A Study of the Relationship between Subjective Image Quality Assessment Scores and Facial Electromyograms

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Summary
In this paper, we examine the 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 this experiment. We also compared the percentage of the measured data and estimated the subjective assessment score using the stepwise regression analysis. Results show that if image quality is degraded, the activity of some muscles increases. The regression equation obtained has shown good results. We identified a visible relationship between fEMG and the subjective assessment score and we argue that fEMG can be effectively applied in the field of image quality assessment.
Keywords:
Image quality assessment, Subjective assessment, Biological information, Facial electromyography.

1. Introduction

In recent years, research in image quality assessment has been focused on the biological information approach [1]. This approach improves on the traditional questionnaire-based method, which suffers from major flaws caused by the difference in response results and the difference in rating scales between subjects. It has been argued that image quality assessment using biological information is less likely to suffer from these issues [2]. We focus our research on Facial Electromyography (fEMG) for biological information extraction.
In previous research [3,4,5], it has been established that facial expressions contain more emotional essence compared to the tone of voice or the content of spoken message [7]. We used this premise to hypothesize a significant relationship between facial muscle activity and image quality assessment and ultimately improving Quality of Experience [8], represented in Fig.1 as the diagram of User Network Interface.
The long term scope of our research is to develop objective evaluation methods for automatically assessing and improving Quality of Experience (QoE). In order to accomplish this goal, we need to identify the relationship between the activity of facial muscles and perceived image degradation. This crucial relationship is still completely unknown and that is why at this stage we are focusing on understanding and quantifying this relationship by using subjective assessment methods.
We physically measure facial muscle activity using electromyogramy and then obtain subjective scores of image degradation from subjects. By establishing a relation between these two results, we can assemble a MOS prediction method, by using the regression analysis [9], as shown in Fig.2.

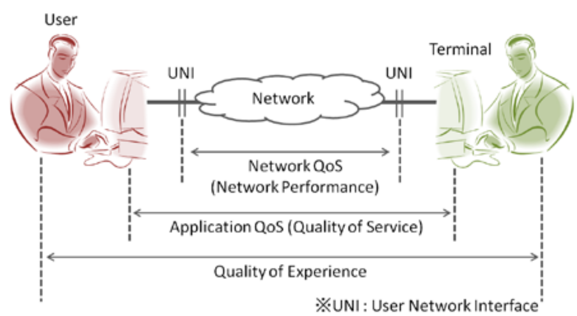

Fig.1. Quality of Experience Illustration

Stepwise regression analysis [10] have also been conducted on an individual basis for each subject from the point of view of QoE. We do 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 [11].

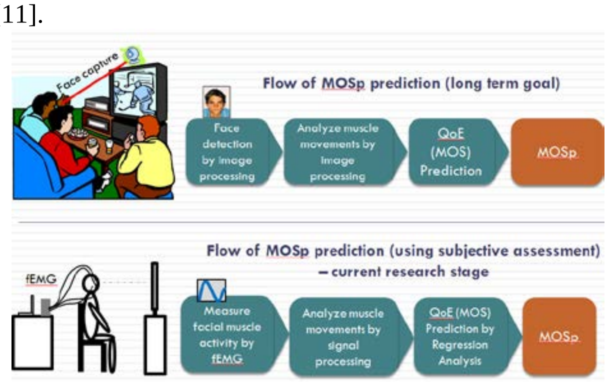

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Fig.2. Workflow of MOSp prediction

2. Facial Electromyogram

Electromyogram derives from three terms: electro, which means pertaining to electric activity; myo, which has a Greek root meaning muscle; and gram, which stands for recording. Eletromyography, or EMG, refers to recording of muscle's electric activities. [12]

The first recording of muscle cells activity is attributed to Hans Piper in 1907 [13], and ever since EMG has emerged as a prolific method of signal recording in medicine. By studying this methodology, we have theorized the novel possibility of applying it to image quality assessment as described in this paper.

Facial muscles are responsible for eyes, mouth and nose movements. Interaction of facial muscles makes for complex expressions. fEMG technique that measures muscle activity by detecting and amplifying the tiny electrical impulses that are generated by muscle fibers when they contract. It primarily focuses on two major muscle groups in the face, the corrugator supercilii group which is associated with frowning and the zygomaticus major muscle group which is associated with smiling [14]. fEMG has been studied in order to assess its utility as a tool for measuring emotional reaction, distinguish and track positive and negative emotional reactions to a stimulus as they occur. A large number of those experiments have been conducted in controlled laboratory environments using a range of stimuli, like still pictures, movie clips and music pieces [15].

fEMG has significant benefits, including the accurate extraction of continuous and scalar data; it does not depend on language, cognitive effort or memory; it is less intrusive than other physiological measures like Facial MRI (fMRI) and EEG [16]. The relationship between emotions and fEMG has already been investigated [17,18,19], thus making it perfect for image quality assessments in our experiment.

3. Experiment

3.1 Measuring Method

We measured the fEMG using an electroencephalograph (EEG-9100) manufactured by Nihon Kohden, depicted in Fig.3.

The fEMG measurement area is comprised of six muscle groups:

- venter frontalis (M1)
- corrugator supercilii(M2)
- orbicularis oculi (M3)
- zygomaticus major (M4)
- orbicularis oris (M5)
- masseter (M6).

These muscles are closely associated with the formation of facial expressions as described in previous studies [20]. The ground was attached to the forehead area (Fig. 4) and fEMG was derived in the bipolar lead. The sampling frequency is 1 kHz.

Fig. 3. Electroencephalograph EEG-9100

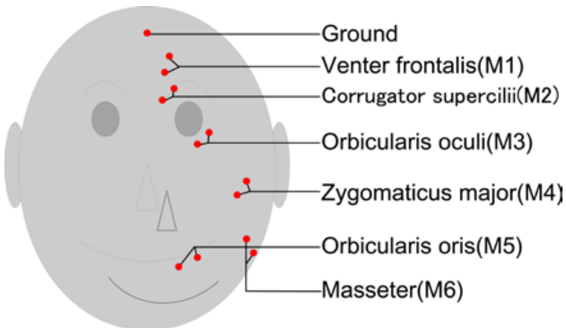

Fig.4. Electrode map

3.2 Experimental Procedure

Before commencing the experiment, we carefully instructed all test subjects regarding experiment proceedings and safety procedures. During the experiment, we took turns in measuring fEMG during Maximal Voluntary Contraction (MVC), followed by the subjective assessment experiment part. For the measuring of fEMG during MVC, subjects flexed six muscles under observation in the experiment. We asked each subject to flex the muscles as much as possible for 10 seconds. This procedure was repeated 3 times, in order to be sure measurement data was accurately recorded. We set the data as a template standard for the analysis.

The next step, for the part of subjective assessment experiment, subjects assessed still images by the Double-Stimulus Impairment Scale (DSIS, five-grade) method [21]. We showed each subject one reference image for 10 seconds, followed by 3 seconds of gray display, followed by one test image for 10 seconds, followed by a 12 second for voting and rest. This cycle was repeated for all 12 images (see Fig. 5).

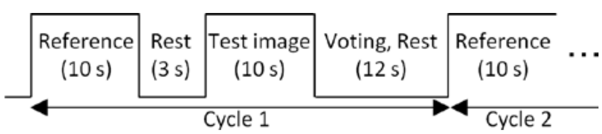

Fig. 5. Experimental Procedure

Subjects noted their answers on answer sheets during voting time. The grading scales are detailed in Table 1. We showed all instructions and contents on a display. The conditions of the experiment are detailed in Table 2. An example of still images used in the experiment is presented in Fig. 6.

Table 1. Gradient scales

Score	Image quality assessment vote
5	Good quality, degradation imperceptive
4	Degradation perceptible, but not annoying
3	slightly annoying
2	annoying
1	very annoying

Table 2. Conditions of the experiment

Subjects	8 Adults (male, females)
Luminance	75-150 [lx]
Display	32 inch LCD (1920 x 1080 [pixel]
Viewing distance	3H (H : Height of image)
Image resolution	1920 ×1080 [pixel]
Encoding	JPEG (QS : 5, 30)
No. of images	Reference : 6, Total : 12

Fig.6(a). QS : 5

Fig.6(b). QS : 30

Fig.6 Example of still image used in the experiment

4. ANALYSIS METHOD

4.1 IEMG

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. 7). In order to compare waveform values, we converted waveform values to quantifiable values. IEMG represents the amount of total muscle activity for a certain period (between the red lines in Fig. 7).

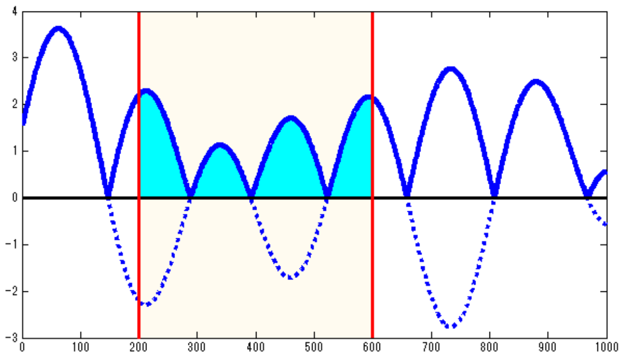

Fig. 7. IEMG

4.2. Amount of muscle activity

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 MIEMG as 100% of IEMG. MIEMG 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 fEMG for each testing session. Then we calculated IEMG for all image assessment results. We also calculated PIEMG which is the percentage of IEMG for all image assessment results, by comparing IEMG with MIEMG., and we identify the amount of muscle activity in Equation 1:

$$P_{IEMG} = \frac{IEMG}{M_{IMEG}} \times 100 \qquad (1)$$

5. RESULTS AND CONSIDERATION

5.1. Comparison of muscle activity

We compared the values of the amount of muscle activity and summarized the results in Tables 3 to 10 for each subject. M1 to M6 represent each muscle (reference section 3.1) and the greater values for each subject are highlighted.

We defined the case where the score value was less or equal to 2 as for subjects that were looking at low-quality images. Special attention was paid to these cases when low-quality were shown. Table 3 shows the results for subject A1. We found a trend where muscles M1 and M2 experienced greater activity at low-quality image observations. Table 4 shows the results for subject A2. We found a trend where muscles M2 and M5 showed greater activity at low-quality image observations. Table 5 shows the results for subject A3. We found a trend where muscles M3 and M4 showed greater activity at low-quality image observations. Table 6 shows the results for subject A4. We did not find any trends for muscle activity at low-quality image observation. Table 7 shows the results for subject A5. We found a trend where muscles M3 and M4 showed greater activity at low-quality image observations. Table 8 shows the results for subject A6. We found a trend where muscles M1 and M2 showed greater activity at low-quality image observations. Table 9 shows the results for subject A7. We found a trend where muscles M2 and M5 showed greater activity at low-quality image observations. Table 10 shows the results for subject A8. We found a trend where muscles M3 and M4 showed greater activity at low-quality image observations.

The results demonstrate the following facts: subjects A1, A2, A6, A7 flexed more the M1 and M2 muscles located around the eyes. Subjects A3, A5, A8 flexed more the M3 and M4 muscles located around the mouth. and M3 when looking at low-quality images. From this results we can conclude a connection between the results provided by the fEMG results and the subjective assessment score.

5.2. Stepwise Regression Analysis

The regression analysis [10] was conducted on an individual basis for each subject from the point of view of QoE. We do 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 this part, we estimate the subjective assessment scores, as we will apply fEMG to the image quality assessment. We conducted a step-wise regression analysis and formulated the estimated regression equations. The independent variables were the amount of muscle activity of M1 to M6. The dependent variable represents the subjective score value.

The results of the step-wise regression analysis are detailed in Table 11. The estimated regression equations are shown in Equations (2) to (9). The graphs are shown in Fig.8 to Fig. 15. These graphs are scatter charts of the predicted score and the subjective assessment score. The horizontal axis represents the score, while the longitudinal axis represents the predicted score.

$$\text{Prediction A1} = -0.25 \times M1 + 8.27 \qquad (2)$$
$$\text{Prediction A2} = -0.17 \times M2 + 8.78 \qquad (3)$$
$$\text{Prediction A3} = -0.20 \times M4 + 6.68 \qquad (4)$$
$$\text{Prediction A4} = -0.64 \times M2 + 10.41 \qquad (5)$$
$$\text{Prediction A5} = -0.22 \times M3 + 6.37 \qquad (6)$$
$$\text{Prediction A6} = -0.25 \times M1 + 8.51 \qquad (7)$$
$$\text{Prediction A7} = -0.18 \times M2 + 9.22 \qquad (8)$$
$$\text{Prediction A8} = -0.19 \times M4 + 7.05 \qquad (9)$$

In Table 7, for subjects A and B, we concluded that the independent variables found in this part refer to the same muscles as in the results of section 5.A. There was no such relationship for subjects C and D. This is an important result found through the stepwise regression analysis.
As can be seen in Fig. 8 to 15, we found a nearly linear relationship between the predicted score and the subjective assessment score for all subjects. We did not find any trends for Subject A4, as was commented in Section 5.1. From these facts, we can conclude that the use of fEMG is feasible in estimating subjective assessment scores.

Table 3. Results of subject A1

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	5	15	13	8	13	6	3
30	5	15	7	8	15	8	3
30	5	24	52	11	16	8	3
30	5	18	10	18	15	13	3
30	4	21	19	11	15	6	3
30	4	18	8	11	16	9	3
5	2	16	6	9	17	10	3
5	2	24	51	12	15	11	2
5	2	22	38	13	15	11	3
5	1	21	19	9	15	7	3
5	1	25	32	45	17	9	3
5	1	26	69	16	18	13	3

Strong activity in the frontalis and corrugator muscles

Table 4. Results of subject A2

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	5	12	28	16	25	26	21
30	4	11	31	19	32	29	24
30	4	10	25	15	24	30	24
30	4	11	28	16	28	29	26
30	4	12	30	19	25	31	26
30	3	12	32	17	24	29	23
5	2	15	38	20	25	26	25
5	2	13	41	19	25	32	23
5	1	12	33	17	27	30	24
5	1	16	45	17	23	30	23
5	1	17	47	21	26	32	26
5	1	13	42	21	27	43	25

Strong muscle activity in the corrugator, orbicularis oris

Table 5. Results of subject A3

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	5	5	10	27	14	20	11
30	5	5	12	32	16	21	9
30	4	5	7	21	13	18	10
30	4	4	10	22	19	23	9
30	3	5	7	22	16	20	10
30	3	4	10	20	20	23	9
5	2	5	19	47	25	24	9
5	1	5	13	55	29	20	11
5	1	5	15	43	24	20	10
5	1	5	15	28	16	21	9
5	1	5	10	44	28	21	10
5	1	5	8	46	31	24	10

Strong activity in the orbicularis oculi and zygomatic major muscles

Table 6. Results of subject A4

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	5	10	10	7	18	9	24
30	5	10	8	7	17	8	22
30	5	9	9	8	19	9	23
30	4	10	9	7	17	8	22
30	4	11	13	9	18	8	23
30	4	9	9	9	18	18	21
5	4	10	11	9	18	8	26
5	3	12	10	8	17	8	22
5	3	13	27	9	19	8	22
5	2	12	11	8	18	9	23
5	2	11	9	8	19	13	24
5	2	11	9	7	18	8	22

No significant muscle activity detected

Table 7. Results of subject A5

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	5	7	10	14	12	15	13
30	5	6	11	11	14	17	7
30	2	7	8	27	33	11	5
30	4	7	10	15	10	9	12
30	1	8	8	42	32	20	13
30	3	6	9	20	19	16	8
5	1	7	10	52	41	19	7
5	1	8	17	49	37	18	9
5	4	8	12	19	14	18	14
5	2	7	13	32	31	17	10
5	5	7	10	16	15	9	10
5	3	6	9	36	28	12	7

Strong activity in the orbicularis oculi and zygomatic major muscles

Table 8. Results of subject A6

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	4	4	13	17	11	3	3
30	4	4	14	18	10	6	4
30	2	12	23	23	9	7	4
30	4	8	10	16	13	5	3
30	1	35	41	22	18	10	3
30	5	5	16	13	15	5	3
5	2	37	34	19	20	8	3
5	2	41	37	20	21	7	3
5	4	19	30	17	17	7	3
5	2	42	41	21	19	4	3
5	4	14	12	20	15	5	2
5	3	31	19	13	17	9	3

Strong activity in the frontalis and corrugator muscles

Table 9. Results of subject A7

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	4	9	15	10	20	18	13
30	5	8	13	11	21	18	13
30	2	9	19	14	20	23	15
30	5	8	15	12	23	17	14
30	2	9	33	20	19	20	13
30	4	7	20	14	18	18	14
5	2	10	40	20	24	36	19
5	1	13	43	20	24	38	20
5	4	10	30	14	18	23	18
5	1	13	40	18	22	36	24
5	4	11	32	17	19	32	17
5	3	10	38	15	18	39	20

Strong muscle activity in the corrugator, orbicularis oris

Table 10. Results of subject A8

QS	Evaluation score	Frontalis	Corrugator	Orbic. Oculi	Zygomatic	Orbic. Oris	Masseter
30	5	7	13	13	16	14	8
30	4	7	11	18	21	11	9
30	2	6	14	24	35	14	7
30	5	7	9	12	19	10	9
30	1	7	14	19	29	17	9
30	3	8	10	17	20	15	9
5	3	6	11	33	36	34	9
5	2	5	10	39	39	23	8
5	1	7	14	41	42	29	7
5	4	6	13	25	31	16	7
5	5	6	9	21	21	16	9
5	3	7	10	16	24	17	9

Strong activity in the orbicularis oculi and zygomatic major muscles

Table 11. Results of step-wise regression analysis

Subjects	Entry variable	Coefficient of correlation
A1	M1	0.58
A2	M2	0.85
A3	M4	0.76
A4	M2	0.68
A5	M3	0.86
A6	M1	0.91
A7	M2	0.77
A8	M4	0.75

Conclusions

In this paper we have theorized and tested the relationship between facial muscle activity and the degree of degradation of visual image quality. We have used Facial Electromyography (fEMG) to acquire the activity of facial muscle movements and analyze the data using using full-wave rectification as signal processing.

We measured the fEMG in the subjective assessment experiment using still images. We studied the relationship between fEMG and the subjective assessment score. As a result, we found a trend where subjects' muscles around the eyes and mouth areas show greater activity when subjects were assessing low-quality images. We also developed estimated regression equations for each subject using the step-wise regression analysis, as well as the possibility of estimating the subjective assessment score. This results show that the fEMG, which uses part of biological information, can be applied in the evaluation of image quality assessment under certain conditions.

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.

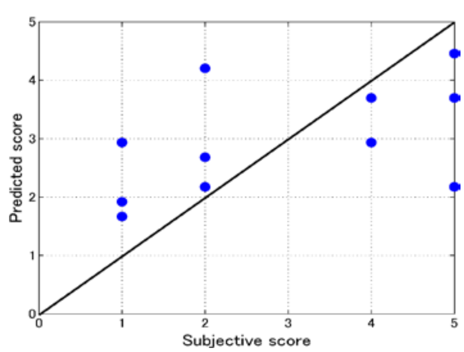

Fig. 8. Relationship between predicted and subjective score for subject A1.

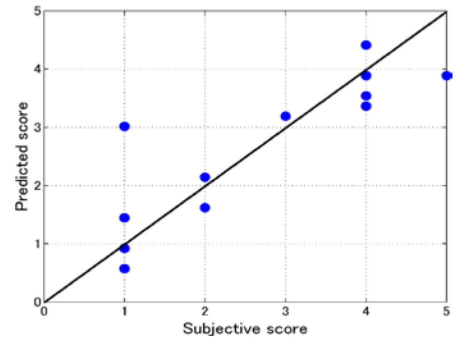

Fig. 9. Relationship between predicted and subjective score for subject A2.

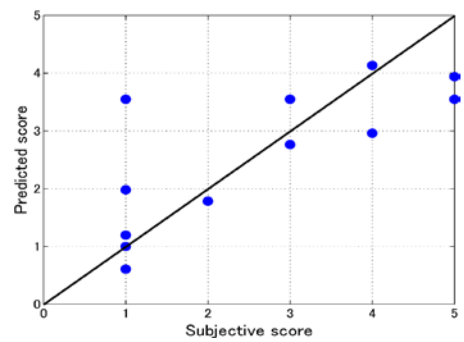

Fig. 10. Relationship between predicted and subjective score for subject A3.

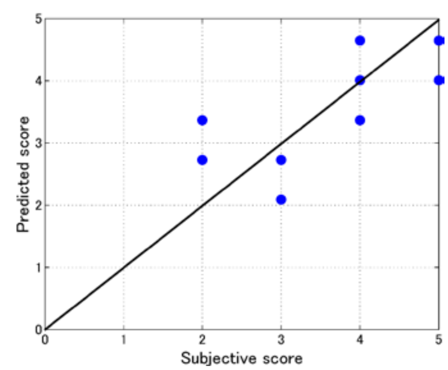

Fig. 11. Relationship between predicted and subjective score for subject A4.

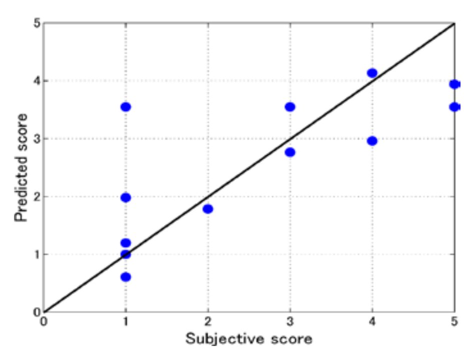

Fig. 12. Relationship between predicted and subjective score for subject A5.

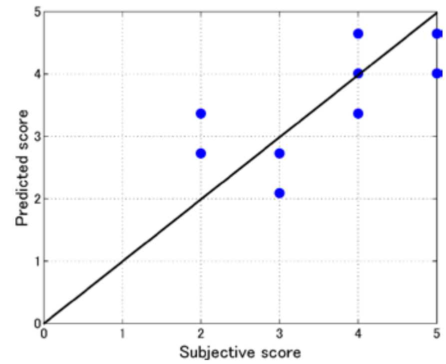

Fig. 13. Relationship between predicted and subjective score for subject A6.

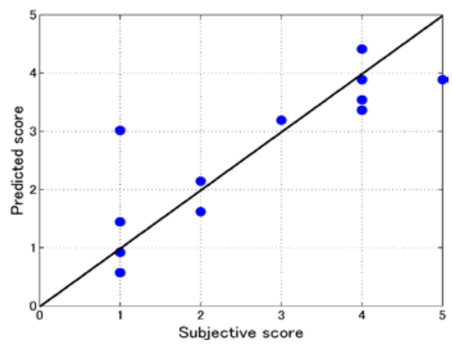

Fig. 14. Relationship between predicted and subjective score for subject A7.

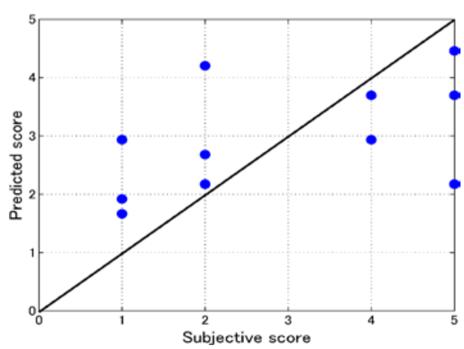

Fig. 15. Relationship between predicted and subjective score for subject A8.

References

[1] Kayvan Najarian, Robert Splinter, "Biomedical Signal and Image Processing, Second Edition", CRC Press, May 4, 2012. P.271-272

[2] Jacques Blanc-Talon, Wilfried Philips et al, "Advanced Concepts for Intelligent Vision Systems: 11th International Conference, ACIVS 2009 Bordeaux, France, September 28--October 2, 2009 Proceedings", Springer Science & Business Media, Sep 15, 2009. PP.156-166

[3] H. Julia Hannay, "Experimental Techniques in Human Neuropsychology", Oxford University Press, 1988, p.457-478

[4] Aimé Lay-Ekuakille, "Wearable and Autonomous Biomedical Devices and Systems for Smart Environment", Issues and Characterization, 2010, p.354

[5] Marco Barbero, Roberto Merletti, Alberto Rainoldi, "Atlas of Muscle Innervation Zones: Understanding Surface Electromyography and Its Applications", Springer, 2012

[6] Gary Kamen, David A. Gabriel, "Essentials of Electromyography", Human Kinetics", 2010

[7] Himabindu Yamana, "Embedded System for Monitoring Human Activities Using 3-axis Accelerometer", ProQuest, 2007

[8] Zhou Wang, Alan Conrad Bovik, "Modern Image Quality Assessment", Morgan & Claypool Publishers, Jan 1, 2006

[9] David Kleinbaum, Lawrence Kupper et al, "Applied Regression Analysis and Other Multivariable Methods", Cengage Learning, Aug 30, 2013

[10] George A. F. Seber, Alan J. Lee, "Linear Regression Analysis", John Wiley & Sons, Jan 20, 2012. pp 391-427

[11] H.R. Wu, K.R. Rao, "Digital Video Image Quality and Perceptual Coding", CRC Press, Nov 18, 2005. PP.559-567

[12] Sazzad Hussain, Mamun Bin Ibne Reaz, "Electromyography Signal Analysis and Characterization: Based on Wavelet Transform and Higher Order Statistics", LAP Lambert Academic Publishing, 2012

[13] Alan J. Fridlund and John T. Cacioppo, “Guidelines for human electromyographic research,” Psychophysiology, vol. 23(5), pp. 567–589, September 1986.

[14] Louis G. Tassinary and John T. Cacioppo, “Unobservable facial actions and emotion,” Psychological Science, vol.3, no. 1, pp. 28–33, January 1992.

[15] Guoping Qiu, Kin Man Lam, "Advances in Multimedia Information Processing -- PCM 2010, Part I: 11th Pacific Rim Conference on Multimedia, Shanghai, China, September 21-24, 2010, Proceedings", Springer Science & Business Media, Sep 3, 2010

[16] Tarek Sobh, Khaled Elleithy, "Innovations in Computing Sciences and Software Engineering", Springer Netherlands, Aug 25, 2010

[17] Roberto Merletti, Philip A. Parker, "Electromyography: Physiology, Engineering, and Non-Invasive Applications", John Wiley & Sons, Jul 26, 2004

[18] Y. Yorozu, M. Hirano, K. Oka, and Y. Tagawa, “Electron spectroscopy studies on magneto-optical media and plastic substrate interface,” IEEE Transl. J. Magn. Japan, vol. 2, pp. 740-741, August 1987 [Digests 9th Annual Conf. Magnetics Japan, p. 301, 1982].

[19] Shanbao Tong, Nitish Vyomesh Thakor, "Quantitative EEG Analysis Methods and Clinical Applications", Artech House, 2009

[20] J. Clerk Maxwell, A Treatise on Electricity and Magnetism, 3rd ed., vol. 2. Oxford: Clarendon, 1992, pp.68-73.

[21] Stefan Winkler, "Digital Video Quality: Vision Models and Metrics", John Wiley & Sons, May 28, 2013

[22] Issues in Diagnostics and Imaging: 2013 Edition, Scholarly Editions, May 1, 2013. P.479-495

[23] Thierry Dutoit, Ferran Marques, "Applied Signal Processing: A MATLAB™-Based Proof of Concept", Springer Science & Business Media, Jun 10, 2010

[24] George C. S. Wang, Chaman L. Jain, "Regression Analysis: Modeling & Forecasting", Institute of Business Forec, 2003. Page 57-70

[25] André Gagalowicz, Wilfried Philips, "Computer Analysis of Images and Patterns: 11th International Conference, CAIP 2005, Versailles, France, September 5-8, 2005
[26] Ajith Abraham, Jaime Lloret Mauri et al, "Advances in Computing and Communications, Part II", Springer Science & Business Media, Jul 8, 2011. pp.
[27] André Gagalowicz, Wilfried Philips, "Computer Vision/Computer Graphics Collaboration Techniques: 5th International Conference, MIRAGE 2011, Rocquencourt, France, October 10-11, 2011. Proceedings". PP.274-284
[28] Ashish Ghosh, Rajat K. De, Sankar K Pal, "Pattern Recognition and Machine Intelligence: Second International Conference, PReMI 2007, Kolkata, India, December 18-22, 2007. PP.87-93
[29] VQEGL Final report from the video quality experts group on the validation of objective models of video quality assessment (March 2004). http://www.vqeg.org/
Ryszard S. Choras, "Image Processing and Communications Challenges 5", Springer Science & Business Media, Jul 19, 2013
[30] Ramón Pallás-Areny, John G. Webster, "Analog Signal Processing", John Wiley & Sons, 1999. PP.234-245

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