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Iteratively Adapting Avatars using Task-Integrated Optimisation

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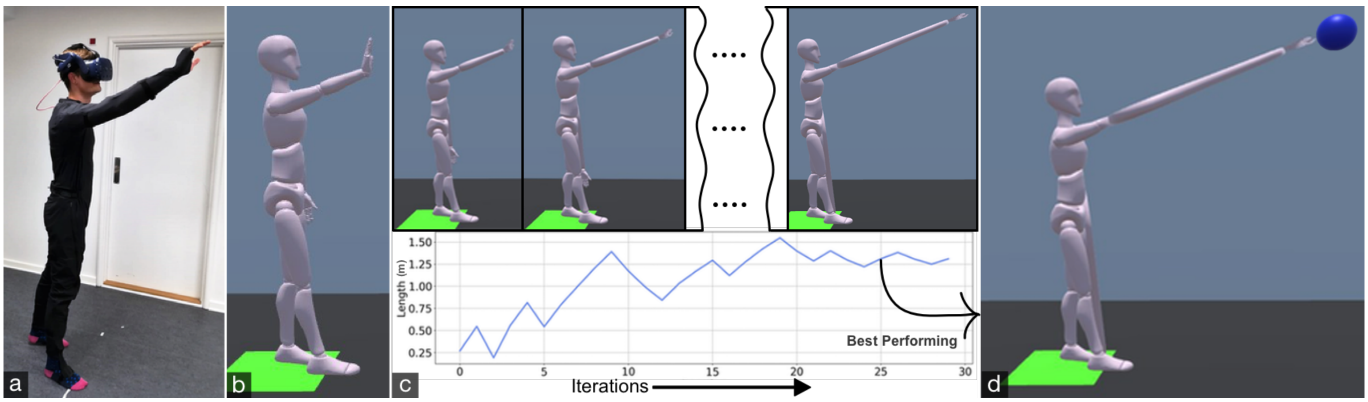

Figure 1: (a) A person (b) embodies an avatar in VR that matches their morphology; however, many non-matching avatars could be better for the given task. (c) Our approach iteratively adapts the avatar to optimise the user's task performance. (d) Here, it produces an avatar with longer arms, helping the user reach a set of targets.

ABSTRACT
Virtual Reality allows users to embody avatars that do not match their real bodies. Earlier work has selected changes to the avatar arbitrarily and it therefore remains unclear how to change avatars to improve users' performance. We propose a systematic approach for iteratively adapting the avatar to perform better for a given task based on users' performance. The approach is evaluated in a target selection task, where the forearms of the avatar are scaled to improve performance. A comparison between the optimised and real arm lengths shows a significant reduction in average tapping time by 18.7%, for forearms multiplied in length by 5.6. Additionally, with the adapted avatar, participants moved their real body and arms significantly less, and subjective measures show reduced physical demand and frustration. In a second study, we modify finger lengths for a linear tapping task to achieve a better performing avatar, which demonstrates the generalisability of the approach.

Author Keywords
Virtual reality; Avatar adaptation; Optimisation

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CCS Concepts
•Human-centered computing → Virtual reality; Human computer interaction (HCI);

INTRODUCTION
Our bodies have evolved to perform tasks effectively in our environments, such as walking and reaching. One large attraction of Virtual Reality (VR) is that its users can embody avatars that differ from their bodies. For example, people can experience ownership of avatar bodies of different appearances [6, 39], with extra limbs [37], or elongated arms [7, 13]. Changes to the avatar may also increase the user's performance in interactive tasks [37].

However, if any avatar is possible, how do we select among them, provided that strict conformity to the real body is not important? In past work, avatar modifications have been selected seemingly arbitrarily. For instance, in an exploration of VR avatars, Won et al. chose adaptations that add a gain to leg movements and reduce the reach of the arm, but gave no rationale for the chosen constants of these modifications [37]. Other papers similarly pick changes to the morphology of the avatar seemingly arbitrarily (e.g., [7, 13, 31]).

Selecting avatar modifications in more principled ways is difficult. For instance, predictive models of human movement (e.g., Fitts' law [8], biomechanical models [2]) may provide information on movement time and energy expenditure, but cannot predict a users' proficiency in controlling an avatar

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nor account for the impact of constraints from the task or the environment. Current approaches do also not allow prediction of body ownership and other non-movement based objectives. Therefore, finding the best avatar for a given task and environment is bound to be arbitrary despite its importance in shaping both experiences and performance in VR.

We propose a *systematic approach* that iteratively adapts the avatar based on measures of performance collected during task performance. The approach treats avatar selection as an optimisation problem where user performance in a few attempts at a task serves as the objective/fitness function. The approach then iterates such attempts to find a better avatar. Not only does this approach test a range of avatar modifications, but it also takes into account user proficiency with them and it allows the avatar to be optimal on non-movement-based objectives.

We explore the approach in two target-selection tasks; earlier work on avatars that differ from users' real bodies have also used target selection [6, 37]. In a first study, we evaluate our approach by adapting avatar forearm length for a 3D tapping task. Targets vary in distance and the performance of the optimised avatar over the entire range of targets is therefore difficult to predict. The findings show that people perform significantly faster in the tapping task with the optimally selected avatar compared to a baseline. We also find that with the optimal avatars, users move their real bodies less and experience less physical demand and frustration. In a second study, we vary the scale of the user's fingers for a tapping task but this time with the targets arranged linearly. This is a novel adaptation that has not been explored previously, and as such, the effect of the optimisation in unknown. Again, the performance-oriented objective is improved in the optimal avatar.

To summarise our contributions, we (1) describe a task-integrated optimisation approach, (2) demonstrate it in adaptation of arm length for tapping, and evaluate the outcome of optimisation against a baseline avatar and (3) show a further demonstration of the approach for a different task and body adaptation, (4) discuss the constraints of our approach, and its applicability to a variety of tasks and adaptations.

RELATED WORK

Virtual reality is attractive partly because it allows users to experience avatars that are different from their real bodies. Next, we describe past work on body adaptations in VR and discuss their positive effects on performance and experience. To clarify, body adaptations in this context refers to changes to the avatar, and not the psychological definition which refers to the human adapting to something. Although we focus on improving task performance in this paper, we also include related work on experience (such as body ownership), since alterations to the avatar are frequently explored in this context and we wish to see how those changes are selected. We also discuss some alternatives to avatar modifications. Finally, we present the attraction of using optimisation for selecting avatars and some open issues that the rest of the paper will address.

Avatars that Differ from Users' Bodies

Most work in VR has aimed to make avatars similar to users' bodies. The assumption has been that this is desirable or even necessary for users to experience body ownership [29, 18]. However, much work has explored avatars that do not conform to the users' body.

Most of this work has focused on the *appearance of the avatar*. Studies have shown that the sense of ownership is maintained even when the avatar has a different skin colour [21] or facial appearance [39]. However, the appearance of the avatar may also affect behaviour. For instance, embodying a taller avatar increases self-confidence during a negotiation [39]. Christou and Michael [6] focused on the effect of appearance and body ownership on performance. They used realistic humanoid avatars with two different textures. The appearance proved to influence one's actions significantly.

Other work has focused on the *morphology of the avatar*, changing the size [13], number of limbs [12], or making body parts disappear [9, 27]. Elongation of the arms are the most common alteration. For instance, Kilteni et al. assessed such an alteration and its influence on ownership [13]. In a study, participants controlled asymmetric bodies with an arm length ranging from normal to four times the normal length. The arm lengths were chosen arbitrarily to investigate the effect on ownership. The feeling was uniform, though ownership faded for arms longer than three times their normal length. Won et al. [37] investigated the ability to use novel bodies to complete a task. Additionally, they assessed the effect of remapping the real-world movement onto an avatar that moves in novel ways. Won et al. conducted two experiments that showed that humans can learn to control bodies that do not fit the human body schema, say, a three-armed avatar, an avatar with extended leg movement, or an avatar where the control of arms and legs are switched.

Still other work has focused on *non-humanoid bodies* (e.g., [15, 14, 31]). For instance, Steptoe et al. [31] explored ownership over an additional appendage — a tail. Their study concluded that there was a strong correlation between the ability to control the tail and the feeling of ownership. The control of the tail is calculated using hip movement, which seems to be a bio-mechanically inspired design. Guterstam et al. also found that a third rubber arm can be perceived as belonging to them [10]. Again, these avatars in some cases offer performance or experience benefits over avatars that conform to the human body.

Avatars that Move Differently from User's Bodies

In some work, avatars change dynamically, for instance with respect to the parameters that control movement speed [34, 25]. A dynamic way of modifying the avatar's arms length was introduced by Poupyrev and colleagues [24]. The *go-go* interaction technique described a way of extending the immediate interaction space through a non-linear mapping, that is, the arm stretches in length depending on where the real arm's position. This technique gave users the possibility to interact with both nearby and father objects by allowing them to control the arm length. There were no measures of performance given in the evaluation of this technique.

In another evaluation, Feuchtner and Müller [7] studied the feeling of ownership over asymmetrically elongated arms. In an Augmented Reality set-up, participants were asked to interact with remote devices using their arms, where the users could control the extension of the virtual arms by using a technique based on go-go. The results show that the illusion of ownership holds up until around twice the normal length of the arm. Laha et al. [16] focused on different control schemes to handle a three-armed avatar. They defined three control mechanisms: head control, uni-manual, and bi-manual. Their findings indicate that the choice of the control schema is relevant for performance. In addition, schemes that delegate the control function between multiple body parts were less efficient compared to schemes keeping the control within one limb. The participants using the uni-manual and head control presented better results than the ones using the bi-manual schema. In both of these examples, the parameters for how the arm is elongated (e.g., rate of change, limits) were selected based on the designers intuition and experience. For instance, from Feuchtner and Müller's work: "After some testing, we found p =4 to be a good value, and both D and k are calculated thus to achieve the maximum length of the virtual arm Rv = 5."

How to Select Avatars?

In the work just reviewed, avatars that look or move differently from the human body were selected in one of two ways. First, they may be selected on theoretical grounds. For instance, skin colour was expected to associate with racial stereotypes [21]. Having such theoretical reasons are rare. Second, avatars may be selected among a range, to be optimal in terms of performance or experience. For instance, Kilteni et al. assessed a set of arm lengths to find ones that could be longer and support performance yet still elicit high body ownership [13]. In some cases, a range isn't even explored, an arbitrary value is just selected. However, typically related work does not offer justification for selecting the exact adaptation parameters of the new body. This is not meant to be a criticism of those papers — on the contrary, it is very helpful to understand the effects of a certain adaptation in a controlled manner. It is based on such findings, that we may apply our novel approach to adapting avatars iteratively in order to improve the effect of a certain type of adaptation.

There are other approaches that are, in our opinion, orthogonal to what we are attempting. Instead of adapting the body, one could instead alter the environment or task directly. Erg-O is an example of this, where the targets are brought to within reaching distance of the user [19].

Perhaps a task is simple and there exists an optimum that can be computed based on bio-mechanics. Analysis of bio-mechanics and performance has in the past been used to create heuristics for the design of 3D pointing interfaces [2]. However, there is one fundamental point which complicates the use of such methods with alternate bodies: We cannot predict how a person uses a virtual body that differs from their own. Additionally, these approaches only work for movement-based objectives, and therefore cannot be used to optimise measures of experience (e.g., body ownership).

Optimising Bodies as an Alternative Approach?

One approach to identifying effective adaptations on body morphology is to sample performance across a range of changes, such as arm lengths. However, it can be ineffective for two reasons. First, the design space can be vast. For example, with keyboards or displays we can assume a limited range of targets for selection and a constrained morphology of the body. Numerous papers demonstrate, for instance, optimisations of touchscreen keyboards for typing with such constraints (e.g., [20]). However, in VR tapping tasks, targets can lie anywhere in the virtual world; near and far, even out of view. One solution is to limit this space by selecting a small set of targets and systematically sample across that set. However, this poses a risk of missing an optimal adaptation outside the sample range or between the intervals, in particular where we do not have prior knowledge of user performance with adapted bodies. Iterative optimisation that departs from a given point but samples progressively without a predetermined sample space, such as intervals and range, can help with these risks. Progressive sampling has previously been applied, for instance in AutoGain [17], which iteratively adapts a gain function of pointing based on performance.

Second, sampling across a range of avatar changes may influence the user's learning. It is unclear how people's motor system learns to control a modified avatar, and if this learning accumulates across trials. This concern extends to systematic increments in the morphology. Sampling on randomised instead of gradual chances may help, but learning across time may still persist. One solution to this is to adapt the interaction technique based on performance in a given task. Thereby, the performance gain for the task is observable, as is the learning (this has previously been done, see for instance [17]). Another benefit of such task-based optimisation would be that it is unobtrusive. Thus, it can in principle be fully integrated in ongoing interactions.

OVERVIEW OF THE OPTIMISATION METHOD

To tackle the open issues in improving performance by adapting avatars, we use *iterative, task-integrated optimisation*. The optimisation here progresses iteratively from an initial, given avatar, from which the next avatar is created based on past task performances, seeking to improve the performance gradually. The assumption here is, that the user performance can be improved by changing a sub-optimal body feature. For example, if the movement time in reaching a target increases, then an arm was too short and its length should be increased. We also assume that there exists a local optimum for the body part which is specific to the task. The gradual adaptive optimisation is ongoing as the user is performing the task, thereby integrating this method into the interaction.

We test this iterative, task-integrated approach in two studies. In the first one we adapt the avatar's arm length to improve it's fitness in tapping targets spanning across a virtual room, and in the other one the lengths of the avatar's fingers in tapping a keyboard. The optimisation process consists of the following steps (Figure 2):

(a) Baseline Avatar — The optimisation takes an avatar as input. It is the departure point for iterative optimisation,

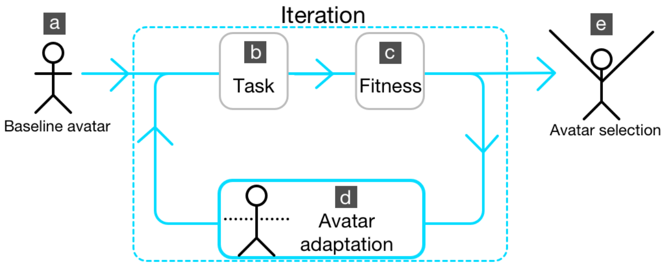

Figure 2: Our iterative approach to optimising avatars based on user performance in a task.

and can also be used later for comparison against a found optimum. We use an avatar with realistic dimensions, but this baseline can also be selected based on a prior knowledge of performance or randomly.

(b) Task — The avatar is optimised for a given task. We use a tapping task with a different target setup for each of our two studies. One iteration can consist of many subtasks, such as tapping all the targets in a set of targets. This set can be any set meaningful for the task.

(c) Fitness — This is the objective function in optimisation. We define fitness as a function of time and distance for both of our studies, but with small differences to match each study design. The fitness score can be based on any metrics meaningful to optimise, but they need to be measurable during the task to allow iterative task-integrated optimisation. They can be, for example, metrics of task performance, such as target selection time and accuracy, or user experience, such as body ownership.

(d) Avatar adaptation — The principle in our optimisation is to adapt the avatar on some selected feature after every iteration. In the studies that follow, these features are forearm and finger lengths, and the adaptation is therefore to increase or decrease the length to optimise its fitness for the given task. The fitness scores are used by an optimisation algorithm to select a new body feature. This adaptation can also be done by using only the previous iteration as input, or by combining multiple previous ones.

(e) Avatar Selection — The outcome of the optimisation is an avatar with an adapted feature or features. We select the avatar with the best fitness score among all adaptations tried. The optimal avatar can also be selected by using a threshold where fitness converges.

FIRST STUDY

In the first study, we adapt the length of an avatar's forearm to optimise performance in a tapping task. Figure 1 shows an example of what the avatar looks like and how it is adapted over iterations. The purpose of this study is to test if the iterative task-integrated optimisation finds a forearm length that improves performance over that with a baseline. The performance is measured as a fitness function comprised of throughput and movement. As mentioned earlier, previous studies have chosen the extension of arms arbitrarily, and it is unclear whether these extensions perform better than a baseline length, and whether they are optimal for the task they are used for. Forearm length is selected because adaptation of arm length has been the most frequent adaptation of avatars in earlier work. Since these adaptations are usually made to improve target selection, we also use this type of task. To do this, we first optimise the forearm length for each participant, and then compare the resulting tapping performance against that with the baseline length.

Optimisation

We used the optimisation process described above with the following parameters.

Baseline Avatar

The baseline avatar in this study is an avatar with an arm length corresponding to the participant's real arm length.

Task

The task was to tap multiple spherical targets as fast as possible. Each iteration consisted of tapping 10 targets, each target appearing one at a time. The number of targets should be sufficiently high to enable a range of targets to be chosen for each iteration, whilst also being fast enough to complete in order to iterate quickly. We found through pilot testing that 10 was a good comprise between time and variation of targets. Some targets were out of the participant's immediate reach with some arm lengths, and the participants then walked closer to be able to tap those. After tapping a target, the participant walked back to a virtual marker on the floor (as shown in Figure 1b) and waited for the next target to appear. The participants were free to use either hand for tapping.

The 10 targets were selected among 20 targets located on a spiral (as shown in Figure 3) spanning across a virtual room. This follows the set-up proposed by Qian et al. [26]. The distance of the 20 targets ranged from 0.5m to 2.66m, with 0.12m spacing between them. The targets could be of any 3 sizes (10, 20, 30cm in diameter), chosen randomly.

Fitness

We defined fitness as the average of *Throughput* and *Movement*.

$$Fitness = \frac{Throughput + Movement}{2}, Throughput = \frac{ID}{MovementTime}$$

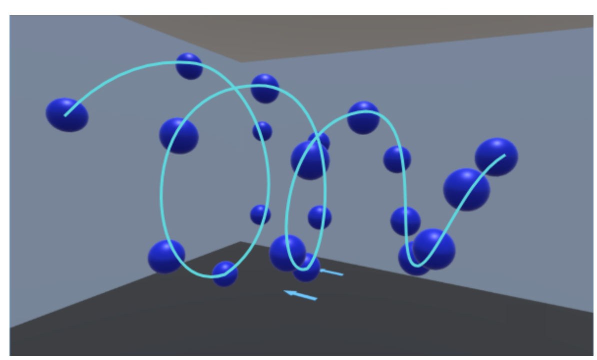

Figure 3: The spiral target configuration used in the first study, originally proposed by Qian et al. [26].

Throughput, as defined by Fitts [8], is a measure of human performance at selecting targets. The *ID* denotes the *Index of Difficulty* of a given target. Research has provided several methods for calculating the index of difficulty for a 3D pointing task. We followed the method proposed by Qian et al. [26]. It is based on the angular size of the target and angular distance to target: $ID = \log \frac{\alpha}{\omega} + 1$, where α is the angular distance between the player and the target ω is the angular size of the target. The *Movement Time* is the time measured from when the target became active until it was touched.

For *Movement*, we use the weighted average of the distances travelled by selected body parts (i.e., torso, upper arms, legs, and hands). The weights for every body part were selected based on the work of Plagenhoef et al. [22]. This movement value is used in the fitness function because the travelled distance may influence user experience with the avatar, such as the experienced fatigue, effort, or physical workload in general.

Avatar Adaptation

The principle in this optimisation approach is to adapt the forearm length l_i after every iteration based on the the previous length's l_{i-1} fitness for the tapping task. It is similar to gradient descent, but the objective function is equivalent to a black-box since it is acquired from data, rather than estimated. For this reason, we cannot use derivatives of the function, and derivative-free optimisation methods must be used (excluding gradient descent).

Therefore, after each iteration, we compute the gradient of the fitness, ∇, that is, the difference in fitness between the previous and the current length. This determines the magnitude of the change together with learning rate α as follows:

$$l_i = l_{i-1} + \alpha * \nabla$$

The magnitude of the gradient, ∇, is determined by the difference in fitness to the previous iteration. In addition to the magnitude, ∇ also consists of a directional component, which signifies whether the difference in fitness was increased or decreased. This determines whether we continue to change the length of the arms in the same direction (increasing or decreasing the length) when the fitness increases, or the opposite direction from the previous length when the fitness decreases.

The magnitude of the change is determined by the fitness score together with a learning rate, α. We set this rate based on piloting, but it can also be set based on theory. The purpose of the learning rate is to adapt the avatar fast enough to optimise with feasibly few iterations for the given task, but slow enough for the user to learn to control the new, adapted avatar. For example, the length change of a forearm needs to enable observing a clear change in fitness, but also should not be too large so as to decrease fitness simply because of the user's difficulties in adapting to the changed body. We need to either input some constant for this rate (i.e., some value to scale the fitness score into the change rate, which are cm in this case), or give an initial value as an input and adapt the rate on-the-go. In this study, we do the latter.

We used pilot testing to determine the parameters for the learning rate. Our testing revealed that an initial learning rate of 0.13 reached high values of fitness with few iterations, without increasing too quickly. This complies with theories of optimal learning rates, known as the 15% (or 85%) rule (e.g., [36]). We borrow an adaptive learning rate shown by Plagianakos [23] in gradient descent, which reduces the learning rate if the direction of the gradient changes between consecutive iterations. Similarly, the rate increases if consecutive iterations retain the same direction.

Avatar Selection

The optimisation method used is not guaranteed to reach a global maximum. Therefore, we set the criteria for selecting a locally optimal avatar based on our aims with task-integration. The criteria were that the study duration was maximum 30 minutes to avoid much fatigue in arms for tapping the targets across the room, and that we had few enough iterations to be realistically performed within a single interactive task but could still find an avatar with a fitness better than the baseline. We tested our approaches in pilots as mentioned above, and set the number of iterations to 30. After the 30 iterations, we selected the arm length as an average of the three lengths with the best fitness values.

Procedure

Before the study, the participants were told that the forearm length will change throughout; the basis for the changes was not mentioned. The participants were also told that their tapping performance would be measured and instructed to tap the targets as fast as possible. The participants did a short training session of six tapping tasks.

The participants were then taken through the **optimisation phase**. It consisted of 30 iterations, wherein the avatar's arm length was adapted as described above. As the last part of the study, the participants performed the **test phase**. In that, the tapping performance with the optimally selected avatar was tested against the baseline avatar in the same tapping task. With each of the two arm lengths, the participants tapped two sets of 10 targets, similar to the iterations in the optimisation. The order of the two arm lengths (baseline and optimal) were chosen randomly.

Participants

Sixteen participants (8 male, 8 female) took part in the study. The age of the participants ranged from 21 to 40 with a mean of 26. The mean height across participants was 175 cm. Half of them did not have any experience with VR, while the other half had limited experience (less than five hours). Three were left-handed.

Data Collection

We collect two types of data: motion data for the optimisation and performance testing, and subjective data on task load to gain insights in performance beyond the fitness function.

The study was conducted with an HTC VIVE head-mounted display for virtual reality. The participants' movements were tracked with a full-body ROKOKO motion-tracking suit [1].

[1] https://www.rokoko.com/en/products/smartsuit-pro

The suit has 19 9-Dof sensors placed on the main body parts (Figure 1a). With these, we tracked the head, torso, hips, upper and lower arms, hands, and legs. The avatars were calibrated using the ROKOKO's software according to each participant's body dimensions. The movement was logged during each trial from the the moment the target appeared to the moment the participant touched it with their hands. These motions were logged together with size and position of the target as well as timestamps, to allow us compute the parameters of fitness.

We measured subjective task load in the testing phase of the study. We asked the participants to fill a full NASA-TLX [11] for each baseline and optimised avatar lengths, after completing the two sets of tapping 10 targets with those.

RESULTS OF THE FIRST STUDY

Next, we present data from both phases of the study: (1) the gradual progression of the avatar leading to a selection of the optimal forearm length and (2) the assessment of the obtained optimal length vs the baseline length.

The goal of the analysis of the data from Phase 1 was to look for possible trends across multiple arm lengths. The main areas of interest were body movement and performance. Additionally, an assessment of the optimisation process was performed.

Phase 2 was designed to answer the question: "Can we adapt an avatar to make people more efficient for a specific task?". Hence, data gathered during Phase 2 were used to make a comparison between the optimal arm length computed in the previous phase and the baseline.

Phase 1: Avatar Optimisation

Figure 4 shows the forearm length changes during Phase 1. The forearm length gradually increases, on average, close to 1.25m. For iterations 8, 9 and 10, the lengths were 1.14m, 1.19m and 1.14m respectively. This indicates that the changes happened quite rapidly within the first 10 iterations. Thereafter, a lower variation in arm length is seen.

Figure 5 displays the absolute distances travelled by different body parts. We subtracted the distance travelled by the body from the other body parts, since the body moves the most and we are interested mainly in relative motion. We observe that on average, the upper arm, body, and legs travelled shorter distances with further iterations. At the same time, the participants were increasing their hand movements. A likely explanation for reduced body and leg movements is the user had to walk less to reach the targets as their arm length grew. However, the reduction in upper arm movement was not expected, and is an interesting insight into how adaptation change movement behaviour.

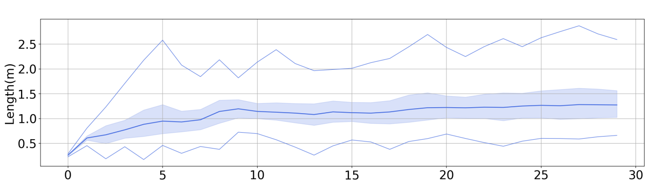

Figure 4: The minimum, mean, and maximum lengths of forearms in every iteration. The shaded area around the mean represents a confidence interval of 95%.

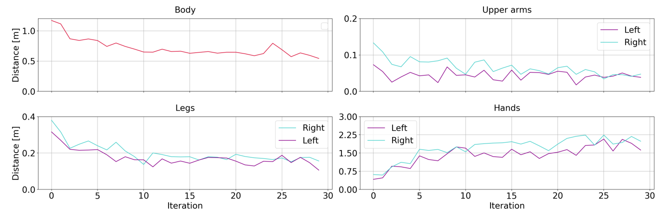

Figure 5: Recorded distances travelled by the selected body parts. The graphs depict average values between all the participants.

Phase 2: Comparison of Optimised vs Baseline Avatars

Performance

The final optimised forearm lengths were on average a scale factor of 5.6. There is little correlation between real length (mean=26.3cm, sd=1.79cm) and optimal virtual length (mean=1.19m, sd=0.389m), Spearman's rho=0.101 (S=605.2, p=0.685).

The three graphs displayed in Figure 6 show the total fitness score, movement time, and throughput obtained with both the optimal and the baseline length. All three measures show considerable improvement when the optimal length is used. The total fitness score and throughput increase while the movement time decreases. On average, the movement time decreases by 18.7%. Based on the Shapiro-Wilk test, the data presented in Figure 6 may be assumed to be normally distributed. We thus proceeded to compare the conditions with a paired t-test. The test shows statistical significance for all three metrics: Fitness ($t = -9.81, p < 0.001$); Movement Time ($t = 7.23, p < 0.001$); Throughput ($t = -9.4, p < 0.001$).

Effect of optimal arm lengths on travelled distances

Figure 7 contains four graphs, each of them displays the travelled distances for particular body parts (Body, Upper arm, Legs, Hands), with comparisons between the baseline and optimised avatars. In line with our findings from Phase 1, we observed corresponding changes in distances travelled. With the optimised avatar, the torso, upper arms, and legs travelled

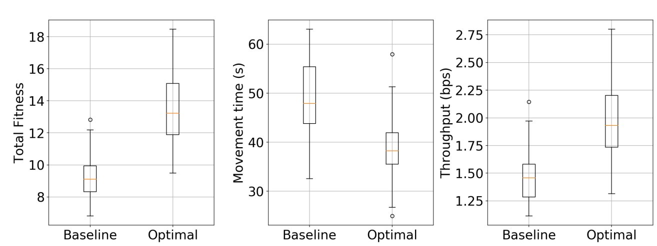

Figure 6: Total fitness, movement time, and throughput for baseline length and optimal length. Medians, interquartile ranges, full ranges, and outliers are shown

shorter distances while the hand travelled further. The average percentage differences in body movement for each body part is as follows: body (47.5%), legs (49.7%), upper arms (42.13%) and hands (211.8%).

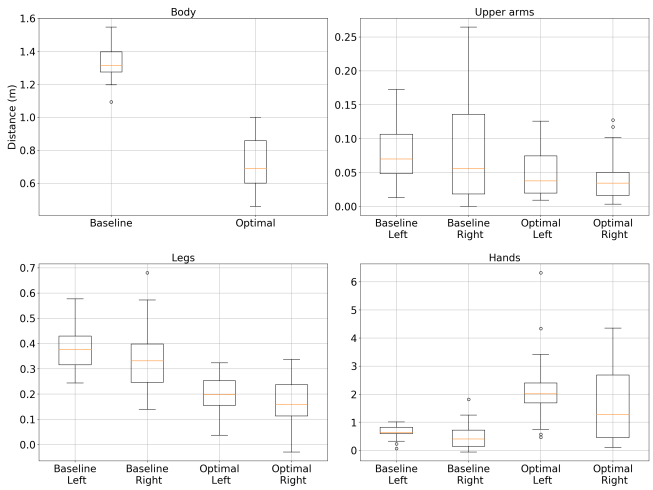

Figure 7: Box-plots for distances travelled by the selected body parts. Each graph contains the results recorded for the baseline and the optimal arms lengths. Medians, interquartile ranges, full ranges, and outliers are shown in the same way as previously.

In order to assess the statistical significance of the correlation between the changes in distances and lengths of the forearms, a Wilcoxon signed-rank test was applied. The results show statistical significance for all body parts ($p < 0.05$), except for the right hand ($p = 0.078$).

Subjective Comparisons

In the NASA TLX questionnaire responses, the interquartile range for all questions in all conditions is quite large, indicating a lot of variability in the answers. We analysed the data using the Wilcoxon signed-rank test, as a Shipiro-Wilks test indicated that the data was not normally distributed ($p < 0.05$).

The test shows no statistical significance for *Temporal Demand*, *Performance*, *Effort* and *Frustration*. All p-values are greater than 0.1 and all W-values are bigger than 30 (the two-tailed critical value for the test with a sample size of 16). However, *Mental* and *Physical Demand* showed significance differences ($p < 0.05$, W-values for both are below the critical value: 24.5, 29.5 respectively). These differences show that the perceived mental and physical demands were significantly lower with the optimal avatar compared to the baseline avatar.

Users' Movements Before and After Learning

Every participant performed four iterations of ten targets with the baseline length. Two of them were at the beginning of Phase 1 when the participants had little experience with the task. The other two were after completing all the 30 iterations during the baseline length assessment in Phase 2. We analysed the data from these two sessions to observe the training effect on the performance and movement of the participants. A slight decrease in fitness and throughput was observed. However, we found the differences not to be significant between the conditions in movement time ($p = 0.795$), using a Wilcoxon signed-rank test.

During Phase 2, participants moved slightly more with their whole body, left leg, left hand, and left upper arm. However, the movement of all right body parts slightly decreased. However, these differences were found not to be significant (Wilcoxon signed-rank test, Body: $t = 67.00, p = 0.95$; Left Upper Arm: $t = 67.00, p = 0.958$; Right Upper Arm: $t = 50.00, p = 0.351$; Right Leg: $t = 62.00, p = 0.75$; Left Leg: $t = 43.00, p = 0.196$; Left Hand: $t = 51.00, p = 0.379$; Right Hand: $t = 43.00, p = 0.196$). This is an important finding because it shows that movement behaviour does not differ significantly over time.

Summary

We found that avatar adaptation happened rapidly within the first 10 iterations. The final optimised arm lengths were on average, a scale factor of 5.6. This length performed significantly better compared to the baseline for Fitness, Movement Time and Throughput. The travelled distances for different body parts also changed significantly, with the hands moving more and the legs, upper arm and torso moving less. Subjectively, the participants exhibited significantly less mental and physical demand for the adapted avatar. Finally, a comparison of normal arm lengths before and after phase 1 showed no significant difference in performance. We will now describe a second study that investigates the generalisability of this approach to another task and adaptation.

SECOND STUDY

The second study investigates if our approach works for a task that differs from the one used in the first study. In this second study, the task requires the user to tap small targets accurately with fingers, an activity required in many virtual reality applications. The scale of the user's fingers are adapted with a fitness determined by the overall hand movement and duration between taps. The rationale for looking at finger scale is that adapting avatars may work differently and perhaps better than adapting the VR environment; this could have straightforward uses in for instance typing in VR. Again, the study has two phases: one where the avatar is adapted and one that compare the best performing adaptation and the baseline hand size.

Optimisation

Baseline and Task

Ten targets were arranged along a single axis, like piano keys (see Figure 8). All targets were visible. When one becomes the current target to select, it is highlighted. The users were instructed to tap the targets as quickly and as accurately as they could. Users could use whichever hand they liked. When the user taps a target, it becomes highlighted and a sound is played. Because the targets are close, errors can occur if the user is not careful with tapping the correct target. If the user incorrectly taps another target than the current one, there is a brief timeout of one second, mainly set to avoid "cheating" the system by running the hands through all the targets with no care for errors. As in study one, participants did 10 targets per iteration and 25 iterations. The baseline avatar here begins with the hands of a default scale which matches their hands.

Fitness
As in study one, the fitness function comprises throughput and movement. We calculate the index of difficulty for throughput as the closest point from the target to the centre of the closest of the hands. The movement is here simply the sum of the distance travelled of both hands. Note that errors are part of throughput through the timeout they incur.

Adaptation
The scale of the user's fingers was adapted. The scaling was done to every finger with the same scale factor, along one axis such that the fingers just became longer. As the fingers become longer, we expected that targets further away can be reached more easily; however, this may also reduce target-selection accuracy. The challenge here is finding the balance between these, something that is not readily obvious from bio-mechanical modelling or predictable without knowing the approach an individual takes to solving the task.

Pilot testing suggested that users' fitness' varied between iterations, even with the same hand scale. This variation causes problems to algorithms such as the gradient descent-like optimiser we used in the first study. We therefore use Bayesian optimisation [4], an optimisation algorithm that is more robust to noise and uses the data from all iterations. In our particular Bayesian optimiser, we used a Gaussian process to estimate the underlying function. The algorithm uses the data from past iterations and directs sampling to areas where an improvement over the current best observation is likely. We take this newly sampled output as the new avatar for the next iteration. The optimiser is initialised with data from the baseline scale (of 1x). It also requires limits to the search space, so we chose an upper limit of 5x, since at that length, it would reach beyond the most distant targets. Bayesian optimisation can take large jumps across the search space. However, we aim to make the avatar difference between iterations small, so we threshold the delta to 0.7.

Selection
For the final testing phase, we selected the avatar with the highest fitness from past iterations (i.e., the scale which performed the best according to the objective function), as in the first study.

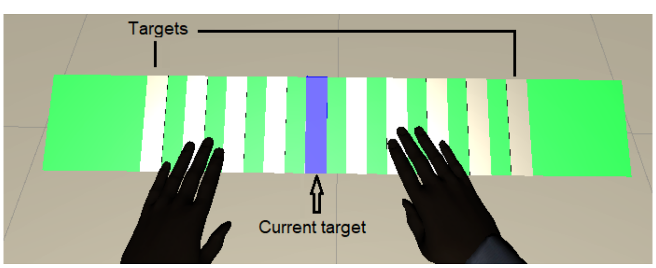

Figure 8: A screenshot from the second study application, from the perspective of the user. The 10 targets are laid out linearly, and the current target to be tapped is highlighted in blue.

Procedure
We used a procedure similar to that of the first study. The main difference is that we conducted this study online. The Oculus Quest was used as the HMD and to track users' hands. Participants were given an APK to install. Instructions were given within the app, which the participants followed until completion.

Before the study, the participants were informed that their fingers will change in length throughout the experiment. However, the basis for the change was not mentioned. The participants were instructed to tap the targets as fast and accurately as possible.

Next they did the main part of the study, wherein their avatar's finger scale was optimised across the 25 iterations as described. This is named the optimisation phase, like in the first study. Also as in the first study, there is a second phase where the tapping performance with the best selected finger scale was tested against their default, baseline hand, in the same tapping task. With each of the two finger scales, the participants tapped two sets of 10 targets, similar to the iterations in the optimisation phase.

The experiment took 15 minutes on average, excluding the time needed to set up and install the application. When the participants had finished the experiment, they were told to mount the storage of the device and to extract and send the data stored within.

Participants
We recruited 40 participants through an online platform, Reddit [2]. All participants owned an Oculus Quest, and conducted the study remotely. They were compensated with games worth up to 15$.

Data Collection and Cleaning
The data collected included movements of users' hands (for travelled distances), tapping time completion (note that here there is no return to neutral/idle position, in contrast with the first study, and therefore "Movement Time" is an unnecessary distinction), tapping errors, target positions, scale and throughput.

Because participants were remote, the experimental control is lower than in the lab. We noticed that some participants had poor hand tracking quality, likely caused by conducting the study in a poor lighting environment. We therefore removed erroneous trials if jitter—measured as a ratio of the number of frames where the tracked movements vary by more than 10cm between frames to the total number of frames—was greater than 1% (five participants).

RESULTS OF THE SECOND STUDY
Next we present data from the two phases of the study.

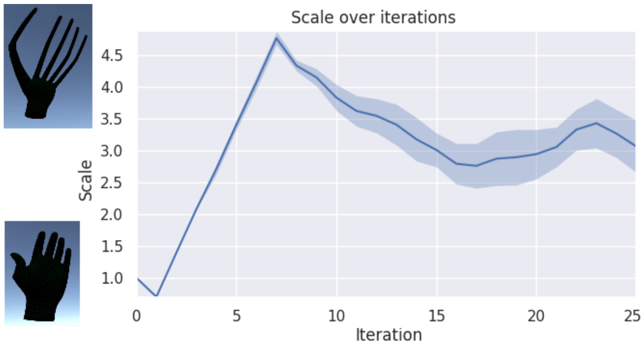

Figure 9: Scale changing over iterations during the study, averaged across all participants. The shaded area around the mean represents a confidence interval of 95%

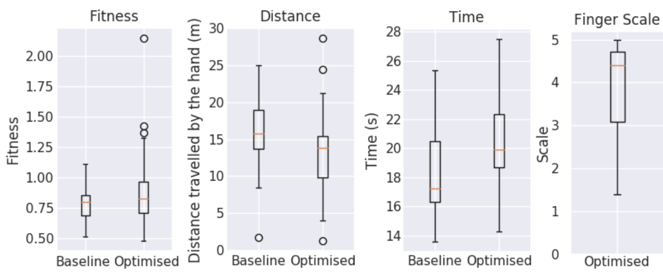

Figure 10: Comparisons between the baseline and optimal avatar for the fitness, distance travelled and task completion time, and then also the final, optimal finger scale (averaged across all participants).

Phase 1: Avatar Optimisation

The change in finger scale across users throughout the optimisation phase can be seen in Figure 9. The Bayesian optimiser searches the space at its limits to begin with, before exploring values inbetween.

Phase 2: Comparison of Optimised vs Baseline Avatars

Scale

The final finger scales, selected as the one which performed the fittest, can be seen in Figure 10. The mean scale was a multiplier of 3.93, with a standard deviation of 1.06.

Fitness

The optimal finger scale saw an increase in fitness by 0.09. A Shapiro-Wilk test for the difference between baseline and optimal was significant ($W = 0.738, p < 0.05$), and is therefore not normally distributed. A Wilcoxon signed-rank test shows that the changes between baseline and optimal fitness was significant ($T = 190.0, p < 0.05$). This shows that the approach has succeeded in creating a significantly more fit avatar, according to our fitness objective.

Travelled Distances

The total distance moved by the hand during the second phase of the task was 15.9m for the baseline, and 13.3m for the optimal. This is a reduction in movement by 2.6m on average. A Shapiro-Wilk test for the difference between baseline and optimal was significant ($W = 0.911, p < 0.05$), and is therefore not normally distributed. A Wilcoxon signed-rank test reveals that the changes between baseline and optimal hand movement was significant ($T = 91.0, p < 0.05$).

Time

The total time taken during the second phase of the task was 18.56s for the baseline, compared to 20.36s for the optimal. This is an increase in time of 1.8s.A Shapiro-Wilk test for the difference between baseline and optimal was insignificant ($W = 0.964, p > 0.05$), and can therefore be assumed to be normally distributed. A T-test for the difference reveals that the differences in total time between baseline and optimal were significant. ($T = -3.702, p < 0.05$)

Errors contribute to increased time due to them causing a timeout, which means that targets cannot be tapped if an incorrect target was hit prior for one second.

A Shapiro-Wilk test for the difference between baseline and optimal error rates was significant ($W = 0.797, p < 0.05$), and is therefore not normally distributed. A Wilcoxon signed-rank test showed the difference between baseline (0.60 ± 0.87) and optimal (1.43 ± 1.93) error rates were significant ($T = 59.5, p < 0.05$). So on average, participants performance in the optimal case was likely to induce almost an additional error (0.83 errors more) per 20 targets.

Summary

The optimally selected finger scale was on average, 3.93. This scale was significantly better than the baseline when measured by the fitness objective. Although the movement has decreased significantly (by 2.6m on average), it is at the expense of greater task completion time (1.8s). The additional time spent during the optimal body performance is partly due to the greater number of errors, since we force a timeout for errors. It appears as though an imbalance in the fitness function causes the optimiser to favour decreases in travelled distances. This seems to occur when there is a trade-off between parameters in the objective function. We theorise that if we calibrate the throughput and movement so that those differences are more similar, the resulting avatar may improve in time, but perhaps sacrifice some movement performance.

DISCUSSION

We have proposed a systematic approach for iteratively adapting avatars. Our first study shows that the approach creates significantly more effective avatars, both on performance metrics and questionnaire results. The task optimised for—touching targets—is one of the most common tasks in VR. In the few examples of work that attempt to find a better performing avatar (e.g., [6, 37]), there is no justification for choosing a particular adaptation of the avatar, nor can one expect to find a good or even locally optimal avatar. The second study demonstrates that the approach can be used for different tasks and different types of adaptation. Although the optimised avatar shows significant higher fitness than a baseline avatar, the avatars perform very differently in terms of distance travelled and task completion times. Next, we discuss our approach and the

[2] https://www.reddit.com/

broader applicability of it to different body adaptations and tasks.

Iteration Cost and Optimisation Algorithms

The duration of each iteration is an important factor. There may also be other factors besides time, that determine iteration cost, such as physical and mental effort. An iteration that is costly in this sense would favour algorithms that arrive at the optimal in fewer iterations.

In general, the choice of optimisation algorithm is highly dependent on the task and goals of the user. If the search space is not bounded, a gradient descent-like algorithm as used in the first study is more appropriate. Bayesian optimisation algorithms are also known for optimising problems with high evaluation costs. So, if for instance the iteration in the task requires a lot of time and effort for the user to perform, the Bayesian optimiser is ideal.

Objective Functions

We employed a naive fitness (or objective) function in the implementations of our two studies, for the purpose of investigating the approach in a straight-forward manner. Still, the results showed that the process yielded an avatar that improved the constituent parts of the function (i.e., Movement and Throughput). However, in the second study, there was an unforeseen trade-off between time and travelled distances, and the outcome was a compromise which favoured shorter travelled distances. This reinforces the importance of prior work which indicate the effects of certain modifications. Indeed, we used prior work as a basis for the avatar modification in our first study, with expected results. A recommendation for future approaches without such prior information would be to search the feature space sparsely to quickly gather information about the effects, which can then better inform the objective function for optimisation. For instance, in the second study, knowing the trade-off and also the relative sizes of Throughput and Movement would have allowed us to have formulate the objective function more effectively.

More complex objective functions could adjust the weighted importance of the parameters which comprise the function. It is then possible to prioritise certain parameters. Taking our second study as an example, we could weight the Movement parameter in the fitness function to further favour reduced movement errors. Furthermore, the objective function does not have to be static — it could be changed dynamically according to the users needs. If feedback on the effect of the adaptation was given to the user, they could adjust this function to their desire. This would be especially easy to do in the case of experience optimisation, as that experience would not have to be fed back to the user.

Other Possible Adaptations and Tasks

We have shown two possible adaptations for two different tasks. In general, any body part can have its length used as a feature for adaptation. The feature could also be the visual appearance of a body part [6, 39], reducing or increasing the number of limbs [27], or the range of movement [37]. Features could also be taken from psychological and philosophical work on key body features [1]. How movement happens in VR may also be optimised. For instance, translational gain has been shown to enable more efficient movement in VR [35]. Gain levels are typically also fixed by decision and could instead be optimised by our approach.

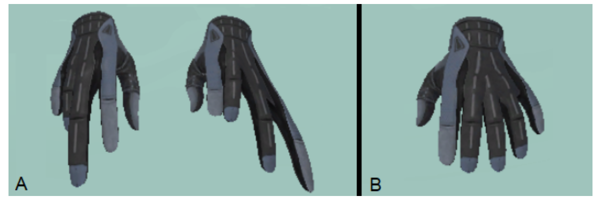

Figure 11: Envisioned adaptations. (A) Multi-dimensional optimisation: optimising each finger individually. (B) Non-humanoid adaptations: optimising the number of fingers and their control by the user.

Related work often study the effects of avatar adaptations on experience, such as body ownership [7] or self-confidence [39]. The features used in these adaptations could be used in our optimisation approach to optimise such effects. Our first study shows an overlap between the subjective measures of physical demand and how much the body has travelled. Won et al. [38] also showed a positive correlation between the feeling of self-presence and task success. In these cases, experience measures can complement physical measures to fine-tune objectives. However, some experiences (e.g., body ownership) may be orthogonal to performance and therefore particularly interesting as part of optimisation.

Physiological data may also be used to infer non-movement properties of the body. Electroencephalographic estimations of emotional state [5] or error related negativity [33] are also examples of features which the optimiser could be directed by.

Optimising Multiple Body Features

Another step for creating more sophisticated, complex, and efficient avatars is to optimise multiple body features. For instance, an enhanced version of our arm length optimisation could consist of two parameters: forearm length and joint range. In the case of our second study, this could be individual finger length scaling. Figure 11(A) shows an envisionment of this complex adaptation.

Many optimisation algorithms are robust to noise and derivative-free, which could be used to support the optimisation of several body features. This includes Spall's SPSA [30], stochastic Nelder-Mead simplex method [32], or even the Bayesian optimisation used in the second study.

Controlling Non-humanoid Avatars

There have been several attempts to control avatars that are different in morphology, such as controlling additional limbs [37], or various animals [28]. These avatars may have features that could be optimised, such as the number of fingers (11(B)). However, the control mapping between the human and the non-humanoid avatar is another complex issue, which may also be optimised.

Limitations of the Current Approach

Iteration Duration and Learning

It is important to consider the time it may take for the user to become familiar with a newly adapted avatar. To mitigate the these effects, we restricted the adaptations to be gradual. However, it may still be the case that users' improved during an iteration. Understanding these effects remains future work, which is an important step for the possibility of non-gradual adaptations.

Dynamic Avatars

The scope of this paper only concerns static adaptations. Dynamically changing avatars like what is shown in the stretch go-go technique [3] could enable better performance than static avatars, particularly when tasks are also dynamic. For instance, a dynamic avatar could enable a user to touch targets close to the body with a normal arm, but then stretch to reach those afar. Controlling how the dynamic avatars change is also a challenge not too dissimilar from that of controlling non-humanoid avatars.

Transfer-ability Across Users

Our first study took slightly longer than half an hour on average. The second study was much shorter due to the faster iterations. Although participants attained a far better performing avatar in a shorter time than this, this would still be inconvenient if switching quickly between new environments or tasks. User specific adaptation is only worthwhile if they are in the environment for any considerable amount of time.

Transferring avatars across users could be a solution to this problem. However, this remains future work.

CONCLUSION

We have proposed a novel approach for systematically adapting avatars to be more effective for a given task. By applying this approach to two VR target tapping tasks and adaptations, we have shown that optimised avatars were more effective. We discuss how this approach is generalisable, and could be leveraged to gain advantages for many other types of adaptations and tasks. Furthermore, we believe this is a foray into an exciting and broad area of research that reaches beyond the constraints of humanoid morphologies and conventional tasks. In that area, avatars are adapted to the environment and to tasks, rather than adapting those for avatars that are morphologically identical to users' real bodies.

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