# DELIVERABLE REPORT

Project acronym: INPUT
Project number: 687795

D8.2, Feedback in Game

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|---|---|
| Dissemination type: | R |
| Dissemination level: | PU |
| Planned delivery date: | 2018-01-31 |
| Actual delivery date: | 2018-01-31 |
| Reporting Period: | 2 |

WP8, Task 8.2, Establish which feedback to use for in-game learning for different types of performers, UMCG

# 1 DESCRIPTION OF THE TASK

Performers differ in their capacity of proportional myocontrol. WP9 establishes whether this difference in capacity also exists for performers of simultaneous proportional control exploited in the prosthetic control device developed in INPUT. Task 9.1 develops a test for this purpose. Participants in the experiments in this task first perform the test developed in Task 9.1 to classify the participants in high capacity and low capacity performers. Task 8.2 uses the game developed in Task 8.1 and varies different types of feedback in the game. It will be examined which type of feedback works best to support low capacity performers and which feedback supports high capacity performers best in order to improve their muscle signals and control quality. This part of the project will be executed with able-bodied and amputee participants.

# 2 DESCRIPTION OF DELIVERABLE

Determine the types of feedback that performers of different capacity can use for in-game learning controlling the avatar in the rehabilitation game.

# 3 IMPLEMENTATION OF WORK

This deliverable continues the work of deliverable 8.1 by experimentally testing the MyoBox game. For a description of the MyoBox game please see the appendix. A large-scale experiment with 50 participants was conducted in the spring of 2017 to compare different sorts of feedback during user training for pattern recognition control. Note that this number of participants is not attainable with individuals with an upper limb deficiency. In addition one participant with an acquired transradial amputation played the MyoBox game.

## 3.1 RATIONALE

To the best of our knowledge no work has been published on the difference between low and high capacity performers regarding producing distinguishable patterns for machine-learning based myocontrolled prostheses and proportional and simultaneous control of grip patterns with such a prosthesis. Therefore it was not known how feedback should differ between these two groups in this field of application. Also, at the start of this deliverable, deliverable 9.1 (Test for evaluating the ability of simultaneous proportional control) had not been implemented, but it was planned for deliverable 9.1 to provide for a metric on the basis of which low and high capacity performers can be distinguished. Based on these two conditions, it was decided to compare the MyoBox game with three variations of conventional training inspired by the literature. In this way we could compare different types of feedback about performance. Since the metric of deliverable 9.1 is based on the EMG itself, participants could be classified as low or high capacity performers after the experiment was conducted based on the pre-test data. In this way, it would be possible to analyse which of the four types of feedback is best for low and which type of feedback is best for high capacity performers.

## 3.2 EXPERIMENT DESIGN

All participants in the experiment followed the same scheme. Each participant had five consecutive days of training of ~30 minutes length. On the first day the pre-test was conducted and on the fifth day the post-test was conducted. All participants trained seven movements (corresponding to 3.5 DOF, as is the ultimate goal to control in this project).

The experiment had four experimental groups; three groups trained using conventional training and one group trained using the MyoBox game. Conventional training constitutes a *learning by doing* approach; participants are trained by conducting the system training followed by the Motion test (Kuiken et al. 2009) as to evaluate their performance. In the Motion test, participants are randomly prompted to conduct one of seven movements, such as hand open/close, wrist extension/flexion, etc. Each movement is conducted three times (21 trials in total) and a movement is successful if the classifier recognises it for two seconds within a three second period. The three groups using conventional training received three different levels of feedback; no feedback (NF), visual feedback (VF) and visual and coaching feedback (VCF).

- The NF group trained following prompts from the experimenter. They received commands such as ”Open hand at 30% force” or ”Pronate at 90% force”. They never received feedback on their performance and did not receive instructions on how to improve.

- The VF group followed prompts shown on a screen and received the same commands from the experimenter as the NF group. They could see how well they did during system training and during the Motion test and received a score after each Motion test.

- The VCF group received the same feedback as the VF group, but in addition also received coaching from the experimenter after each Motion test. The coaching was focusing on the most problematic pair of movements based on the metrics proposed by Bunderson (Bunderson and Kuiken 2012). To improve the participants’ performance they were instructed to perform variations of the problematic movements as to make them more distinct from one another. As an example; if key grip and fine pinch were the problematic pair, the participant could be instructed to extend the three lower fingers while performing fine pinch to make it more distinct from key grip. The exact recommendations were based on the polar plot, see figure 1.

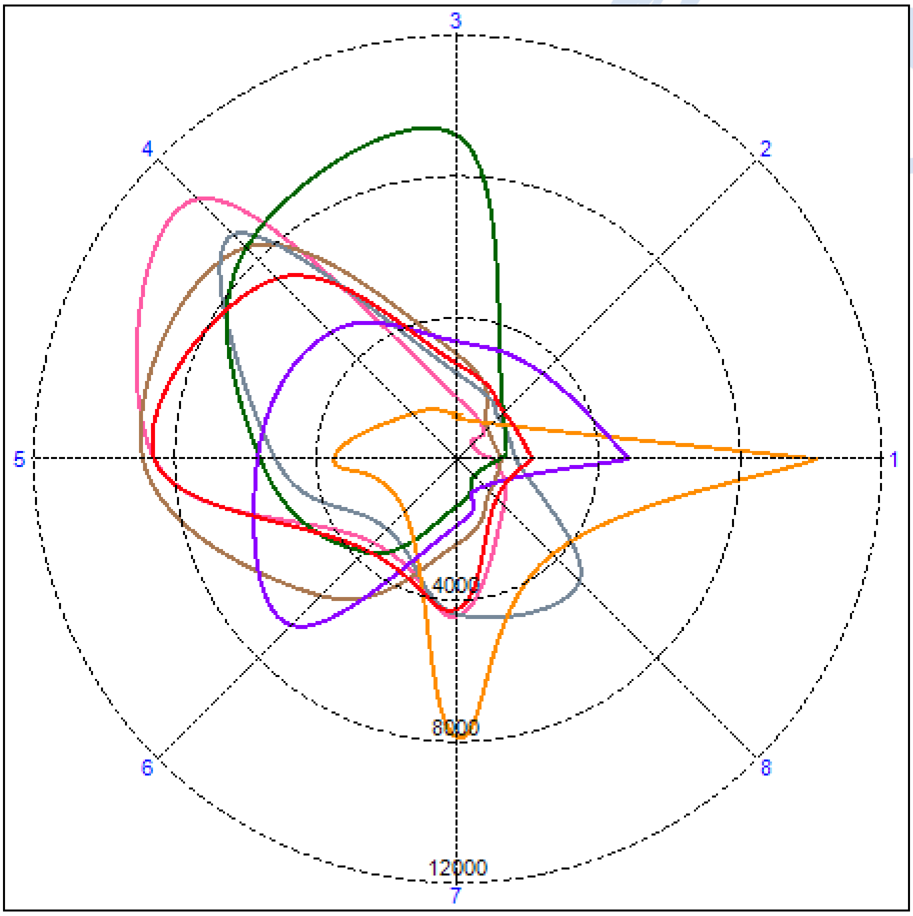


Figure 1. 8 channel polar plot showing a visual representation of the EMG patterns for 7 movements. Each coloured shape represents a movement and each axis is a channel. Activity on each of the channels are plotted for each movement and lines are connected to get an idea of the 'shape' of the movement in feature space. By visual appraisal it can be determined how to make EMG patterns more separate.

Besides the groups that followed conventional training, one group also trained using the MyoBox game. The MyoBox group trained by playing MyoBox for 20 minutes followed by a system training and Motion test. In the system training, they trained the system to recognise the movements they learned by playing MyoBox. This means that instead of performing “Open Hand”, they performed the movement corresponding to “Move game avatar upwards”.

Please see figure 2 for an overview of the groups and the experimental procedure.

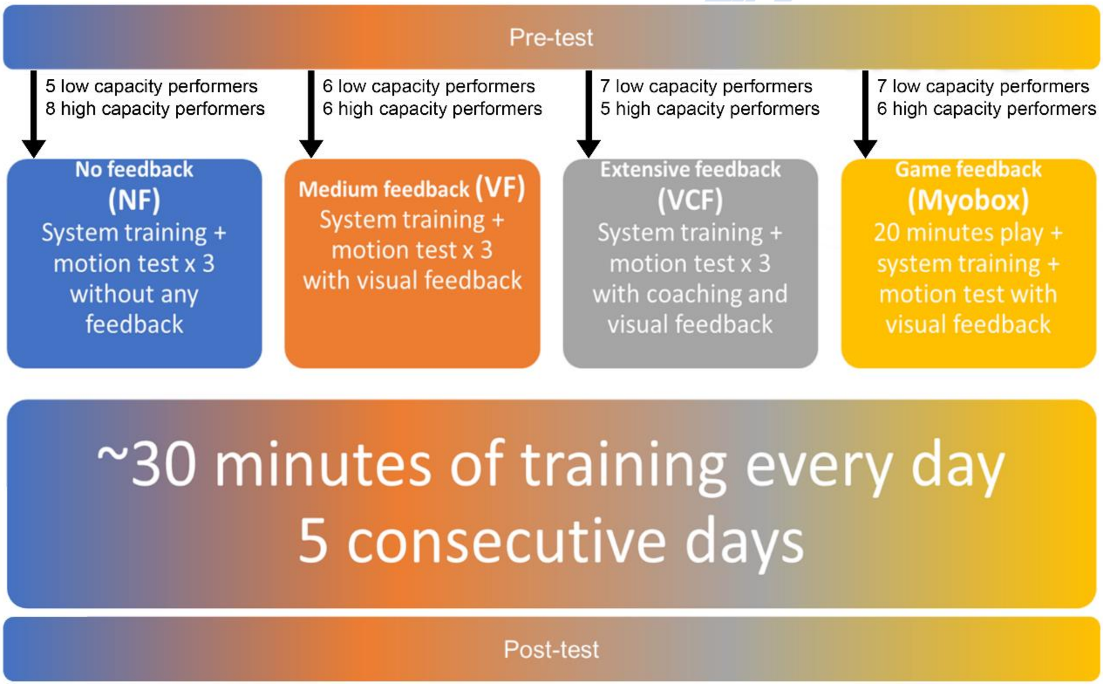


Figure 2. Overview of the experimental groups and the experimental procedure.

Main outcome measures were online accuracy and the number of completed movements in the Motion test. To establish the effect of feedback on training outcome, results from the pre- and post-test were analysed. The analysis was conducted using two repeated-measures ANOVA with test (pre-test vs post-test) as within-subject factor and group (NF, VF, VCF, and MyoBox) and capacity (low capacity performers vs high capacity performers) as between-subjects factors using online accuracy and the number of completed movements as dependent variables.

# 4 Results

The experiment was successfully conducted with all 50 able-bodied participants, see table 1.

| Group | Number of participants | Gender | Mean age (standard deviation) | Capacity |
|---|---|---|---|---|
| NF | 13 | 8 male, 5 female | 21.5 (1.38) | 5 low, 8 high |
| VF | 12 | 6 male, 6 female | 21.16 (1.51) | 6 low, 6 high |
| VCF | 12 | 5 male. 7 female | 22.33 (3.19) | 7 low, 5 high |
| MyoBox | 13 | 7 male, 6 female | 21.3 (1.58) | 7 low, 6 high |

Table 1: Demographic details per group and the number of low- and high capacity performers per group.

Participants were classified as low- and high capacity performers using the SI (Mahalanobis modified II) metric resulting from work package 9.1 on the pre-test data (for details, see delivery report for work package 9.1). The results of Deliverable 9.1 showed that the scores of participants on the metric rating the separability of the patterns for different movements are uniformly spread over the continuum from good to bad separability. Therefore classification is based on the median. Participants with a metric value below the median are classified as low capacity performers and those above as high capacity performers. See figure 3.

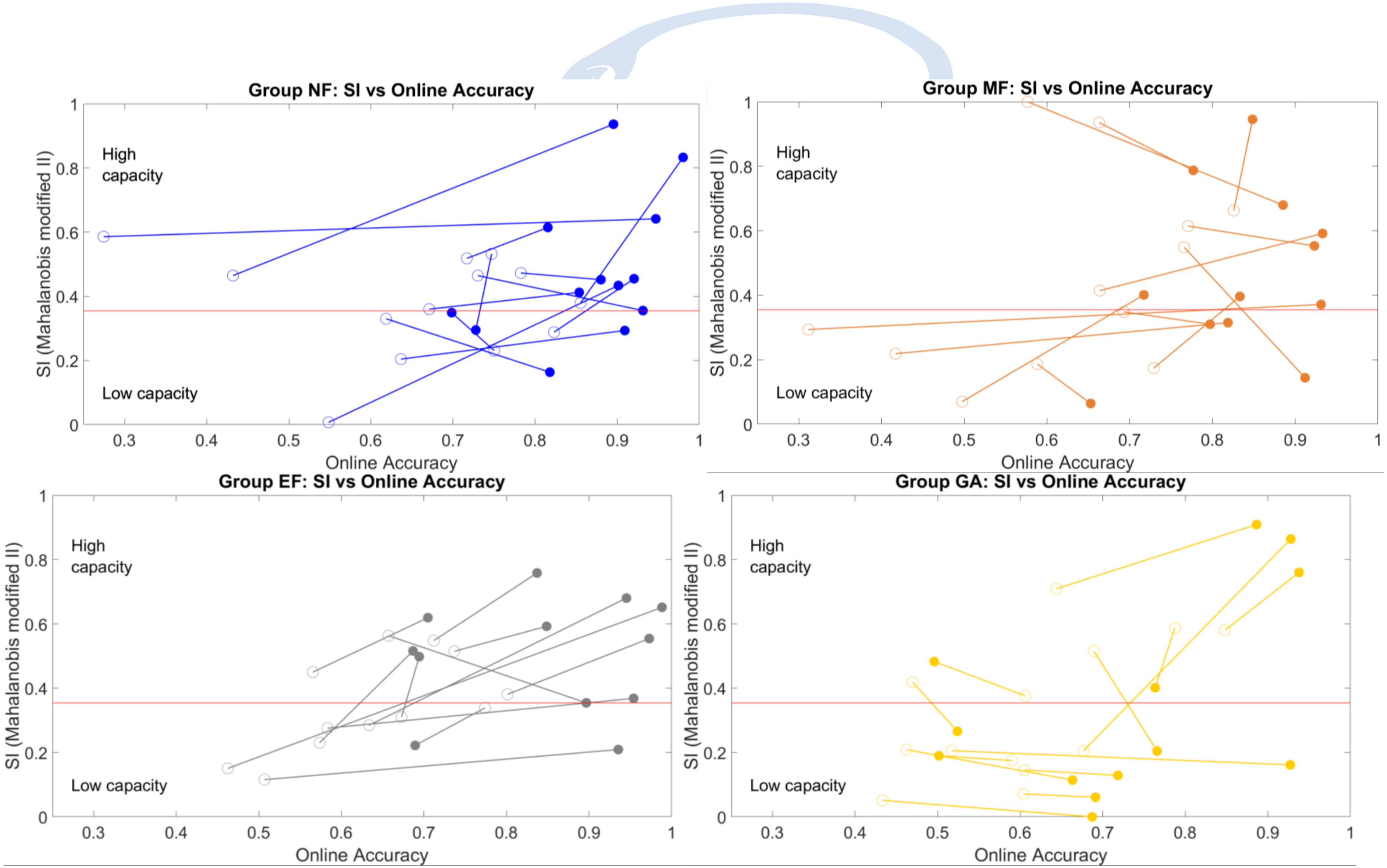


Figure 3. Plots showing the relation between the EMG metric and online accuracy from the pre-test (circles) to the post-test (dots). Each plot shows one group. From top left: NF, VF, VCF and MyoBox. The red line shows the median.

Looking at figure 3 and table 1, it can be seen that participants are divided in two groups of roughly equal size of low and high capacity performers in each group, respectively. In Figure 3 we showed all the individuals and how they changed over the learning. What can be see in this figure is that the changes over learning a not systematic between groups of within groups. This observation is confirmed in the statistics.

The online accuracy demonstrated a significant improvement from pre- to post-test ($F(1,42) = 48.496$; $p < .0001$) with an increase in mean from 63% to 81%. None of the other effects were significant (no main effect of group or capacity and no interaction effects). The number of completed movements also demonstrated a significant improvement from pre- to post-test ($F(1,42) = 163{,}221$; $p < .001$) with an increase in mean from 3.48 to 9.24. Also the main effect of group ($F(3,42) = 3.580$; $p = .022$) was significant. Post-hoc t-test reveals that the game group achieved significantly fewer completed movements at the post-test ($F(48) = 4.423$; $p = .041$).

## 4.1 PATIENT TESTING

From the results from the experiment we saw that the MyoBox group achieved fewer completed movements compared to the other groups. What we saw in the experiment was that participants had problems to transfer the movements they learned in the game without the game as feedback. To assess if this would also be the case with a patient, we recruited a patient to conduct a MyoBox trial. The trial followed the procedure of the MyoBox group from the experiment, but was limited to one day due to availability of the patient.

The patient was a 30 year old male with an acquired transradial amputation (the 'UMCG experienced user' of deliverable 9.1). After one training session he achieved an online accuracy of 62.2 and 9 completed movements. In comparison, the MyoBox group achieved a mean online accuracy 56.6 and a mean number of completed movements of 2.92 after their first game trial. Although the patient achieved better results than the mean of the MyoBox group, he reported that transfer from the movements trained in the game to the Motion test was hard and he had difficulties to perform the movements without the game as feedback.

## 4.2 CONCLUSION

Low or high capacity performers were influenced in a similar way by the four types of feedback. As such, none of these types of feedback stood out as being more preferable in either low capacity performers or high capacity performers to improve the production of distinguishable patterns for machine-learning based myocontrolled prostheses. These results have taught us that the way feedback affects training is more complex than initially expected. The assumption that high and low capacity performers require different feedback to improve does not seem to hold. We base this conclusion on the fact that low capacity performers showed similar improvements to high capacity performers in all groups. This was also confirmed with a trial of an individual with a transradial amputation who showed similar performance as the experimental group. Apparently, it is not that straightforward to provide effective feedback for improving the skill to produce separate patterns for different movements, which is exemplified by the fact that also the NF group scores within the range that the other groups score. For this reason no further work has been put into developing a version of MyoBox for low capacity performers and a version for high capacity performers. Instead work has been focusing on making an improved version of MyoBox. What we saw in the experiment and patient testing is that not everyone can transfer the movements they learn in the game to the test without the game as feedback. Our hypothesis is that learning to conduct seven new movements in a robust manner is not feasible with limited training. To mitigate this we suggest two improvements. Firstly, the game should support an incremental increase in movements, so that performers can start by learning two movements and incrementally add movements when they feel proficient. Secondly, the game should be compatible with the normative movements used in conventional training (corresponding to the movements of the prosthesis), so that if a user has four (out of seven) good normative movements, they only need to learn three more by playing the game. It is our belief that these changes will improve MyoBox over the whole range of performers. These ideas will be implemented in the improved MyoBox game and will be tested soon in experiments with individuals with an amputation.

To summarise: the MyoBox game developed in deliverable 8.1 has been experimentally tested against conventional training (part of deliverable 8.3) with varying feedback. This was done in an effort to assess the optimal feedback for low- and high capacity performers. The results from the experiment showed that the assumption that low- and high capacity performers benefit from differentiated feedback does not hold. Therefore work has and will be focused on improving MyoBox for both low- and high capacity performers and make this ready for testing with individuals with an amputation.

# 5 Subcontracting

All of the work was done within the UMCG by Morten Bak Kristoffersen with help from his supervisors. No subcontracting occurred.

# 6 References


Bunderson, Nathan E., and Todd A. Kuiken. 2012. “Quantification of Feature Space Changes with Experience during Electromyogram Pattern Recognition Control.” *IEEE Transactions on Neural Systems and Rehabilitation Engineering* 20 (3): 239–46. doi:10.1109/TNSRE.2011.2182525.

Kuiken, Todd A, Blair A Lock, Robert D Lipschutz, Laura A Miller, Kathy A Stubblefield, and Kevin B Englehart. 2009. “TargetedMuscle Reinnervation for Real-timeMyoelectric Control ofMultifunction Artificial Arms.” *JAMA : The Journal of the American Medical Association* 301 (6): 619–28. doi:10.1001/jama.2009.116.

# 7 APPENDIX

The following description of the MyoBox game is adapted from the report of deliverable 8.1.

In the MyoBox game, the user controls a ball (avatar) and the goal is to collect boxes. This game is controlled using the EMG of the user. Each direction of the ball is mapped to an electrode. For example; the EMG from electrode 1 (placed on the volar side of the forearm) will move the avatar upwards, electrode 2 (placed slightly more ulnar than electrode 1) will move the avatar up and to the right, electrode 3 (placed on the ulnar side) will move the avatar to the right etc. The direction of the ball will be calculated based on the total activation of all electrodes. If there is equal EMG activation on the electrodes corresponding to the opposite directions such as up and down or left and right, the avatar will not move. If there is activation on the electrodes corresponding to directions up and left, the avatar will move upwards and to the left at the same time. The purpose of this game is to train performers to improve their myocontrol e.g. their control of the EMG. The idea is that after playing the game for a sufficient amount of time, the user will have learned to control the ball in 8 different directions by producing 8 unique EMG patterns robustly. These EMG patterns can then be used to control the prosthesis. See figure A1.

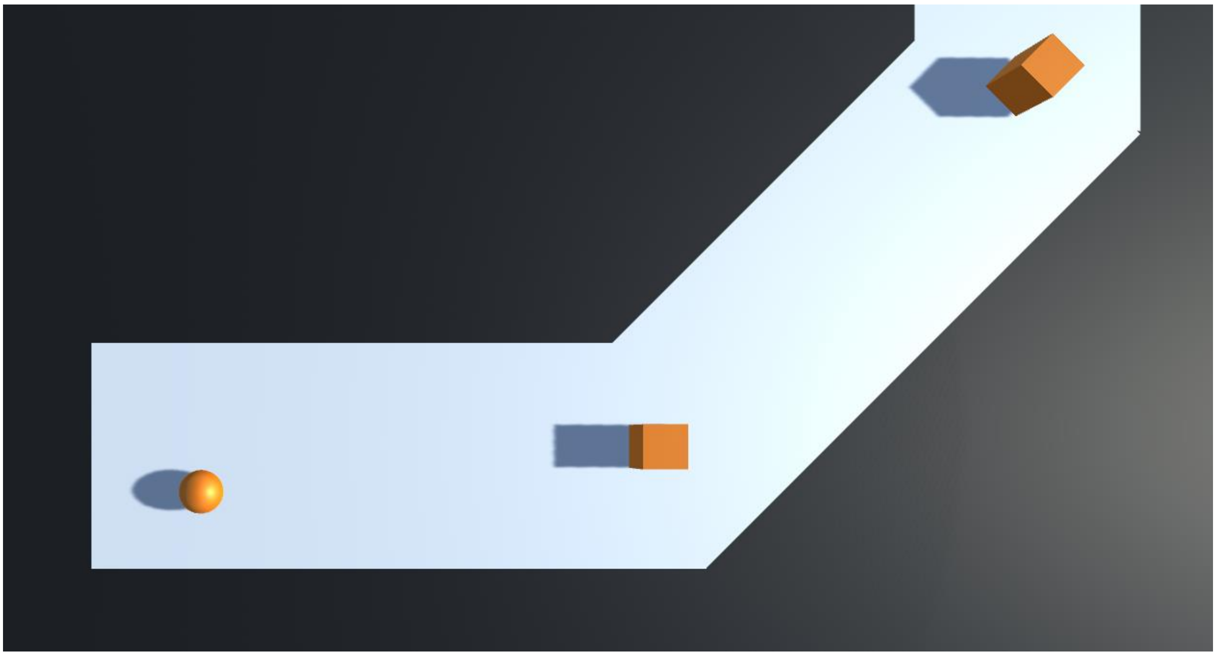

Figure A1. The game interface for MyoBox. The player avatar is the orange ball on the left hand side of the interface and the goal of the game is to collect the orange boxes (middle and right hand part of the interface).