Improved Modeling Approach for the Usage of Mixed Linear Effects Models in Empirical Digital Human Models

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Abstract

When designing the interior of automated cars, it is necessary to take the non-driving related tasks and the take-over maneuver into account. These take-overs are critical moments since the driver needs to take back control of the vehicle as fast as possible. To facilitate this, interior designers need to design the cabin with enough space to carry out this movement. This paper presents a revised modelling approach using mixed linear effects models to predict the grasping movement of the hand during take-over scenarios. A study with 52 participants doing grasping movements was carried out to model the data obtained via motion capture. The participants were instructed to carry out movements from predefined grasping elements mounted in front of them. The trajectory of the hand was recorded using a marker-based motion capturing system. It is observed that the trajectories can be assumed as a two-dimensional phenomenon, since they seem to lie on one plane. Thus, the trajectories were modeled as a 1+2-dimensional problem. A one-dimensional model for the plane and a second two-dimensional model for the trajectory. The model of grasping trajectory described in this paper was modeled using 4th degree polynomials. In older approaches, the trajectory was modeled in four different models for each constant of the polynomial. In this paper a new modeling approach is used to merge the polynomial into one model. This increased the R^2_m and R^2_c drastically and led to three major discoveries on the nature of human grasping movements: Task factors, such as grasping handle and handle position, play the major role in the grasping trajectory. Body height plays a role in the modelling of hand trajectories. Gender, age, and dominant hand show only negligible influence on the trajectory. Other individual human factors not evaluated in this study do not seem to heavily influence the hand movement.

Keywords: Mixed Linear Effects Models, Automated Driving, Take-Over, Grasping.

Introduction

Automated driving seeks to revolutionize the way people travel by car. With increasing automation levels, the driver becomes a passenger and is able to carry out non-driving related activities. When the automation reaches its limit, the driver needs to again take-over the driving task again. Non-driving related activities and the take-over are new scenarios for tools used in the design of the cars (Albers et al., 2021). Digital human models are no exception to this. Current models used for vehicle design focus on ingress/egress (Björkenstam et al., 2020; Lu et al., 2013; Reed et al., 2010; Robert et al., 2013) , sight (Marshall et al., 2020; Remlinger & Bengler, 2016) or the driving task (Bubb et al., 2006; Bubb et al., 2021; Reed et al., 2006). To predict the take-over, a method is needed for predicting directed grasping movements. There are different approaches to simulate such a motion. Fritzsche et al. (2011) and Brauns (2017) use a set of motion captured movements that are manipulated according to the user defined tasks. Obentheuer (2020) uses biomechanical simulation with optimized muscle activity control to generate a forward kinematic. Faraway (2001), Faraway (2003) and Faraway and Choe (2009) use regression models on the trajectory of the hand. The later models need to be expanded by an inverse kinematic model of the rest of the body. Compared to the biomechanical models, the regression models require less computational power for the user of the model and less skilled operators of the model. Biomechanical models on the other hand are easier to be generalized, while regression models often fail to find universal truths.

When looking at the human grasping movement it can be observed that the trajectory moves through the room on a two-dimensional plane (Arlt, 1999; Cherednichenko, 2007). This understanding can be used to split the three-dimensional problem into a one-dimensional and a two-dimensional problem. Since start and end point of the simulation are already known, it is only necessary to find one additional point to define the plane (Fleischer et al., 2021). The trajectory can be modeled as a two-dimensional polynomial on this plane. In this paper only the trajectory model is described and compared to an older approach described by Fleischer et al. (2020).

Fleischer et al. (2020) modeled the same data set used in this paper to predict grasping trajectories. Four separated mixed linear effect models were used to predict the four coefficients (C_{1-4}; $C_0 = 0$). But the determination coefficients indicate a poor goodness-of-fit (Ferguson, 2009). R^2_m never surpasses .1 and R^2_m is below .333 for all four models. Three major insights are described:

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1. *Task factors (handle type and handle position) play the major role for the grasping trajectory.*
2. *Body height plays a role in the modelling of hand trajectories. Gender, age, and dominant hand only show negligible influence on the trajectory.*
3. *Other individual human factors not evaluated in this study seem to heavily influence the hand movement.*

“ - Fleischer et al., 2021, p. 184

Methods (Fleischer et al., 2021)

A participant study with 52 participants was carried out in a laboratory setting to model the grasping trajectories of take over movements. The subjects were asked to perform 24 grasping movements and the data were recorded using VICON Nexus (four MX T10S and four MX10 cameras, 100 Hz recording frequency, 12mm reflective markers, VICON Nexus 1.85). Four different grasping elements (see Figure 1) were presented on two orthogonal wooden boards: One-finger contact handle, three-finger contact handle, a ball, and a cylinder.

Figure 1. Grasping handles from left to right: One-finger contact, three-finger contact, ball, cylinder.

The four handles were mounted on the horizontal board, while two additional cylinder handles were fastened to the vertical board. As shown in Figure 2 the four handles were positioned either directly under the vertical cylinders or laterally offset to the right. The position of the handles on the horizontal plane was shifted halfway through the trails.

Figure 2. Experimental setup with the one-finger contact handle and the cylinder handle directly under the vertical cylinders and the ball and the three-finger contact offset to the right.

Before the measurements, the participants had time to train the movements to perform the tasks routinely. The participants were instructed to grasp the handles on the horizontal plane and to carry out a grasping movement to the handle on the vertical board. Four handles in two positions each with three repeated measures resulted in 24 recorded grasping trajectories for each participant. Two participants were excluded from the sample due to measurement complications.

Table 1. Individual data of the collective

N = 50	
Average body height	174.5 cm [SD = 8.1 cm]
Average age	26.8 [SD = 10.7]
Right hand dominant	90 %
Male gender	62 %

The recorded trajectory data is transformed into two-dimensional data with the following approach: For each trajectory a best fitting plane is determined using principal component analysis. The trajectory is then projected onto this plane resulting in data points with two coordinates x and y. X is the distance travelled and y is the elevation above the direct connection of start and end point. This data were written in the dataframe “df” and used for the modeling. The model is fitted using the R-package “lme4” (Bates et al., 2020) using a polynomial of the 4th degree:

*mdl <- lmer(y.coordinates ~ poly(x.coordinates, 4, raw = TRUE) * gender + poly(x.coordinates, 4, raw = TRUE) * height + poly(x.coordinates, 4, raw = TRUE) * grasping_handle + poly(x.coordinates, 4, raw = TRUE) * grasping_position + poly(x.coordinates, 4, raw = TRUE) * age + poly(x.coordinates, 4, raw = TRUE) * dominant_hand + (1 | name) , data = df)*

Gender, body height, the type of grasping handle, the position of the handles, the age and the dominant hand are modeled as fixed effects. The participant is modeled as a random intercept to account for factors not measured.

Results

The Q-Q-plot (Figure 3) shows a heavily tailed distribution in the upper quantiles. The scaled residuals (Figure 4) show a linear homoscedastic behavior. The x-axis is clearly visible on the lower left of the data points.

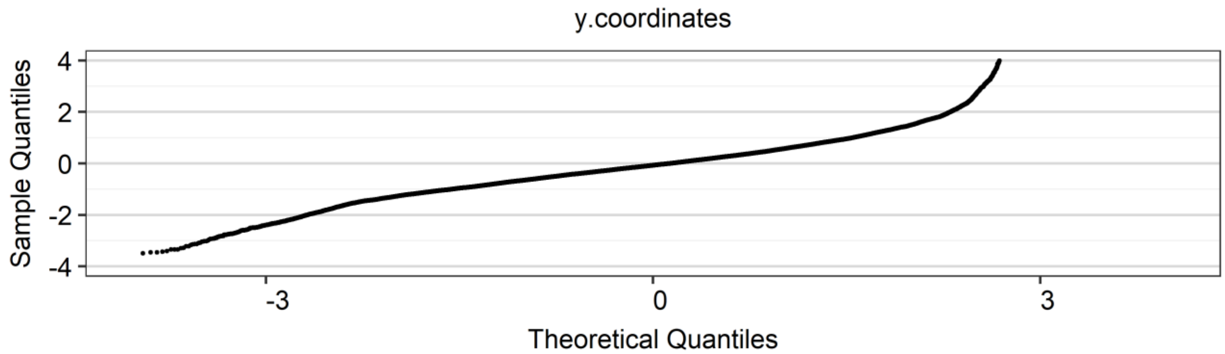

Figure 3. Q-Q Plot of the model

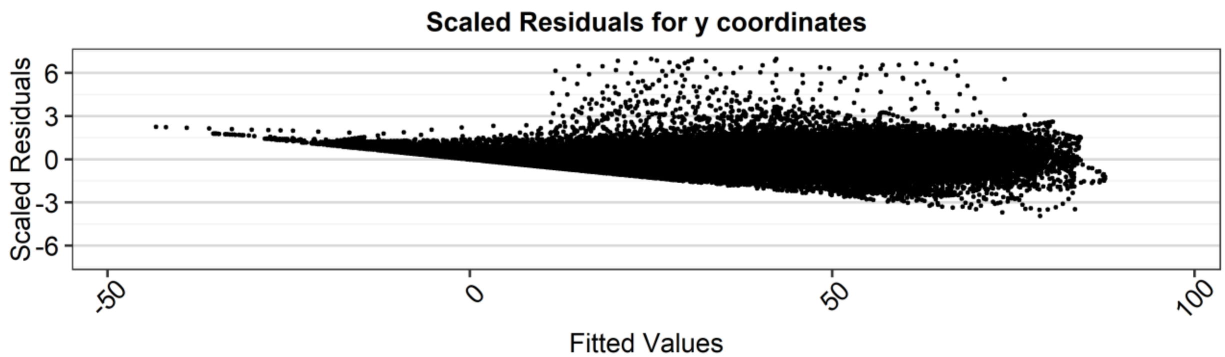

Figure 4. Scaled residuals of the model

The determination coefficients are $R^2_m = .5$ and $R^2_c = .56$. The significant main effects of the model are the grasping element ($p < .001$) and the position of the grasping element ($p < .001$).

Discussion and Conclusions

Compared to Fleischer et al. (2020) the key insights needed to be revised:

1. Task factors (handle type and handle position) play the major role for the grasping trajectory.
2. None of individualistic factors recorded has a significant effect on the trajectory.
3. Other individual human factors not evaluated in this study do not influence the hand movement.

Insight 1 stays the same, since these are the significant main effects. Compared to the older models the body height is no longer a relevant factor. The other individualistic factors remain insignificant. Insight 3 is the biggest change on the nature of grasping trajectories. The two determination coefficients are close to each other, thus the random effect does not influence the model as much as in Fleischer et al. (2020). Also the R^2 greater than .5 can be interpreted as moderate to strong effect sizes (Ferguson, 2009) and have improved greatly compared to the modeling method of Fleischer et al. (2020). This can be attributed to two aspects. With the improved modeling method each data point can be used for the fitting, while the older method reduced every trajectory to the polynomial coefficients. Also, the four coefficients are now modeled in the same fitting process. This accounts for correlation of the coefficients between each other.

Mixed linear effects models need to fulfil the assumption of linear homoscedasticity. The scaled residuals show a good fit for this criterion, but due to the trajectories only having positive y-values the x-axis is clearly visible on the lower left of the plot. The data are not normally distributed, but according to Gelman and Hill (2007) this criterion is obsolete by today's standards.

The modeling approach seems promising due to the high determination coefficient. Especially compared to biomechanical digital human models, the computational effort and user expertise needed is greatly reduced. Although the applicability of empirical models is less general. In the model presented here, balance is irrelevant, as the persons sit during the movement. It is to be researched to which extend the grasping model can be transferred to different scenarios.

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