Δentropy

Subject	Multiple R	Adjusted R	Max Error
A1	0.816	0.735	2.016
A2	0.885	0.838	1.622
A3	0.893	0.849	1.055
A4	0.930	0.902	0.768
A5	0.911	0.875	1.217
A6	0.850	0.786	1.435
A7	0.953	0.934	0.925
A8	0.918	0.885	0.985

From the results of the regression analysis in Table 3-5, we can conclude that the best performance is the use of all 3 variables (muscle activity, entropy and Δentropy. For this case, the estimated regression equations are represented in Equations 11-18:

$$\text{Prediction A1} = -0.01 \times \text{M1} + 2.40 \times \text{Ent} + 1.08 \times \Delta\text{ent} - 13.54 \quad (11)$$
$$\text{Prediction A2} = -0.12 \times \text{M2} + 2.31 \times \text{Ent} + 1.86 \times \Delta\text{ent} - 10.27 \quad (12)$$
$$\text{Prediction A3} = -0.10 \times \text{M4} + 2.50 \times \text{Ent} + 1.68 \times \Delta\text{ent} - 13.39 \quad (13)$$
$$\text{Prediction A4} = -0.26 \times \text{M1} + 4.08 \times \text{Ent} + 3.40 \times \Delta\text{ent} - 23.82 \quad (14)$$
$$\text{Prediction A5} = -0.06 \times \text{M3} + 4.23 \times \text{Ent} + 3.83 \times \Delta\text{ent} - 26.90 \quad (15)$$

$$\text{Prediction A6} = -0.11 \times \text{M4} + 2.89 \times \text{Ent} + 2.21 \times \Delta\text{ent} - 16.42 \quad (16)$$

$$\text{Prediction A7} = -0.08 \times \text{M5} + 3.33 \times \text{Ent} + 2.62 \times \Delta\text{ent} - 19.24 \text{ ` } (17)$$

$$\text{Prediction A8} = -0.07 \times \text{M3} + 3.48 \times \text{Ent} + 2.77 \times \Delta\text{ent} - 20.94 \quad (18)$$

From the results detailed in Table 3 and 5 we can see that by introducing entropy and Δentropy in the prediction model, the regression coefficient R, the adjusted regression coefficient R, and the maximum prediction error have all returned improved results. Therefore, we can deduce that Entropy and Δentropy are effective indicators for predicting the overall image quality for image quality assessment methodology.

5. ANALYSIS AND CONCLUSIONS

In our previous research [1], we have successfully established a relation between the activity of facial muscles and perceived image degradation. This crucial relationship previously unknown, has set a premise for further improvement of a robust model for image quality prediction. Previously we have used a subjective image quality assessment test to obtain results from subjects observing images on a screen. We have also employed the use biometric technology of Electromyography for observing the same subjects' facial muscle movements, while observing images. The comparison of the two results provided evidence of strong correlation between subjective assessment and facial muscle activity.

The results of the Multiple Regression Analysis using the additional variables of Entropy and ΔEntropy have proven that image contents is a crucial factor in establishing a robust image quality prediction model. As can be seen by looking at the test images, some contain large portions of obvious image degradation (i.e. image 8, 12). However, compared with the human eye, it is very difficult to express these indications in quantifiable measurements, unless we use content-dependent variables like Entropy. The closer an image's Entropy level is to 8 bits/pixel, the more image contains a higher level of details, which makes subjective assessment higher. The lower an image's Entropy level is to 8 bits/pixel, the more image contains a lower level of details, which makes degradation less perceptible to the human eye. These are very important factors, which have helped improve the accuracy of the prediction model.

With this first step of introducing the usage of facial muscle activity, we can further develop our work towards non-intrusive objective methods for assessing video quality and improving image quality assessment technology using biological information.

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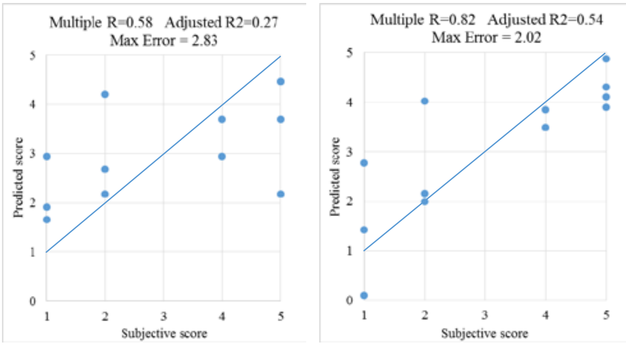
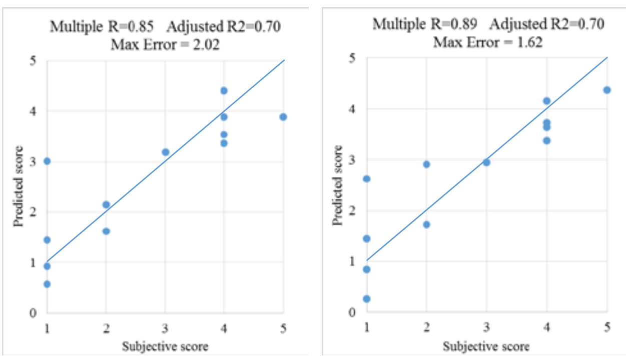


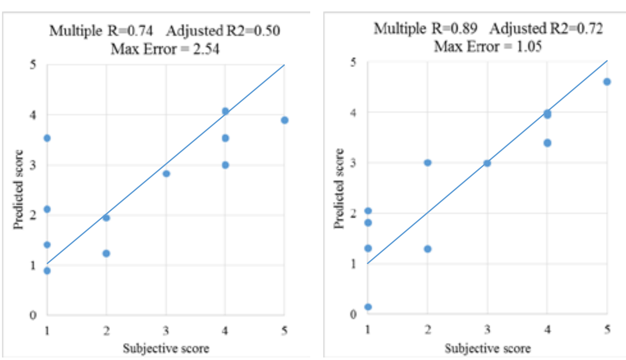
(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 4. Subject A1



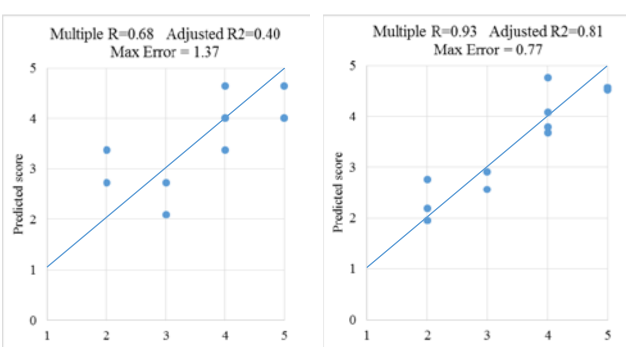
(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 5. Subject A2



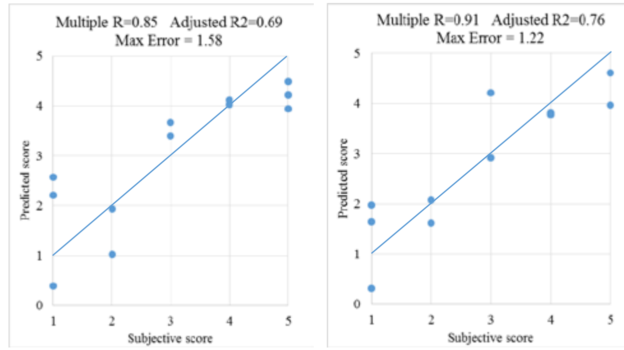
(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 6. Subject A3



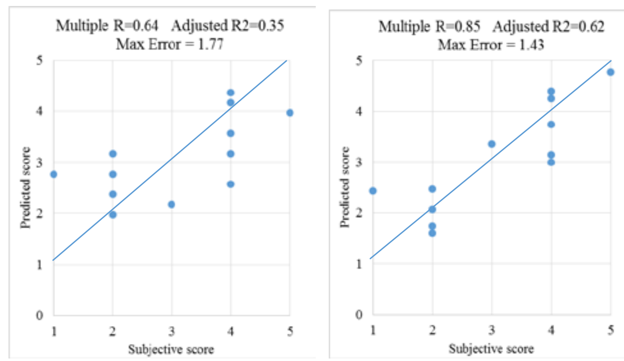
(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 7. Subject A4



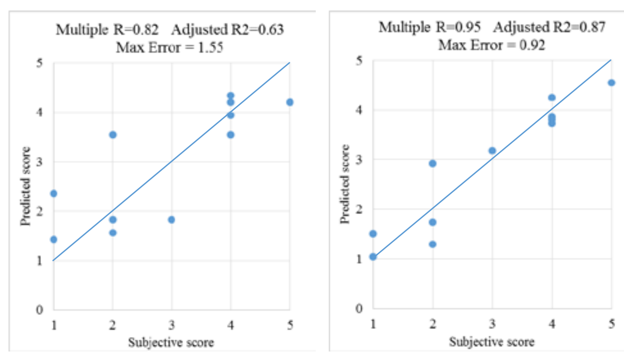
(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 8. Subject A5



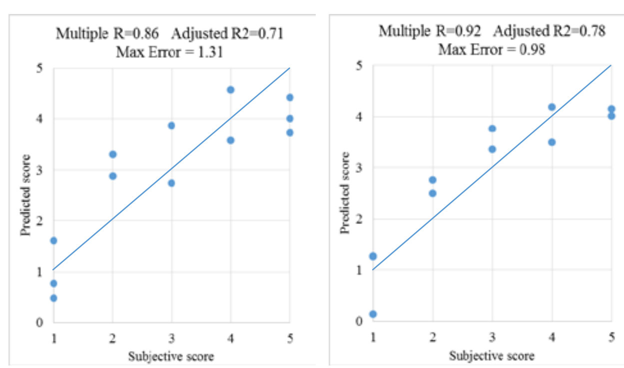
(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 9. Subject A6



(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 10. Subject A7



(a) Muscle Data only *(b) Muscles + Entropy + Δentropy*

Fig. 11. Subject A8