# Counterbalancing Virtual Reality Induced Temporal Disparities of Human Locomotion for the Manufacturing Industry

Short Paper

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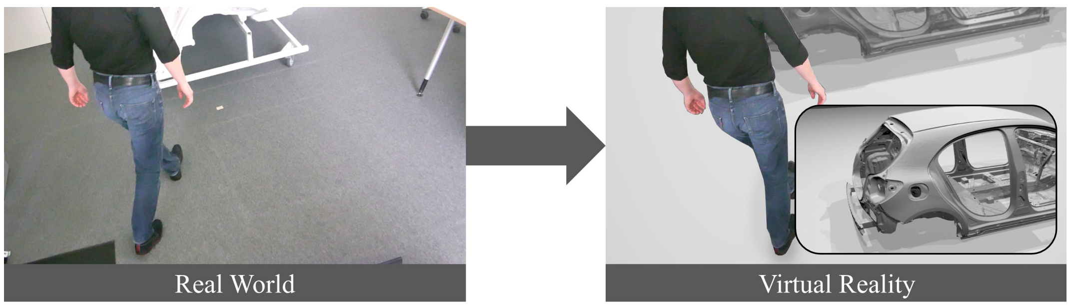


**Figure 1: Locomotion is affected by virtual reality, however, the effects can be counterbalanced to correctly predict real world behaviour.**

## ABSTRACT

Recently, the significant technological developments of head-mounted displays and tracking systems have boosted a widespread use of immersive virtual reality in the manufacturing industry. Regardless of the respective use-case, however, methods to ensure the validity of the human motion being performed in such virtual environments remain largely unaddressed. In the context of human locomotion, previous work present models quantifying behavioral differences between virtual reality and the real world. However, those findings are not used in control experiments to post-hoc counterbalance VR-induced performance modulations. Consequently, the prediction quality of previous analyses is not known. This paper bridges this gap, by testing such a behavior model in the context of an independent experiment ($n = 10$). The evaluation shows that a model derived from literature can indeed be used to post-hoc correct temporal disparities between locomotion in the real world and in virtual reality.


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## CCS CONCEPTS

• **Human-centered computing** → **Virtual reality**; **Empirical studies in HCI**; *User studies*; User models;

## KEYWORDS

Behavior analysis, human locomotion, virtual reality, validity, temporal disparity, automotive industry

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## 1 INTRODUCTION

In recent years the use of virtual reality technologies has become more widespread due to the significant technological improvements of head-mounted displays (HMD) and tracking systems. As a consequence of this development, former prototype systems and technical demonstrators have reached a high degree of maturity, thus enabling the productive use of immersive virtual reality (VR) across various domains within the manufacturing industry [Otto et al. 2016].

However, the validity of the user's motion (i.e., walking), being performed in a virtual environment while wearing a HMD, is still unadressed to a large extent. In this context, a small number of recent works start to investigate the behavioral disparity of human locomotion between the real world (RW) and virtual reality, pointing out significant differences [Agethen et al. 2018; Fink et al. 2007; Gerin-Lajoie et al. 2008; Janeh et al. 2017; Mohler et al. 2007]. Even though quantifying the deviation, the prediction quality of those models to compensate deltas in independent control experiments, is largely unknown.

To bridge this gap, this paper counterbalances VR-induced effects using regression models describing the behavioral disparity. Building upon the work and models being presented by Agethen et al. [Agethen et al. 2018], a control experiment is conducted, which comprises 10 participants carrying out multiple locomotion tasks in RW and VR. Subsequently, those regression models are utilized to predict the locomotion performance reduction in virtual reality. Using this knowledge, the motions being captured in VR are eventually corrected. Finally, both data-sets (RW and counterbalanced VR) are statistically compared in order to evaluate the prediction quality of this behavior model.

The remainder of the paper is structured as follows: First, the state-of-the-art in the context of behavior analysis of human locomotion in virtual worlds is reviewed. Next, a control experiment is introduced which analyzes the prediction quality of the models being presented in [Agethen et al. 2018]. The paper concludes with an assessment and an outlook on further optimization potentials.

## 2 RELATED WORK

On a conceptual level, techniques for navigation in virtual environments can be divided into locomotion using dedicated hardware devices and natural walking techniques. The former comprise approaches, which utilize locomotion interfaces (e.g., treadmills, joysticks or gamepads) to steer through the space [Darken et al. 1997; Ohshima et al. 2016; Slater et al. 1995]. These techniques, however, are not applicable to plan and assess human labor, as the resulting travel routes correlate with the chosen parametrization of the metaphor (e.g., travelling velocity). Consequently, dedicated hardware devices are not considered further.

In contrast, the second category - namely natural walking techniques - is ideally suited for manufacturing purposes, as the user can unrestrictedly move through the virtual environment. Simultaneously, human labor can be analyzed, as the resulting walk paths are derived from an actual person. Natural walking techniques can be generally subdivided into isometric and non-isometric approaches [Steinicke et al. 2013]. While isometric methods apply mappings between the virtual and the real space, which preserve distances and angles, their non-isometric counterpart guides users on varying paths in VR and RW. The reason for the utilization of non-isometric mappings is to allow for the navigation in virtual spaces, which are larger than the physically available tracking space [Razzaque 2005]. This is mainly achieved by rotating the virtual world below the perception threshold while walking along straight routes. Using isometric mappings, the user is able to navigate in an artificial scene with the identical dimensions as the physical counterpart.

Comparing the behavior of human locomotion in RW and VR, only limited research has be carried out. Furthermore, most of the presented studies utilize head-mounted displays comprising considerable lower resolution and longer photon-to-motion latencies (compare to current state of art technology). In this context, Fink et al. [Fink et al. 2007] and Gerin-Lajoie et al. [Gerin-Lajoie et al. 2008] investigate walking in RW and VR when avoiding obstacles. Combining their findings with the study of Mohler et al. [Mohler et al. 2007], it can be concluded that participants walked significantly slower in VR, while an increased clearance distance to obstacles can be observed. In addition, Janeh et al. [Janeh et al. 2017] analyze similar aspects for linear walking, supporting preceding studies. Recently, Agethen et al. [Agethen et al. 2018] investigate locomotion in multiple scenarios using an HTC Vive, pointing out a deviation up to 13 % regarding travel time. Moreover, multiple regression models are introduced, summarizing the behavioral differences.

Even though recent publications give a good overview of the evident differences between RW and VR, the presented models have not been used to predict and post-hoc counterbalance this delta. Moreover, the findings are not validated using an independent control data-set.

## 3 EXPERIMENT OVERVIEW

In this paper the regression models presented by Agethen et al. [Agethen et al. 2018] are validated using an independent control-experiment. Moreover, by correcting VR-induced travel-time differences, the prediction quality and usefulness of those models for practice is reviewed.

The presented study comprises one independent variable (RW or VR) and one dependent variable (travel time). Moreover, the experiment is executed using repeated measures. For this purpose, first, a representative assembly workplace is designed and set up, both in the real world and virtual reality. Building on the experimental setup, next, a list of multiple assembly tasks containing multiple walk paths is defined, which in turn is performed in both conditions by a group of 10 participants. Having conducted the experiment, third, the travel time for each walk path is subsequently determined. Finally, the data being recorded in the context of virtual reality are post-hoc corrected using regression models. Comparing the un- and adjusted values with RW allows to draw conclusions regarding the prediction quality of previous work.

## 4 PARTICIPANTS

In order to quantify recent work regarding the behavioral differences in RW and VR, a group of 10 participants was recruited for this experiment. The age of the group, which consisted of one female and nine males, ranged from 22 to 29 ($\mu = 25$, $\sigma = 1.94$). Size was ranging between 1.70 m to 1.90 m ($\mu = 1.79$ m, $\sigma = .06$ m). No vision, balance or perception disorders were reported, which could alter the results. Three of the participants wore glasses and 9 had previous experience with HMDs. All participations were voluntary and results were anonymized. Furthermore, every participant gave prior consent regarding their participation as well as the further use of their collected data for future research and publications.

## 5 APPARATUS

For the experiment all scenarios regarding RW were conducted in a room with the dimensions of 7.0 m × 6.0 m (ceiling height of

3.0 m). All scenarios regarding VR were conducted in a second room with the dimensions of 7.0 m × 5.0 m (ceiling height of 3.0 m) and a covered tracking space of 4.0 m × 3.0 m aligned to the center of the room. Following the reasoning by [Agethen et al. 2018] the *HTC Vive* HMD (Edition 2016) was used for the virtual reality parts of the experiment. The *HTC Vive* comes with a high display refresh rate of 90 Hz, a large field of view (100° horizontal, 110° vertical), and high display resolution (1080 horizontal × 1200 vertical per eye) [HTC 2017; Kelly et al. 2017]. Furthermore, to not restrict the participants in their freedom of walking, the *HTC Vive* was additionally equipped with the *TPCAST Wireless Adapter*. The corresponding stationary PC was equipped with a *GTX 1080* graphic card and an *Intel Core i7-6700k* with 4.0 GHz. For video recording the *Panasonic Lumix DMC-G6* was used resulting in a frame rate of 25 Hz and in a resolution of 1920x1080.

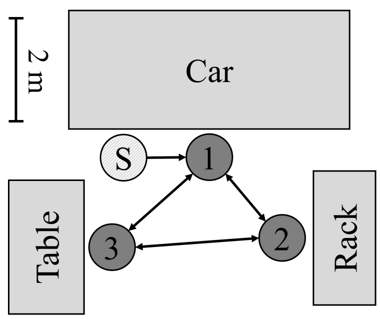


**Figure 2: Setup of control-experiment comprising a rack, a table, a car and a common starting point (see *S*) with following walk path lengths:**
$Start \longrightarrow 1 = 1.35m$, $1 \Leftrightarrow 2 = 1.4m$, $1 \Leftrightarrow 3 = 1.6m$, $2 \Leftrightarrow 3 = 2.7m$

## 6 PROCEDURE

At the beginning of an experimental run the conditions and aim of the experiment were orally explained to the participant in a standardized manner. Following [Mohler et al. 2006; Ruddle et al. 2013] each participant subsequently had the possibility to practice the presented tasks in RW and VR for 5 minutes to ensure similar conditions in terms of training level. Afterwards, in order to rule out take-over effects, each participant was randomly assigned to one of two groups. One half started in VR and the other half started in RW. As walk paths three sequences were previously designed. The three scenarios were Start-1-2-3-2-3-1, Start-1-3-1-2-1-3, Start-1-2-3-1-3-2 (see Figure 2) with six stations each. For each participant a randomized order of these three walk sequences was selected. This individual ordering however was kept the same for both environments.

Once a participant reached a station no interaction had to be performed, but the participant had to wait for an audio signal telling him the next station to go to, whereas walking was performed at self-selected, natural speed (see Figure 3). The speech synthesis of the words *"table", "car"* and *"rack"* created by the webservice *fromtexttospeech.com* was used and played over boxes. Moreover only the participant and the experimenter stayed inside the laboratory during the experiment to avoid any kind of distraction. In general every participant was allowed to take breaks or stop the experiment at any time if they felt any kind of motion sickness. However, no participant reported such kinds of problems or aborted the experiment.

Moreover, each experimental run was video recorded to be able to extract the travel times in a post-processing step. Therefore, as shown in Figure 3, the start of a walk path from one station to another was defined as the moment where the audio signal was played. A trajectory ends when the person reaches the announced station and is positioned in front of it in double stance. To allow accurate cutting and thus accurate travel times, the color of a screen positioned in the field of view of the recording camera changed according to the played word (*"desk"* ⇒ *"yellow"*, *"car"* ⇒ *"blue"*, *"rack"* ⇒ *"red"*). The reason for this definition regarding the determination of travel times is, that in practice, the key performance indicator for a station transition is not only including the actual period of walking, but also the time required for signal processing and orientation (see Figure 3).

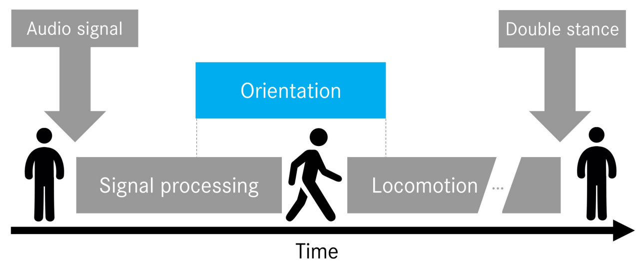


**Figure 3: Procedure to determine travel time: time-span between start of audio signal and double stance of participant.**

## 7 RESULTS

Having conducted the above described experiment, each participant executed three sets of walk paths in VR and RW, each comprising seven sub-routes. Please note that the pre-defined scenarios contained the identical walk paths with predefined stopping points, however, in a varying order. To allow a meaningful analysis, corresponding routes (e.g., $1 \longrightarrow 2$) are extracted, thus resulting in three travel times for each of the seven walk paths (in VR and RW). Next, the three trials, being performed by one participant in the context of one experimental condition, are averaged: for instance, walking from point 1 to point 2 while wearing no HMD. The result of this procedure are seven mean travel times per participant, both in VR and RW. Taking into account the entire group, in turn, 10 averaged times are hereby obtained for each walk path and experimental condition.

Figure 4 shows the resulting travel time distributions in form of boxplots. The upper half depicts the uncorrected values, while each of the seven pairs disaggregate the behavioral differences per walk path. Descriptions above the plots point out the associated walk paths. In order to choose adequate statistical methods, a Shapiro-Wilk test is initially performed for each 14 data-sets (SPSS), pointing out normal distributions regardless of walk paths and experimental conditions ($p$ = .951 to .057). Consequently, the pairs of boxplots are compared using paired-sample t-tests (SPSS, confidence level 95%). Finally, the test's power is calculated using G*Power [Faul et al. 2007].

In particular, the point to point connection $Start \rightarrow 1$ comprising a distance of 1.35 *m* shows a mean deviation of 6.1% between both experimental conditions (see Table 1). For the walk paths $1 \Leftrightarrow 2$ (= 1.4 *m*), this delta rises to 9.4% and 7.7%. The highest mean behavioral difference can be observed for $1 \Leftrightarrow 3$ (= 1.6 *m*), ranging between 11.3% and 14.3%. In contrast, both routes with the longest distance of 2.7 *m* (i.e. $2 \Leftrightarrow 3$) show the lowest deviation: 1.9% / 4.5%. Figure 4 also reflects these findings. Comparing the pairs of data-sets with the help of paired-sample t-tests, statistically significant differences in combination with a sufficient test power of over 80 % can be observed in all cases - except for $Start \rightarrow 1$ and $2 \Leftrightarrow 3$. Furthermore, for quantitative measuring the magnitude of the described phenomenon, an effect size measurement based on differences in mean was used. With these values being predominately above .5, one can conclude a medium effect size following the definition given by Sawilowsky [Sawilowsky 2009], except for $2 \rightarrow 3$ pointing out a small effect.

Having analyzed the initial conditions of the control-experiment, travel times being recorded in VR are subsequently adjusted. For this purpose, the velocity regression model (see [Agethen et al. 2018]) is applied by means of utilizing the knowledge about walk paths length. The predicted delta travel times are thus subtracted from the measured values. The lower halves in Figure 4 and Table 1 depict the counterbalanced result. It can be seen that the regression model reduces the deviation between RW and VR. In particular, the mean travel time differences range from 1.3 % over 2.9 % and 1.2 %, 4.0 %, 6.6 %, 7.5 % to 4.9 %. Same applies for the adjusted effect sizes and statistical tests. After these corrections, statistically significant differences can be exclusively observed for $3 \rightarrow 1$.

## 8 DISCUSSION

The presented results show, that the initial objective of this work, namely counterbalancing temporal disparities between walk times in real world and in virtual reality as determined by [Agethen et al. 2018] using the presented regression model by the same authors, is applicable.

Comparing the gathered results with the state-of-the-art study, it becomes apparent, that the findings match the reported deviations of up to 13 %. To allow conclusions the presented walk path lengths are within the interval .5 *m* and 3.0 *m* used in the study. Even though in this paper the measure is defined to be the time-span between audio signal and double support, the results still correspond to those in [Agethen et al. 2018]. Here walking is defined as an initial gait-cycle to double support. Consequently, processing of the audio signal and orientation within the virtual scene did not have a considerable impact on the overall-disparity. This can be interpreted as an indicator, that orientation is not significantly affected by the HTC Vive - given a comparable low tasks complexity. In contrast, the predominant proportion can be attributed to locomotion.

Furthermore, this assumption is also supported by the fact that the regression model, which does not consider any form of human orientation or signal processing, effectively compensates the behavioral disparity. In particular, the initially four statistically significant differences (highlighted in Figure 4) are hence reduced to the walk path $3 \rightarrow 1$. A similar reduction can also be observed for proportional deviation and effect size. Summarizing all aforementioned findings, it can be concluded, that the state of art regression models can be utilized to post-hoc counterbalance VR-induced effects. Furthermore, the analysis being presented in [Agethen et al. 2018] is capable of predicting scenarios including navigation and audio guidance.

## 9 CONCLUSION AND FUTURE WORK

This paper presented a control-experiment, testing the findings being presented by Agethen et al. [Agethen et al. 2018]. Furthermore, the prediction quality of the introduced regression models is investigated. The preliminary evaluation points out their usefulness and practical applicability even when additionally considering orientation with the scene.

Future work will extend this evaluation by means of using shopfloor data, which will be captured in the context of automotive final assembly lines. In addition future generations of head-mounted displays and their impact on the behavioral disparity will be holistically analyzed.

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**Table 1: Descriptive statistic of original and corrected travel times, both for VR and RW.**

| | | *Start* → 1 | | 1 → 2 | | 2 → 1 | | 1 → 3 | | 3 → 1 | | 2 → 3 | | 3 → 2 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | RW | VR | RW | VR | RW | VR | RW | VR | RW | VR | RW | VR | RW | VR |
| Original | $\mu$ | 3.006 | 3.188 | 3.529 | 3.861 | 3.511 | 3.782 | 3.513 | 3.910 | 3.311 | 3.785 | 3.923 | 3.996 | 3.907 | 4.082 |
| | $\sigma$ | .231 | .320 | .322 | .517 | .367 | .363 | .425 | .472 | .331 | .386 | .380 | .537 | .235 | .398 |
| Corrected | $\mu$ | 3.006 | 2.967 | 3.529 | 3.633 | 3.511 | 3.554 | 3.513 | 3.655 | 3.311 | 3.531 | 3.923 | 3.628 | 3.907 | 3.715 |
| | $\sigma$ | .231 | .320 | .322 | .517 | .367 | .363 | .425 | .472 | .331 | .386 | .380 | .537 | .235 | .398 |

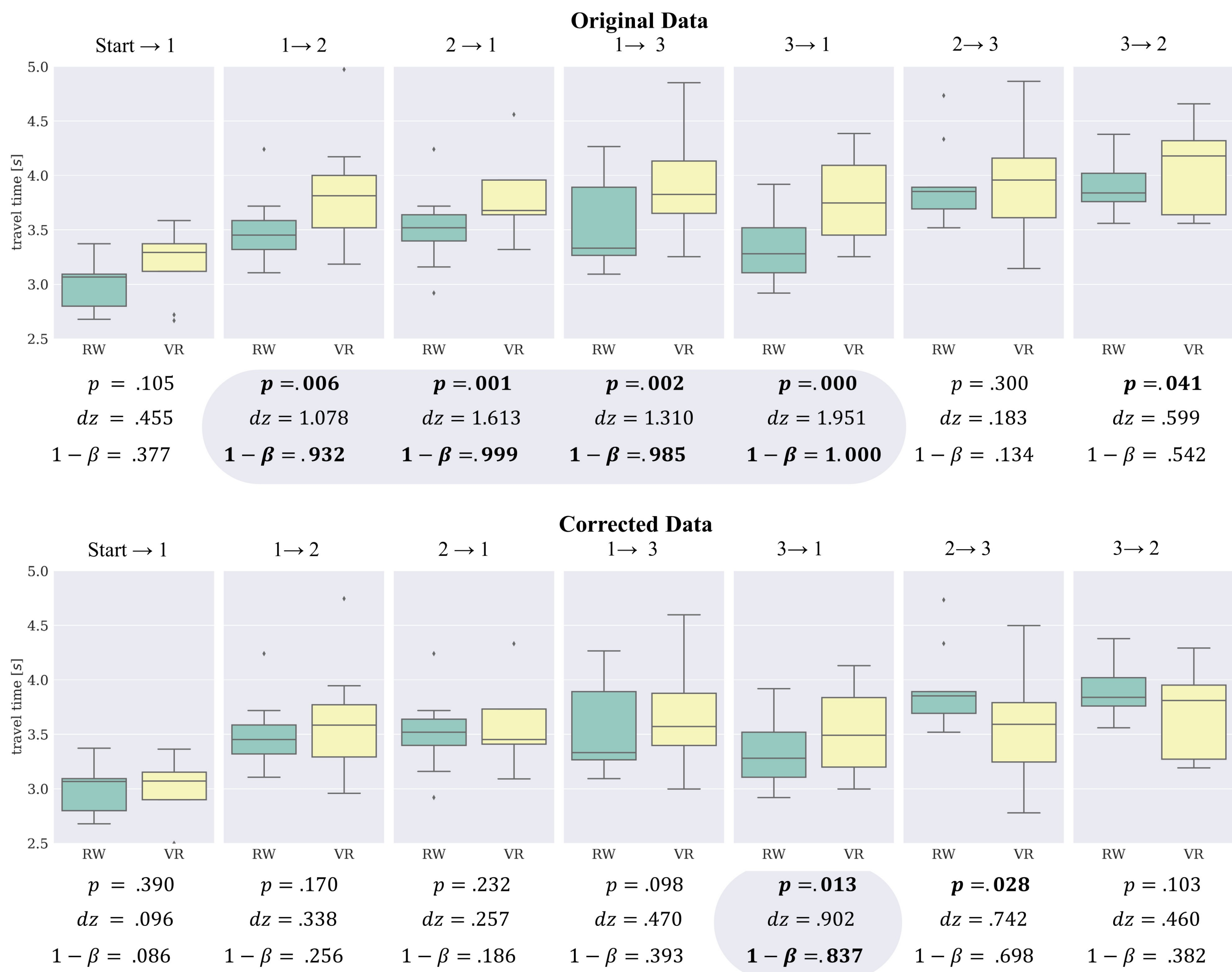


**Figure 4: Boxplots of original (upper half) and corrected travel times (lower half) including statistical analysis. Color blue highlights statistically significant differences between VR and RW.**

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