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GeniePutt: Augmenting human motor skills through electrical muscle stimulation

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Abstract: Motor skills are omnipresent in our daily lives. Humans seek to learn new skills or improve existing ones. In this work, we explore how the actuation of the human body can be used to augment motor skills. We present GeniePutt, which augments the human performance via electrical muscle stimulation (EMS). We conducted a user study in which we controlled the turning angle of the wrist through GeniePutt to increase participants' accuracy in a mini-golf scenario. Our results indicate that the best accuracy can be achieved when human capabilities are combined with augmentation performed through EMS.

Keywords: Motor skills, Proprioception, Electrical Muscle Stimulation

ACM CCS: Human-centered computing → Human computer interaction (HCI) → Interaction devices → Haptic devices

1 Introduction

Humans use motor skills for almost any task they perform in daily life. Walking and grasping objects are just two basic examples of motor skills that we master from early childhood [29]. Throughout life, we acquire different types of motor skills [20], for example, discrete motor skills, such as standing, aiming and throwing a ball as well as serial motor skills, such as dancing, doing sports, or playing



Figure 1: A user testing GeniePutt in a mini-golf scenario. The EMS system supports the user by turning the wrist so that the club faces the target.

an instrument. Traditionally, we learn these skills by observing an instructor demonstrating them. We then try to mimic the exact behavior, thus adding a new skill to our repertoire [9]. Research showed that people improving a skill based on observing the outcome (external focus) can more quickly adjust their movement later on, compared to people who improved a skill by focusing on the movement itself (internal focus) [39].

In this work, we explore how we can use wearable technology to augment human motor skills and, thus, improve motor control. In contrast to the common way of improving motor skills through training, we augment the learning process with computing technology. Computing technology has been used to provide feedback through projection to the user based on their performance [14]. While providing a feedback channel (i. e., auditory or visual) can help users reanalyze their motor skills and, thus, improve it, we provide an embodied way of supporting improvement. To achieve this, we use electrical muscle stimulation (EMS) [27]. EMS allows the movement of user's limbs to be manipulated, which we exploit to let the user perform a specific movement. Thus, the user automatically performs the movement in a way defined by a computer. To test our approach, we use a mini-golf scenario in which the rotation of the club is controlled by a computer. We conducted a user study to analyze how our approach improves accuracy. To do so, we use a tracking system. We show that augmenting the motor skills provides a benefit to users, particularly, if they did not master the skill before.

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1.1 Contribution

The contribution of this work is twofold. First, we present *GeniePutt*, a system that improves motor skill performance in mini-golf putting. Second, we report on a user study evaluating *GeniePutt* by comparing participants performance while playing mini-golf on their own with being supported by *GeniePutt* (augmented) and with being fully controlled by *GeniePutt*.

2 Background and related work

One of the human brain functions is to control various muscles across the human body to generate motion. Part of these movements are known as motor skills, which are movements elicited by the human as a result of perception-action coupling leading to a known action [37, 33]. There are different categories of motor skill learning [37]. Wolpert et al. [36] suggest that some are not unitary experience (e. g., tennis game), but rather divided into four main sub-processes: (1) gathering sensory information (i. e., sensory input guided by previous experience), (2) learning key features of the task, (3) setting different classes of control and (4) anticipating and countering the opponent's strategy. Applying these sub-processes to a mini-golf game, only the first two points would be of relevance, as the last two are more concerned with games that need fast interceptive reactions (e. g., basketball). Our work aims at (2), improving the learning of the key features of a task.

2.1 Brain muscle interaction

Motor skills are controlled mainly by the motor neurons which are present in the neural cells [30]. They are initiated in the primary motor cortex M1 [32] and communicated to the body through electrical signals transmitted via the spinal cord to the muscles across our body [30]. Whenever these signals target certain muscles, they control the direction to which we perform a movement [32]. They can also manipulate the muscle stiffness through varying the signal intensities which by its turn regulate the muscle force [4]. In the 18th century, Luigi Galvani discovered that externally induced electrical signals would actuate the muscles, laying also the foundation of research in HCI [27].

2.2 Electrical muscle stimulation

The use of electrical muscle stimulation (EMS) started to spread first in sports followed by health and then HCI.

In the 1960s, EMS was used to train the Russian Olympic team by strengthening their muscles [35]. The effect of EMS on the muscle mass was further explored in several studies [5, 2]. Research on EMS in HCI started with the seminal work of Tamaki et al. who controlled the movement of a hand using EMS [31]. Recent studies have been examining the use of such technology across various application scenarios. One strand of research uses EMS to provide feedback to users. This can either be done to add haptics to public displays [25] or to virtual and mixed realities [17, 18]. Next, research also focused on implicitly controlling the user. Examples include the work of Lopes et al., who communicate affordances of everyday objects to the user and let them perform certain movement to use such objects as intended (e. g., shaking a spray can) [16]. Similarly, Pfeiffer et al. use EMS to control the walking direction of users [23], as they rotate the leg to let the users either turn right or left. Other researchers examined the possibility of using EMS to either control the foot strike posture in running [8] or control the maximum contraction of upper limb muscles by actuating facial muscles [21].

Other research direction is more focused on improving the users' cognitive abilities. Kasahara shows how EMS can accelerate the users' reaction time [11]. Similarly, Lopes et al. used EMS to control users' hand movement to improve their technical drawing capabilities (e. g., wind tunnel results) through calculations performed by computers [19].

We build upon this work and explore how good the combination of user and actuation system is. Further, we investigate how externally controlling the human body would augment the human performance.

3 Improving motor skills

Motor skill improvement systems currently provide feedback on the performance to the user. In professional sports, players analyze their motor skills by watching a video recording and discussing their decisions and movements with coaches. They then need to correct their performed action to improve the execution of a certain motor skill.

Interactive computing technology is already capable of providing feedback in real-time. For example, Kosmalla et al. grant real-time feedback on users' posture while slack lining [14]. They show an avatar of the user to help improve the posture. Similarly, climbers can correct their posture [13].

The main idea of our work is to automatically augment the users' motor skills rather than providing feed-



Figure 2: Anterior forearm showing the pronator quadratus, the actuated muscle that lead to the rotation of the hand (image: <https://www.kenhub.com/de/library/anatomie/musculus-pronator-quadratus>).

back on their performance. We rely on the effect of proprioception on motor learning, which was investigated initially by Adams et al. [1] and recently in more detail in several studies [7, 3, 38].

Early research showed that proprioception provides sensory input, affecting the perception of body position and movement [28]. We leverage this effect using EMS as the relation between proprioception and EMS was shown in previous work [15]. In particular, EMS triggers the motor movement of the user by mimicking the signals that are normally generated by the human brains based on users' cognition.

We envision two different forms of support through EMS. First, EMS takes over full control of the user's body and performs the movement completely. Throughout this work, we refer to this as *actuation*. Second, EMS works in combination with the user. According to Galati et al. [6], humans need multi-modal sensory inputs to execute fine movements. Therefore, users are actuated by EMS and are additionally capable of influencing motion based on their visual perception. In contrast to actuation, in this condition they receive additional input from the visual sensory information. As subsequently motor skills as augmented, we refer to this mode as *augmentation*.

3.1 Mini-golf application scenario

To explore the idea of improving motor skills, we first explored different scenarios. Given the current state of the art of EMS actuation, we chose a scenario that requires users to perform a motor skill with a small number of actuated muscles. For that, we decided on a mini-golf scenario, where we constructed a play-field in a closed room, in which the target, the golf club head and putt could be tracked.

The objective is to make the user adjust the clubface so that when the ball is hit, it moves in a straight line to the target. For this, we needed to actuate and adjust the angle of the user's hands prior to hitting the ball. We achieve this by actuating the pronator quadratus muscle of the user. This muscle is used to rotate the hand and, thus, the angle of the clubface.

4 GeniePutt implementation

The GeniePutt system is composed of the wearable EMS control hardware, the training loop, and the learning algorithm.

4.1 EMS control hardware

We used the *Let Your Body Move* toolkit [22], consisting of an Arduino nano with control software and Bluetooth module. The toolkit has a wired connection to a signal generator and self-adhesive electrodes that are attached to the user's muscle. An Android application communicates the system's output to the toolkit via Bluetooth.

4.2 Training control loop and learning algorithm

We used an OptiTrack system that sends its tracking data to a PC via UDP. An actual physical golf club and a golf ball were used. Three markers were mounted on the club to indicate the orientation of the head. The target was marked with a triangle-shaped marker. The target and the club markers were enough to indicate the angle to which the player should aim. We tracked the angle between the center of the club and the target center. This allowed the system to apply EMS feedback for correction.

We use a genetic algorithm to calibrate the EMS signal given the limited data points and variance of the data available, due to the user dependence of EMS. For implementing the algorithm, we used the Jenetics library.¹ First, we define a function that takes the current angle between club and goal as input and provides an EMS actuation as output. We then generate random sets of parameters that define a certain actuation. These sets of parameters are evaluated and the best ones are selected (i. e., the ones resulting in the best actuation). The selected parameters are

¹ <https://jenetics.io/>

now used to generate new parameters that slightly differ from the ones that performed best. This set is again evaluated and the parameters performing best are selected. This process is repeated until a certain goodness is achieved. Thus, a function is defined that is optimized for a specific user in changing the club rotation in a way that matches the current rotation.

4.2.1 Population generation

The process starts by generating a random set of solutions to the targeted problem, each solution is called an individual. A group of individuals form what is known as a population. An individual is defined through a set of variables so called genes. Each gene is represented usually in a binary form (i. e., 0 or 1) Multiple genes are then attached together to form a string named chromosome, and several chromosomes are the representational form of an individual (i. e., solution). In our work, each solution has 2 chromosomes: the intensity of the signal and the duration of the signal. Furthermore, each chromosome has constraints. In our case, the chromosome that represents the intensity is limited to a certain range of values that does not go below the value that starts actuating the hand of the participant and is lower than the pain threshold of the participant. After having both values of the participant from the calibration process (cf., Section 5.2.1), these values are used to set the minimum and maximum values of the chromosome representing the intensity of the signal. Also, the chromosome that represents the duration of the signal has constraints (i. e., by trial it is between 900 milliseconds and 1300 milliseconds).

4.2.2 Evaluation for fitness

To be able to decide which individual (i. e., solution) is the best one, a fitness function is used to set a fitness value for each individual. The fitness function is context-relevant, which compares the individual performance with that of the most optimal targeted value within a certain problem. The higher the fitness value resulting from a fitness function is, the higher the probability that it would be used for reproduction is.

The fitness value in our work is based on the best results obtained from the tracking system by measuring the angle between the golf club and the goal. That is the angle confined between the vector representing the club base and the vector joining the projection of the centroid of the club and the goal tip point (see Figure 4). We defined the

optimal angle as 90° . Thus, angles in the range between 70° and 110° are considered acceptable. Angles that equal exactly 70° and 110° were given fitness values of 50. Angles greater than 70° to 90° were given fitness value proportional to how near they approach 90° (i. e., the optimal value). The values are calculated by the Equation 1 (e.g, angle = 80° was given fitness value $100 - (90 - 80) \times 2.5 = 75$) and Equation 2 (e. g., angle 100° was given fitness value $(110 - 100) \times 2.5 + 50 = 75$). This process was done once for the dominant arm and once for the non-dominant arm.

$$\text{Fitnessvalue} = 100 - (90 - \text{angle}) \times 2.5, 70 < \text{angle} < 90 \quad (1)$$

$$\text{Fitnessvalue} = (110 - \text{angle}) \times 2.5 + 50, 90 < \text{angle} < 110 \quad (2)$$

4.2.3 Selection

The idea behind the selection stage is to choose the best genes to be passed on to a next generation of population. Therefore, the fitness value of all the individuals of a population is compared, the two individuals of the highest fitness values are then used for reproduction, and hence called parents. The Genetics library has many types of selectors. For the survivor selector and the offspring selector, a Tournament Selector is used. The Tournament Selector, as the name implies, imitates tournaments so that the individual of the worst fitness value never survives, and the individual of the best fitness value always survives.

4.2.4 Recombination and mutation

In order for two parents to reproduce a new child (i. e., individual) a mating process known as variation is used. While there are two types of variations (i. e., recombination and mutation), one is used before the other. The first one is a recombination, where a random crossover point is chosen in the binary formation of the two parents. An offspring (i. e., child) is then generated by exchanging the two genes-sets separated by the crossover point. Afterwards, a mutation process is applied, where according to a probability that we predefined, one or multiple bits (i. e., those in the genes) are flipped in the new offspring. The main aim of the mutation process is to expand the diversity of individuals for exploration. Each new child is then added as an individual to the population. Given a constant number of individuals in a population, the fitness values are re-evaluated and the ones with the least fitness values are eliminated.

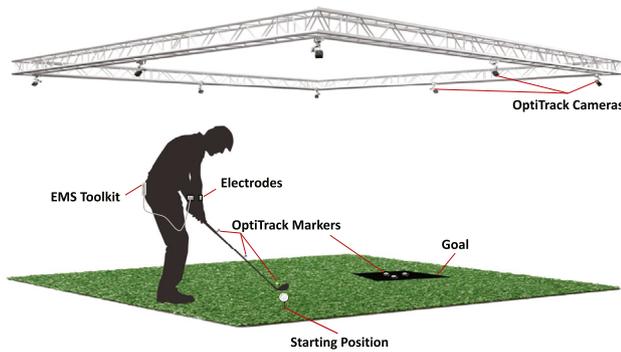


Figure 3: Setup of the user study. The participant is standing within the OptiTrack tracking space holding the club and EMS electrodes attached to the arm.

4.2.5 Termination

Each new set of individuals (i. e., children) is considered as a new generation. The algorithm keeps producing new generations till the difference computed between the parents and the children is no more significant. Meaning, the fitness values of the children and the parents both reach a certain preset threshold. Applying this in our case means that the actuation signal parameters remain almost constant.

5 User study

The goal of this lab study is to evaluate the idea of improving motor skills through EMS. We setup a mini-golf course within our lab that allows for a simple putting tasks. We deliberately started with a non-complex example to examine the overall feasibility of this approach.

5.1 Study design

We designed the study as a repeated-measures experiment. The independent variable is the actuation level that was either none (i. e., free condition), augmented, or (fully) actuated. For the actuation, we blindfolded participants so that they could not visually perceive the stimuli and, thus, fully relied on the actuation. For each condition, participants performed a putting action 10 times. As dependent variable, we measured the deviation angle from the target.

5.2 Setup and procedure

We invited 12 participants (11 males, 1 female) aged between 21 and 50 ($\mu = 26$, $\sigma = 7.97$) via University mailing

lists and personal contacts. None played mini-golf or golf regularly. As participants arrived at the lab, we explained the overall purpose of the study and the EMS system. The study met the ethics regulations of our institution. We particularly explained the safety regulations of the EMS signal generator and made sure that participants understood them. After filling in an consent form, we first showed the basic functionality of the EMS system on the participant's wrist. Our study consisted of 3 main sessions, namely, the calibration, the training, and the testing sessions. The overall study duration was approximately two hours.

5.2.1 Calibration

We started with the calibration session, in which, we depended mainly on visually observing the inward-rotation of the hand as a result of inducing the electrical signal. We started with the dominant hand followed by the non-dominant hand. For each participant, we started the calibration phase with $5 \mu\text{A}$ and increase it with a step of $2 \mu\text{A}$. The highest intensity value of each hand is then considered for the training part. We found a high variety in actuation possibilities so that for some participants, a two handed rotation and for others a one handed rotation performed well.

5.2.2 Training

In the training session, we asked participants to hold the golf-club with both hands. The evolutionary algorithm then controls the intensity and duration of the signal. Using the OptiTrack, the angle between the clubface vector joining the centroid of the club projection and the tip point of the target is measured. Based on this angle, the fitness value of the individual for the evolutionary algorithm is determined. The learning algorithm is then executed twice. The first time, it runs on the dominant hand, using a starting position of the club base line parallel to the line joining between the goal triangle base points. The values (i. e., intensity and duration of the signal) produced from the first run are used to set the initial rotation of the dominant hand to rotate the club in the second run.

The communication works as follows: the command is sent to the LYBM toolkit, waiting for the duration of the signal that is induced. The OptiTrack records frames for 1 second and an angle calculations is performed. Then, participants move their hands back to the initial position. The second time it runs on the non-dominant hand, starting from the same starting position as in the first run. A signal

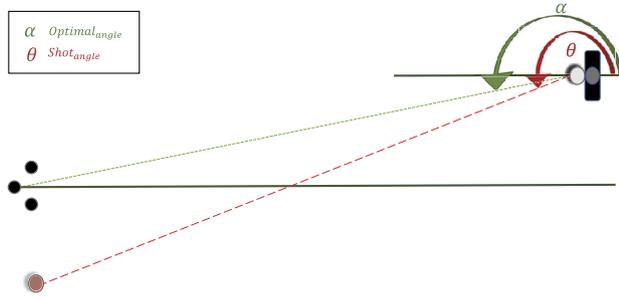


Figure 4: Graphical representation of the setup, where the α angle represents the optimum angle from the starting position till the goal. The θ represents an example of an actual shot deviating from the optimal angle.

is produced to rotate the dominant hand with the best values produced from the first run and then the evolutionary algorithm tries a value on the non-dominant hand.

5.2.3 Testing

Participants then performed ten shots in each condition, separated by 2 mins breaks. We randomized all presented conditions. In each condition, we video-recorded all shots from top view, which we later used for the analysis.

6 Results

To evaluate the performance of the participants across the three conditions (i. e., free, augmented, and actuated), we calculated the angle of deviation between the goal and the actual ball trajectory. Each participant performed 10 repetitions for each condition. We then computed the mean for each participant. To calculate the angle of deviation, we recorded top videos we analyzed post-hoc (i. e., using a protractor software, as shown in Figure 4). For calculations, we used either the one-handed or two-handed actuation based on the better calibration results. Furthermore, we removed outliers (i. e., when the ball was not hit properly and was moving in an entirely wrong direction) using the Tukey method [10].

Comparing the deviation angle of the three conditions we found that *augmentation* performed best, followed by *free* and *actuation* (cf., Figure 5). A repeated measures analysis of variance could not show statistically significant differences, $F(2, 22) = 2.998$, $p = .071$. We further used a Pearson correlation to analyze the relationship between the regular performance (i. e., free) and the change in performance through EMS. We found a strong negative corre-

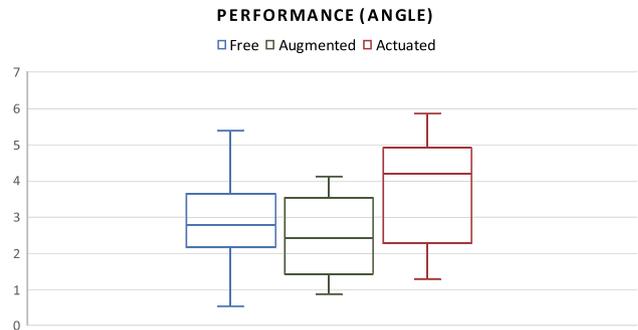


Figure 5: Boxplot of the performance of each condition reflected in the measured angle (degrees).

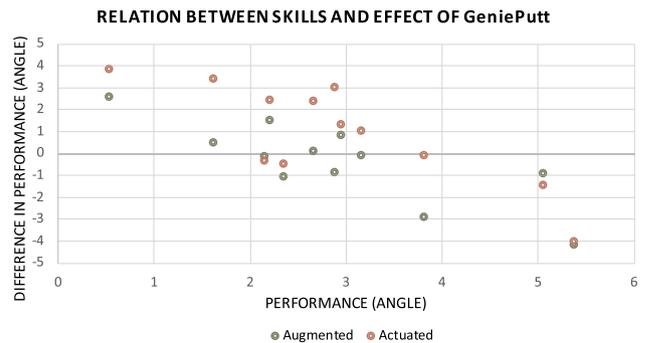


Figure 6: Scatterplot of change in performance based on the performance in the free condition. The worse the participants performed without EMS, the more actuation and augmentation improved their performance.

lation between the results of the *free* condition (i. e., user is not actuated at all) and the change through *augmentation*, $r = -.801$, $p = .001$, and *actuation EMS_{only}*, $r = -.805$, $p = .002$. A scatter-plot summarizes these results (cf., Figure 6).

7 Discussion

7.1 Combining human and computer

The results of our study indicate that combining external actuation (i. e., through EMS) and user does provide the best results. This is in line with the findings of Vahdat et al. that suggest the process of executing new movements to be affected by both the sensory and motor changes, which eventually prompt a new behaviour [34]. Most of the human motion is a result of multiple simultaneous muscles' movements. In our case, the implemented actuation in this work allows us to stimulate individual muscles. When an individual muscle is actuated, the user, consequently, can

assist this movement. The results of our study indicate that inhibiting the visual sensory input and only allowing the computer actuation led to the worst performance. This finding is in line with Galati et al. who showed that both sensory and motor contribute to the formation of spatial body-centered coordinates [6].

Following the classification of Wolpert et al. [36], the putting scenario consists of a set of control classes (e. g., swinging the arm, stiffening and twisting the wrist). While users still need to perform some of the control classes on their own (e. g., the swing of the club), the twist in the wrist is controlled by the GeniePutt system. This reduces the number of control classes users need to take care of.

7.2 Motor skill level of users

The strong negative correlation between the *free* and both the *actuated*, as well, as the *augmented* conditions shows that the level of motor skills of the participants influence the performance in the EMS conditions. The lower the performance is (i. e., the higher the angle), the more does the intervention of the EMS improve the performances of the user. This observation also complies with the classification of Wolpert et al. [36] as they divided the experience of performing a certain movement into sub-processes, highlighting that one of the main sub-processes is learning the key feature of the task. In our case, that was reflected as the individual's ability in playing mini-golf apart from the actuation process. Furthermore, this suggests that a system such as *GeniePutt* mainly supports users with a lower skill level. However, with further improvement in EMS actuation, this might in the future also work for users with better motor skills.

7.3 Challenges of EMS

Motor skills are divided into fine and gross motions. Given current technology, actuating on a fine level is still challenging and, thus, most actuation is done on a gross level. Furthermore, EMS systems use surface electrodes to actuate muscles. Surface electrodes are limited in terms of the muscles they can be applied to. As soon as muscles are covered by other muscles or are simply too small, surface electrodes cannot actuate the muscles.

7.4 Agency

Electrical muscle stimulation takes over the control of certain movements of the human body – in our scenario of

the turning of the wrist. Users need to let the system actuate the muscle and should not work against the actuation. Prior work demonstrated that while EMS is able to suggest certain movements, users can at any time override this [16, 24]. For our work, this means users can at any time decide not to benefit from the advantages our system provides. Given that the GeniePutt system is used for a particular period (i. e., while playing golf), we expect users to not fear the lose of control.

7.5 Application scenarios

Augmenting certain motor skills has various potential applications. While we focus on a sports application, augmenting motor skills can also be useful in everyday life. One example would be preventing users from slipping by actuating their gait. Given that slipping is one of the main reasons of injuries, particularly for elderly [26], posture control and regain of balance mechanisms have, therefore, been of particular interest for researchers [12].

7.6 Limitations

We acknowledge the following limitation to our study. The duration of the user study might influence the results. The used evolutionary algorithm requires multiple rounds of actuation. When actuating the same muscle multiple times, fatigue effects might come into play. These effects might not always be well modeled by the evolutionary algorithm since they change over time. Also, while we investigate the effect of the system on improving the human performance, we didn't explore the long term learning effect.

8 Conclusion

We presented GeniePutt, a system that augments the performance of users in executing accurate motions through EMS. We conducted a user study with 12 participants comparing actuation, augmentation, and raw performance of the participants. Our results indicate that the best performance achieved was in the case of augmentation, closely followed by no augmentation. Looking deeper into the data, we found that the approach works best for users that perform rather bad without actuation. This shows that the current technology might provide benefit in terms of improving motor skills but are still limited and cannot improve users that execute their motor skills on a specific level. Nevertheless, the results provide promising first insights into how the interplay of human and computer can improve motor skills.

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