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Elapsed time estimates in virtual reality and the physical world: The role of arousal and emotional valence

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ABSTRACT

Virtual reality (VR) allows for a close approximation of the real world, but interacting with VR differs from experiencing the real world in some key elements, one of which may be the perception of time. The main goal of the current experiment was to determine whether a time compression effect exists for VR and if so, to examine whether this is the result of the medium of VR itself, or the content used in VR. Participants viewed movie clips in either a real-life cinema or a VR replica of this cinema and were asked to rate the arousal and emotional valence they experienced during each clip. They estimated the duration of each clip in seconds. Results indicate that both level of arousal and valence as experienced by the observer positively contribute to the observed time compression effect, regardless of the viewing condition. Our data suggest there is no difference in the perception of temporal duration between VR and real life, and that the time compression effect that takes place is most likely the result of the materials displayed. So, even though VR has been claimed to result in time compression, for instance in clinical contexts, this may be caused more by the emotional content of the materials used, rather than the medium of VR itself.

1. Introduction

The quality and number of applications of virtual reality (VR) environments are rapidly increasing. VR allows for a controllable approximation of the real, physical world that can be used in a wide range of situations (e.g., for entertainment or medical purposes). Yet, there appear to be limitations to the extent to which the physical world can be imitated. For instance, distance has been found to be underestimated in VR environments (e.g., Finnegan, O'Neill, & Proulx, 2016; Knapp & Loomis, 2004; Stefanuci, Creem-Regehr, Thompson, Lessard, & Geuss, 2015) and the accuracy by which spatial information is perceived can easily be manipulated in VR (e.g., Linkenauger, Bülthoff, & Mohler, 2015; Cuperus & van der Ham, 2016; Cuperus et al., 2018). Such effects could have substantial impact on experimental and practical implementations of VR, as they may interfere with perceptual processes relevant to the task at hand. Underestimation in VR environments may also extend to the temporal domain, as essential cues supporting time estimation ('zeitgebers') such as the position of the sun are lacking or can easily be manipulated (Schatzschneider, Bruder, & Steinicke, 2016).

Several therapeutic applications of VR support a time compression effect; for instance, breast cancer patients underestimated elapsed time after VR-mediated chemotherapy, whereas they overestimated it after music-mediated chemotherapy (Chirico et al., 2016). VR can also be used as a distraction method during medical procedures, in order to relieve pain (Indovina, Barone, Chirico, De Pietro, & Giordano, 2018). Thus, VR may be used during stressful procedures like chemotherapy to produce an elapsed time compression effect. It then serves mainly as a distracting circumstance, as it is thought to reduce the overall impact of the medical procedure by making it seem to last shorter. However, the extent of this effect has been found to depend on the type of cancer patient exposed to a VR element in their treatment. Breast cancer patients were more likely to experience altered time perception, whereas lung cancer patients were less likely. The cause of such individual variation remains unclear (Schneider, Kisby, & Flint, 2011). Furthermore, other more exploratory findings suggest a deviation of time perception in the opposite direction; a pilot study making use of a head mounted device found longer perceived elapsed time for the virtual display compared to the real world (Bruder & Steinicke, 2014).

The precise mechanisms underlying such distraction are unclear as of yet. It has been suggested that mainly attentional and affective factors play a role in this process (e.g., Sharar et al., 2016). Such attentional processes could potentially also connect to VR specific time compression effects, analogous to the established spatial underestimation in VR (e.g., Stefanuci et al., 2015). Therefore, the main goal of the current experiment was to determine whether time compression effect exists for VR and if so, which factors of VR presentation cause this effect. A better understanding of the working mechanism of this process could help to optimize future medical interventions based on VR.

So far, studies on time perception in VR are limited and do not reflect on the precise sources of such an effect: is it medium of VR itself

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that affects time perception, or could it alternatively be caused by the content displayed in VR, as this is often not strictly controlled for in comparisons between real world and VR time perception. Literature concerning temporal processing highlights several factors as key players in distortions in time perception, identical to those mentioned as likely mediators in the process of pain relief by VR (Sharar et al., 2016). Emotion, as expressed by affective valence and arousal level, is of particular importance. In addition, attentional processes are often mentioned in relation to emotion; emotional input draws more attention (Angrilli, Cherubini, Pavese, & Manfredini, 1997; Burle & Casini, 2001; Droit-Volet & Meck, 2007; Matthews & Meck, 2016; Noulhiane, Mella, Samson, Ragot, & Pouthas, 2007). Angrilli et al. (1997) have studied time perception in relation to these factors and found that different patterns of temporal processing are present for different levels of arousal; high arousal stimuli result in shorter time perception and are emotion-driven, whereas low arousal stimuli are linked to longer time perception and appear to be attention-driven.

So, the few VR studies on this matter suggest VR is linked to time compression and would predict that time is perceived to go faster in VR compared to the physical world. As VR has been found to elicit emotional responses (e.g., Felnhoger et al., 2015), one viable explanation is that VR itself is the cause of distortions in temporal perception. Alternatively, it may be the content of VR presentation that results in the elapsed time compression effect, as this may well differ in level of arousal and emotional valence. Literature suggests that in this case, high arousal stimuli are perceived to go faster than low arousal stimuli (e.g., Angrilli et al., 1997). Therefore, we conducted an experiment comparing time estimation of videos presented in VR to those presented in the physical world, in a highly similar visual environment. The videos varied in their emotional content, and participants' individual ratings of valence and arousal were included in the analyses.

A better understanding of time perception in VR will not only help understand how humans process virtual environments, but may also clarify how VR can best be used in medical settings such as chemotherapy or other painful procedures. Is it really VR itself that functions as a ‘time compressor’ or is it the content used, and could these also be presented through a means of presentation other than VR?

2. Methods

2.1. Participants

Twenty-nine participants took part in the study (15 male, 14 female, mean age = 24.8, *SD* = 3.13). Exclusion criteria were a self-reported history of psychiatric or neurological disorders, proneness to motion sickness, and visual impairments. The study was approved by the Leiden University Ethical Committee of the Institute of Psychology (CEP16-0309/124).

2.2. Setting and materials

Participants viewed movie clips in a VR setting and in real life (RL). The RL situation for this experiment was a movie theatre (Cinemec in Utrecht, the Netherlands), with a 5 by 9 m digital cinema projector (DP2K−19B; Barco; Kortrijk, Belgium). Participants were seated in an empty theatre, in a central position to the screen. The images shown in the VR setting accurately resembled this setting; when participants wore the VR headset (Samsung Galaxy S6 + Gear VR; Samsung Electronics; Daegu, South-Korea), they saw the movie screen from the same position, with highly similar colour scheme and lighting (see Fig. 1).

In both conditions, participants viewed a series of short movie clips. Two sets of movie clips were created, each with a total duration of 18 min, containing 10 different clips of varying lengths (range: 7–90 s). The content of these movie clips was based on the international affective picture system (IAPS; Lang, Bradley, & Cuthbert, 1997). Appropriate movie equivalents of the pictures in this system were selected by two of the experimenters, to reach a stimulus set with substantial differences in levels of arousal and affective valence (e.g., crawling spider, starving lion, people fighting, coconut shells).

2.3. Task design and procedure

Participants signed the informed consent form and proceeded with filling out a basic questionnaire concerning demographic information. Then, they were instructed to put away any watches or phones or devices with a clock before starting the experiment. Participants were then shown a set of movie clips in either the RL movie theatre setting or the VR environment. After each clip a blank screen appeared for 60 s, during which they were asked to estimate the duration of the clip in seconds. For each movie clip, the difference between the estimated time (ET) and actual time (AT) was computed, and divided by the actual time to compensate for the difference in actual time of the clips. This provides the relative difference (RD) in time estimation: RD = (ET − AT)/AT, where RD = 0 indicates the estimated time was equal to the actual time, positive scores indicate the proportional overestimation of actual time (i.e., time compression), and negative scores indicate the proportional underestimation of actual time (i.e., time expansion). Furthermore, participants rated level of arousal and affective valence they experienced while viewing the clip on a Likert scale ranging from 1 *calm/very negative* to 9 *aroused/very positive* (see Agrilli et al., 1997).

Each participant viewed both sets of movie clips; one in the RL setting and one in VR. Participants were evenly distributed across the four experimental conditions, with the two types of environment and two sets of movie clips combined in pseudorandomized order.

2.4. Statistical analyses

The main interest of this study is the effect of condition (VR vs RL), arousal, and valence of movie clips on the relative difference in time perception. This can be analysed by means of a regression analysis. However, the data contain a dependency within participants: the measurements for different movies are nested within the participants (i.e., each participant responds to multiple movies). Therefore, we analysed the data using a multilevel model that can account for this dependency. The model was specified as follows:

$$\begin{aligned} \textit{Relative Difference in Time Perception}_{im} &= b_{00} + b_{0c} * condition_{im} \\ &\quad + b_{0a} * arousal_{im} + b_{0v} * valence_{im} + u_{i0} \\ &\quad + e_{im} \end{aligned}$$

In this model the *Relative Difference in Time Perception* for person *i* and movie *m* is explained by a grand intercept (b_{00}), with individual variation (*u_{i0}, random intercept)*, the condition in which person *i* watched movie clip *m* (*$condition_{im}$, 0 = RL, 1 = VR)*, the subjective level of arousal of the movie *m* (*$arousal_{im}$)* and subjective affective valence of the movie (*$valence_{im}$*), and the residual error (e_{im}). Note that the main difference with a normal regression is that in the current model a random intercept u_{i0} is included. This parameter accounts for individual differences in how people estimate time duration: One person might generally overestimate duration, while another person might generally underestimate time duration, but the effect of condition, arousal and valence can still affect their personal baseline score similarly. Finally, rather than estimating this individual effect for every person, a multilevel model assumes that these individual deviances from the grand mean/intercept are normally distributed, with a mean of 0, and a variance τ_u^2. If this variance is 0, there is no individual variation.

Using the model above, we tested three informative, competing hypotheses:

H1. $b_{0c} = 0$, $b_{0a} > 0$, $b_{0v} > 0$

H1c. not H1.

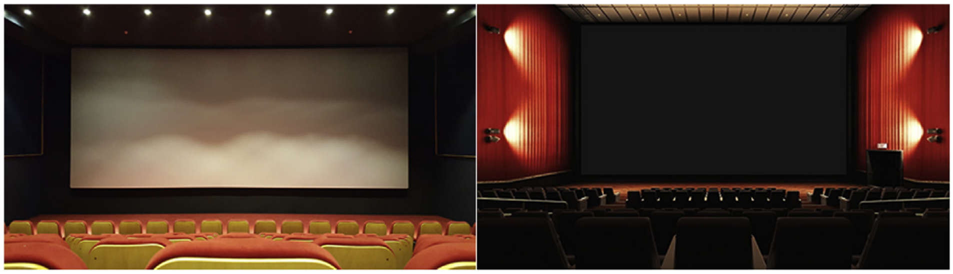

Fig. 1. Experimental set up in A) the RL cinema and B) the virtual rendition of the RL cinema.

H2. $b_{0c} > 0, b_{0a} > 0, b_{0v} > 0$

H1 expresses that there is no effect of condition on the relative time estimation (i.e., time estimation for VR and RL are similar), and that both arousal and valence have a positive effect on relative time estimation (higher scores on valence/arousal correspond to a stronger overestimation of movie clip duration). H1c is the complement of H1, which means that it encompasses all other possible combinations of the parameters in H1. Finally, H2 specifies the same effects of arousal and valence, and additionally that the VR condition results in larger relative time perception scores. We are interested in comparing H1 with H1c to learn whether this model is better than its complement and comparing H1 with H2 to test the effect of condition.

These hypotheses are not in the traditional format of null and alternative hypotheses. They are more specific and can be considered 'informative hypotheses' (Hoijtink, 2012). These hypotheses cannot be evaluated with frequentist analyses, and therefore a Bayesian model was adopted. This makes for two substantial differences compared to more standard analyses. First, a prior distribution has to be specified for all parameters. Second, the Bayesian evaluation of hypotheses does not result in *p*-values, but in two Bayes factors quantifying the relative evidence for H1 versus H1c and for H1 versus H2. Both these elements will be discussed in more detail in the results section.

3. Results

The hypotheses of interest cannot be compared to one another using frequentist statistical analyses. Bayesian methods allow for the comparison of the specified hypotheses. We used the Bayesian software Bain (Gu, Mulder, & Hoijtink, 2018; Hoijtink, Gu, & Mulder, 2018) that is designed to evaluate hypotheses that may consist of inequalities (larger, smaller than) and equalities between parameters. Bayesian analyses require the specification of a prior distribution for the parameters. The software Bain computes a minimally informative prior distribution using a minimal training sample of the data (Hoijtink et al., 2018). This minimal training sample is based on the estimates and covariance matrix of the relevant parameters. To obtain these estimates the multilevel model was run using JAGS version 4.3.0 (Plummer, 2003) in R version 3.4.2 (R Core Team, 2013) with vague priors (see Appendix 1 for the full JAGS code, including the prior distributions used).

Table 1 presents the Highest Posterior Density (HPD) estimates of the parameters in the model (Bayesian equivalent of parameter estimates) along with the 95% Credible Interval (Bayesian equivalent of confidence interval) and the standardized regression coefficients. This table shows that there is reason to believe that the intercept is indeed random; the variance of the random effect (u_{i0}) is larger than 0, indicating that individuals differ in their average time perception. Furthermore, it is evident that condition is the strongest predictor for time perception through comparing the standardized regression coefficients.

In addition to the hypotheses, estimates and estimated covariance matrix, Bain requires the sample size. The sample size determines the fraction of information taken from the data to compute the prior distribution (Hoijtink et al., 2018). The available data consist of 20 repeated measures for each of the 29 individuals, resulting in a total of 580 data points. These data points do not all contribute unique information because they are nested in the 29 individuals. Computing the prior distribution using a sample size of 580 would unfairly assume we had 580 independent pieces of information. The sample size should be somewhat smaller than 580. If no variation existed among the measurements in each participant, the effective sample size would be 29. Simulations researching power in multilevel models tell us that observed power is a function of both the number of clusters and the number of measurements (e.g., Maas & Hox, 2005; Scherbaum & Ferreter, 2008). The effective sample size is between the number of clusters (29 individuals) and the number of measurements (580).

Table 1
Parameter estimates.

Parameter	HPD Estimate (95% CI)	Standard error	Standardized coefficient
B00	−0.241 [-0.440: −0.043]	.100	-.221
B0a	0.009 [-0.009: 0.028]	.010	0.019
B0c	0.014 [-0.056: 0.084]	.036	0.028
B0v	0.010 [-0.011: 0.030]	.010	0.019
Tau e	5.164 [4.570: 5.793]	.313	1.368
Tau u	14.038 [7.151: 23.872]	4.311	3.756

Highest posterior density parameters estimates obtained from the Bayesian analysis, with a 95% Credible Interval, standard error and standardized parameter value. B00 denotes the intercept, B0a, B0c and B0v the regression coefficient for arousal, condition and valence, respectively, Tau e denotes the residual variance and Tau u the individual intercept variance.

We executed the analysis for different choices of sample $N_{effective}$ = *29, 180, 380, 580*. The minimum considered sample size of 29 reflects the sample size if no variation existed in within-person measurements. This can be considered a 'worst case scenario': the computed prior contains very little information and estimation because fairly unstable. The maximum considered sample size reflects the sample size if there is no between-person variation. This choice would overfit the estimation, because any between-person variation is not accounted for. The sample sizes of 180 and 380 are the sample sizes we consider to reasonable reflect the within-between person variance balance. By considering this range of sample sizes for the computation of the prior distribution, we can compare the results and evaluate the impact of the dependency on the results.

Table 2 shows the Bayes factors that describe the evidence in the data for H1 relative to H1c and H2. Both BF_{1c} and BF_{12} increase as the effective sample size increases. The direction and strength of the evidence is rather stable for $N_{effective}$ = 180, 380, 580. Both BF_{1c} and BF_{12} are considerably weaker only for $N_{effective}$ = 30. The sensitivity analysis shows that for the more reasonable effective sample sizes, strengths of evidence are similar.

The hypothesis that there is no effect of condition, in combination with an effect for arousal and valence (H1), is supported over its complement (in the first row in Table 2 the Bayes factor is always larger

Table 2
Bayes factors.

Effective sample size	29	180	380	580
H1 vs H1c	8.53	21.25	30.87	38.14
H1 vs H2	2.23	5.54	8.05	9.95

Bayes factors expressing the relative evidence in the data for H1 versus H1c (top row) or H2 (bottom row) for effective sample sizes 29, 180, 380 and 580. Bayes factors for the unstandardized analysis are presented here. Bayes factors are similar for the standardized analysis.

than 1, indicating that H1 is 8.53/21.25/30.87/38.14 times more supported than H1c), and is preferred over H2 where there is an effect of condition (presented in the second row in Table 2).

Note that other than the within-participant dependency, there is an additional dependency within the clips viewed (i.e., for half of the participants first set of movie clips was presented in the VR condition, and the second set in the RL condition, and vice versa for the other half of the participants). This might create noise in the analysis if a particular clip is structurally rated higher in the VR condition than in the RL condition or vice versa. The fragments in each set of clips were selected to be similar, so the expected effect of this dependency should be small or negligible. To check whether there was dependency within movies, the hypotheses were evaluated in a more elaborate model that accounts for the within-movie dependency in addition to the within-person dependency. For every movie, a random intercept is included in the model. This model resulted in very similar results (see Appendix 2 for the more elaborate model and the results).

4. Discussion

The use of VR is rapidly increasing in a range of applications, including clinical treatment protocols. One characteristic of VR use in clinical context is that it is claimed to result in compressed time perception, yet evidence is limited and the potential source of such temporal compression is unclear. Analogous to compression found in the spatial domain, the virtual display itself could be the cause. Alternatively, the affective nature of the content displayed in VR may cause temporal compression. In this study we first addressed the question whether time is perceived to pass by faster in VR. Next, we examined if such an effect wasrelated to the medium of VR itself, or the content of the materials used, in terms of emotional valence and arousal.

Given the characteristics of the dataset, a Bayesian approach was used in which 3 hypotheses were tested and consequently compared based on the evidence. The hypothesis with the strongest relative evidence was that both arousal and valence positively contribute to the observed time compression effect, regardless of the viewing condition. Thus, there is no evidence for a difference in temporal processing between VR and RL. So, when filtering out the impact of the content of stimuli, the medium of VR itself does not affect time perception in our experiment.

Furthermore, this finding suggests that the time compression effect that takes place is most likely the result of the emotional content of the materials displayed. This finding is in line with Angrilli et al. (1997), as higher arousal is linked to shorter time perception. Moreover, this would also mean this process is mainly emotion-driven, not attention-driven, given Angrilli et al.'s (1997) description of the characteristics of higher arousal. This finding is analogous to a potential explanation for how VR may cause pain relief during medical interventions, which has been suggested to rely on affective factors (Sharar et al., 2016).

Reports on reduced time perception within clinical contexts, where unpleasant clinical procedures are performed when VR is employed do not necessarily conflict with these findings. As those comparisons typically use different visual materials in the VR condition, the emotional content participants are exposed to also differs between the VR and RL conditions. The current experiment's set up uniquely allowed for a direct comparison, as it made use of a VR environment highly similar to the RL environment, with identical video materials.

It should be noted that the analyses do not allow for a distinction between negative and positive emotional valence, as valence was represented as a continuous scale instead of a dichotomy. Other limitations of the current study concern the demographics of the participants; possibly gender has and effect (Hancock & Rausch, 2010) and age range in particular may be different in clinical populations in which such VR interventions are used and could therefore be considered in future research.

The current study taps into a relatively new area: how time is perceived when engaging in virtual environments. This has implications for both experimental and clinical context. The use of VR is increasingly popular in cognitive experiments and is often considered a reliable source of information concerning human behavior in the real world. Yet, the current data suggests that some caution is warranted. Even though the medium itself does not affect how time is perceived, the emotions evoked by the stimuli at hand may cause a difference. This could affect measures of time-related cognitive abilities, such as episodic memory. In clinical context, this shows that it may be possible to achieve the desired time compression effects through other means than VR, as the main cause appears to be the affective content rather than the medium itself. Future research should be directed at isolating the contributions of negative and positive valence, and other formats of stimulus display.

5. Conclusion

The current findings shed light on how humans temporally process virtual environments: this process is highly similar to that in RL. The emotional content of the materials used affects temporal processing, regardless of condition. This may contribute to the implementation of VR in therapeutic settings, as VR itself may not be necessary to achieve the desired time compression effect during medical procedures. To this aim, future research could be directed at separating the roles of negative and positive emotional valence.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chb.2019.01.005.

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