

# Research on Respiratory Signals for Visual Fatigue Caused by 3D Display



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**Abstract** In order to study the relationship between visual fatigue and respiratory characteristic parameters caused by 3D display, 30 subjects were invited to watch 3D videos for 90 min. A questionnaire survey was performed in the initial state and every 15 min after watching the video to obtain the subjective data, and 7 groups of data were collected. The characteristic parameters of breathing were acquired synchronously using breathing sensors. The data was analyzed using SPSS. The results show that subjective fatigue increases with the increase of time spent watching 3D videos, and subjective visual fatigue increases extremely significantly from 45 to 60 min. The mean of power, index of the respiratory frequency domain, and the corresponding standard deviation show a highly significant linear negative correlation with time and the consistency with subjective fatigue score reached 0.970, indicating that the power value is effective for visual fatigue assessment. Therefore, based on the power mean or standard deviation of the breathing signal, the time is used to estimate or evaluate the time of watching 3D display.

**Keywords** Visual fatigue · respiratory signal · Respiratory frequency domain · Power index · Correlation analysis

## 1 Introduction

The development of 3D technology has involved all aspects of life, such as medical, industrial, military, education, entertainment, film, and television. The application of 3D technology also brings a new problem-visual fatigue. Many scholars have carried out related research, such as: Wang [1] studied the effect of visual fatigue on 3D polarized displays based on medical eye symptoms. Yano [2] pointed visual fatigue was induced if the images were moved in depth according to a step pulse function even if images were displayed within the corresponding range of depth of focus. Kooi et al. [3] proposed that crosstalk and blur may be the factors that

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S. Long and B. S. Dhillon (eds.), *Man-Machine-Environment System Engineering*, Lecture Notes in Electrical Engineering 645, [https://doi.org/10.1007/978-981-15-6978-4\\_76](https://doi.org/10.1007/978-981-15-6978-4_76)

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cause visual fatigue. Matsuura [4] proposed that the influential factors affecting the viewing conditions in 3D stereo vision are interpupillary distance, visual function, and viewers. Alhaag et al. [5] confirmed that 3D display at short distance is more likely to cause visual fatigue than 2D display, but 3D display at a long distance has a lesser effect on visual fatigue.

For the measurement of visual fatigue, the most extensive subjective measurement is a questionnaire. For example, Lambooi [6] gave a visual fatigue questionnaire recognized by most scholars, namely the questionnaire for visual symptoms of Sheedy; Li et al. [7] used EEG and ERP signals to measure 3D visual fatigue and concluded that binocular parallax has effect on 3D visual fatigue. Tam et al. [8] indicated that there is a significant difference in 3D tolerance among individuals, and it is still impossible to distinguish whether it is caused by the stereo or the individual. Park and Mun [9] mentioned that it is also good to use eye movement parameters and physiological signals as 3D visual fatigue evaluation index when measuring visual fatigue. Kim et al. [10] used ECG, GSR, and SKT to measure the degree of fatigue affected by watching 3D video, indicating that skin electrical response (GSR) and skin temperature (SKT) may also be used to assess the extent of 3D visual fatigue. Bruce [11] measured drivers' fatigue by recording heart rate and skin power. Ashrant et al. [12] used physiological indicators such as heart rate, EEG, and infrared temperature to detect the physical fatigue of construction workers. Zhu et al. [13] extracted the cycle, period standard deviation, amplitude, amplitude standard deviation, and frequent yawns of respiratory signals as characteristic parameters for determining driving fatigue. Yu [14] proposed a model for judging the current fatigue level and design and apply it to the mobile terminal (mobile phone application). Xu [15] judged the driver fatigue based on physiological signals EEG and ECG (heart rate signal). Ye [16] used physiological signals to classify driving fatigue and established a driving fatigue evaluation model by collecting and analyzing EMG and ECG. Fu et al. [17] used the wireless measurement equipment of physiological signals to detect the driver's fatigue state, and the prediction results based on the Bayesian model and reached a good agreement with the subjective score results.

In the current research, many scholars use physiological signals to evaluate fatigue, but the evaluation of respiratory signals is mainly for driving fatigue, which is different from visual fatigue caused by 3D display. Therefore, it is necessary to further correlate the respiratory characteristic parameters with 3D visual fatigue.

## 2 Experiment

### 2.1 Subject Selection

Thirty subjects (15 males and 15 females, aged from 19 to 45) were selected. The subjects had naked eye or corrected vision of 5.0. They did not perform strenuous exercise or watch movies and mobile phones for a long time before the test.

## 2.2 Equipment Parameters

LG42LW4500 (resolution 1920 × 1080, non-flash (i.e., polarized) 3D technology, screen ratio 16:9) was used with the parameters of contrast 95, backlight 100, and brightness 50 (recommended 3D optimal brightness). The measured brightness value in the mode is 102.12 cd/m<sup>2</sup>, and the photometer is Photo Research PR-680 model in the USA).

## 2.3 Experiment Procedure

1. Fill in the participant information record form and survey questionnaires.
2. Wear physiological signal sensor and setting the viewing distance to 1.5 m.
3. Measure the physiological parameters in the initial state for 5 min in a quiet state.
4. Fill out a questionnaire every 15 min, with a total of 6 times.
5. Keep and back up the test data and export the data.

## 3 Data Analysis

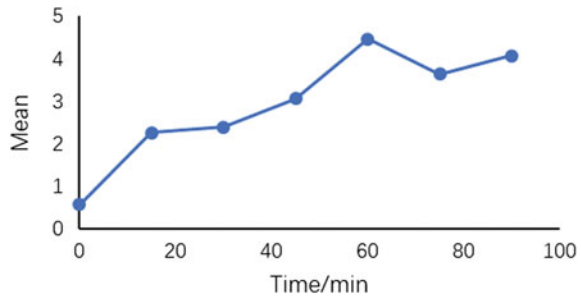
### 3.1 Questionnaire Data Processing and Analysis

Subjective data obtained from subjective questionnaire surveys. The mean statistics of the total subjective fatigue scores are shown in Table 1. The line chart of the changes in scores over time is shown in Fig. 1. At 60 min, due to the limited backup battery, battery replacement and recalibration procedures will be performed, which will make the subjects have 90 s rest time, so 60 min to 75 min, the score may not rise but may be the reason for getting rest. This also shows that during the period of visual fatigue, a short rest period can make people recover to a certain extent.

**Table 1** Statistics of questionnaire score

Time duration/min	Minimum	Maximum	Mean	Std. deviation
0	0.00	3.00	0.57	0.90
15	0.00	10.00	2.27	3.37
30	0.00	7.00	2.40	2.29
45	0.00	8.00	3.07	2.49
60	0.00	10.00	4.47	3.41
75	0.00	8.00	3.64	2.41
90	0.00	8.00	4.07	2.63

**Fig. 1** Polyline for mean of fatigue score



Correlation analysis showed that at a test level of 0.01, the correlation coefficient between the fatigue score of the questionnaire and the time spent watching 3D videos was 0.894, which was extremely strong relationship. The Shapiro–Wilk test method was used to test the fatigue score data for normality. The test results are shown in Table 2.

Table 2 shows that the data for 45 min and after watching the 3D video conform to the normal distribution, and the p-values of the previous data are less than 0.05, which do not conform to the normal distribution. The Wilkerson symbol rank test and the paired t-test were used to compare the different viewing times with those when not watching, and the differences were analyzed. The results are shown in Table 3.

From the pairwise comparison in Table 3, it is known that the *p*-value of the baseline data compared with the data of 30 min, 45 min, 60 min, 75 min, and 90 min are all less than 0.05. It shows that with the increase of time, subjective visual fatigue has shown a significant increase. In addition, the comparison of the data of the adjacent two groups shows that there is significant difference in the comparison between 30–45 min and 45–60 min, which indicates that the subject has a stronger sense of fatigue during this process, especially in the process of 45–60 min, which also has statistically significant at the significance level of 0.01.

**Table 2** Results of normality test for the questionnaire

Time duration/min	Shapiro–Wilk		
	Statistic		Sig
0	0.701		0.000
15	0.686		0.000
30	0.867		0.031
45	0.922		0.205
60	0.886		0.059
75	0.960		0.684
90	0.925		0.231

**Table 3** Pared comparison for fatigue score

Comparison	Test method	<i>p</i> -value
0 versus 15	Wilcoxon signed-rank test	0.058
0 versus 30	Wilcoxon signed-rank test	0.015
0 versus 45	Wilcoxon signed-rank test	0.004
0 versus 60	Wilcoxon signed-rank test	0.002
0 versus 75	Wilcoxon signed-rank test	0.002
0 versus 90	Wilcoxon signed-rank test	0.001
15 versus 30	Wilcoxon signed-rank test	0.796
30 versus 45	Wilcoxon signed-rank test	0.039
45 versus 60	Paired samples t-test	0.001
60 versus 75	Paired samples t-test	0.253
75 versus 90	Paired samples t-test	0.463

### 3.2 RESP Signal Analysis

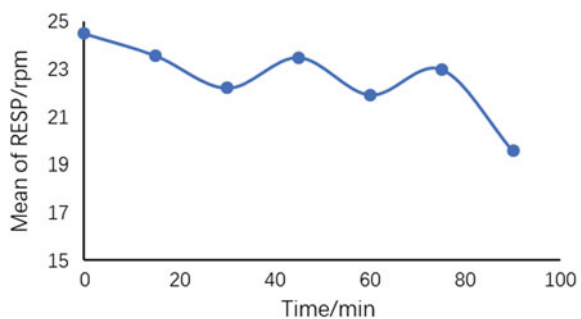
#### 3.2.1 Time Domain Analysis

Perform time domain analysis on the RESP signal, and analyze the average value of the RESP over a period, that is, the average value of the respiratory frequency.

First, the data was tested for abnormality. Under the criterion of  $z = 3$ , there were no abnormal values. Correlation analysis of respiratory frequency to time showed that the respiratory frequency was significantly negatively correlated with time, with a correlation coefficient of  $-0.784$  and a *p*-value of  $0.037$ .

Descriptive statistics of the mean respiratory frequency showed that the mean value decreased from 24.5 rpm to 19.5714 rpm, but there was no significant change in the entire data and time, as shown in Fig. 2. The normality of each group of data was tested, and all groups were normally distributed. The paired samples t-test was performed on the results. The test results are shown in Table 4. The results show that, under the significance level of 0.05, although the mean value of respiratory frequency is significantly lower than that of the non-watched 3D video when watching 90 min of

**Fig. 2** Mean of RESP value to time



**Table 4** Paired samples t-test results

Comparison	<i>p</i> -value
0 versus 15	0.391
0 versus 30	0.174
0 versus 45	0.576
0 versus 60	0.127
0 versus 75	0.389
0 versus 90	0.078
15 versus 30	0.438
30 versus 45	0.346
45 versus 60	0.403
60 versus 75	0.562
75 versus 90	0.226

3D video, this change has not shown statistical significance. Therefore, visual fatigue under 3D display cannot be accurately measured with the time domain characteristics of respiratory indicators.

### 3.2.2 Frequency Domain Analysis

The frequency domain analysis indicators of the breathing index are power and peak, respectively. The two indexes represent the power of the breathing band and the maximum value of the breathing frequency, that is, breathing power and breathing peak. Descriptive statistics of the two indicators are shown in Table 5.

Correlation analysis between power and peak values and viewing time shows that the average and standard deviation in power are strongly correlated and extremely correlated with time, while all parameters in the peak index are extremely weakly correlated or unrelated. Therefore, only the power value is analyzed.

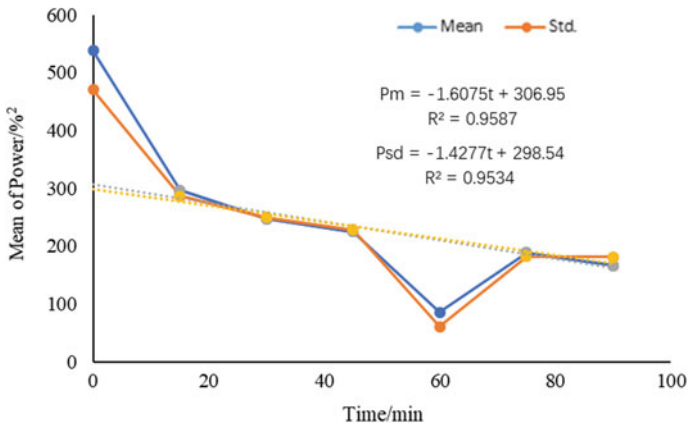
In the power indicator, it can be seen clearly that the average value and the standard deviation decrease gradually. The power value decreases from  $538.6423\%^{2}$  in the initial state to  $166.24\%^{2}$  in the 90 min.

The data was abnormal at 60 min, which is consistent with subjective measurement data. It shows visual fatigue sharply from 45 to 60 min. And after adjustment, it returns to the normal level at 75 min. Removing the data at 60 min, a curve was drawn for the mean of power and standard deviation as showed in Fig. 3. It shows a general trend of slow decline. This indicator also reflects the decline of the human's breathing power, and the breathing gradually slows down. Combined with the subjective questionnaire, it appears along with visual fatigue caused by 3D video viewing.

After entering the 3D video viewing state, the power mean basically shows an obvious linear distribution. Pearson correlation between power mean and time is  $-0.803$  with sig.(2-tailed) 0.030, while the stand deviation is  $-0.779$  and  $0.039$ , separately.

**Table 5** Paired samples t-test results

Index	Duration/min	Mean	Std	95% confidence interval of the difference	
				Lower	Upper
Power (% <sup>2</sup> )	0	538.6423	471.1533	253.9272	823.3574
	15	296.8508	287.2676	123.256718	470.444821
	30	247.7692	249.6864	96.885269	398.653192
	45	225.02	228.5998	86.878503	363.1615
	60	85.8908	60.96885	49.047659	122.733880
	75	188.9823	181.9452	79.033900	298.930715
	90	166.24	181.1512	56.771437	275.708563
Peak (HZ)	0	0.6214	0.09750	0.5651	0.6777
	15	0.6500	0.08549	0.6006	0.6994
	30	0.6357	0.074495	0.5927	0.6787
	45	0.657 <sup>*</sup>	0.085163	0.6080	0.7063
	60	0.6714	0.091387	0.6187	0.7242
	75	0.6357	0.08419	0.5871	0.6843
	90	0.6214	0.089258	0.5699	0.6730



**Fig. 3** Power mean and standard deviation along with time

The trend lines are added separately to find that the relationships between the power mean ( $P_m$ ) for the breathing frequency domain and the time  $t$  for viewing the 3D video is consistent with:

$$P_m = -1.6075t + 306.95, R = 0.9587.$$

**Table 6** Power indicator normally test

Duration/min	Shapiro–Wilk	
	Statistics	Sig
0	0.888	0.092
15	0.859	0.037
30	0.799	0.007
45	0.845	0.024
60	0.919	0.243
75	0.843	0.023
90	0.758	0.002

Relationships between the standard deviation of the power mean ( $P_{sd}$ ) and the time  $t$  for watching 3D video:

$$P_{sd} = -1.4277t + 298.54, R = 0.9534.$$

It can be seen from the fitting degree of the two trend lines that their fitting degrees are both greater than 0.95, which indicates good fitting degree of the regression line to time. Correlation analysis was performed between the mean and standard deviation of power and subjective scores, the correlation coefficients were both  $-0.971$ , and the  $p$ -value was 0. Therefore, visual fatigue can be evaluated using power or standard deviation. And the 3D video viewing time (greater than 15 min) can be estimated based on the power value of the RESP indicator, which provides guidance for the application of future physiological indicators to monitor 3D visual fatigue.

In order to observe the regularity of the data distribution further, a normality test was performed on the power value. The results are shown in Table 6.

Based on the normality test results, under the test level of 0.05, five groups of power indicators do not meet the normal distribution, and two groups of peak indicators do not meet the normal distribution. The initial time is compared with the value of each the remaining time periods, and the paired sample t-test and Wilkerson signed-rank test are used for pairwise analysis, respectively. The results are shown in Table 7. There are significant differences between the viewing time and the initial time, while the  $p$ -value does not show a significant change trend. Among the comparison of neighboring 15 min, there are significant differences between 45 and 60 min and between 60 and 70 min, which is consistent with the questionnaire analysis.

## 4 Conclusions

1. Questionnaire survey showed that subjective visual fatigue increased significantly after watching 3D videos for 30–60 min, especially during the period of 45–60 min, subjective visual fatigue increased significantly.



**Table 7** Pair test of power mean

Comparison	Test method	<i>p</i>
0 versus 15	Wilcoxon signed-rank test	0.039
0 versus 30	Wilcoxon signed-rank test	0.046
0 versus 45	Wilcoxon signed-rank test	0.046
0 versus 60	Pared samples t-test	0.005
0 versus 75	Wilcoxon signed-rank test	0.009
0 versus 90	Wilcoxon signed-rank test	0.016
15 versus 30	Wilcoxon signed-rank test	0.701
30 versus 45	Wilcoxon signed-rank test	0.279
45 versus 60	Wilcoxon signed-rank test	0.009
60 versus 75	Wilcoxon signed-rank test	0.028
75 versus 90	Wilcoxon signed-rank test	0.6

2. The consistency of the power mean and standard deviation in the breathing frequency domain to subjective visual fatigue is 0.971. The power mean and standard deviation shows strong correlation with time, and the correlation coefficient is  $-0.779$  and  $-0.803$ , respectively.
3. After watching the 3D video for 15 min, the relationships between the power mean ( $P_m$ ) and standard deviation ( $P_{sd}$ ) in the breathing frequency domain and time  $t$  meets:  $P_m = -1.6075t + 306.95, R^2 = 0.9587; P_{sd} = -1.4277t + 298.54, R^2 = 0.9534$ .
4. The increase in 3D visual fatigue leads to a decrease in respiratory frequency, but the average respiratory frequency does not reflect the working time of visual fatigue; there is no significant correlation between peak value and visual fatigue.

**Acknowledgements** This work is supported by National Key R&D Program of China (2017YFF0206604) and General Project of China University of Labor Relations (20XYJS020).

**Compliance with Ethical Standards** The study was approved by the Logistics Department for Civilian Ethics Committee of China University of Labor Relations.

All subjects who participated in the experiment were provided with and signed an informed consent form.

All relevant ethical safeguards have been met with regard to subject protection.

## References

1. Wang YJ, Gao XL, Shi HM, Zhang YL, Wang Q, Bai Y (2016) Influence of polarized 3D displayer on visual function. *J Tianjin Med Univ* 22(04):328–331
2. Yano S, Emoto M, Mitsuhashi T (2004) Two factors in visual fatigue caused by stereoscopic HDTV images. *Displays* 25(4):141–150
3. Kooi FL, Toet A (2004) Visual comfort of binocular and 3D displays. *Displays* 25(2–3):99–108
4. Matsuura Y (2019) Aftereffect of stereoscopic viewing on human body II. In: *Stereopsis and hygiene*. Springer, Singapore, pp 89–99

5. Alhaag MH, Ramadan MZ (2017) Using electromyography responses to investigate the effects of the display type, viewing distance, and viewing time on visual fatigue. *Displays* 49:51–58
6. Lambooij M, Fortuin M, Heynderickx I, IJsselsteijn W (2009) Visual discomfort and visual fatigue of stereoscopic displays: a review. *J Imag Sci Technol* 53(3):30201-1
7. Li HCO, Seo J, Kham K, Lee S (2008) Measurement of 3D visual fatigue using event-related potential (ERP): 3D oddball paradigm. In: 2008 3DTV conference: the true vision-capture, transmission and display of 3D video. IEEE, pp 213–216
8. Tam WJ, Speranza F, Yano S, Shimono K, Ono H (2011) Stereoscopic 3D-TV: visual comfort. *IEEE Trans Broadcast* 57(2):335–346
9. Park MC, Mun S (2015) Overview of measurement methods for factors affecting the human visual system in 3D displays. *J Display Technol* 11(11):877–888
10. Kim CJ, Park S, Won MJ, Whang M, Lee EC (2013) Autonomic nervous system responses can reveal visual fatigue induced by 3D displays. *Sensors* 13(10):13054–13062
11. Mehler B (2015) Recording heart rate & electrodermal activity as measures of cognitive load in the driving environment. <https://doi.org/10.13140/RG.2.1.2050.6329>
12. Aryal A, Ghahramani A, Becerik-Gerber B (2017) Monitoring fatigue in construction workers using physiological measurements. *Autom Constr* 82:154–165
13. Yuhong Z, Haiping L, Fusheng Z, Mantian LI, Wei G, Pengfei W (2014) Real-time monitoring system for driver's fatigue states based on respiratory signal. *J Jiangnan Univ (Nat Sci Ed)* 13(01):55–59
14. Yu Q (2018) The design and implementation of the mobile terminal heart rate analysis engine based on photo-plethysmograph imaging technology. Master Thesis of Beijing University of Posts and Telecommunications, Beijing University of Posts and Telecommunications, Beijing
15. Xu S (2012) The study on the discriminating method of driving fatigue based on physiological signal. Master Thesis of Beijing University of Technology, Beijing University of Technology, Beijing
16. Ye CW (2018). Research on automobile driving fatigue based on ECG signal and EMG signal (Doctoral dissertation). Master Thesis of Hefei University of Technology, Hefei University of Technology, Hefei
17. Fu RR, Tian YS, Wang SC, Wang L (2019) The recognition of driver's fatigue based on dynamic Bayesian estimation. *Chin J Biomed Eng* 38(06):759–763