Motor learning in Mixed Reality

Stefan Paul Feyer
HCI Group, University of Konstanz

November 7, 2019

Abstract

- Overall aim of the Seminar thesis: how to investigate the influence of perspectives on virtual avatars in MR for motor learning
- therefore analysis of motor learning, related work, research questions
- propose study setting

Contents

1 Introduction

1.1 Motivation

In recent years, Mixed Reality (MR) devices became more affordable [1], portable [2] and usable in more conditions. Not only academic researchers are interested in this technology, commercial companies also found MR devices helpful to explore new possibilities to use it profitable. With this development, learning and training in MR became possible for many cases, too. EON [3] for example calls themself "the world leader in Virtual Reality based knowledge transfer for industry, education, and edutainment". They develop MR programs for several platforms, eg. with the aim to guide workers, reducing mistakes and thus reducing costs. These programs address a lot of usecases in the field of education, energy, health & medical, manufacturing & industrial, defence & security and aerospace. Tasks include eg. ground crew training for a Boeing 777, augmented reality (AR) assembly training, exploring or anatomy simulation to mention only a few, compare 1.1. Mircosoft also stepps into this topic with partners, developing tools for apprentice, maintenance, or remote training. Eg. The Smart Glass experience Lab[4] of the Fraunhofer Institute use the hololens for remote maintenance, compare figure 1.2.
For developing MR learning and training environments, research put much afford in developing how-to's and guidelines to ensure proper systems [**?**]. However - as we will see in Chapter 4 - there is a research gap about the perspective in these systems. For example, a student wants to learn a speacial task from a teacher. In the real world, the teacher stands in front of the student preforming the task and the student tries to mimic it. This perspective is called exocentric or 3rd person. In contrast, in MR we have the possibility to change this perspective what we cannot do in the real world. We can "step into" the teachers virtual body and see the instruction from the 1st person view of the teacher, also called egocentric view. Changing the perspective could have influence on the learning. This rises

[1] **TODO**
[2] **TODO**
[3] https://www.eonreality.com/ accessed: 14.12.2018
[4] https://www.fit.fraunhofer.de/de/fb/cscw/smart-glasses-experience-lab.html

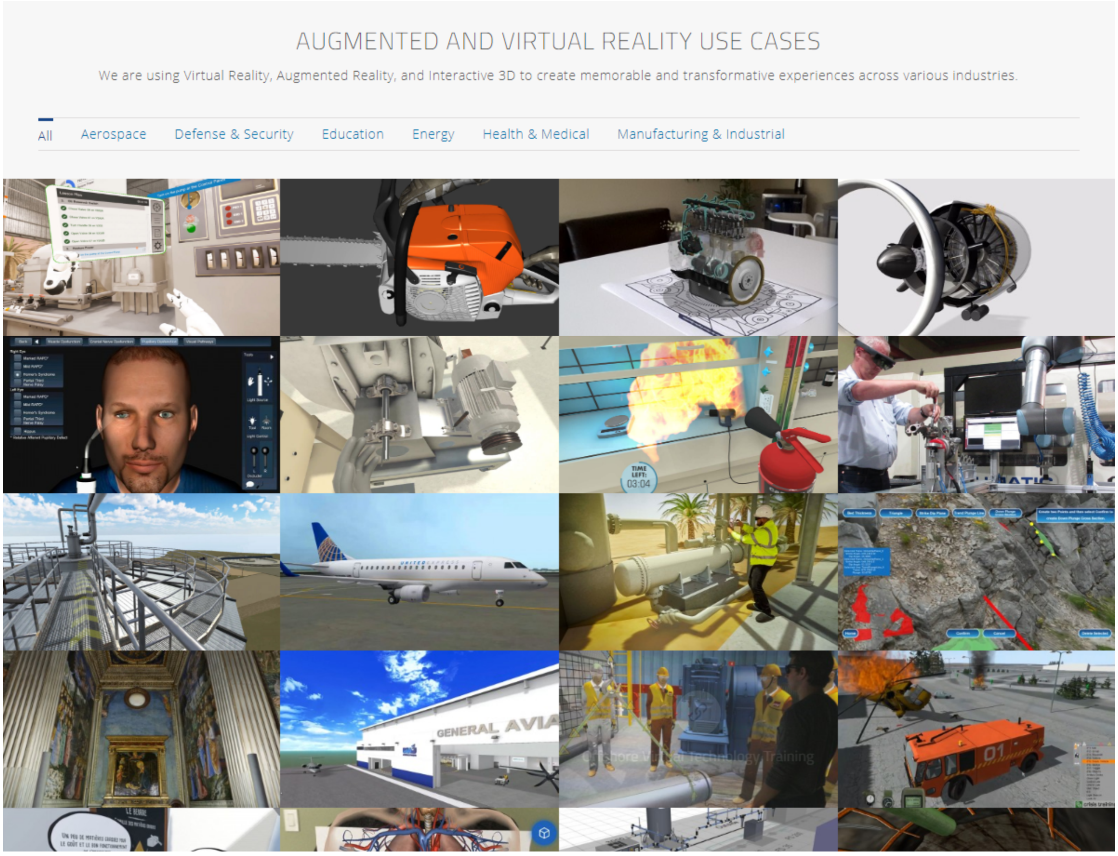


Figure 1.1: Usecases by EONReality on their AVR plattform. https://www.eonreality.com/use-cases/ (accessed 30.07.2019)

the following question: Does the perspective has influence on learning in MR environments? Furthermore, to develop guidelines for MR learning environments, it would be helpful to know if the there are conditions where either of this perspectives is more suitable than the other. Since learning and training in MR is a vast area, the topic is narrowed down to the subset of motor learning. This seminar thesis is the first out of three parts, followed by a Masters Project and a Masters thesis. The overall aim of this work is to answer to following research question:

RQ1 Does the perspective on a virtual avatar has influence on learning in MR environments.

The outcome in this work is a study design that will be able to address the research questions. In the Masters project the proposed study setting will be implemented, to be able to conduct the study and collecting the data necessary to answer the

Figure 1.2: Remote maintenance with Hololens by Smart Glass Experience Lab. The on site worker wears a Hololens, while the remote trainer draws green hints to resolve a miswiring, taken from https://www.youtube.com/watch?v=1QFMPo5k6p0, accessed (30.07.2019)

question. The Masters thesis itself will take the generated data to answer the research question.

1.2 Outline

For a proper study design many aspects must be taken into consideration. The main aspects this thesis will discuss are defined in the following, while further aspects like algorithms are discussed in the masters project.

S1 Visual perspective

S2 Motor learning

S3 Mixed reality

C1 Study Task

C2 Perspective implementation

C3 Guidance visualisation

C4 Dependent Variables

Each of these aspects must be chosen wisely. In order to do so this seminar thesis will systematically go through every one of them. Chapter 3 sets the scope of the study and provides general knowledge about the domain. The following chapter 4 analyses the work of researchers and their systems, to find suitable components for the scope that has been set in chapter 4. Here, the remaining aspects are analysed from a more practical view and it is investigated how researchers decided about the aspects and why. Whenever a decision is made to be used in the proposed
A* study design, a symbol on the side of the text can be found . After all aspects are clear and reasoned, a study design is proposed in chapter 5. In the end, an outlook on further work on the Masters thesis is given and highlighted what aspects are still to decide of.

TODOgraphical representation

2 Theory and Scope

Motor learning in MR builds on many aspects, eg. suitable technology for MR representations and what perspectives to use. Furthermore, human motor learning must be suitably transfered in the digital world. And eventually, we need to match movements and measure the error correctly to derive adequate from the performance of a learner. In this chapter we take a look into these topics. If not other indicated, adopted from the book Motor Learning and Skills [12].

2.1 Visual Perspectives

Wang and Milgram [16] describe the perspectives on the centricity continuum see figure 2.1. On the most left hand side of the continuum the egocentric perspective is located. Egocentric means that the anchor of the viewport camera is located inside the object to control - for simplicity, this object in question is referred as avatar. On the left hand side the exocentric perspective is located. This viewport camera is a fixed camera in the scene not to be controllable. The exocentric perspective gives the user the possibility to examine the scene from a bird's-eye view. The movement or angle of the avatar has no influence on the cameras position or angle. So the main difference is the so called tether distance and the degree of freedom of the camera. Milgarm and Wang investigated on tethered cameras and define it as the distance between the avatar and the camera which is following the avatar. This describes the middle part of the continuum. Zero-distance camera describes the egocentric perspective. The longer the tether distance the more the perspective is located on the right of the scale to the exocentric perspective. They also distinguish between dynamic and rigid tethering relation ships. A dynamic tethered camera is controlled by the user in all six dofs (**TODO**) while a rigid stands like a pole and can only be controlled in 3 dofs. Rigid tethered cameras are common in modern 3rd person computer games.

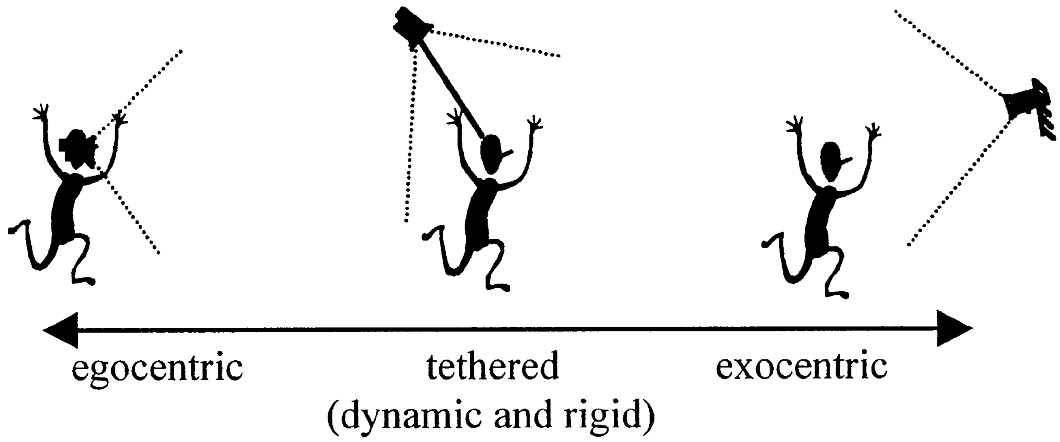


Figure 2.1: Centricity continuum by Wang and Milgram 2001 [16]

Degree of realism of teacher avatar

first some paper collection about how the virtual avatar looked like, and then decide for what rebeccas work proposes. its a lot about related work, so maybe
A14 this should go in the next chapter. what would be more work.

Feedback and instruction behaviour

feedback **TODO**can be given verbally, in MR visually ... example 1,2 and 3, but in the end: we do not want to evaluate feedback so there will be none in
A15 the study . In addition, for high validity instructions must be the same, so a
A11 pre recorded instructions necessary partly answered, but lets look in next chapter about continuity in instruction.

2.2 Motor Learning

Learning movements

In the real world Motor learning takes place by instruction, trying, imitation or a combination of two or all three. A learner can observe another person and imitate the movement, try to accomplish a task by themself or can follow instructions. Instructions can be written, visual or verbal. Written instructions are not bound to words solely, eg. Rudolf van Laban developed a dace notation system, compare section "quantify movements" 2.2 and figure 2.4. Visual or verbal instruction include a trainer, teaching the student movements. In this case verbal and physical

feedback also plays a role in the learning process. The process of motor learning is divided in three parts. Once a student starts learning using what ever technique, it starts in the *cognitive* state. In this stage the students tries to figure out what is to be done to achieve the task. For this high cognitive activity is required, strategies are evaluated. The performance gains dramatically and is larger than in any other stage, but also inconsistent. The use of instructions and other training techniques are most effective. The next stage is the *fixation*. It begins when the student had determined the most effective way of doing the task. Performance increases more gradually but becomes more consistent. In the last *autonomous* stage, the performer gains proficiency and other tasks are less likely to interfere. Since the use of training techniques and the high performance gain in the *cognitive* state, tasks in this stage are best suited for the study. This will be considered in the next chapter, too.
In the digital world most of this remains like it is in the real world. But with computational power new learning techniques can be used to teach motor learning. Instructions can be given visually by a teacher without the teacher being physically in the room, eg. by video instructions or virtual avatars. Also remote instructions become more practical eg. in video conferences.

Movement classification

For a simplified discussion a classification of movements is provided in the following. There are two important classification schemes. The first one is based on the particular movements performed and are divided into *discrete*, *continuous* and *serial movements*. The second one is based on perceptual attributes of the task and are divided into *open* and *closed skills*. Both classification representing a continuum.

Discrete, Continuous and Serial Movements

Discrete movements are located on the one end of the continuum. These are movements with a recognisable beginning and end. The end of a discrete movement is defined by the task itself and can be very rapid like blinking or longer like making the signing. Examples are kicking a ball, shifting gears in a car or striking a match
Continuous movements are located on the other end of the continuum. These movements don't have a recognisable start and end, with behaviour continuing till the movement arbitrarily stopped. Continuous tasks tend to be longer than discrete tasks. Examples are swimming, running or steering a car.
Serial movements are located in the middle part of the continuum. Following the nature of a continuum these movements are neither discrete nor continuous.

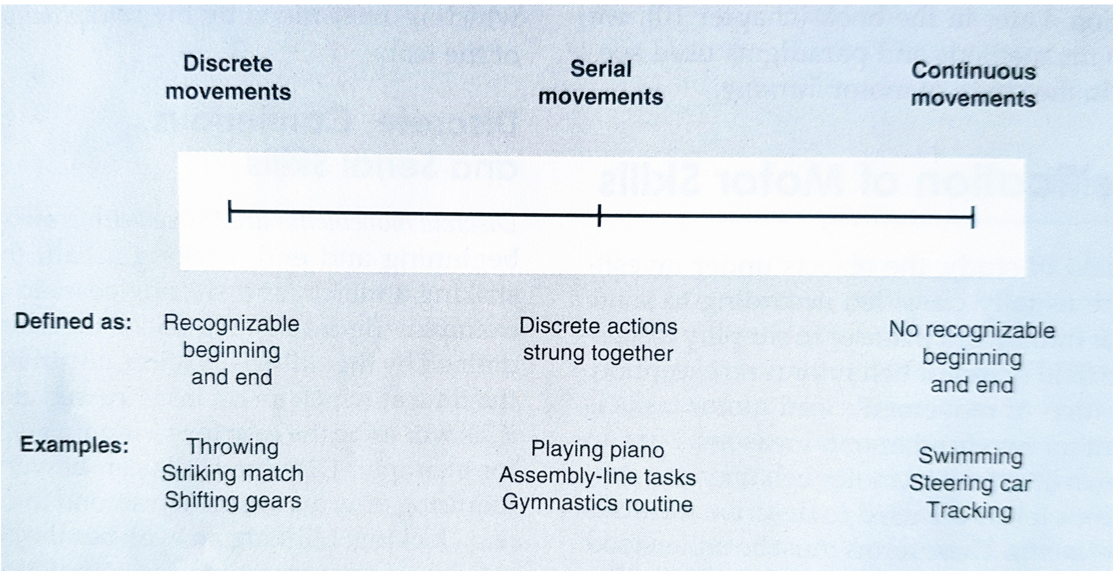


Figure 2.2: Continuum of movements buch [12]

They can consist of smaller movements tied together. Furthermore, discrete movements can be rather long but are not stopped arbitrarily. Serial tasks can be seen as many discrete tasks strung together and the order (and sometimes timing) is important. Examples are starting a car or preparing and lighting a wood fireplace. The nature of *Continuous movements* having no recognizable beginning and end makes it hard to describe a distinctive task for a study design while *discrete movements* are to short for a proper task, *serial movements* are choose for the study
A3 task .

Open and Closed Skills

Open skills: The environment is constantly, unpredictably changing, so the performer cannot plan his activity effectively in advance. Own movements depend on the environment. For example, if a ice hockey player shoots a shot in ice hockey, his own movement is dependent on the movement of the keeper. Another example is driving on a free way. The driver needs to adjust his own driving dependent on the behaviour of the other cars. Success in open skills is largely determined by the extend to which a individual can adapt the planned motor behaviour to the changing environment.
Closed skills: The environment is predictable, mainly because it is stable. This means that the performer can plan his activity in advance. Examples are bowling, archery or singing. To evaluate only the motor learning and not environmental in-

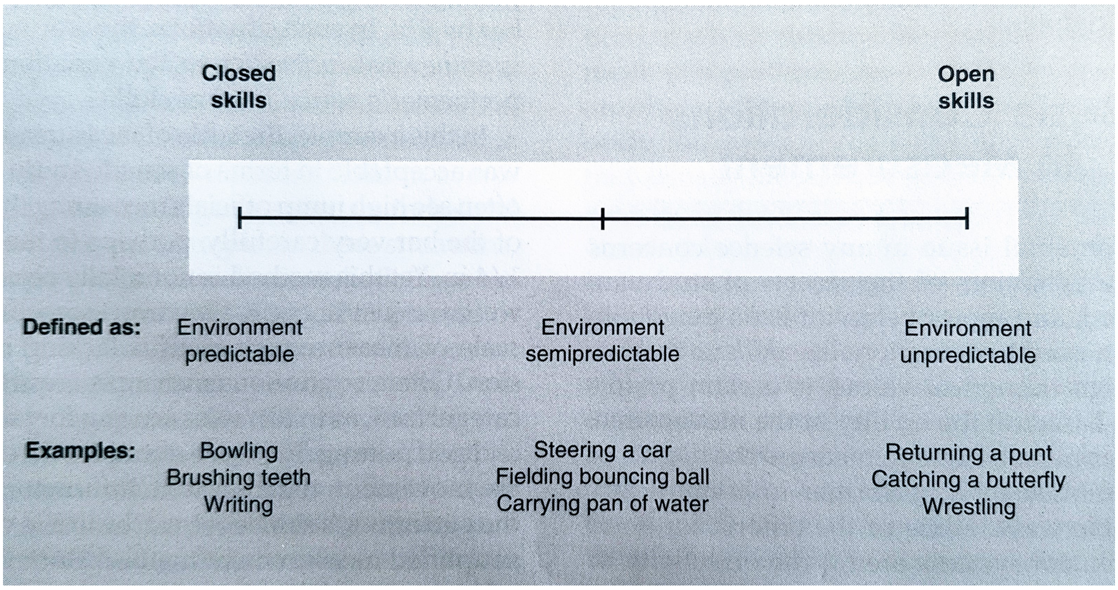


Figure 2.3: Continuum of skills [12] TODOseite

fluences the study is conducted in a controlled environment in a laboratory. Thus only *closed skills* are taken into consideration .

Quantify movements TODOin measures

Judging motions and matching them to a given motion is not a trivial task. Since eg. dancing is a pure physical task, movements must be recognised, digitalised and judged. One approach is to use a analog descriptions for dancing and translate them in the digital world. Choensawat [6] began with Rudolph von Laban - a professional dancer. Von Laban developed a broadly used dance notation. His work lead to the *Laban Movement Analysis* with which human movements could be quantized.[1] There are four main components to systematically describe movements in the *Laban Movement Analysis*: body, effort, shape and space. Each component can describe movements independently or combined. Hachimura et al. [9] used the methodology of *Laban Movement Analysis* and adopted it to for digital movements.
Yoshimura et al. [17] followed a similar approach from another dance movement description theory called *furi*. *Furi* is also described by four so called *indices*: *kamae*, *jyu-shin*, *koshi*, *uchiwa*. Yoshimura at all could map these indices to concrete markers on the body of a performer. Qian et al. [8] developed a gesture recognition

[1] Brockhaus, Rudolf Laban. http://www.brockhaus.de/ecs/enzy/article/laban-rudolf (accessed 2018-10-25)

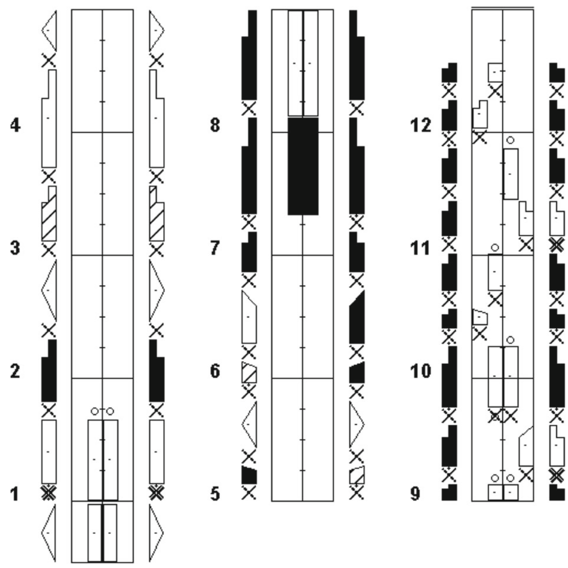


Figure 2.4: Laban notation. Generated through automatic movement interpretation by Choensawat [6]

system for performing arts. To match the motions ten body parts were defined: head, torso, upper arms, forearms, upper legs and lower legs. For each body part the Mahalanobis distance is calculated to an ideal point. The Mahalonobis distance describes the distance between point p and distribution D.
So the takeaway message is, there is a need to digitalise movement and then apply suitable algorithms to judge these movements. The algorithms will be discussed in the Masters project.

Measuring movements

In order to judge if a movement is performed correctly methods need to be applied to measure the error of a performed action. In literature, three main categories are listed: *error of a single subject*, *measures of time and speed* and *measures of movement magnitude*. As chapter 3 will show, *error of a single object* is most commonly used, the latter two are only discussed in short.

Measures of Error for a Single Subject

Measures of error for a single subject represent the degree to which the target was not achieved. A target can be to perform an act at a particular time (time stamp), move with a certain force (amount of force) or hit a spatial target (a point in spatial volume). The attribute of the target serves as the variable in question, see braces behind the examples. The error itself describes the distance - in regard to the dimension - from the target. The following list gives an insight to the most important error measures.

- ***Constant Error*** describes the average error between the actual accuracy and the target. Means, in average the performer missed the target by CE.

$$CE = \frac{\sum_i (x_i - T)}{n} \tag{2.1}$$

  with x_i: score, n: number of values, T: target value.

- ***Variable Error*** measures the inconsistency in movements. The more consistent the movements, the smaller VE. VE does not depend on whether or not the subject was close to the target.

$$VE = \sqrt{\frac{\sum (x_i - M)^2}{n}} \tag{2.2}$$

- ***Total Variability*** describes the total variability around a target. The combination of VE and CE represents the total amount of spread about the target. It is an overall measure how successful was the subject in achieving the target.

$$E = VE^2 + CE^2 = \sqrt{\frac{\sum (x_i - T)^2}{n}} \tag{2.3}$$

  with x_i: score, n: number of values, T: target value.

- ***absolute error*** is a measure of the overall accuracy in performance.

$$AE = \frac{\sum |x_i - T|}{n} \tag{2.4}$$

  with x_i: score, n: number of values, T: target value.

- ***Absolute Constant Error*** is the absolute value of CE. Because of negative and positive values can cancel each other out

$$ACE = |CE| \tag{2.5}$$

Measures of Time and Speed

Basic to this idea is, a performer who can accomplish more in a given amount of time or who can accomplish a given amount of behaviour in less time is more skillful. Measures here are $\frac{time}{unit}$ or $\frac{units}{time}$.

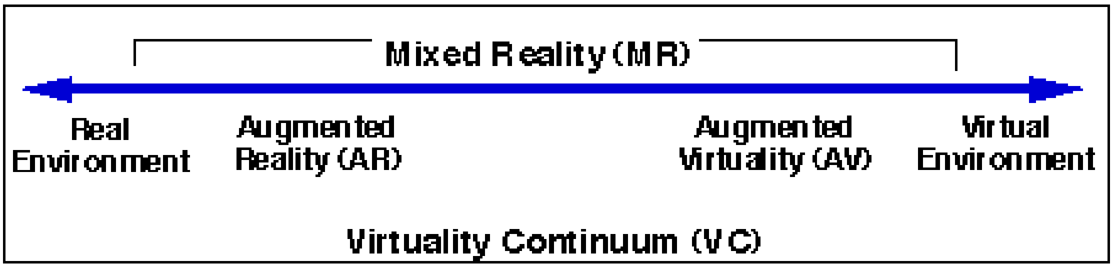


Figure 2.5: Mixed reality continuum by Milgram et al. [11]

The two most common examples are *reaction time* (RT) and *movement time* (MT). Reaction time describes the amount of time between a stimuli and the regarding start of a movement. This time span is important for two reasons. On the on hand, RT has a high validity for real-life tasks, and, on the other hand, RT measures the time taken for mental events like stimulus processing or decisinón making.
Movement time is the time interval between the end of the RT phase, though the start of the response, and the completion of the movement. The sum of RT and MT is called *response time*.

Measures of Movement Magnitude

To measure a skill, the produced magnitude of a behaviour can used. Eg. the distance a discus is thrown. A famous example is the "ski simulator". Rubber bands hold a plated centred between two poles. The magnitude in this case is the the dislocation of the board from the centre by using full body movements.

2.3 Mixed Reality

Mixed reality continuum [11] and something about when AR or VR is better. 2.5
A7 **TODO**

VR Technologies

HMD,3D screens, tablets.... **TODO**or in project

Motion Tracking Technologies

External vs. internal tracking. Drift problem, accuracy... **TODO**or in project.

2.4 Conclusion

we dicided for A1 A2 ... will be used in study ... some aspects missing, lets have a look how other researchers choose there, what we do in the next chapter.

3 Related Work

TODO: remake description!
Define study parameters by analysing related work.

3.1 Overview

aggregated overview over the rest of the papers goes here.

table with overall conclusion

Study Task	Implemented Perspective	Guidance Visualisation	Dependent Variables	Results	

Table 3.1: Table of the conclusion

3.2 Analysis

Study task

The task in Chua's [7] **Tai Chi trainer** is – as the name indicates – a Tai Chi motion. A professional Tai Chi trainer was invited to perform a so called *Tai Chi form* and recorded offline. This *form* was segmented in four ca. 20 seconds long sequences (Motion 1-4). "Motion 1 featured simple hand movements and a 90 degree turn to the right; motion 2 had little hand motion, a 180 degree turn of the feet, and some turning of the upper body; motion 3 featured slow hand motions, large movement of the feet, and some turning of the thorax; and motion 4 featured swift hand movement and turning of the thorax and hips but little movement of the feet." [7]. Error measurements indicated that all motion but motion 1 had the same difficulty, being significantly easier. This movements can be classified as *sequential movements* according to chapter 2 **TODO**ref. 40 volunteers conducted the movements in a study to evaluate their system. They randomized the condition (described in next chapter, compare figure 3.2 condition a-e) and the motion to minimize learning effects. For each motion and condition pair, the Tai Chi student were asked to match the Tai Chi teachers demonstration during twelve repetitions.

YouMove by Anderson et al. [2] is a movement training system, suitable for a vast range of moves. A movement can be recorded and then edited by an authoring tool. After the editing, the movement is added to the internal library, from which it can be chosen by a student. For the study itself, an author or the paper – though no professional – recorded four movements. Two of them from ballet and two abstract movement. The authors decided to variate the difficulty of the task, namely "the ballet movements [...] were easier to conceptualise and required only moderate movement.", while "the abstract movements were more difficult to perform, as they were a series of postures with no clear structure and required substantial movement." The movements consisted of four keyframes. Keyframes are important points during the movements, determined and set by the person recording a movement.

Jacky Chan et al. developed a **VR Dance trainer** [5]. For their system they invited professional Hip-Hop dancers and recorded their movements. The learner of the movement can choose a movement out of a database. One movement lasts around 2 seconds. First, the teacher appears and the student watches the demonstration, while he can adjust the demonstration speed and viewpoint. After that, the student practices the dance moves by mimicking the teachers avatar. Finally the student can see a slow motion replay of the performance. One hole session takes 15 minutes.

In contrast to all other systems, **Lightguide** by Sodhi et al. [14] build on abstract movements to evaluate their system. Sodhi et al. focus on single arm movements, directed by an guidance visualisation on the hand. The participants perform five movements, namely a line, a "N", a square, a circle and a bowed line, compare figure 3.1 left. All movements were performed in three different angles, like shown in figure 3.1 right.
TODOThese movements were performed with six conditions resulting in 90 dataset per participant (6 conditions x 5 path x 3 angles).

Onebody by Hoang et al. [10] is designed for sports or physical activity training like yoga, dance or martial arts. For the study they used a Martial Arts movement. Each participant started with a training session in which a remote instructor teaches a posture physically and verbally. Verbal feedback was given and the training repeated until the student was confident. After that the final posture was recorded. This applied for four postures with different complexities.

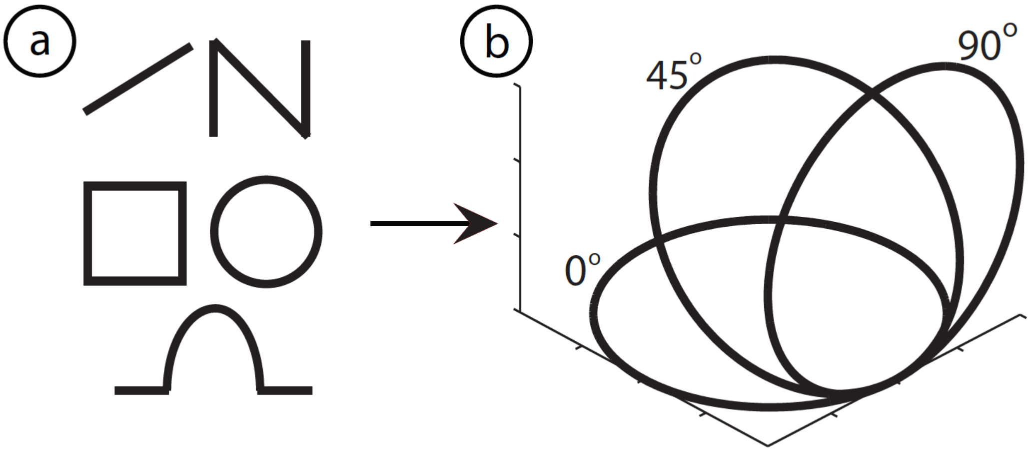


Figure 3.1: movements by lightguide [14]

Physio@Home by Tang et al. [15] aim to support rehab exercises for patients at home. Tang et al. chose the shoulder segment as study object, because particpants could do this movement easily while standing, and the ball-socket joint gives more dofs than eg. the knee. In the study itself, 4 tasks had to be completed: straight, angled, elbow and combo.

straight "Abduction of arm along the frontal plane up to shoulder level, followed by adduction of arm back to the participant's side. This is a simple frontal plane exercise. Angled."

angled "Abduction of the arm at 45° from the frontal plane, followed by adduction back to the side. This is an angled variation of the Straight exercise, where interpreting the angle may be difficult."

elbow "External rotation of forearm away from the center of the participant's body until 90° from the sagittal plane, followed by an internal rotation back to center. This exercise requires the participant to keep their elbow tucked against their side and is a difficult exercise to understand without depth cues (i.e., with just a frontal view)."

combo "Abduction of the arm along the frontal plane up to shoulder level, internal rotation of the arm until pointing forward, followed by an external rotation of the arm back to the frontal plane, and adduction of the arm back to the participant's side. This is a more complex exercise than the previous three, involving many components."

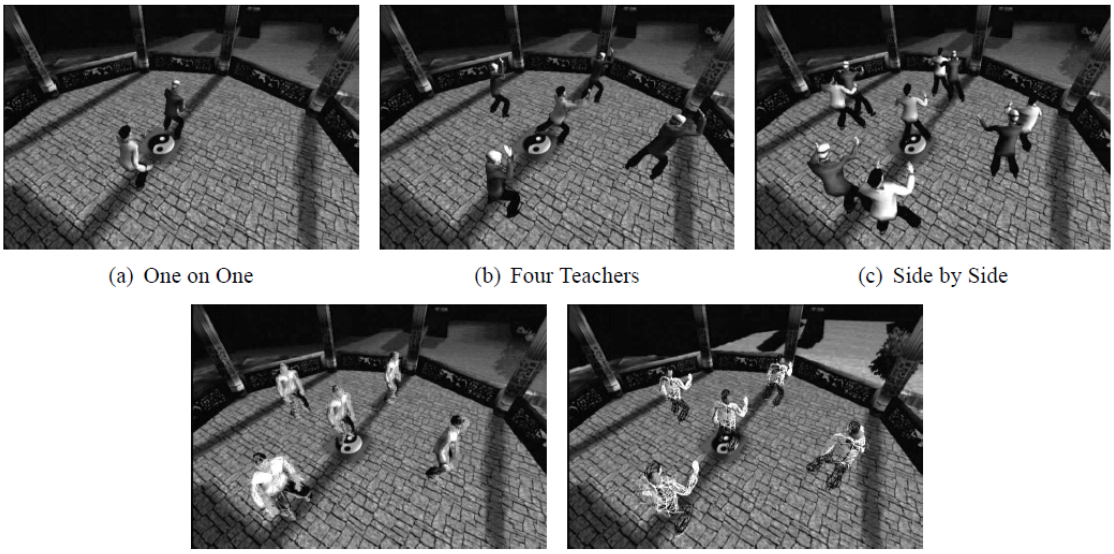
Conclusion

As we see in this section, there is a verity of tasks to evaluate movement learning. Namely a Tai Chi form (Tai Chi Trainer [7]), dance movements (YouMove [2] and VR Dance Trainer [5]), physiological rehab movements (Physio@home [15]), abstract movements (YouMove, LightGuide [14]) and Matial Arts (OneBody [10]). For the latter is to mention that the evaluation aimed for postures and not movements. To gain valid data some choose to have tasks with comparable complexity ([7], [2] inside Ballet tasks and inside abstract tasks, [14]), therefore eg. one Tai Chi form was taken and split into four sub forms. Physio@home and YouMove (between ballet and abstract) chose to have different complexities of tasks. All but Tai Chi Trainer proofed to be valid for evaluation of movements. But the authors of Tai Chi Trainer see the reason in the hardware performance, what could be overcome with today's technology. All systems but LightGuide aim to be a teaching system for real world tasks. The aim of this thesis is to evaluate the influence of the perspective on guidance visualisations itself, though, both tasks – abstract and real world tasks – seem suitable for our system. Max, hier dann entscheiden ob was für tasks.

Implemented Visual Perspective

Chua et al. [7] implemented five different perspectives to teach with **Tai Chi Trainer**, compare 3.2. There are three exo-centric perspectives (a-c, further called conditions a-c) and two ego-centric perspectives combined with exocentric (d,e, further called conditions d,e). In **One on One** the student stand next to one teacher, which is closest to a real world training scenario 3.2(a). In con – **Four Teachers** – the student is surrounded by four teachers, with the student in the middle 3.2(b). The **Side by Side** 3.2(c) condition shows four pairs of teacher and student in the same formation as in condition (b). The first ego-centric & combined condition is called **Superimposition 1** 3.2(d). Here the formation still remains, but the student in the middle is surrounded by four more students. On each of the student a red wireframe teacher is superimposed. **Superimposition 2** 3.2(e), is similar to Superimposition 1 and differs only in the visual representation: the student is now a green, transparent wireframe. Chua et al. use no pure ego-centric perspective, since in the latter two conditions the teacher can be seen also from the exo-centric perspective.

YouMove uses Microsoft Kinect (**TODO**ref) to record motions and to track the student. The recorded instruction as well as the students movements are projected on an AR mirror. The special about this mirror is, that the degree of reflection can be changed by simply adjusting the light in the room. With this, the student



(a) One on One (b) Four Teachers (c) Side by Side

(d) Superimposition 1 (e) Superimposition 2

Figure 3.2: Used perspectives at [7]

can see his own real body as reflection as well as the projection of a beamer simultaneously. If the room is bright, the student sees only his reflection and in a dark room only the projection is visible.
YouMove provides multiple stages for the learning process: (1) Demonstration, (2) Posture Guide, (3) Movement Guide, (4) Mirror, (5) On your own. In stages 1-3, the student sees the guidance visualisation in the exo-centric perspective. In (1) the user sees a video of the movement. In stage 2 & 3 the user is superimposed by a skeleton. Stage 4 & 5 does not allow a view on the teachers representation. After each stage a feedback is given. This view provides multiple views for the four keyframes: a skeleton of the teacher and student superimposed, a video of the teachers demonstration and a video of the moves of the student.

Tai Chi Trainer. Chan et al. [5] facilitate a 3D screen for rendering the avatars. The student is tracked by an optical motion capturing system. In the first phase (demonstration) only the teacher is shown on the screen. In the second phase (practise) teacher and student can be seen simultaneously, standing side by side. Additionally, both avatars are mirrored, so the exo centric viewer can observe the avatars from back and the front at the same time, compare figure 3.3. In the final phase (feedback) the student sees the teacher and the students performance in slow motion side by side.

LightGuide [14] achieved an ego-centric guidance without using a HMD. The student stands under a depth camera and a projector. The depth camera tracks the hand of the student. This position is utilised and the guidance visualisation is projected directly on the users hand. During the evaluation of the system, four conditions used this ego-centric position. The remaining conditions shown exo-centric on a screen or directly on the hand.

Onebody [10] show the guidance visualisation in an ego-centric perspective, too, but with an HMD. The teacher is projected inside the body of the student. Both, teacher and student are tracked by skeletal tracking, using a Microsoft Kinect **TODO**. The visualisation of the teacher is attached to the hip of the student. To overcome different body sizes, the avatars are normalised and scaled to the size of the student. For a second condition an exo-centric view is provided with a HMD, too. There the teacher stands in front of the student.

Physio@Home by Tang et al. [15] used a Microsoft Kinect in combination with a screen forming together an augmented reality mirror. The participant stands in front of the screen and is tracked by the Kinect. On the screen the participant is augmented by moving instructions. The perpective on the guidance visualisation is exo-centric. Tang et al. faced the problem, that the front facing projection lacks of 3D queues. Their solution was the multi camera views. A second view is provided from above, aiming to help the participant to maintain a correct angle of the arm. In the study, four conditions were examined: videoSingle, videoMulti, wedgeSingle and wedgeMulti. Here, video and wedge indicate the guidance visualisation, single and multi indicate the numbers of visualisations.

Conclusion

There are multiple ways of realising ego-centric, exo-centric or combination perspectives on guidance visualisations. Ego-centric views are realised through superimposition of the teacher and the student like seen in Tai Chi Trainer and OneBody or projected movement instructions directly on the student like in LightGuide. The first two use an HMD to realise the ego-centric perspective. For the exo-centric perspective more possibilities exist like an augmented reality mirror (YouMove), screens or 3D screens (Tai Chi Trainer, Physio@Home) or projectors (LightGuide). Exo-centric perspective can also be achieved with HMD's (OneBody, Tai Chi Trainer). One main benefit of HMD's is the easy visualisation of ego-centric and exo-centric perspectives simultaneously. Because of this I decide to use an HMD for my study. The Tai Chi Trainer achieved the simultaneous perspective by placing the teacher inside the student and outside the student, but did not achiev any significant differences in learning performance; but this could be overcome by today's technology. This representation is chosen for the study. In addition, the authors of the paper state the importance of multiple view (Physio@Home, Tai Chi Trainer, YouMove), if the avatar is rendered on 2D screens, because of missing 3D queues. This can be partly overcome within a VE. But to provide multiple angles on the guidance visualisation could still be necessary. Therefore I decide to let the student moving freely around the guidance visualisation. Since other factors like feedback play also a role for the perspective, the exact definition of the perspective to implement is given in the conclusion of this chapter.

Guidance visualisation

Chua's **Tai Chi training** scenario takes place in pure VR using a HMD. The lessons are conducted in a virtual pergola standing in a nature or park environment. In condition a to c (compare 3.2), the student and the teacher are rendered as non transparent, high realism degree avatars. However, in condition d and e, the visual appearance changes. In condition (d) the student is still rendered normally but the teacher is now represented as a red wireframe. Condition (e) was introduced late in the development of the system based on early subject feedback. The students here are rendered as green wireframe avatars and the teacher as red wireframe avatars.
In terms of guiding technique, the student is presented the pre recorded motion of the teacher. The teacher avatar performs the motion in question and the student tries to mimic this motion. During the mimicking process no feedback is provided to the student. But in condition (d) and (e) the teacher is superimposed on the students avatar. This can be interpreted as feedback since the difference between the students e.g. arm position and the teachers arm position can be seen easily.

The visualisation of the teacher in **YouMove** is rendered in a low degree of realism – only a stick figure in yellow. During the feedback screen after each stage, the student is also rendered as a stick figure but in blue. For teaching, YouMove utilise the above mentioned five training stages. In the first stage (Demonstration), a video of the teacher performing the movements is shown. The student only sees the video and not the reflection of the own body. The second stage (Posture guide) a video and the stick figure of the student are shown, but still not the own reflection. The student is asked to match they postures at specific keyframes, where the demonstration stops. After matching the posture of a keyframe, the demonstration moves on to the next keyframe. In the third stage (Movement Guide) the demonstration no longer stops at the keyframes. Furthermore, the reflection and the projection are visible simultaneously, the student is superimposed by the teachers stick figure. (**TODO**change skeleton to stick figure). Stage four (Mirror) is like the name indicates: the student stands in front of the mirror seeing only his

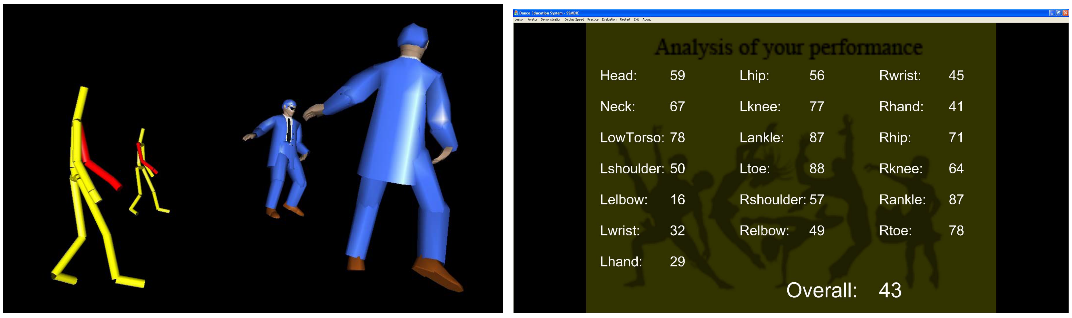


Figure 3.3: **TODO** [5]

own reflection but additionally audio queues are provided. In the last stage (On you own) even the mirror is removed and the student performs the movements without any guidance.
In terms of feedback, Anderson et al. state "[...] the availability and modality of feedback can greatly impact skill acquisition". To match this, feedback is a part of YouMove. During the second stage (Demonstration), red circles indicate misplaced limbs. The bigger the circle the bigger the misplacement. Additionally, a side view on the scene is faded in. At the end of each stage, a so called "summary feedback" is provided. Here the both stick figures of the teacher and student are superimposed and a video of both can be seen. Eventually a score is provided, which will be explained in the next chapter.

The visualisations in Chan et al. **VR Dance Trainer** choose two different visual representation. The teacher is show as a high realism degree avatar, while the student is shown as a low realism degree stick figure. The students stick figure serves additionally as feedback regaring the students performance. The body parts are coloured from green (perfect motion match) over yellow (acceptable motion match) to red (poor motion match). In all phases these visual representations stay consistent. In the first phase (demonstration) no feedback is given, in the second phase (practise) the student gets immideate feedback in the colour code descibed above. The last phase provides a slow motion replay showing with feedback in the same colour code. Additionally, the student can get feedback by the socre board see figure 3.3 right. Here all body parts are shown with a nummeric indicator (0-100) how good the motion was performed on the specific body part.
LightGuide [14] compare six guidance visualisations:

- Follow Spot: Moving light spot with elevation information. System sets pace.
- 3D F-Arrow: 3D arrow indicates the direction to move. System sets pace.

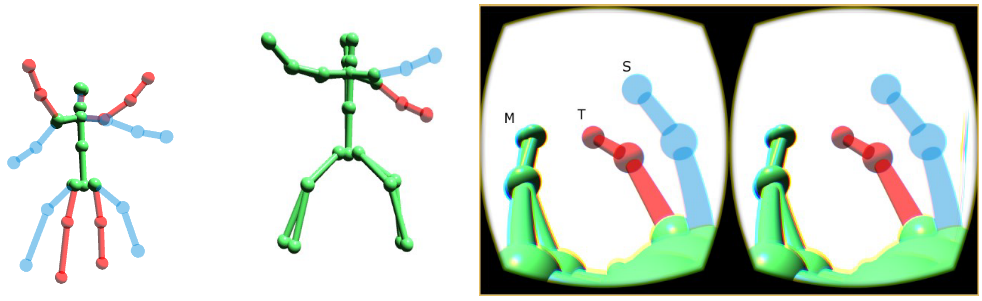


Figure 3.4: Left: student avatar (blue) and teacher avatar (red). Green limbs are matching limbs. Right: students view on the scene. [10]

- 3D SG-Arrow: 3D arrow indicates the direction to move. User sets pace.
- 3D Pathlet: a line indicates the direction to move next. Current position indicated by a red spot.System sets pace.
- Video on hand: Instruction video projected on the hand. User sets pace.
- Video on screen: Traditional instruction video .User sets pace.

The main idea behind a guidance visualisation directly on the students body itself, is that the student can concentrate on the bodypart in question and not share the with a instruction medium. The last condition proofed to be better than the second last, supporting this theses. The student gets instant feedback by comparing the indicators with the hand. A larger offset results in increased indication in real time.

OneBody [10] use low realism degree avatars. Both, the student and the teacher are visualised by stick figures. The teachers avatar is red, the students avatar is blue. For feedback, if the students joints are matching joints of the teacher, these joints turn from blue to green, like shown in figure 3.4 left. Figure 3.4 right shows the scene from the first person perspective. The guidance itself takes place in real time. The remote teacher can give instructions by performing the postures and additionally verbally. The student mimics the postures and can compare his own joint positions with the positions of the teacher to correct the own joints. Hoang et al. compare the performance of the students achieved in Onebody with the performance in three other systems, namely with traditional video based learning, video conferencing and a 3rd person perspective in VR. The latter is very similar with Onebody but the teacher stands in front of the student. The system differe in exactly one aspect to each other, see figure 3.5. **Physio@Home** by Tang et al. [15] use two guidance techniques. In the first, a video shows the movements instructions, the second they called "the wedge". The latter is a 3D plane showing

	Video	*Skype*	*VR-3PP*	*Onebody*
Synchronous Interaction	No	Yes	Yes	Yes
VR Medium	No	No	Yes	Yes
1st Person View	No	No	No	Yes

Figure 3.5: Training methods and their differences used in the study to evaluate Onebody [10]

the way of movement with direction indication. As feedback the current angle of the arm is shown. **TODO**figures

Conclusion

The visual appearance of the guidance visualisations differ. The Tai Chi Trainer, YouMove, VR Dance Trainer and OneBody use person like avatars. These avatars perform a movement and the student mimics these movements. LightGuide and Physio@Home use direction indicators to visualise the movement in question. Movement indicators like arrows are less obtrusive for single body-part movements but become overwhelming for full body instructions. This work aims to analyse full body movements, therefore I choose here as visual appearance a person shaped avatar. The degree of realism of the avatar rage from stick figures to high realistic looking persons. Since Weber**TODO**showed a preference for realistic avatars I hereby choose high realism degree avatars as guidance visualisations. In addition, there is a difference in completion time based on the guidance technique. If the student sees the movement before hand completion time is significant lower. If the student grasp the movement by performing it, completion time is significant higher. A study must ensure that for all conditions the student could see the movement before performing the movement or not. Comparing with the real world, normally the student sees the movement before hand. This is why my study will provide this, too. Sodhi et al. state, that it is hard to compare self paced and system paced movements. To ensure comparability, only system paced movements will be evaluated. This ensures also only to evaluate precision of movements. In all systems feedback plays a role. Immediate feedback as well as aftermath feedback. For comparability, feedback must be consistent over all conditions. As Anderson et al. made clear, it is an important part for movement learning. This thesis does claim to provide full training system but an evaluation tool. For this reason only immediate feedback during learning will be provided. To ensure, that only the perspectives and not feedback is evaluated, exactly one and the same feedback method will be provided in all conditions. I choose here the overlay feedback without colour coding, where the student align his/her body with the body of the teacher avatar. Eventually, all authors point out the importance of scaling. To correctly match teacher and student, the teacher must be scaled to the students body.

Dependent variables

In the Tai Chi trainer by Chua et al. [7], the students task is to mimic the motion of a pre recorded teacher. While the independent variables are the above mentioned perspectives (conditions a-e) and the motions, the independent variable is the precision of the performed movements. To measure this precision, twelve bones of the students were tracked, namely: upper and lower arms, hands, upper and lower legs, and feet. The bones are hierarchical structured with a parent and child end. After a normalization of the parents position and bone length, an error was calculated:

$$\textbf{TODO} \tag{3.1}$$

This error can be seen as the euclidean distance between the teacher's and the student's position of a bone. This error was calculated for every frame of the roughly 20 seconds with a rate of 60 fps:

$$\textbf{TODO} \tag{3.2}$$

The last four out of twelve trials were considered. So the measure of precision is described as:

$$\textbf{TODO} \tag{3.3}$$

This measure is an implementation of chapter 2 ref **TODO**. Chua et al. found two major faults in this method of precision determination: yaw shift (**TODO**add in chapter 2 a definition of dofs) and time shift. To overcome the first, the initial position of the student was taken into account, the latter was fixed with a time frame comparison of 120 frames. Eventually this result was normalized with the difficulty (average number of errors per motion) of the motion task. This will be discussed in detail in the Projects Report. In addition, a post questionnaire was conducted where the students were asked to rate the difficulty of the representations. The results are discussed in the next section.

While Chua et al. calculate the error of the performed movement over all tracked limbs, Anderson et al. take one single joint with the greatest error and – even more constricting – only the keyframe joints (important joints, specified by the teacher) are taken into consideration. The dependent variable is a score between 0 and

10. An offset 15 cm results in a score of 7.5 and no error results in a score of 10. The offset is imply the eucledean distance. This error measurement corresponds to chapter 2 **TODO**. To overcome time shift errors, a window of 0.5 seconds is added. If the teacher specified that timing is important, this window is halved, if precision is set as important, 15cm offset results in a score of 7.5. "[]This values are determined by experimentation".

Chan et al. evaluate the students performance with the VR Dance Trainer. Therefore they specified 19 body parts (compare 3.3 right) and calculate a score between 0 and 100. The average over the 19 numeric indicators results in the overall performance. Before and after the training session of one move this score was calculated. Additionally, a postcourse survey asked the student specific questions about the system. This survey had the aim to evaluate if the "[...] system is interesting and able to motivate subjects to learn." [5] and if the "[...] the system can provide them an easy way to learn" ibidem.

Sodhi et al [14] compare in **LightGuides** evaluation the five conditions where the instruction in directly on the body of the user with a baseline condition where the instruction is on a screen. To measure the performance of the student, Sodh et al. developed two measures: movement accuracy and movement times. Movement accuracy describes the absolute euclidean distance from the closest point. Movement times is devided in two sections by the reason that half of the conditions were self timed and the half the pace was set by the system. For the self timed conditions the completion time is taken as measure, for system paced conditions the time before or after is taken as measure. Though, independent variable are the conditions, dependet variables are performance.

Hoang et al. [10] use six different measures to evaluate **Onebody**. *Accuracy*, *completion time*, *instructors score*, *ease to understand*, *perceived precision* and *preference*. For *accuracy* the angles of limbs of the student and teacher were compared. This corresponds to **TODO**. For *completion time* the time between start and "[...] the student feeling confident" was measured, but caps at 2 minutes. *Instructors score* is a subjective score of the instructor after each posture. The data for the last three measures were gathered by post questionnaires. These scores were calculated for all four independent variables (video, video conference, 3rd person, Onebody) Physio@Home by Tang et al. [15] use three performance measures to judge the students performance. Two distance measures, one for the elbow an one for the hand, and one angle measure for maximum of rotation. They ignored speed as a measure, because they were mainly interested in the precision of the movements. Additionally, two subjective measures were gathered: perceived accuracy and preference for method and preference for perspective.

Conclusion

All previous works use a performance measurement. These measurent varies but have a precision score in common. Some specify important body parts and give weights on these body parts. The error is measured in the eucledean distance. To overcome timing issues, an time frame between teachers and students movement apply. In addition, a second measurement is used: time. Completion time measures the time a student needs to feel confident to perform the movement. As subjective measurements, perceived accuracy and preference of method is widely used. Additionally OneBody asks the participants to judge the ease to understand. For my study I propose to implement a performance measure with a 0.5s time shift which proofed to be suitable. Furthermore, a completion time could give insights a objective perceived precision and speed of learning. As subjective scores, ease to understand, prefered method, perceived precision will be taken.

Results

Tai Chi Trainer. Chua et al. compare different perspectives (conditions a-e) on the teacher and the student. The independent variables are the above mentioned precision of the students performance. By comparing the results they found condition a (One on One), b (Four Teachers), c (Side by Side) and e (Superimposition 2) aim the same precision. Only e (Superimposition 1) aimed significantly worse than the others. At the same time, the questionnaire indicated that the subjective difficulty of condition d and e (Superimposition 1 and 2) was the highest. "In fact, all of the subjects who tried Superimposition 2 thought it was the most difficult. Interestingly, although subjects considered Superimposition 2 very difficult compared to the other layouts, average error on that layout was not significantly greater than the other non-superimposed layouts." [7]. The Authors argue this result as following:

- simultaneously watching the teacher and performing own movements could interfere each other.
  Chua et al. suggests to choose wisely for the task to suit into VR training.

- latency and performance correlates strongly. A lower latency could lead to better performance.
  Since Chua et al. [7] was developed in 2003, there is a large improvement in latency nowadays.

- To reduce latency a low polygon count on the high realism degree avatars was used. More polygons could lead to better performance.
  The system was run on a Pentium 3 processor. Today's graphic cards and processors are way above this mark, a higher polygon count is easily achievable.

- The field of view was very small.
  Today's VR HMDs probably provide a higher field of view (e.g. HTC Vive, 110°).

Anderson et al. compared **YouMove** with traditional video training, resulting in the independent variables *YouMove* and *Video*. The study was conducted with eight participants in a two factor repeated-measures design. Each participant had one ballet and one abstract task with both conditions. *YouMove* scored significantly better than *Video* by a factor of 2. **TODO**: elaborate a little bit more.

Chan et al. investigated three topics with the **VR Dance Trainer**. First the learning outcome, to proof if the student really got better with the system. Second, the "Arousing Interest" to inversigate weather the system motivates the students to learn. Eventually they compared the system with a traditional Self-leraning method. Comparing the the baseline score befre a training with the VR Dance Trainer with the score after the training session proofed a significant better performance. The post survey is interpreted by the authors with "Overall speaking, the subjects enjoy learning dance with our proposed system." ibidem. To compare the system with a traditional learning method, a control group conducted the same study only with the demonstration and no feedback. The basline scores showed no significant difference between the two groups but the post training scores did. Questionable remains, if a recording of a professional dancer rendered as an high realism degree avatar on a 3D screen can be called a traditional dance learning method.

Main finding of Sodhi et al. while evaluating **LightGuide** is an 85% higher accuracy of ego-centric on body projections compared to a exo-centric video instructions. Per student 90 datasets are generated (6 conditions x 5 path x 3 angles). The performance measure they applied, the conditions scored (best to worst): Follow Spot < 3D F-Arrow < 3d G-Arrow < 3D Pathlet < Video Hand < Video Screen. Especially the relation between video on screen and video hand shows the importance of attention during guidance instruction. The instruction on the bodypart it self scored better than seeing the instruction on a screen. In terms of *movement times*, both video conditions lead to lower movement times. Sodhi et al. see the reason therefore, that it makes a difference if the student sees the whole path before hand than or figuring out the movement as they moved along. Additionally, in an interview, participants of the study stated that self paced guidance are subjectivly like more than system paced. For system paced movement speed 30mm per second scored best in an pilot test. Further they suggest to plan regular recovery rests to exclude fatigue effects.

Onebody [10] proved to be significantly better over the other training measures in terms of *accuracy*. Interestingly, no significant difference was found between the exo-centric 3rd person view and video conference. On the same time Onebody has a higher *completion time* than the other systems. The instructors score showed no significance between the methods. Valuable for this work is, that the ego-centric perspective seems to be slightly better to *understand* than the exo-centric perspective, but not significant. But both, ego and exo centric perspectives, are significantly harder to understand that the video based methods. Furthermore, the *perceived precision* ego-centric perspective is significantly higher than the exo-centric perspective, but nearly on the same level as the video conference method. Eventually, Onebody is more *preferred* by the participants of the study than 3rd person view. Hoang et al. conclude "[...] that synchronous training and 1st person view have a positive effect on posture accuracy." If this applies also to movements could be interesting to investigate.

Physio@home by Tang et al. [15] investigated two subjective measures. The perceived accuracy ranked videoSingle ¡ videoMulti ¡ WedgeSingle ¡ wedgeMulti. For the preferred method aimed for no clear preference. The study results show a higher performance with the multi view perspectives and also the wedge visualisation. The wedge visualisation in combination with multi view perspective achieved the highest performance. The authors see the reason in the ability to grasp the correct angle is much easier with the multi view perspective. Furthermore, the "corrective" feedback of the wedge encouraged the participants to correct themself. Tang et al. further state, that visualisations should contain as least as necessary information to not overwhelm the practitioners.

Conclusion

LightGuide showed that ego-centric guidance performed better than exo-centric. On reason they see in the shift of attention. When the student can focus on the body part which is to move itself, the non shared attention plays a positive role in learning outcome. The ego-centric OneBody system proofed to be better that the exo-centric perspectives. Since OneBody only evaluates posture guidance, it could be interesting to find out if this also applies for movement guidance.

3.3 conclusion

In the scenario of one student learning from one teacher there are five main perspectives that can be thought of, excluding multiple copies of the teacher or the student on different positions. Tai Chi Trainer overcome the view angle issue with multiple copies, but I decided to tackle the issue by letting the student move freely around the teacher, like he could in the real world. This gives addditionally the possibility to observe how a student interacts with the virtual avatar, e.g. he walks side by side to extinct the right/left confusion while standing in front of the avatar. Comparing with figure 3.6 1. is the ego-centric perspective, here the teacher stands inside the student. 4. is closest to the real world, where a teacher stands in front of the student, representing an exocentric view. But as we found above, by standing the teacher inside the student, the student can align his body with the teacher. This is a form of feedback, because missplacement is easy to see. 1. thereby has feedback and 2. don't which makes it hard to compare. 2. is a exo-centric view on the teacher and the student stands inside of the teacher, providing a similar feedback to 1. what maintains the comparability of these two perspectives. 3. is the combination of the ego-centric perspective and the exo-centric perspective. The student sees the teacher in front of him and inside of him. Consequently, 5. is also ego-centric and exo-centric. The teacher standing in the student and the student in the teacher provides double feedback. **Max, hier müssen wir uns für die perspectiven entscheiden.**

abschließende worte...

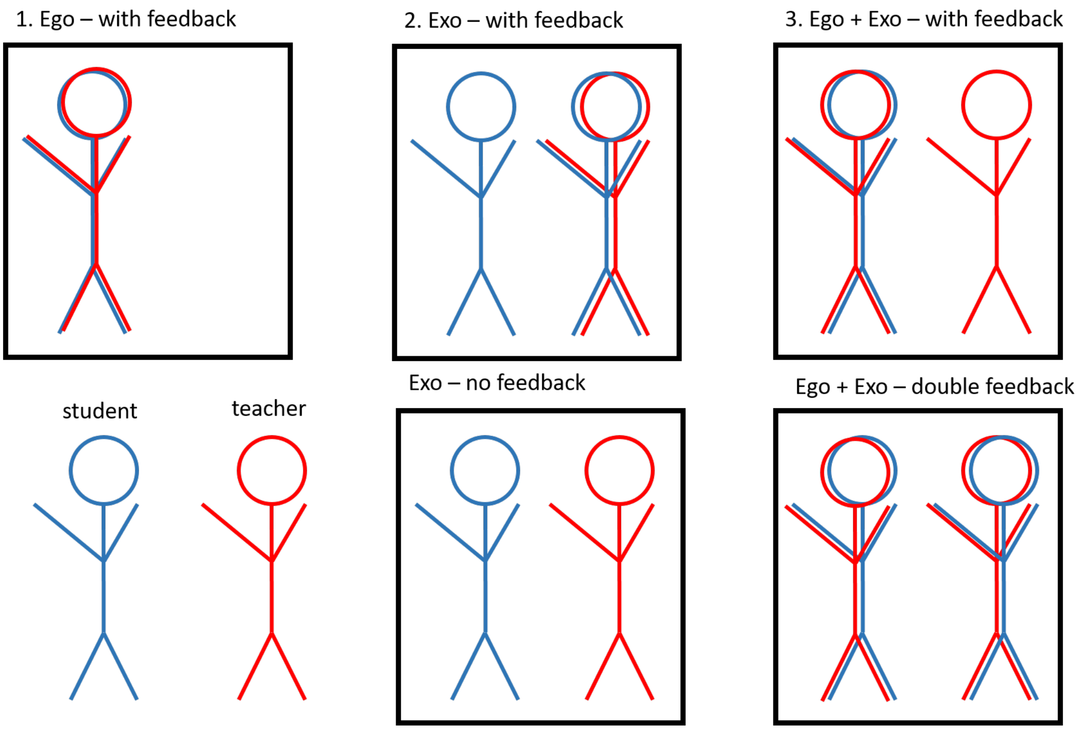


Figure 3.6: possible perspectives

4 Proposed Study Design

4.1 Hypothesises

4.2 parameters

task, perspectives, measures...

als erinnerung hier noch was wir das letzte mal diskutiert haben:

4.3 Variables

Independent Variables

- ego-centric
- exo-centric
- combined
  - variation of combined: sequetial - parallel

further variations that could be interesting:

- body parts
- sitting/standing
- visual representation
- degree of realism of avatar
- guidance techniques: stopping at keyframes vs. fluent instructions
- audio queues
- feedback
- fixed position of teacher and avatar, vs walking around

Dependent variables

Score. Combination of objective and subjective measurements.

- precision
- subjective opinion of participant
- stress level (EKG, HRV)
- cognitive load
- retention
- reaction time

4.4 Task

- Tai Chi form, split in subtasks
- Dance moves from single dance

variations:

- difficulty
- complexity
- abstract vs. real world
- operate a control panel
- escape the room
- game

5 Outlook

Outlook about what is next, open questions like, tracking algorithms, filters, error handling...

5.1 Timetable

Bibliography

[1] Akhlaq Ahmad, Mohamed Abdur Rahman, Fraser Anderson, Tovi Grossman, Justin Matejka, Omid Dehzangi, and Zheng Zhao. New York, NY, USA, 3272–3276. DOI:. 2016.

[2] Fraser Anderson, Tovi Grossman, Justin Matejka, and George Fitzmaurice. YouMove : Enhancing Movement Training with an Augmented Reality Mirror. pages 311–320, 2013.

[3] Sophia Bakogianni, Evangelia Kavakli, Vicky Karkou, and Maroussa Tsakogianni. Teaching traditional dance using e-learning tools: Experience from the WebDance project. *Proceedings DVD of the 21st World Congress on Dance Research*, (May 2014):1–16, 2007.

[4] Jacky Chan, Howard Leung, Kai Tai Tang, and Taku Komura. Immersive Performance Training Tools Using Motion Capture Technology. *Proceedings of the ImmersCom*, 2007.

[5] Jacky C P Chan, Howard Leung, Jeff K T Tang, and Taku Komura. A Virtual Reality Dance Training System Using Motion Capture Technology. 4(2):187–195, 2011.

[6] Worawat Choensawat, Minako Nakamura, and Kozaburo Hachimura. GenLaban: A tool for generating Labanotation from motion capture data. *Multimedia Tools and Applications*, 74(23):10823–10846, 2015.

[7] Philo Tan Chua and Russ Schaaf. Training for Physical Tasks in Virtual Environments : Tai Chi.

[8] Gang Qian, Feng Guo, T. Ingalls, L. Olson, J. James, and T. Rikakis. A gesture-driven multimodal interactive dance system. (January):1579–1582, 2005.

[9] Kozaburo Hachimura, Katsumi Takashina, and Mitsu Yoshimura. Analysis and evaluation of dancing movement based on LMA. *Proceedings - IEEE*

International Workshop on Robot and Human Interactive Communication, 2005:294–299, 2005.

[10] Thuong N Hoang, Martin Reinoso, Farnk Vetere, and Egemen Tanin. Onebody : Remote Posture Guidance System using First Person View in Virtual Environment. 2016.

[11] Paul Milgram and Fumio Kishino. A TAXONOMY OF MIXED REALITY VISUAL DISPLAYS. IEICE Transactions on Information Systems, Vol E77-D, No.12. *IEICE Transactions on Information Systems*, E77-D(12):1–15, 1994.

[12] Richard Schmidt and Tim Lee. *Motor Control and Learning: A Behavioral Approach*. 2011.

[13] Ronald Sidharta and Carolina Cruz-Neira. Cyclone Uppercut, a boxing game for an immersive environment. *Ace 2005*, (January 2005):363–364, 2005.

[14] Rajinder Sodhi. LightGuide : Projected Visualizations for Hand Movement Guidance. pages 179–188, 2012.

[15] Richard Tang, Anthony Tang, Xing-dong Yang Scott, and Joaquim Jorge. Physio @ Home : Exploring visual guidance and feedback techniques for physiotherapy exercises. 2015.

[16] Wenbi Wang and Paul Milgram. Dynamic Viewpoint Tethering for Navigation in Large-scale Virtual Environments. *Human Factors*, pages 1862–1866, 2001.

[17] Mitsu Yoshimura, Norio Mine, Tamiko Kai, and Yoshimura Isao. Quantification of Characteristic Features of Japanese Dance for. pages 188–193, 2005.

List of Figures

List of Tables