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THE UTILIZATION OF EEG SIGNAL IN VIDEO COMPRESSION

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ABSTRACT

Due to technology advances in multimedia, larger storage spaces, large internet bandwidth and high-transmission speed are required for the transmission of videos. Video compression techniques play a vital role in reducing video size; therefore, smaller storage space and lower internet bandwidth are eventually required. In this paper, the EEG signal is used to modify the compression ratio of videos based on the interest of the viewer. This is performed by associating the compression ratio applied to the video with the degree of interest using a group of frames. This interest for a group of frames is measured using the EEG signal to demonstrate the viewer responses to videos. Statistical techniques applied to the EEG signal (such as peaks-over-threshold and time-of-peaks-over-thresholds) are used to extract the frames of interest. Peak signal-to-noise ratio (PSNR), Structural Similarity Index (SSIM) and Mean-Square Error (MSE) are used to compare the performance of the proposed technique with the MPEG-4 technique. The results show a reduction of 15 % in the video size compared with the MPEG-4 technique without deteriorating the quality of the videos.

KEYWORDS

Video compression, EEG signal, MPEG-4, PSNR, SSIM, Brainwaves.

1. INTRODUCTION

Nowadays, multimedia plays an essential role in various human activities, such as learning, leisure and communication. High-definition videos require large bandwidth and storage space. Therefore, video compression techniques are used to minimize the number of bits to represent data. This results in more free storage capacity, rapid file transfer and efficient use of bandwidth when compared with uncompressed versions.

Video compression can be categorized into lossy or lossless compression. Lossy compression results in high compression ratio (when unnecessary information is removed) and lower bits with an acceptable level of quality. However, the original data cannot be accurately recovered [1]. Lossless compression results in complete recovery of the original data with lower compression ratio. International Telecommunications Union (ITU) and the International Standards Organization/International Electrotechnical Commission (ISO/IEC) developed the standards of video compression. Examples of these international standards are MPEG [2] and H.263 [3]. MPEG or MPEG-1 is the first true multimedia standard that has specifications for coding compression, transmission of audio, transmission of video and data streams in a series of synchronized mixed packets. MPEG-2 is used to perform high-quality transmission, multi-channel and multimedia over a broadband network like ATM. MPEG-4 provides high-compression characteristics of MPEG [4]. MPEG-4 supports all features of MPEG-1 and MPEG-2 and supports lower bandwidth-consuming applications (e.g. mobile phones). It is mainly utilized in digital television, interactive graphics applications (synthetic content) and the World Wide Web [5]. Recent techniques have emerged to target improving compression of high-dimensional or new video formats based on perceptual coding. Ki et al. presented a novel discrete cosine transform (DCT) model and applied it for perceptual video coding (PVC) [6]. The model was applied to high-efficiency video coding (HEVC). To further enhance the compression performance based on perceptual video coding, Prangnell and Sanchez proposed a novel JND-based PVC method to reduce the bit rate [7]. For

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optimizing video streaming, Takeuchi et al. introduced a perceptual video quality encoding solution [8]. They developed an estimator utilizing support video regression (SVR) to fulfill this function. Helmrich et al. proposed a simple algorithm, based on the human visual system, using perceptual video coding QPA [9]. As a result of the subjective tests run, the QPA was adopted in VTM (VVC). There are also other techniques aiming to improve the compression performance based on control of bit rate. Perez-Daniel and Sanchez proposed a multi-R - λ-model approach [10]. Using the peak signal-to-noise ratio (PSNR) metric, the results show that their approach is comparable with current RC techniques used in HEVC.

The High-Efficiency Video Coding (HEVC), aka H.265, is the latest video coding standard, which is a joint project of the ITU-T Video Coding Experts Group (VCEG) and the ISO/IEC Moving Picture Experts Group (MPEG) [11]. H.265 is the successor of H.264 (MPEG-4, Part 10). We would like to point out that HEVC is also applicable for our work, since the core spatial and temporal compression techniques of H.265 are the same as those used in its predecessors. The newest coding techniques, such as scalable video coding and 3-D/stereo/Multiview video coding [11] that were added to H.265, are irrelevant to our work in this paper.

Electroencephalography (EEG) is a technique used to record the electrical activity of the brain at different positions on the scalp [12]. The recorded activities represent the voltage potential induced due to the ionic motion within the neurons in human brain cells [13]. EEG signal plays a key role in many applications, e.g. diagnosing patients for different disorders, like a seizure, neuromarketing, brain-computer interfaces (BCIs), clinical and psychiatric studies [14].

One of the modern applications of the EEG signal is image and video compression [15]-[16]. The information in the EEG signal can be utilized to improve the compression ratio, especially in the era of the internet. Few researchers have addressed this topic; however, the published research has mainly focused on still images. Li et al. found that 3D visual fatigue can be detected using the EEG signal [17]. Lea Lindemann and Marcus Magnor concluded that the EEG signal might be used as a tool for evaluating image quality, where much information is implicitly encrypted in the signal [16]. Evaluating images using the features of the EEG signal improves image quality [18]. The utilization of the features of EEG signals may also be considered as an ultimate goal to produce more efficient video-compression algorithms. Tan et al. proposed a deep transfer learning algorithm suitable for knowledge transfer. Their approach was approved by applying their algorithm in EEG classification tasks [19].

The use of EEG or BCI in multimedia has made some progress in recent years. Engelke et al. presented a review of psychophysiology-based assessment for Quality of Experience (QoE) in multimedia [20]. Furthermore, Bosse et al. presented and discussed different approaches for multimedia quality assessments using BCI and addressed the challenges relevant to its community [21]. Additionally, Bosse et al. [22] evaluated still images using steady-state evoked potential (SSVEP). They used SSVEP, which represents neural response (the EEG signal), to assess the quality of texture images. Avarvand et al. presented a study for quality assessment of stereoscopic images using the EEG signal [23]. They measured the event-related potential (ERP) for 2D and 3D images and analyzed their measurements using time domain and frequency domain. They reported an increase in the amplitude of 3D images compared to 2D images. Many other studies in the literature have addressed image-quality assessment using various techniques, e.g. ERP [24]-[26]. In addition, Bosse et al. presented a video-quality assessment based on psycho-physiological techniques [27]. The EEG signal has been also considered in the literature to measure and determine video quality [28]-[30]. Although techniques related to assisting video quality using the EEG signal are not well developed, it is promising that these techniques may attain comparable results in the near future.

Video compression is a very helpful technique to facilitate video transmission, as the size is reduced, thereby preserving the bandwidth and increasing the transmission speed. Currently, the algorithms used in video compression (ex. MPEG) utilize a fixed compression ratio for the entire video. Generally, modifying the compression ratio of the video based on the Region-of-Interest (ROI) frames will improve the compression efficiency. This can be performed by determining the interesting frames in the videos and manipulating the compression ratio accordingly (i.e., increasing the compression ratio for the frames of less interest and *vice versa*). In this paper, the EEG signal is used to extract the interests of the video viewer by means of feature extraction and utilize them to manipulate the rate of video compression. The video is projected in the EEG signal as an evoked potential, which varies according to the interests of

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the viewer. The correlation between the features of the EEG signal (as the response of the video viewer) and the amount of compression will be accordingly identified.

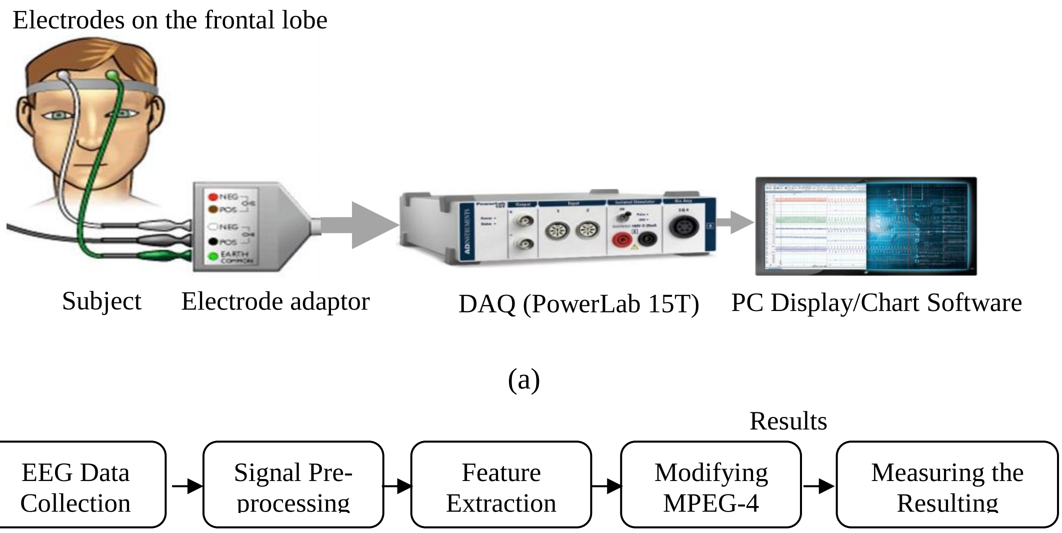
2. MATERIALS AND METHODS

2.1 Measurement Setup

Measurements were performed using a hardware system equipped with software provided by AD Instrument system (i.e., PowerLab 15T). The EEG signal was measured using electrodes placed at the frontal lobe, as shown in Figure 1(a). The electrode-skin impedance was reduced using gel (paste) to the range of 5 kΩ for the best EEG signal quality. Various tests were used to ensure the proper signal-to-noise ratio, as the EEG signal is a random signal. These tests were performed at the beginning of each measurement. The tests performed with the EEG signal are:

- Eye blinking test: This test includes determining the existence and number of the eye blinking artifact in the EEG signal when the subject blinks repeatedly;
- Alpha-wave test: This test includes requesting the subject to close his/her eyes and be calm without any brain activity. The EEG signal variations (existence of the alpha-wave) can be noticed when the subject opened his/her eyes;
- Clenching teeth test: This test includes clenching the teeth and accordingly, the amplitude and the frequency of the EEG signal increase.

The EEG signals were measured while the subjects were watching the videos. The signals were stored through the input terminals at the front panel of the setup. The EEG signals were recorded using two electrodes with about 2 cm above the hairline and 5 cm separation. A third electrode was placed on the earlobe or clavicle (i.e., ground reference electrode). The onset of the measurements was synchronized with the start of the video. A data acquisition system (DAQ) was used to transfer the measured signals to the computer with a sample rate equal to 1 kSPS. Afterwards, the signals were handled according to the procedure illustrated in Figure 1(b).



(b)

Figure 1. (a) AD Instrument acquisition system used in the measurement and (b) a block diagram of the signal processing procedure applied to the EEG signals.

2.2 Video Characteristics

Three uncompressed muted video-clips were selected carefully, which include some important stimuli, such as rapid motion, luminance and color variation. The test videos were uncompressed videos and are usually used in compression evaluation in typical studies. In spite of the short duration of these videos, their characteristics contain the main features that are needed for the evaluation of the proposed compression techniques. The videos were muted to measure the participant's attention according to the video features only.

The first video contains a colorful Chinese city with many details and vehicles crossing the camera in various directions. Such a video test guarantees the existence of two important parameters (i.e., motion vector and color variation). It involves local motion (motion of objects; i.e., cars), while the global motion (camera motion) was relatively small. On the other hand, the spatial information was large, as the frames were colorful.

The second video was about sea waves hitting the coast with a slow movement in the camera. This involves the presence of the bluish color with the small motion vector. It involves less local motion (motion of objects; i.e., sea waves), small global motion (camera motion) and very limited spatial information, as the frames contain small color variations (i.e., mainly blue).

The third video was about two guys playing table tennis. The motion is fast and thus the motion vector is large due to the sudden change in the players' position. It involves local motion (motion of objects; i.e., athletes), while the global motion (camera motion) was relatively small. On the other hand, the spatial information was relatively small.

The EEG features have been extracted from each subject for each video to evaluate the degrees of the subjects' attention and interest to each video segment (i.e., a group of frames). Video details are shown in Table 1, while Figure 2 shows a sample image of one of the videos used in this study.

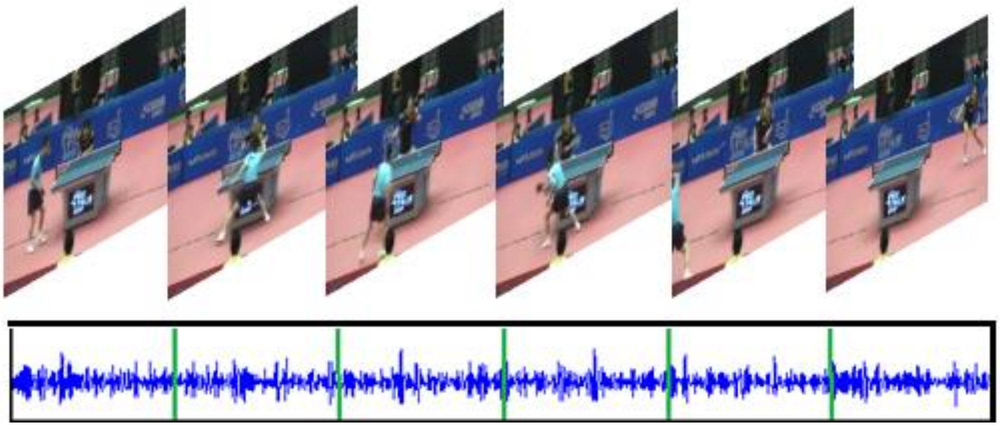


Figure 2. Sample images of one of the test videos used in this study.

Table 1. Details of the test videos.

Video	Size (kB)	Resolution	Number of Frames
1	13609	1280×720	460
2	13185	1280×720	300
3	13100	320×240	1200

2.3 EEG Data Collection

EEG data signals were collected from twenty subjects who participated in the experiments. The subjects were distributed as follows; eight males, nine females (with ages between 18 and 30 years) and three children (with ages between 8 and 12 years). During the measurements, the subjects were asked to be calm with reduced movement and minimum possible eye blinking. They were seated in a comfortable position on a chair with none of the electrodes placed on the subjects' heads. Once the subjects got familiar with the surroundings, the electrodes were connected to their positions. Figure 3 (a) shows a sample of the raw EEG signal acquired in this study with its decomposed components in Figure 3 (b).

2.4 Signal Processing

MATLAB environment was used for performing signal processing on the measured EEG signals. Signal processing involved filtration, frequency conversion and feature extraction. Power-line noise appeared

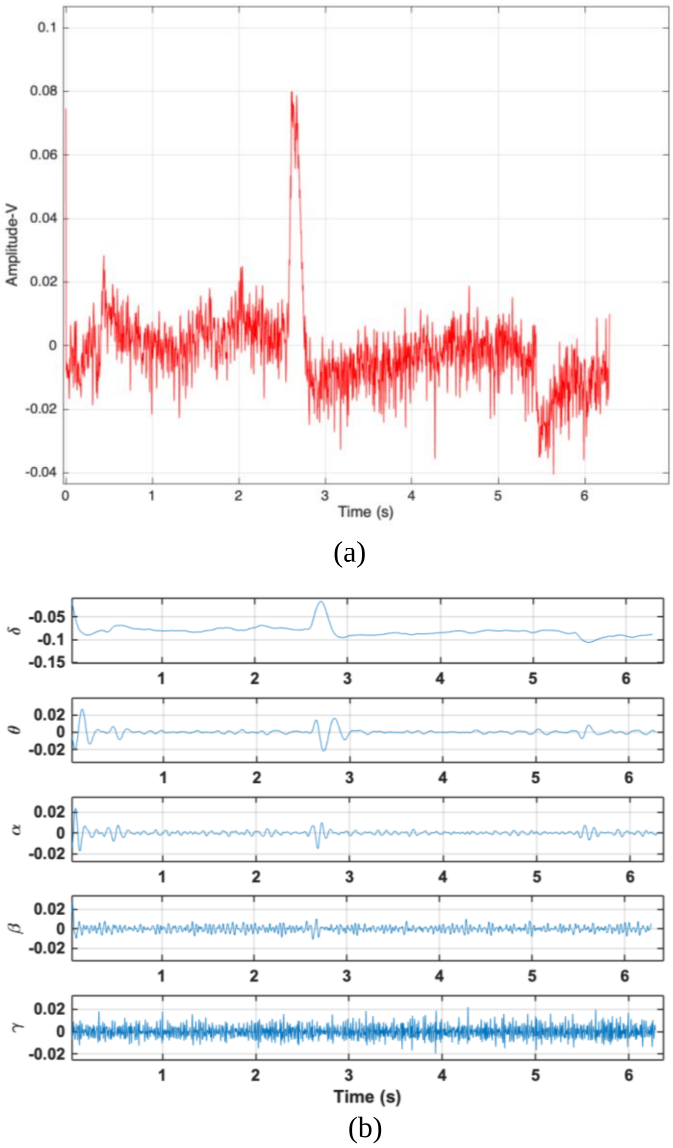
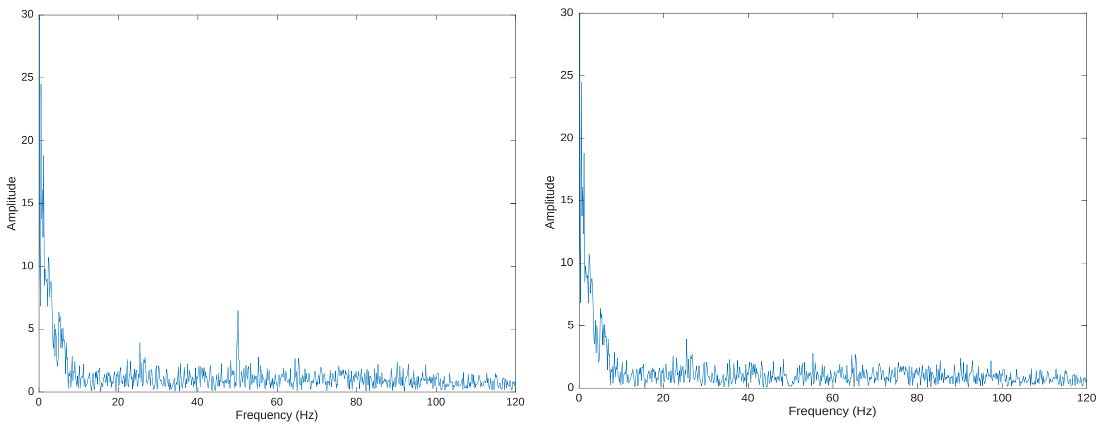


Figure 3. A sample of the EEG signal: (a) the raw signal and (b) the decomposed and processed components.

in the measured signals, which was removed with a notch-filter with a narrow frequency-band (49-51 Hz). Figure (4) shows the signal before and after the filtration process. High-frequency noise was also removed using a low-pass filter with a corner frequency of 100 Hz. The other sources of noise which normally appear in any EEG signals, like human artifact (low frequency) and electromagnetic noise superimposed on EEG, EMG and EOG signals, did not appear due to the careful procedure followed to reduce sources of noise. The EEG signals were decomposed into their corresponding waves. Beta-wave in the EEG signal has been used in the analysis, since it is registered during high activity. Beta-wave exists when the subject is concentrating and while performing brain activities (i.e., thinking or during visual stimuli) [31]-[33]. The extracted features show that there is a brain activity represented by the following features (i) Average of peaks-over-threshold (ii) Average duration of peaks over threshold and (iii) Power spectrum of the signals. Those features were chosen, as they provide a good indication of the brain activity, which is directly related to the stimulus. The peaks-over-threshold values were selected according to the central-limit theorem. Each segment is composed of 8 frames.

2.5 Feature Extraction

The EEG signal was used to extract the interesting frames in the video for the viewers using statistical analysis techniques. The statistical distribution of the EEG signal was calculated and a threshold was obtained above 5 % of the distribution. The amplitudes above the threshold with a certainty of 95% were



(a) (b)

Figure 4. An example of a frequency-domain representation of the EEG signal: (a) raw signal and (b) filtered signal.

calculated to denote a higher activity in the brain due to stimulus (i.e., video frames). The time of these peaks above the threshold was also determined. The average peaks and average times were used to locate the region of interest (ROI).

As an essential requirement for feature extraction, the onset of the video was synced with the recording of the EEG signal. The EEG signals were decomposed into their corresponding brain-waves. Data analysis was performed on the Beta-wave (i.e., frequency contents of 8 Hz to 14 Hz), which appears during high-mental activities. Therefore, in the following text, wherever the EEG signal is used, the Beta-wave is meant to be. For each frame, the length of the EEG signal was determined (according to Equation (1)) and afterwards, the segment of the signal for each group of frames was determined. Within the MPEG-4 coded video stream, the Group of Pictures (GOP) was chosen to be 8 with a 34 Quantization Parameter (QP) in the frames' analysis. The applied steps for the proposed technique were as follows:

1. The length of the EEG signal for each frame was calculated using Equation (1).

$$L_{EEG}=N/T \tag{1}$$

   where L_{EEG} is the length of the EEG signal per frame (i.e., the EEG signal segment), N is the length of the entire EEG signal and T is the number of video frames.

2. Each frame corresponding to an EEG sequence was computed according to Equation (2).

$$EEG_{segment(i)} = v*L_{EEG} \tag{2}$$

   where v is the index of the frame.

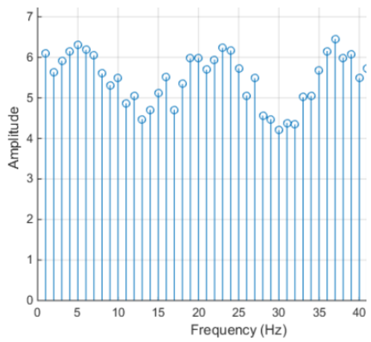


Figure 5. An example of EEG mean value for each segment distributed along the frequency range.

Due to the random property of the EEG signal, each EEG sequence was represented by one value (i.e., the mean value of the amplitude of segments). Figure 5 shows the corresponding averaged EEG signal for each video segment.

2.6 Modification of MPEG-4 Algorithm

The MPEG-4 technique is modified for each frame, where the averaged values of the EEG signal were used to choose the I-frames, P-frames and B-frames of MPEG-4 video. The threshold values were selected according to the EEG signal frequency range and the brain-wave associated with it. The frames with the maximum average amplitudes and maximum average times were correlated with the region of activation (in the EEG signal), in such a way that the first frame in this sequence represents the I-frame. The thresholds used to find the I-frame were determined experimentally, so that the video quality was assured, represented by the PSNR and Structural Similarity Index (SSIM) parameters. The best threshold that matches the previous criterion was found to be 0.8 for the I-frame and 0.6 for the P-frame, while the threshold for the B-frame was <0.6.

3. RESULTS AND DISCUSSION

The efficiency of the proposed approach was evaluated and compared with the MPEG-4 standard approach through (i) comparing the video size before and after the compression process (ii) calculating the PSNR and (iii) calculating the SSIM and comparing it with that of the original video. PSNR, SSIM and Mean-Square Error (MSE) parameters were used in the evaluation of the compression technique as an indication of image quality and to predict the human visual response. Therefore, PSNR and SSIM were used for making the comparison between the proposed method and the MPEG-4. The results show that the proposed method does not deteriorate the quality of images. PSNR (in dB) was computed according to Equation (3).

$$PSNR = 10 \times log_{10}\left(\frac{MAXI^2}{MSE}\right) \tag{3}$$

where, *MAXI* is the maximum pixel value of each frame and MSE is:

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \tag{4}$$

where, I is the original uncompressed frame and K is the coded video frame; i and j are the row and column pixel index, respectively. SSIM can be calculated using Equations (5-9) with SSIM equals one if the two images are identical [34]:

$$\mu_x = \frac{1}{T}\sum_{i=1}^{T} x_i \tag{5}$$

$$\mu_y = \frac{1}{T}\sum_{i=1}^{T} y_i \tag{6}$$

$$\sigma_x^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - x)^2,\ \sigma_y^2 = \frac{1}{T-1}\sum_{i=1}^{T}(y_i - y)^2 \tag{7}$$

$$\sigma_{xy}^2 = \frac{1}{T-1}\sum_{i=1}^{T}(x_i - x)^2(y_i - y)^2 \tag{8}$$

$$(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{9}$$

where, c_1 and c_2 are stabilizing coefficients.

The MPEG-4 algorithm was modified by varying the compression ratio based on the degree of interest instead of using a constant compression ratio. The portion of the videos with higher interest was less compressed compared with the portions with less interest. The videos were shown two times: trial version and testing version for each subject. Repeating the measurements during the experiments didn't influence the results in terms of the features extracted from both trials. For the first video, the size of the uncompressed version was 13609 KB, while for the conventional MPEG-4 compression, it was 7173 KB (see Table 1). Applying the modified MPEG-4 algorithm on the uncompressed version of the first video revealed that the average video size has reduced to 5992.2 KB. Table 2 summarizes the size of the compressed video using the proposed approach (i.e., modified MPEG-4 algorithm) for each participant (P). The results show clearly that the size of the compressed video is lower compared with the conventional MPEG-4 algorithm. The quality of the video has not deteriorated significantly by using the modified MPEG-4 algorithm, as indicated by the PSNR, SSIM and MSE results. These results are obtained by the measurements performed on all participants.

Table 2. Compression of: (a) first (b) second and (c) third test video using the proposed method for different participants.

(a)		(b)		(c)	
Sample	**Video size (KB)**	**Sample**	**Video size (KB)**	**Sample**	**Video size (KB)**
P1	6021	P1	5829	P1	6021
P2	5973	P2	5733	P2	5973
P3	6117	P3	5832	P3	6069
P4	6021	P4	5829	P4	6021
P5	5925	P5	5877	P5	6069
P6	5973	P6	5781	P6	5973
P7	5925	P7	5733	P7	6069
P8	6021	P8	5877	P8	6117
P9	6165	P9	5781	P9	5925
P10	5877	P10	5829	P10	5973
P11	6069	P11	5877	P11	6165
P12	6021	P12	5781	P12	6213
P13	5973	P13	5733	P13	6261
P14	5877	P14	5829	P14	6117
P15	6021	P15	5684	P15	5877
P16	6069	P16	5532	P16	6021
P17	5877	P17	5877	P17	5973
P18	5925	P18	5829	P18	6117
P19	6021	P19	5781	P19	6060
P20	5973	P20	5829	P20	6261

The same procedure has been performed for the second and third test videos. The sizes of the uncompressed versions were 13185 KB and 13100 KB, while for the conventional MPEG-4 compression, these sizes were 7074 KB and 6933 KB for the second and third test videos, respectively (see Table 2). Applying the modified MPEG-4 algorithm on the uncompressed version of the videos resulted in reducing the average video sizes to 5792.65 KB and 6063.75 KB for the second and third videos, respectively.

Based on these results, the average difference between frames for the three videos was calculated and found to be 2.1242 KB, 1.1258 KB and 2.4242 KB, respectively. The large difference in video frames indicates low compression ratio and *vice versa*; the low difference in video frames represents high compression ratio. All the three test videos have shown a possibility to increase the compression ratio without deteriorating significantly the quality of the video (i.e., decrease the videos sizes with 1180.8, 1281.35 and 869.25 KB, respectively, compared with MPEG-4 method).

PSNR is usually used to measure the quality of reconstruction of lossy compression codecs. To assess the quality of the compressed videos using the proposed approach, PSNR was determined and compared with PSNR for the same videos using the MPEG-4 method. All the results of the three test videos using the modified MPEG-4 compression approach show low variations in the average value of PSNR when

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compared with the typical MPEG-4 method. Figures 6 and 7, respectively, show examples of the frame-by-frame PSNR results for the compressed videos using MPEG-4 and the proposed technique for the first video (see Table 3).

SSIM is an image quality assessment method used to measure the similarity between two images. For the compressed video and the original video, SSIM was determined for the MPEG-4 method and the proposed approach. The results show that the compressed videos using the proposed approach have comparable similarity values compared with the MPEG-4 approach (see Table 4). The difference between the two methods was less than 2% in the worst scenario for all participants.

Table 3. Average PSNR of the tested videos using the MPEG-4 method compared with the proposed approach.

Video	Average PSNR (dB)	
	MPEG-4 Method	The Proposed Method
1	46.90	40.69
2	48.74	45.13
3	46.87	45.50

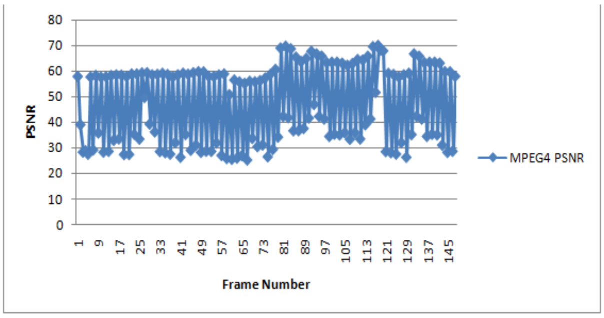

Figure 6. PSNR for the first video using MPEG-4 compression.

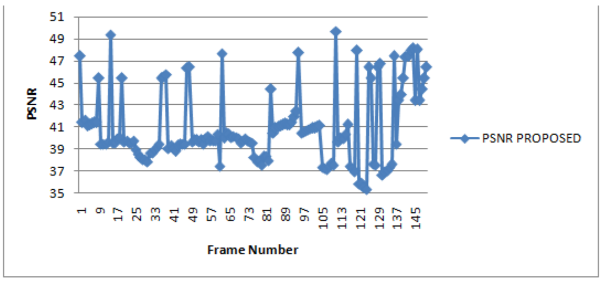

Figure 7. PSNR for the first video using the proposed approach.

Table 4. Average SSIM of the tested videos using the MPEG-4 method compared with the proposed approach.

Video	Average SSIM (%)	
	MPEG-4 Method	The Proposed Method
1	91.81	90.75
2	94.61	92.64
3	93.25	92.33

MSE has been used to check the performance of the proposed compression technique relative to the standard MPEG-4 technique. The results show that there is no significant difference between the video played with the MPEG-4 and the same video compressed with the proposed technique. For the three test videos, compared with the MPEG 4 videos, the averaged absolute differences between frames using the proposed technique were found to be 1.7259, 1.200, 1.9856, respectively. Figures (8-10) show examples of different frames for the MPEG-4 videos compared to the videos with the proposed technique together with the MSE graphs for each frame.

Figure 8. The absolute difference in the first video for frame number 10.

Figure 9. The absolute difference in the first video for frame number 100.

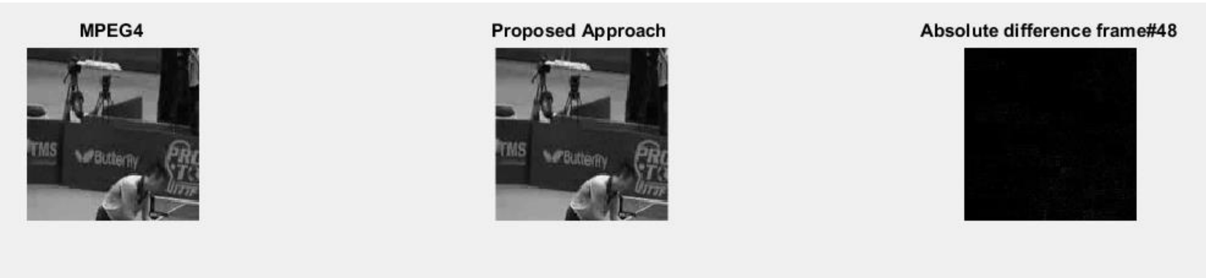

Figure 10. The absolute difference in the third video for frame number 48.

4. CONCLUSIONS

Videos require a large space for storage in addition to a wide internet bandwidth, which necessitates an efficient video compression technique. Electroencephalogram (EEG) signals can be used to measure the responses of video viewers and their interest in different segments of the video. Since the interest through the video varies, an adjustable compression ratio could be applied (i.e., used by conventional compression algorithms). Therefore, the EEG signal can be used to adapt the compression rate. The MPEG-4 was modified to comprise an adjustable compression ratio, so that a high compression ratio is applied to the frames with low interest and a low compression ratio is applied to the frames with high interest. The results obtained illustrate a possibility to reduce the size of the compressed video based on the video content and achieve higher compression ratios. The features of the EEG signal, which represent the viewer's attention, were used to compress videos to a lower size than in the MPEG-4 technique. In terms of video quality and based on PSNR, SSIM and MSE parameters, the proposed approach showed a comparable quality to the MPEG-4 technique.

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ملخص البحث:

في هذه الدراسة، تستخدم إشارة تخطيط الدماغ من أجل تعديل معدل الضغط للفيديوهات بناءً على درجة اهتمام المشاهد. ويتم ذلك من خلال ربط معدّل الضغط الذي يخضع له الفيديو بدرجة اهتمام الشخص الذي يشاهده باستخدام مجموعة من الأُطُر. ويقاس اهتمام المشاهد بمجموعة من الأُطُر باستخدام إشارة تخطيط الدماغ من أجل بيان استجابة المشاهد للفيديو. وتُستخدم تقنيات إحصائية تطبق على إشارة تخطيط الدماغ لاستخراج الأُطُر موضوع الاهتمام بالنسبة للمشاهد. وقد تم تقييم الطريقة المستخدمة في هذه الدراسة قياساً على عدد من المتغيرات (أعلى نسبة إشارة الى ضجيج، ومؤشر التماثل البنيوي، والخطأ التربيعي المتوسط)، وذلك بمقارنة أداء التقنية المقترحة بتقنية (MPEG-4) التقليدية. وبينت النتائج خفضاً في حجم الفيديو بنسبة 15% مقارنة بتقنية (MPEG-4) دون الإضرار بجودة الفيديو.