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Cognitive modelling of human-virtual player interaction: using a PI controller to track motion

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Abstract

Patients suffering from motor impairments often require long medical treatments. We propose the first step in their treatment: to create a virtual player which follows the human player in order to create a synchronous movement, creating a bond between the human and the virtual players. While such coordination between a human and a virtual player has been studied in previous investigations, the potential use of such virtual environments in the field of motor rehabilitation is still unexplored. This paper uses a PI controller to accurately track the human player's position and velocity and shows the spatial and temporal errors in the tracking and proposes future improvements to the study.

1 Introduction

The act of coordinating the movements of two or more individuals has been found to have various effects on the emotional interactions between them. This concept was researched by William H. McNeill who gave it the name 'muscular bonding' [McNeill, 1997]. There are many instances in everyday life in which we can see synchronisation which could create a relationship. For example, studies have shown that people walking in step with each other rather than randomly are more likely to behave in a cooperative and altruistic manner [Herbert, 2009]. This property of human behaviour has proved a useful tool in therapy for motor rehabilitation as well as for other purposes such as helping people who struggle with social interactions. Synchronisation is becoming an increasingly important area as people begin to develop a deeper understanding of the problems that it can be beneficial to. The successful union of technology in various areas of medicine and rehabilitation has allowed artificial intelligence (AI) to present stimulating yet safe and ecologically viable environments to facilitate recovery [Riva et al., 1997] [Sisto et al., 2002]. These computer generated virtual environments enable doctors to provide personalised treatment sessions whilst keeping the rigour required in experimental protocols. [Sveistrup et al., 2003].

Despite all the help currently available, treatments are rarely effective in regaining complete muscle function for the individual. This is why it is so important for new forms of therapy to be tried and experimented so there is an improvement in reversing motor loss function. In this report we explore the phenomenon of using muscular bonding to propose innovative rehabilitation strategies for people with motor impairments. Our method for rehabilitation involves encouraging a patient to try and copy an autonomous virtual avatar which will help them regain their motor function as much as possible. This is aimed to be an improvement in current rehabilitation in which the patient simply repeats set tasks periodically. We aim to build a satisfactory model of a virtual avatar in the form of a slider trying to follow the side-to-side motion of the user. The motion of the virtual avatar will be designed to be as human-like as possible in order to increase the chances of creating a relationship between the avatar and the subject. We will also try to use some basic control theory and implement a basic PI controller in our model. We will aim to relate this back to how the rehabilitation of patient with inhibited motor skills can be affected. All the coding behind the data produced and analysed in the paper can be found at *https://github.com/vedangjoshi2000/MDM2Group6*

2 Methodology

2.1 Literature review

2.1.1 Comparing Different Control Approaches to Implement a Human-like Virtual Player in the Mirror Game

This study [Alderisio et al., 2016] attempts to create a human-like virtual player(VP) able to play the mirror game with a human player(HP) in real time. Two alternative control strategies are presented in the study to implement its cognitive architecture, PD control and a receding horizon optimal control strategy. To compare the performance of these control strategies, the study uses experimental data collected from two human players so as to evaluate the human-like performance of the VP when playing together with a human. The main purpose of this study is to "present an informed comparison of different control strategies and models to drive the VP such that its motion exhibits human-like features". The VP is modelled through two parts: a model of its intrinsic dynamics and a "control algorithm monitoring the motion of the human player and driving that of the VP accordingly". This is a very detailed and thorough study which really goes into depth about the relationship between a human player and a virtual player. We aim to use a few introductory ideas on AI motion from this paper in our own models.

2.1.2 An organising principle for a class of voluntary movements

This paper [Hogan, 1984] presents a mathematical model of a class of voluntary arm movements observed in monkeys. This a very similar study with similar aims/ goals with this report. The movement which is being observed are large amplitude, single joint, elbow motions at intermediate speed. It also explores whether the primates are perturbed or not and how this affects their movement. A very detailed study which relies mainly on experimental and observational data. Differential equations are used to model the movement of intact and deafferented monkeys (monkeys whose central nervous system neurons are interrupted to study the spontaneity of their motion [Hanakawa, 2012]). The specific movement being observed is a voluntary pointing movement of the forearm to a visually presented target, done at an intermediate speed. There are still a few limitations with this study. The study is conducted on monkeys and despite their closeness with the human species, the results of this study cannot be completely generalised if we apply them to human beings. The paper assumes the elbow joint to have a centre of rotation and the forearm is treated as a rigid body. Despite this being a reasonable assumption, the arm and muscle force are both complicated to model. We use a mouse as a tool to facilitate motion between the user and the virtual environment in our experiment, to evade this problem.

2.2 Model Development and Results

2.2.1 Preliminaries

Our aim was to create a virtual environment in which a patient, or human player (HP), interacts with an artificially intelligent virtual player (VP) with human-like kinematic abilities, serving to rehabilitate victims of stroke suffering from upper-extremity motor impairment. The interaction throughout the tests will entirely be a leader-follower interaction with the HP leading for the VP to follow. The VP will be created in such a way that it will be able to simulate human movement and generate a range of motion defined by predetermined arbitrary parameters. In order to achieve easier synchronicity and more readable results, both players will be moving along a one dimensional slider. The motion of both players will be tracked, and analysed, allowing us to produce a variety of graphs illustrating the interaction. In effect, it is a mirroring game that generates artificial motion with a built in time delay to simulate the delay between signals in the human brain. This technique was introduced in 2011 [Noy et al., 2011], and a cognitive architecture to drive the motion of the VP was created [Zhai et al., 2016], where a control mechanism was used to track the motion of the HP. This paper attempts to recreate this experiment and provide insight into human-AI relationships. Human motion can be thought of as a naturally occurring dynamical system. These physical processes are categorised as piecewise-smooth functions (PWS) [Bernardo et al., 2008]. A function f(x) can be defined as PWS if the function itself and its derivative is continuous for a finite domain but may be discontinuous for some finite values within the domain [Doshi, 1998]. We use PWS as the benchmark for determining human like motion in our paper.

2.2.2 Initial model: A discrete data-set plot approach

The first step taken in the creation of our VP was the development of a simple GUI based game in python. The game consists of 2 sliders, one for each player, which allows the motion of a button controlled by a computer mouse. We set a time lag of 200ms in the simulation to model the reaction times in human beings [Thorpe et al., 1996]. The simple VP was programmed to move at a constant velocity in a direction based on the HP's cursor position relative to that of itself.

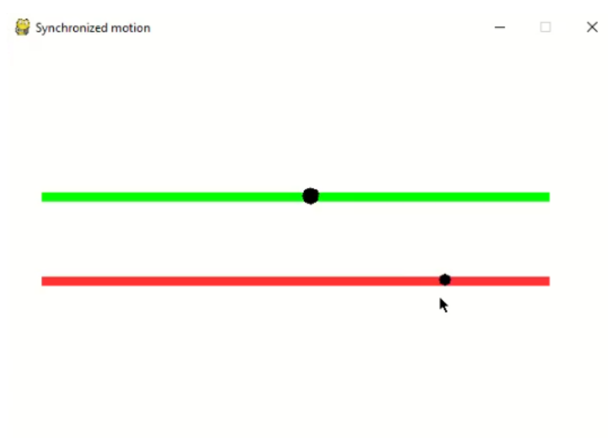

Figure 1: The virtual environment where the user manipulates the red slider and the green slider attempts to track the human player positions

Once the game has been started, both players' positions will be tracked, along with the time over which the game is played. From this data we were then able to graph the positions of the two buttons, allowing us to have a visual representation of the interaction throughout the game.

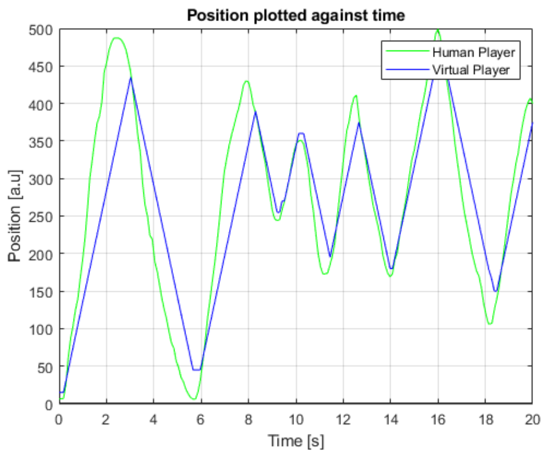

Figure 2: Position of players plotted against time

By plotting both paths on a graph we were able to analyse the motion of our VP. Figure 2 can be used to show that, although achieving a leader-follower interaction, our first model cannot be considered as humanoid or artificially intelligent. The graph clearly shows that the VP is capable of tracking the HP, although all VP motion appears linear, with sharp peaks and troughs making change of direction of motion evident. The visuals of this curve alone are enough to suggest that our VP is not a reliable simulation for a human.

By further analysis and discrete data manipulation we can also produce a graph capable of visually comparing the velocities of each player. The discretised data points are used as inputs for the experiment and the data is not continuous, yet we observe a constant magnitude of velocity. This results in sharp rises and drops in amplitude as shown in Figure 3. These rises and drops are graphed as the graphing software cannot distinguish between discrete and continuous datasets. The discontinuity of our velocity graph means that the VP motion can't be considered as a PWS function, leading to the decision that the initial model is insufficiently human-like.

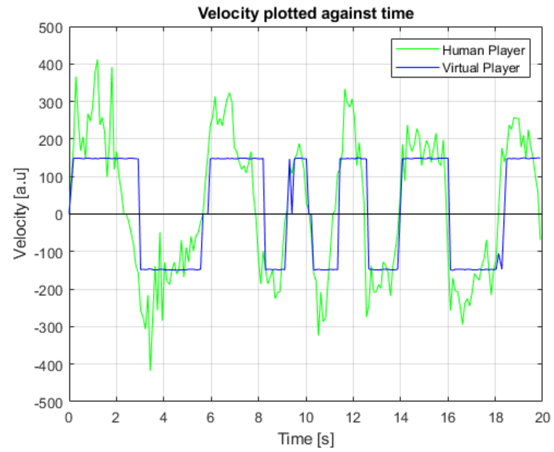

Figure 3: Velocity of players plotted against time

2.3 Secondary model: A piecewise-smooth approach

The aim of our second model was to produce a motion well represented by a PWS function, before changing a set of parameters to create the most human-like AI we can. In order to achieve a smooth dynamical system to model our VP we further developed our initial model by implementing some of the ideas behind control theory engineering. Control theory is responsible for managing the behaviour of dynamical systems, and a controller in particular will manipulate the input to system to alter the output in a certain way [Simrock, 2008]. Applying this theory to our model required us write an algorithm which acted as a PID controller regulating the drive applied to the VP. A PID controller will produce an input to a system based on a Proportional (P), an Integral (I) and a Derivative (D) component, each of which is responsible for changes in input. All 3 parts of the PID controller adjust their values based on an error $\overline{x} - x$, defined as the difference between a desired set point (SP) and a process variable (PV)

We begin with the proportional component of our controller, which consists of a proportional constant K_P simply multiplied by the error at that given moment in time. The P component of the controller applies a drive to the PV simply based on its distance from the SP, obviously we are going to see that P becomes less effective the closer we get to our SP.

$$P = K_P(\overline{x} - x). \tag{1}$$

The integral component of the controller computes the amount of effort to apply based on the sum of all previous errors, or the integral of error over time.

Much like the P component it requires it's own constant of integration K_I. Not only does the I component help to smooth out the sharp peaks and troughs we saw in figure 2, but it also helps to eliminate controller offset caused by $\overline{x} - x = 0$ not being steady.

$$I = K_I \int_0^t (\overline{x} - x). \tag{2}$$

The final component of the controller alters its effect on the system input based on the derivative of the error at that time, multiplied by a derivative constant K_D. It is required to act as a dampener on the system and acts to negate the effects of P and I as the PV approaches the SP at a faster rate.

$$D = K_D \frac{d}{dt}(\overline{x} - x). \tag{3}$$

The final development of our algorithm came with the application of a closed control loop to the PID controller. A closed control loop, demonstrated in figure 4, consists of a controller, a plant (the system being controlled) and the feedback elements which read and send the feedback to the controller. Our control loop consists of a PID algorithm (the controller), the VP's position (the plant), and a variable capable of reading and storing $\overline{x} - x$ (the feedback element). Creating such a loop allowed us to produce a final PID equation 4, which calculates μ, the distance moved by the VP after each loop, from the continually changing error e(t).

$$\mu = K_P(e(t)) + K_I \int_0^t (e(t)) \ + K_D \frac{d}{dt}(e(t)). \tag{4}$$

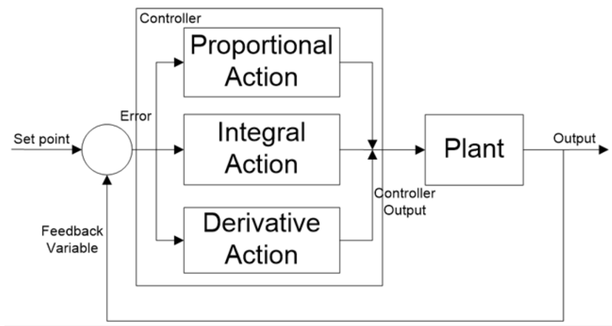

Figure 4: A simple diagram showing flow of operations for a closed control loop [Kansagara, 2018]

One of the major assumptions made before the development of our second model was that the derivative component of the PID control would only have a minimal effect on μ due to behaviour of human motion. Throughout our updated model we treated K_D as equal to 0, and essentially removing it from our model. We observe a similar approach in solving the same problem where the integral component is replaced by the derivative component in the model [Alderisio et al., 2016]. Following on from the application of our controller, we tracked, stored and manipulated the discrete data as done before.

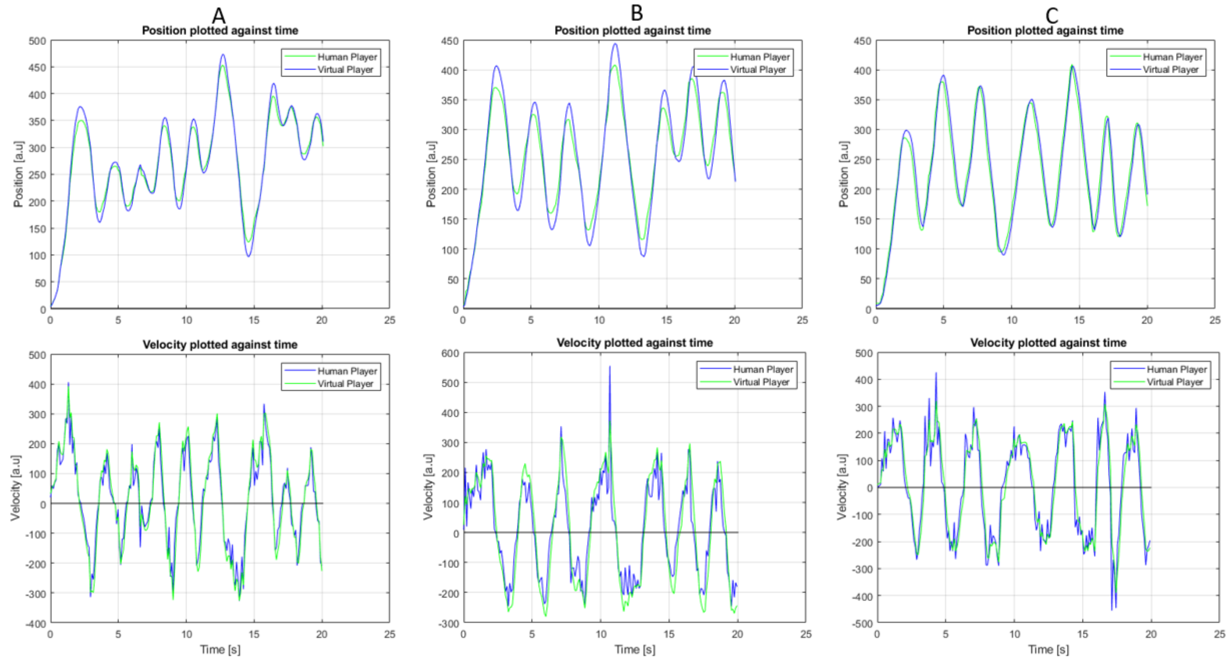

Figure 5: Control model for the leader-follower game. The top line of graphs shows the position of the HP vs VP and the respective velocity time series graphs of the HP vs VP are plotted below each position time series graph. *For column A* : $K_P = 0.6, K_I = 0.1$,for column B: $K_P = 0.4, K_I = 0.08$,for column C: $K_P = 0.5, K_I = 0.02$

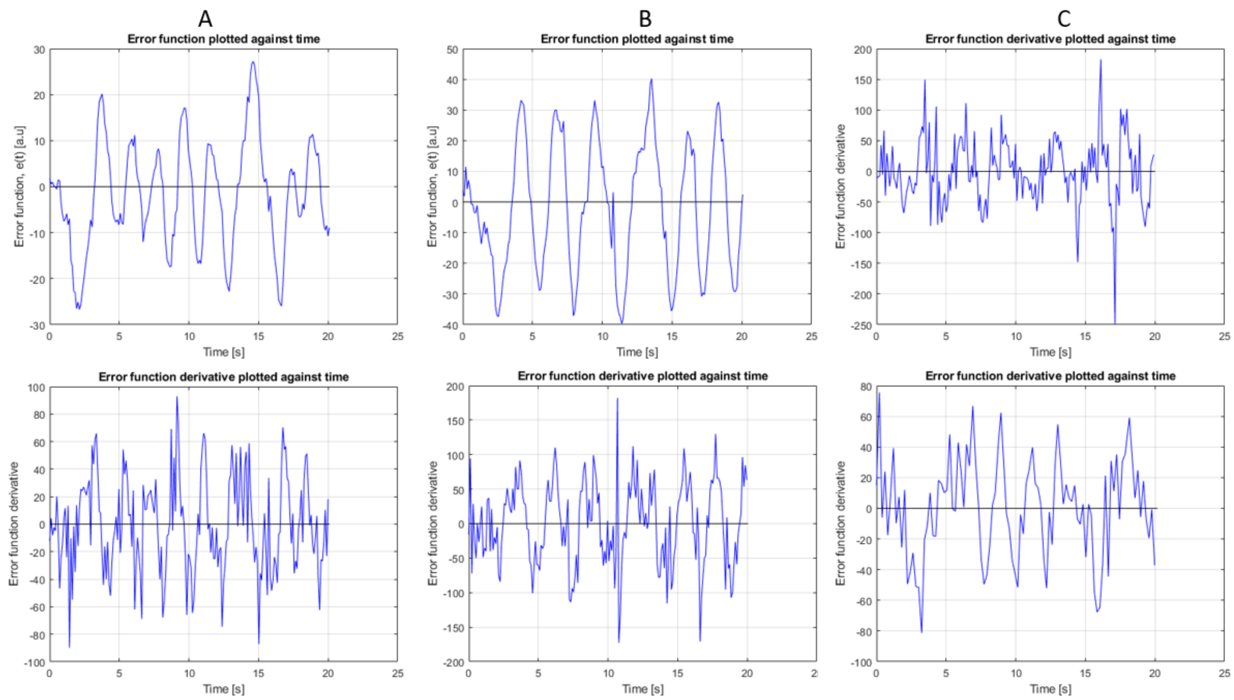

Figure 6: Error function and the error function derivative for the leader-follower game. The top line of graphs shows the position of the HP vs VP and the respective velocity time series graphs of the HP vs VP are plotted below each position time series graph. $For\ column\ A$: $K_P = 0.6, K_I = 0.1$,for column B: $K_P = 0.4, K_I = 0.08$,for column C: $K_P = 0.5, K_I = 0.02$

3 Discussion

3.1 Analysis of Results

The position time series recorded in the experiment for both players are shown in figure 5). In all games we observed a complex motion by the HP and the VP (ref fig). The player performed sinusoidal-like motions throughout the event. We observed abrupt changes between the amplitude and frequency in the velocity times series graphs. To analyse the motion, we segmented it into periods of zero-velocity events (n = 43 segments in the experiments conducted). We observed the difference between the times in which the players reached zero velocity and found that 63% of the time, the times were equal to 200 ms, the set time lag in the simulation. This shows that the PI controller does an effective job of mimicking human motion. We observe as well that the VP displayed a jittery motion. Thus, rather than remaining behind the leader, we observed that the VP overshoots and undershoots the HP's motion with a certain frequency. This jittery motion is similar to that of the 1–2 Hz jitter studies of computer generated oscillating bodies [Miall et al., 1993]. The greater number of jitters observed in the VP stems from the PI controller successfully predicting the motion of the HP based on the tracking error [Kobori and Haggard, 2007]. As the VP acts as a follower, the increased value for the integral component coefficient across varied motions shows the gradual decrease in the error in the positions for the HP and VP. This shows a high level of coordination between the motions for the HP and VP. Alternatively, with the definition for the phase leadership [Dörfler et al., 2013], the positive phase in the graphs mentioned above confirms that the VP accurately tracks the HP in the experiment.

3.2 Limitations

Despite being a successful model in many ways, there are many limitations for using a method such as this for rehabilitation. The fact that this model is only developed for movement in one dimension is the first critical issue. Limiting the degrees of freedom used for the simulation hugely limits the positive effects on the patient as it will only affect particular muscles. With this, is the problem of the tasks not being engaging enough. If patients are not stimulated by the task, they are less likely to feel motivated to cooperate. This could result in the patient lacking in effort when following the AI or being reluctant to repeat the task multiple times which is necessary for any improvement [Hung et al., 2016]. Another disadvantage of this model is that having the AI copying the patient's motions rather than the other way round is more difficult to code. We decided to still choose this method however as it would be a struggle to create an AI that would move in a randomised manner that is still human-like. In making the VP the follower, we avoid this issue, and are able to compare the motion of our VP to that of the HP it is following.

The greatest set back with our model comes with the fact that the user interface is currently restricted to mouse movement. Although the graphical game interface is confined to 1 dimensional motion, the human user could be moving in any direction, having only the horizontal component of their motion tracked. This means that our VP may not always be accurately tracking the full motion of the human and thus lack of synchronicity could affect rehabilitation. Another issue with using a mouse is that non-smooth surfaces would lead to friction causing abrupt changes in motion of the VP.

3.3 Potential Further Advancements

In future models we propose that the AI becomes the leader and the human attempts to copy the AI's behaviour. We propose that the proportional and integral coefficient constants can be changed from our model and taken into the next game where the HP follows the VP. In this game the VP is initially similar to the HP as much as possible to allow for greater synchronicity between the two. The VP will then employ deep learning techniques to change the K_P and K_I values. This will allow the AI to develop a wider range of motions and will aid in synchronicity with the HP. We also propose adding a derivative component to the system to dampen the system as and when required. This will allow for more flexibility in the treatment of the patients as the therapists will have a wider range of parameters with which to test the patient.

Following on from the limitations of our project, a major advancement in our model would be moving to using more advanced technological interfaces. An aim for the future could be to try and advance the model, allowing for 2, or even 3, dimensional movement. Allowing for a greater range of motion in the rehabilitation would essentially increase the number of treatments available, and possibly the effectiveness of the treatment. Finally, a benefit of advancing from using a computer mouse would allow for the VP to fully track the motion human themselves, rather than a device they are holding.

4 Conclusion

Humans that are affected by conditions such as stroke, autism and motor neuron diseases have a severely decreased range of motion. Their ability to fully control their muscles has diminished and in most cases continues to worsen. The rehabilitation process may take place in one of two ways. We have modelled the AI following the human, perhaps to give the patient some semblance of control during the therapy process. This acts as a suitable first stage for the therapy process.

This paper succeeds in accurately tracking and modelling the human player motion with the use of a PI controller. The plotted data (Figure 5) shows the sharp rises and drops in amplitude; we understand that the human player swings the slider from side to side in an attempt to outwit the VP, which was an expected outcome of the experiment. Such instances of togetherness are rare in daily life, yet our simulation is the first step in assuring patients and their therapists that synchronicity can be an effective way of treating motor impairments. The mirror game-like simulation that we have worked on also taps into a fundamental human emotion, the ability to connect with another being, even if it is virtual. Such bonding forms the basis of parent-children relationships [Winnicott, 1967], and children playing [Eckerman and Stein, 1990], and rapports between people [Chartrand and Bargh, 1999]. These rapports form an integral part of the human experience which is the main aim of our project. This was achieved through the VP simulations.

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