Università degli Studi di Napoli Federico II

SINCRO

Sincronizzazione e Controllo
di Reti e Processi

Modeling, Control and Design of Artificial Avatars for Human/Machine Interaction

by

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PhD School Italo Gorini – 8th September 2021

Outline

- Introduction and motivation
- The mirror game and the need for a virtual player
- Previous approaches
  - Reactive Predictive models [Noy et al, 2011]
  - Human Dynamic Clamp [Dumas et al, 2009; 2014]
- A feedback control approach
  - adaptive control
  - optimal control
- Validation and performance evaluation
- Movement coordination in larger human ensembles
- Conclusions

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Social Robotics

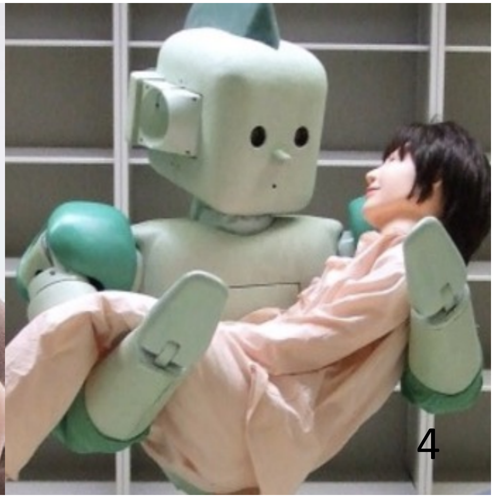
- A social robot is an autonomous robot that interacts and communicates with humans or other autonomous physical agents by following social behaviours and rules attached to its role.

- Human/Machine interactions can be potentially useful as they can affect people's wellbeing, behaviour and interaction with others.

- Social robots can interact with people in their own space and provide healthcare, rehabilitation and lifestyle support, while being reliable and inexpensive.

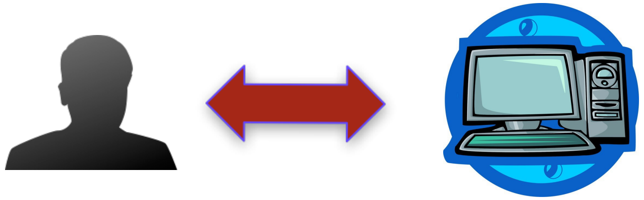
Rod Walsh, Tampere University of Applied Sciences, The first DMU workshop on Assisted Living Technologies (ALT 2012)

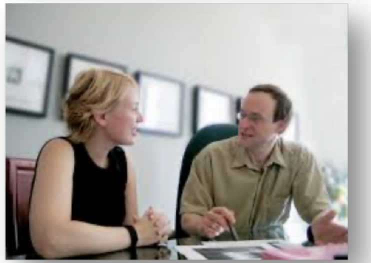




Human Movement Coordination

- The emergence of coordinated behaviour between humans is a complex phenomenon characterised by highly nonlinear behaviours.
- At the core of the interaction lies a fundamental feedback mechanism between the players.





- The aim of current research is to understand how processes of motor coordination can be modelled and how they are influenced by specific features of the individuals involed (e.g. similarity/dissimilarity).
- The use of virtual avatars (VP) has been proposed as an effective methodology to explore these effects as their properties can be changed at will.

A design pipeline

- To design cognitive architectures able to drive virtual avatars or robots in interacting with humans we need some paradigmatic case of study
- We will focus here on **motor coordination** between two or more players
- We will then

1. Explore how to model the coordination process among individuals and what influences the level of coordination between them
2. Exploit the model to synthesize cognitive architectures to drive a virtual avatar in interacting with humans
3. Validate through appropriate metrics the performance of such interaction

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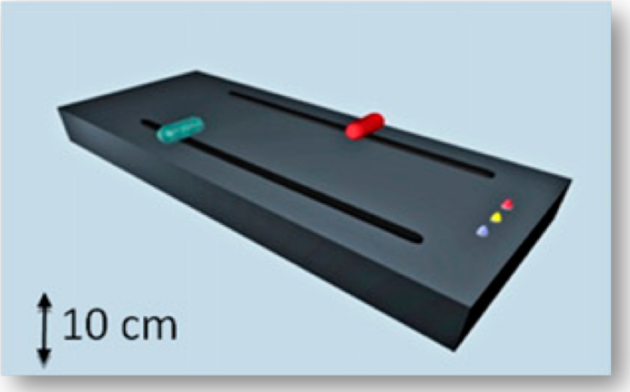
The mirror game: a paradigmatic example

- We use the mirror game as a simple yet effective paradigm.
- In its simplest formulation, the mirror game features two people imitating each other's movements at high temporal and spatial resolution.
- It can be played in different conditions:
  - *Leader-Follower* (LF)
  - *Joint Improvisation* (JI)
  - Solo condition (S)

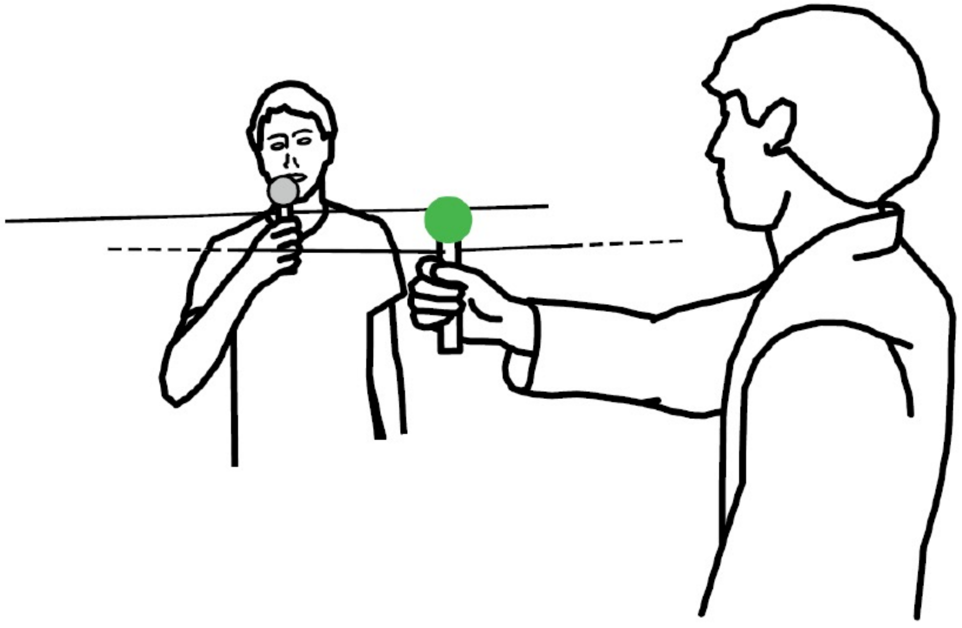


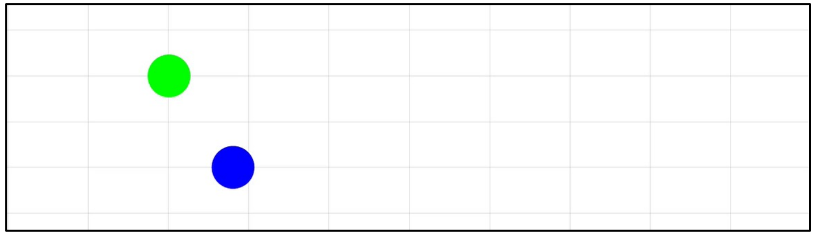
Noy, Lior, Erez Dekel, and Uri Alon. "The mirror game as a paradigm for studying the dynamics of two people improvising motion together." Proceedings of the National Academy of Sciences 108.52 (2011): 20947-20952.

The mirror game

- Powerful paradigm for studying human motion and interpersonal human coordination

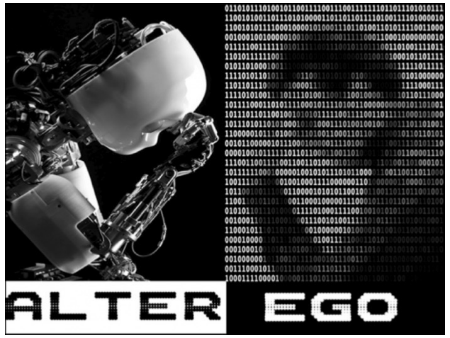
- We focus on the problem of exploring how differences in the way the players move when playing solo (on their own) affect their interaction.





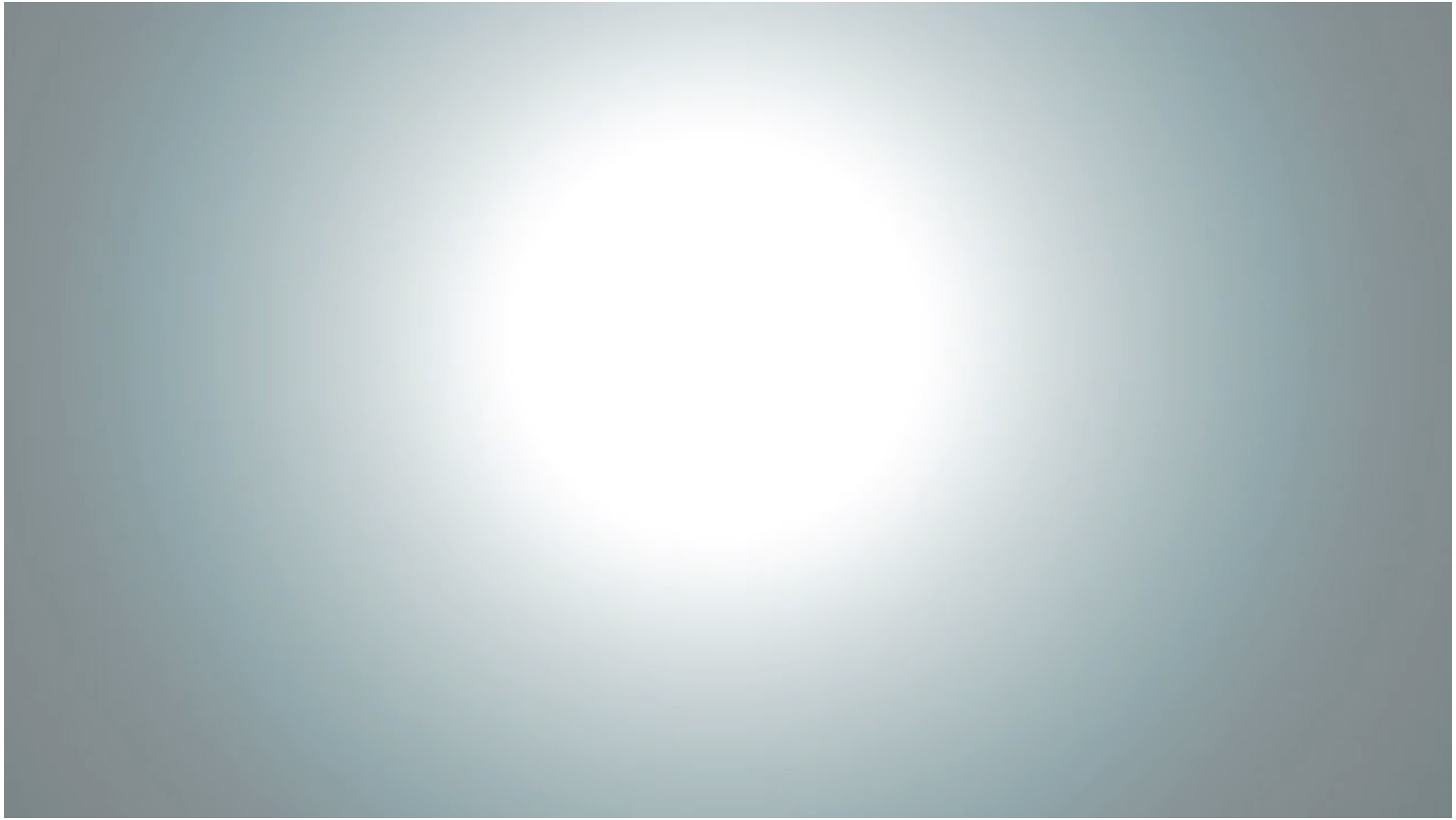
Motivation

- Coordination games can be used to help people suffering from social disabilities (as for example schizophrenia) improve their social skills.
- In order to implement an effective rehabilitation, the patient should ideally interact first with people who are similar to him/her, and then gradually with someone who is totally different.
- To implement this scenario it is necessary to create an avatar or virtual player (VP) able to play the mirror game.
- This was the goal of the **EU project ALTEREGO.**
- We will focus on the problem of *designing a control architecture (or cognitive architecture) able to drive the virtual player* as a:
  - leader;
  - follower;
  - joint-improviser.



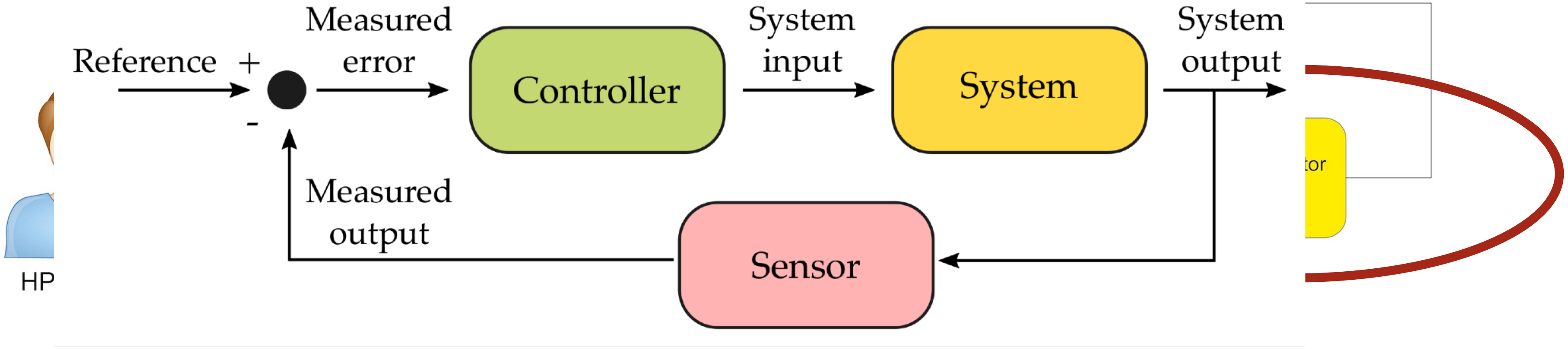
www.euromov.eu/alterego

Motivation



Why feedback control theory?

- The problem of designing a virtual player able to coordinate its motion with a human player can be seen as a **control design problem.**
- The goal is that of designing a *cognitive architecture* able to drive the motion of the VP interacting with a human player in **real-time** while exhibiting different features (e.g. different kinematic signatures).
- This is a typical nonlinear control design problem…



Control = sensing + computation + actuation

- We also need a **model of the system we wish to control.**

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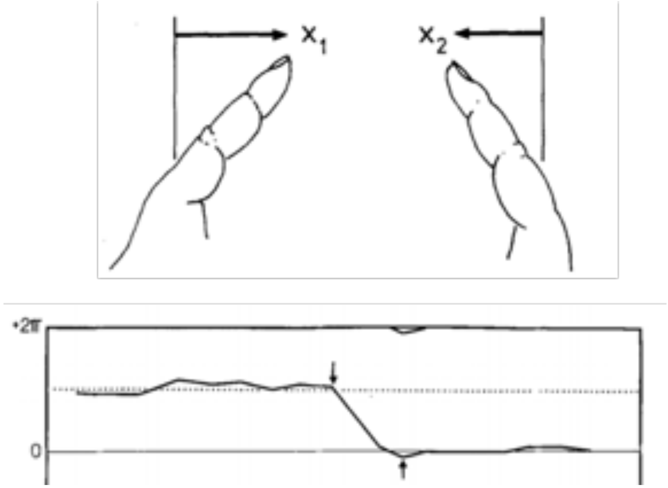
The Haken-Kelso-Bunz (HKB) oscillator

- One of the earliest model is the HKB oscillator
- Originally developed to explain some phenomena observed in the bimanual experiments [3], and then vastly used later on in different contexts dealing with coordination between two people.



$$\begin{cases} \ddot{x}_1 + (\alpha x_1{}^2 + \beta \dot{x}_1{}^2 - \gamma)\dot{x}_1 + \omega^2 x_1 = \left[a + b\left(x_1 - x_2\right)^2\right]\left(\dot{x}_1 - \dot{x}_2\right), \quad x_1 \in \mathbb{R} \\ \ddot{x}_2 + (\alpha x_2{}^2 + \beta \dot{x}_2{}^2 - \gamma)\dot{x}_2 + \omega^2 x_2 = \left[a + b\left(x_2 - x_1\right)^2\right]\left(\dot{x}_2 - \dot{x}_1\right), \quad x_2 \in \mathbb{R} \end{cases}$$

- We can think of this model as a control system of the form

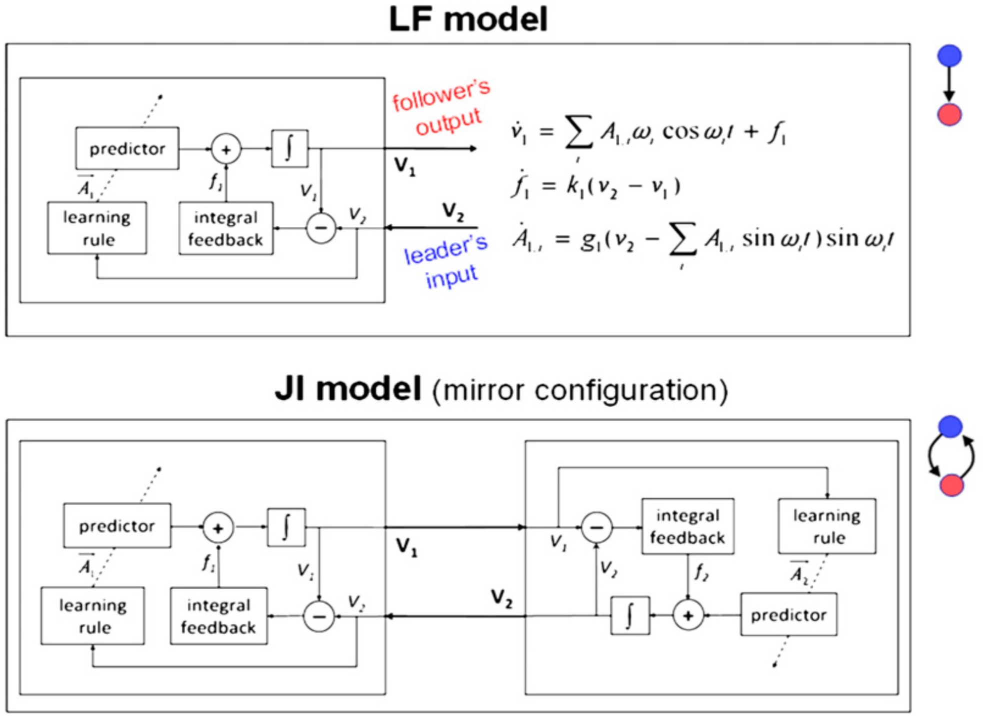
$$\ddot{x} + (\alpha x^2 + \beta \dot{x}^2 - \gamma)\dot{x} + \omega^2 x = u(t, x, \dot{x}, y, \dot{y})$$

[2] Słowiński, P., Zhai, C., Alderisio, F., Salesse, R., Gueugnon, M., Marin, L., ... & di Bernardo M. , Tsaneva-Atanasova, K. (2015). Dynamic similarity promotes interpersonal coordination in joint-action. Royal Society Interface, 2016

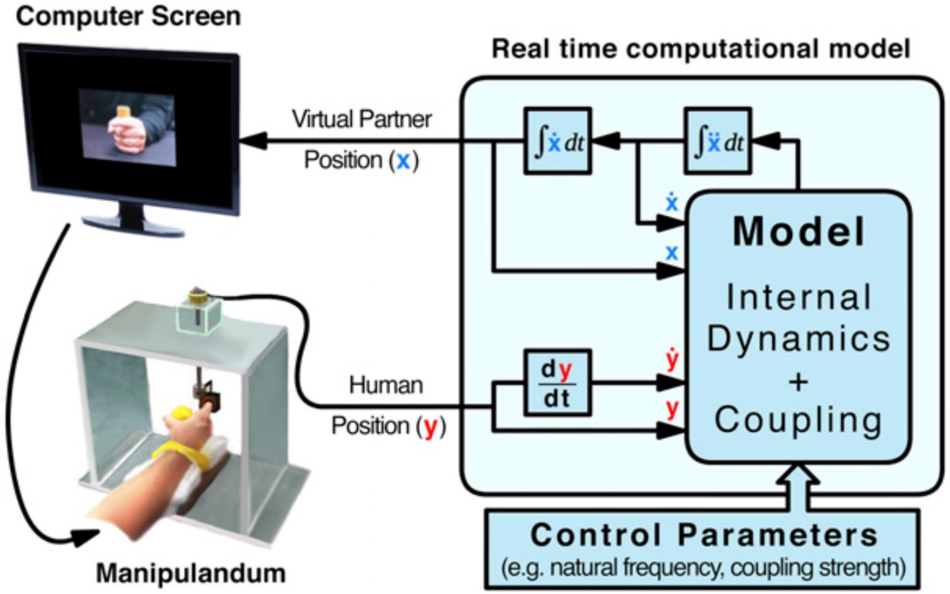
[3] Haken, H., Kelso, J. S., & Bunz, H. (1985). A theoretical model of phase transitions in human hand movements. Biological cybernetics, 51(5), 347-356.

Other approaches

- Other modelling approaches have been proposed in the literature that relate to this control architecture:
  - The **reactive-predictive control (RPC)** proposed by Noy et al (2011);
  - The **Human Dynamic Clamp (HDC)** proposed by Dumas et al (2009; 2014).



$$\dot{v}_1 = \sum_i A_{1,i}\omega_i \cos\omega_i t + f_1$$
$$\dot{f}_1 = k_1(v_2 - v_1)$$
$$\dot{A}_{1,i} = g_1(v_2 - \sum_i A_{1,i}\sin\omega_i t)\sin\omega_i t$$



Reactive-Predictive Controller model

- In the RPC the motion of each player is modelled as

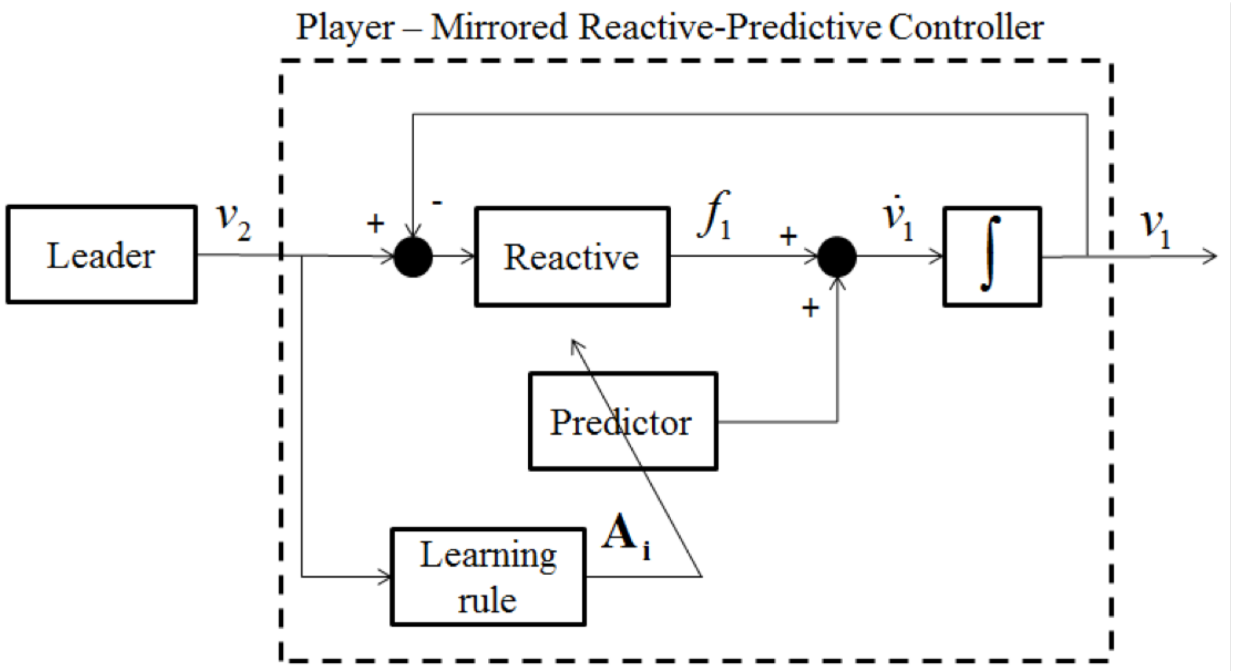
$$\ddot{x} = \sum_{i=1}^{5} A_i \omega_i \cos(\omega_i t) + f_1$$

with the coupling determined by

$$\dot{f}_1 = k(v_2 - v_1), \;\; k > 0$$

and the parameters of the series expansion being computed adaptively as

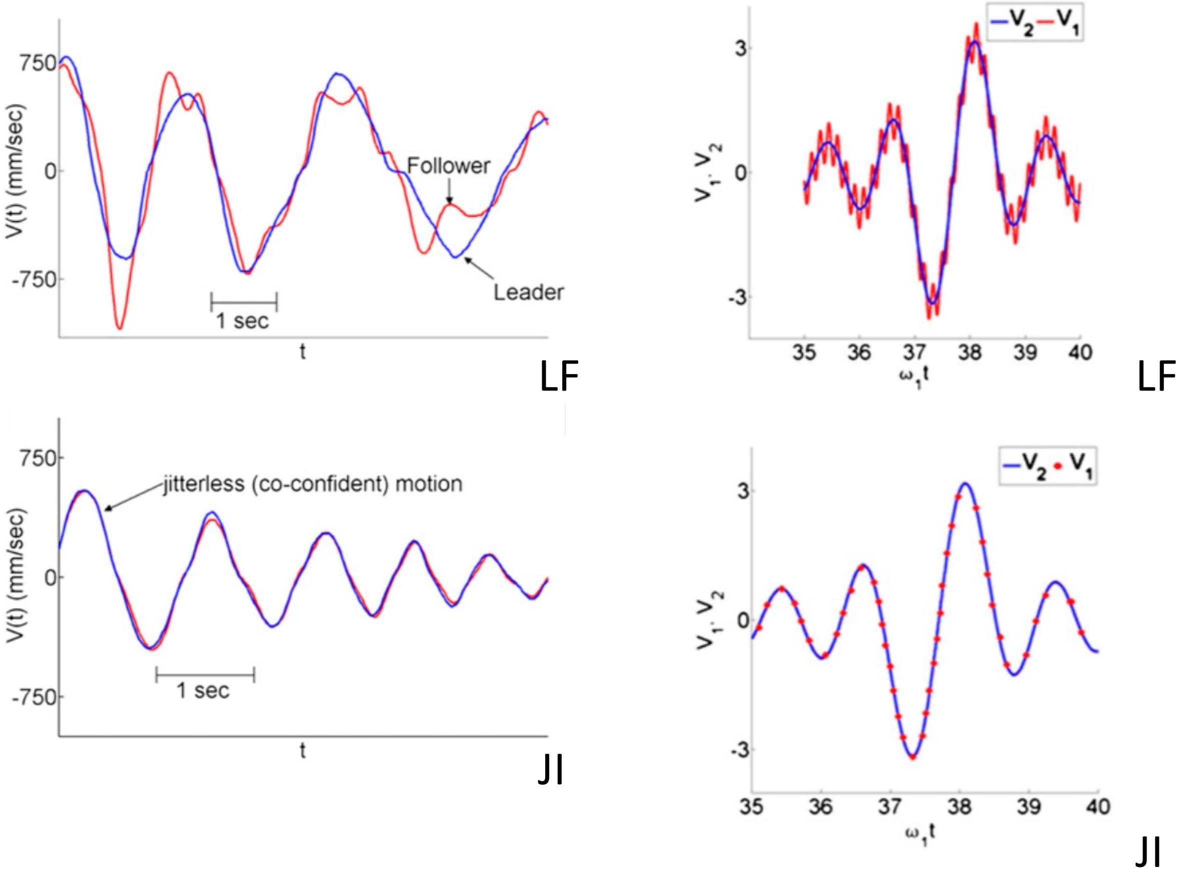
$$\dot{A}_i = \lambda \left[v_2 - \sum_{i=1}^{5} A_i \sin(\omega_i t) \right] \sin(\omega_i t), \;\; \lambda > 0$$



Noy, Lior, Erez Dekel, and Uri Alon. "The mirror game as a paradigm for studying the dynamics of two people improvising motion together." Proceedings of the National Academy of Sciences 108.52 (2011): 20947-20952.

RPC model performance

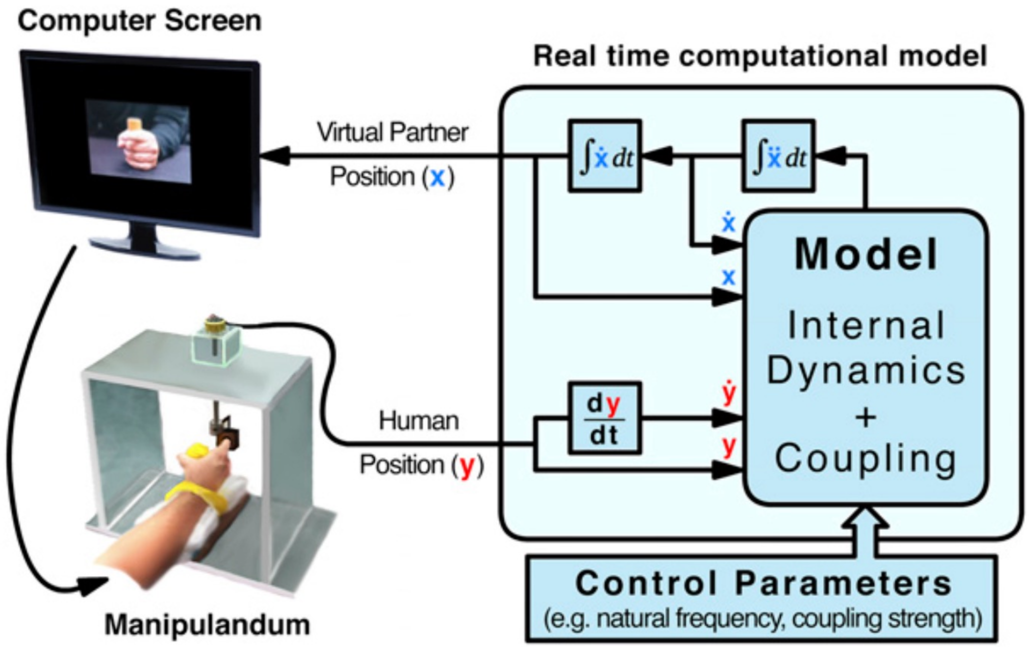
Experimental Data Model



- RPC manages to reproduce:
  - ⋆ jitter motion in LF condition;
  - ⋆ jitter-less accurate motion in JI condition;
- ⋆ Clearly the generated motion is simple,
- ⋆ not very accurate in terms of temporal correspondence.
- Also no control of the signature.

Human dynamic clamp

- The HDC paradigm is introduced to directly manipulate the interaction between a HP and a VP based on the use of a mathematical model.
- It is used to model the interactions between HP and VP in different scenarios:
  - rhythmic behaviour;
  - discrete behaviour;
  - adaption to changes of pacing;
  - behavioural skill learning as specified by a virtual "teacher".
- Different model for each scenario.



Dumas, de Guzman, Tognoli, Kelso. "The human dynamic clamp as a paradigm for social interaction". Proceedings of the National Academy of Sciences, 111.35 (2014): 3726-3734.

HDC – Rhytmic behaviour

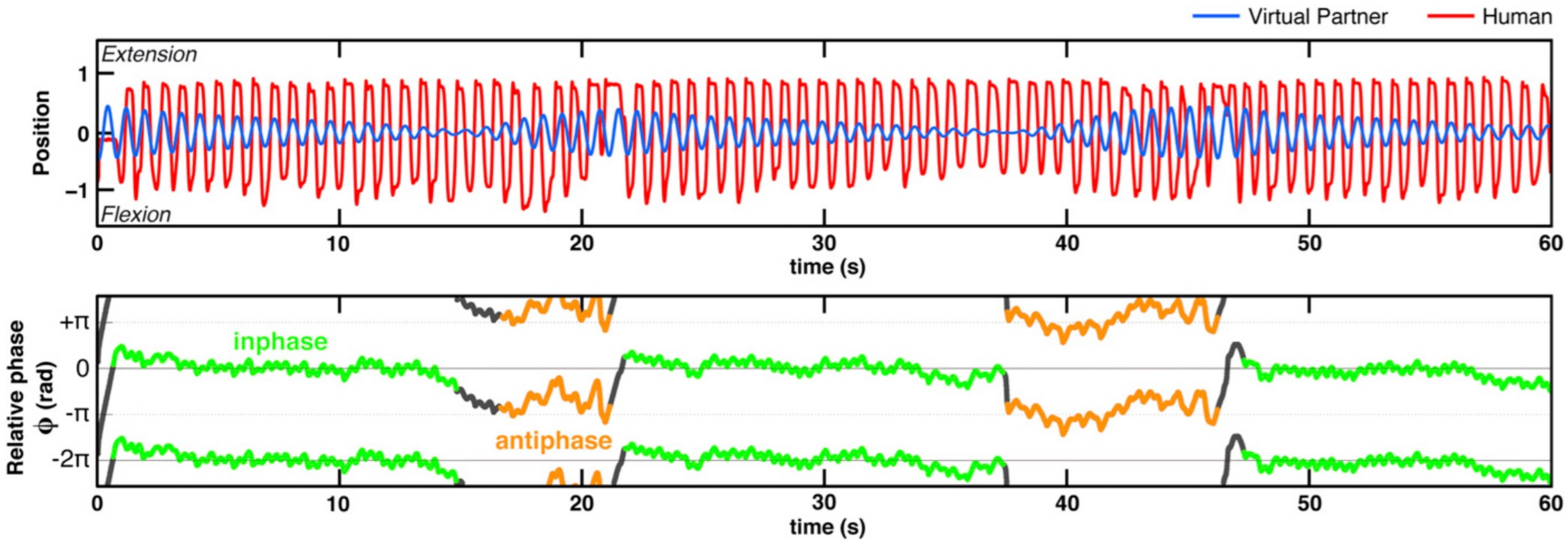
HKB model

Control input

$$\ddot{x}+\left(\alpha x^2+\beta\dot{x}^2-\gamma\right)\dot{x}+\omega^2 x=\boxed{\left[A+B(x-\mu y)^2\right](\dot{x}-\mu\dot{y})}$$

- $x,\dot{x}$: position and velocity of the VP;
- $y,\dot{y}$: position and velocity of the HP;
- α,β,γ: tunable parameters;
- ω: oscillation frequency;
- A,B: coupling parameters;
- μ: determines in phase (1) or anti-phase (-1) coordination.

Anti-phase coordination $(\mu=-1)$: HP is supposed to follow VP



HDC – Discrete Behaviour

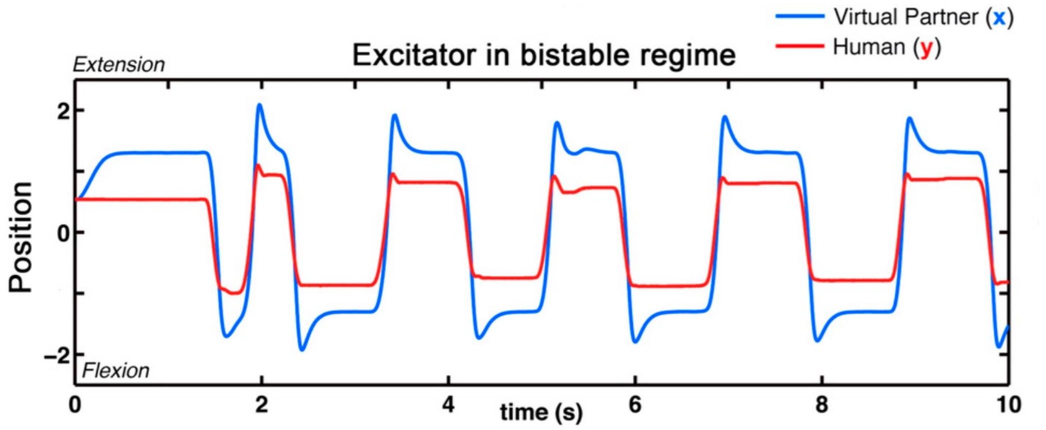
Jirsa-Kelso excitator model

Control input

$$\ddot{x}+\tau\omega\left(x^2+x^4-1\right)+\omega^2\left(x-a-b\left(\frac{\dot{x}}{\tau\omega}-x+\frac{1}{3}x^3+\frac{1}{5}x^5-y\right)\right)=\boxed{\left[A+B\left(x-\mu y\right)^2\right]\left(\dot{x}-\mu\dot{y}\right)}$$

- $x,\dot{x}$: position and velocity of the VP;
- $y,\dot{y}$: position and velocity of the HP;
- τ: time constant;
- ω: oscillation frequency;
- a,b: tunable parameters;
- μ: determines in phase (1) or anti-phase (-1) coordinat.;
- A,B: coupling parameters.

In phase coordination $(\mu=+1)$: VP is supposed to follow HP



Adaption to changes of pacing

Jirsa-Kelso excitator model

Control input

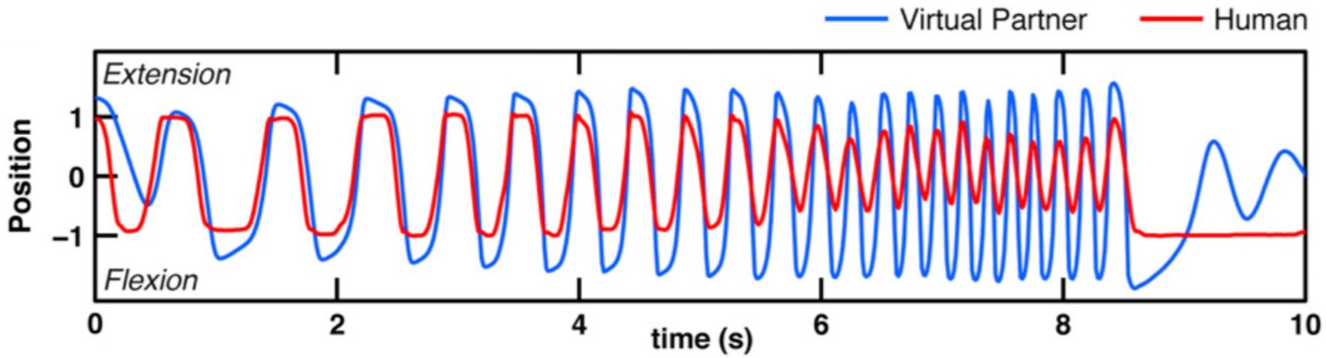
$$\ddot{x}+\tau\omega\left(x^2+x^4-1\right)+\omega^2\left(x-a-b\left(\frac{\dot{x}}{\tau\omega}-x+\frac{1}{3}x^3+\frac{1}{5}x^5-y\right)\right)=\boxed{\left[A+B(x-\mu y)^2\right](\dot{x}-\mu\dot{y})}$$

$$\boxed{\dot{\omega}=v\left(\omega_0-\omega\right)\pm ky\frac{\dot{x}}{\sqrt{x^2+\dot{x}^2}}}$$

Adaptive parameter

- k : strength of the adaptation;
- ω_0 : preferred frequency;
- v : strength of the preferred frequency.

In phase coordination $(\mu=+1)$: VP is supposed to follow HP



Some remarks

- In all these cases, a **nonlinear feedback control input** is used to steer the dynamics of some model of the VP motion in real time, e.g.

$$\ddot{x} + (\alpha x^2 + \beta \dot{x}^2 - \gamma)\dot{x} + \omega^2 x = u(t, x, \dot{x}, y, \dot{y})$$

- Both the HDC and RP control have some **key limitations**
  - The movement to be reproduced is almost periodic and it is rather simple in terms of amplitude and frequency;
  - no control of the "tracking error" between the players ; (temporal correspondence)
  - no control of the VP kinematic features (we want the VP to exhibit *human-like* behaviour)
- Also, the VP cannot generate spontaneous movements (i.e., it cannot act as a Leader).
- Convergence and stability are not guaranteed analytically.

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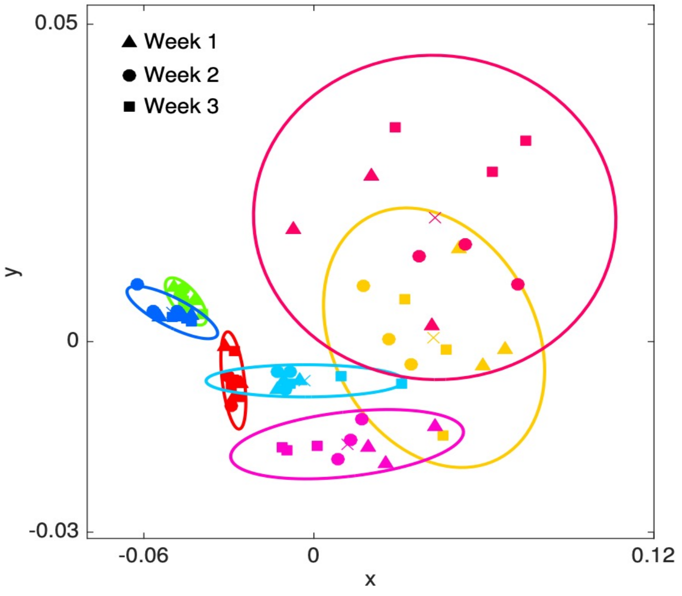
Multi-objective strategy

- We want to design a different control strategy for the VP able to achieve:
  1. the desired game condition (L, F or JI);
  2. bounded tracking of the human player motion (temporal correspondence);
  3. desired kinematic properties, e.g. a given kinematic signature (velocity pdf), which is unique and time-persisting for each human.

Individual Motor Signature (IMS)

- Participants were asked to perform three solo sessions separated by at least one week.
- Within each session, participants were required to perform three 60s rounds.
- Different colours refer to different participants in the "similarity space".

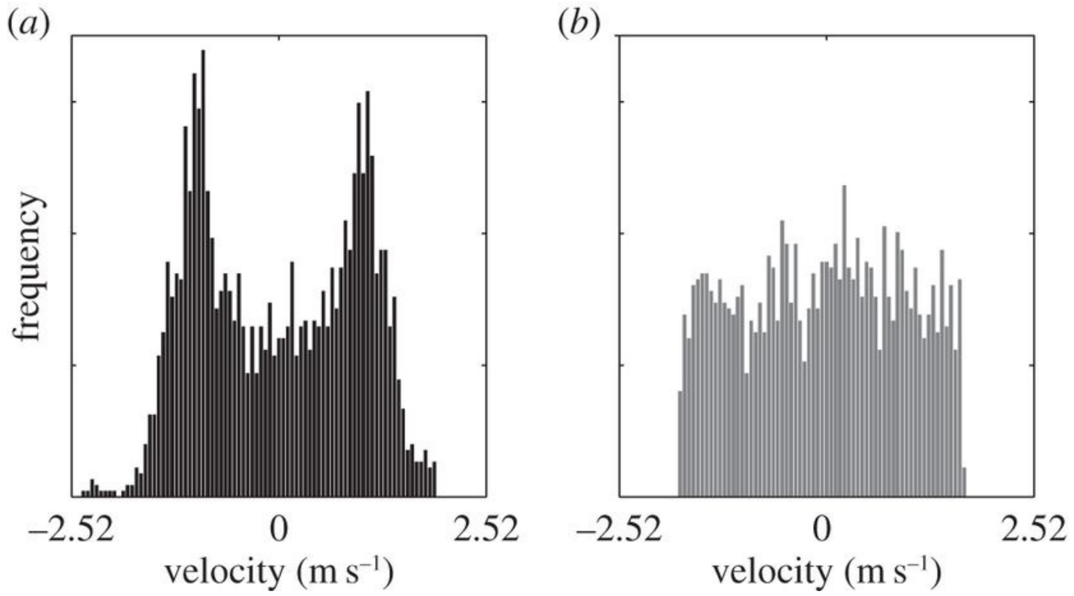
Słowiński, Piotr, et al. "Dynamic similarity promotes interpersonal coordination in joint action." Journal of The Royal Society Interface 13.116 (2016): 20151093.

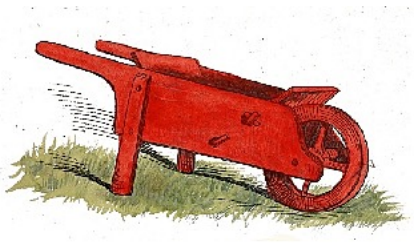


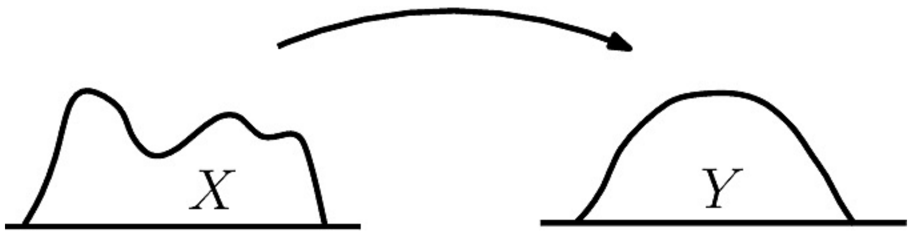
Individual Motor Signature

Individual Motor Signature

- We found that *similarity* in the velocity profile (pdf) of each player when improvising motion in the mirror game influences the level of coordination between them
- To compare pdfs we used the Earth Movers' Distance or EMD as a metric to measure their similarity







$$EMD(p_1, p_2) = \int_Z \left| CDF_{p_1}(z) - CDF_{p_2}(z) \right| dz$$

Mirror game as a control problem

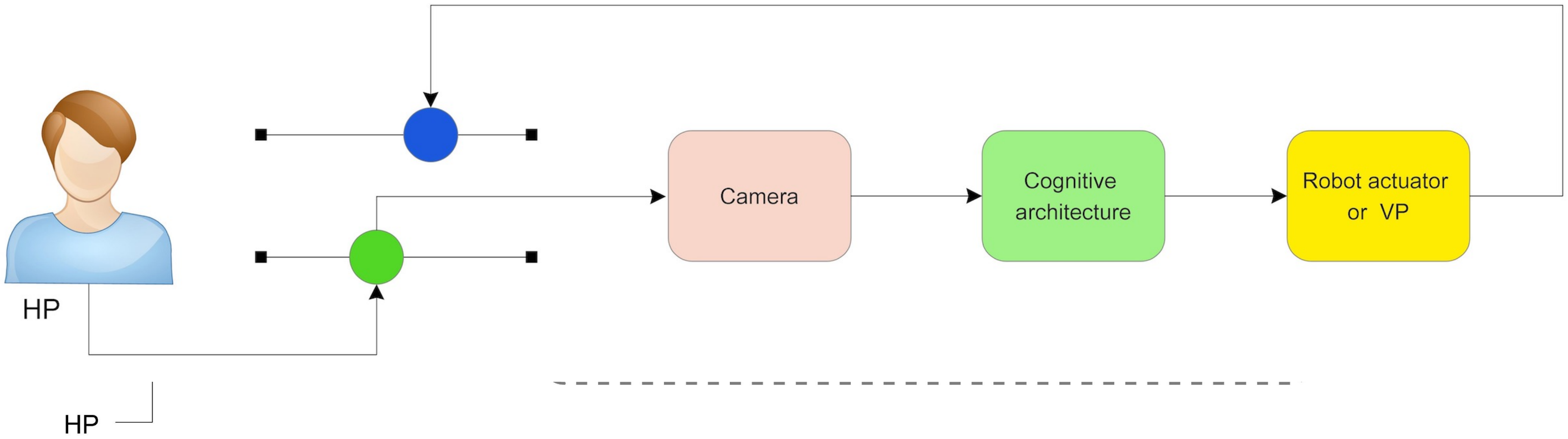
- As a model of the VP movement we use an HKB oscillator but redesign the control input to achieve the control goals:

$$\ddot{x}+\left(\alpha x^2+\beta\dot{x}^2-\gamma\right)\dot{x}+\omega^2 x=\boxed{u(t,x,\dot{x},r_p,r_v)}$$

with x: position of the VP; r_p and r_v: position and velocity of the HP.

- In the following we will:
  - ✦ start with controlling temporal correspondence between the players in a leader-follower condition;
  - ✦ move onto controlling kinematic similarity as well;
  - ✦ explain how to implement a joint-improvisation condition.

Temporal correspondence



- The velocity of the HP is estimated by the following backward difference rule

$$\hat{r}_v = \frac{r_p(kT) - r_p((k-1)T)}{T}, \quad t \in [kT, (k+1)T], \; k \in N^*$$

so that the position of the HP can be predicted by

$$r_p(t) = r_p(kT) + \hat{r}_v(kT)(t - kT), \quad t \in [kT, (k+1)T], k \in N^*$$

Control design

- We started from the **classical HKB coupling but with adaptive parameters** chosen so as to guarantee convergence

$$u(t) = \left[a(t) + b(t)(x - r_p)^2\right](\dot{x} - \hat{r}_v) - C_p e^{-\delta(x-\hat{r}_v)^2}(x - r_p)$$

with

$$\begin{aligned} \dot{a} &= -\frac{1}{a}\left[(x - r_p)(\dot{x} - \hat{r}_v) + (x - r_p)^2\right] - (\dot{x} - \hat{r}_v)^2 \\ \dot{b} &= \frac{1}{b}(\dot{x} - \hat{r}_v)\left[\omega^2 x + (\alpha\dot{x}^2 + \beta x^2 - \gamma) + u_c\right] - (x - r_p)^2(\dot{x} - \hat{r}_v)^2 \end{aligned}$$

- We then added **an extra term** to control the tracking error when the velocity mismatch between the player is small (and the coupling tends to zero).
- We were able to prove and estimate convergence.

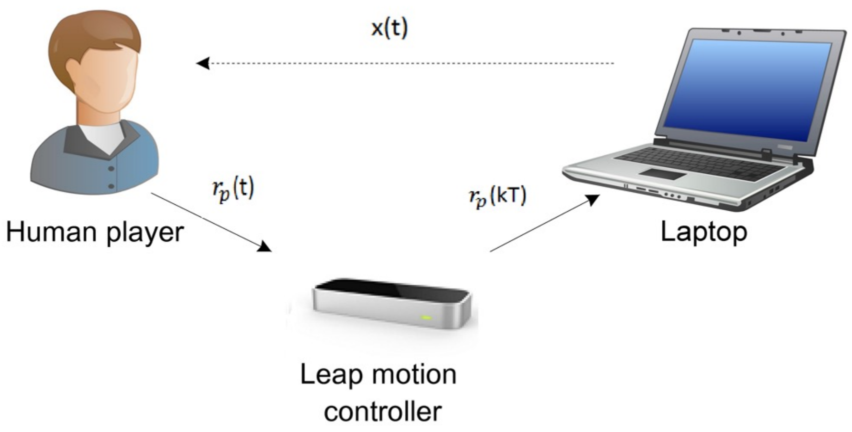
Zhai, C., Alderisio, F., Tsaneva-Atanasova, K. and di Bernardo, M. "Adaptive Tracking Control of a Virtual Player in the Mirror Game," Proc. IEEE Conference on Decision and Control, 2014, pp. 7005–7010.

Zhai, C., Alderisio, F., Tsaneva-Atanasova, K. and di Bernardo, M. "A novel cognitive architecture for a human-like virtual player in the mirror game." Proc. IEEE International Conference on Systems, Man, and Cybernetics, 2014, pp. 754-759.

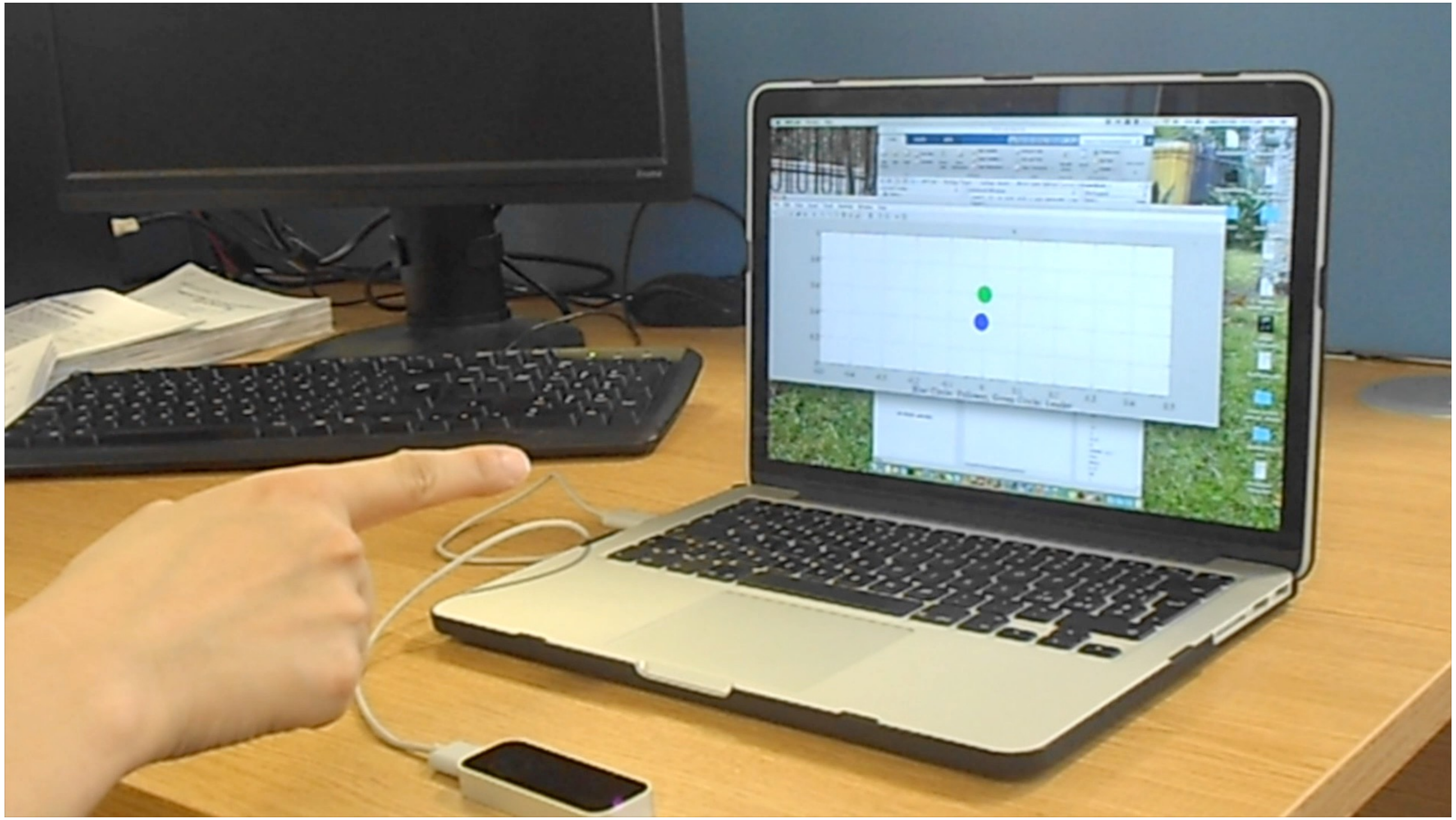
Validation

- We carried out the numerical and experimental validation of our strategy (adaptive feedback control, AFC) comparing it with the performance of the RPC proposed by Noy et al.
- For the experiments we use two set-ups: one based on a leap motion controller (used in the paper in the proceedings) and the other to be used with patients.

Experimental Setups



Experimental set-up (Bristol, UK)



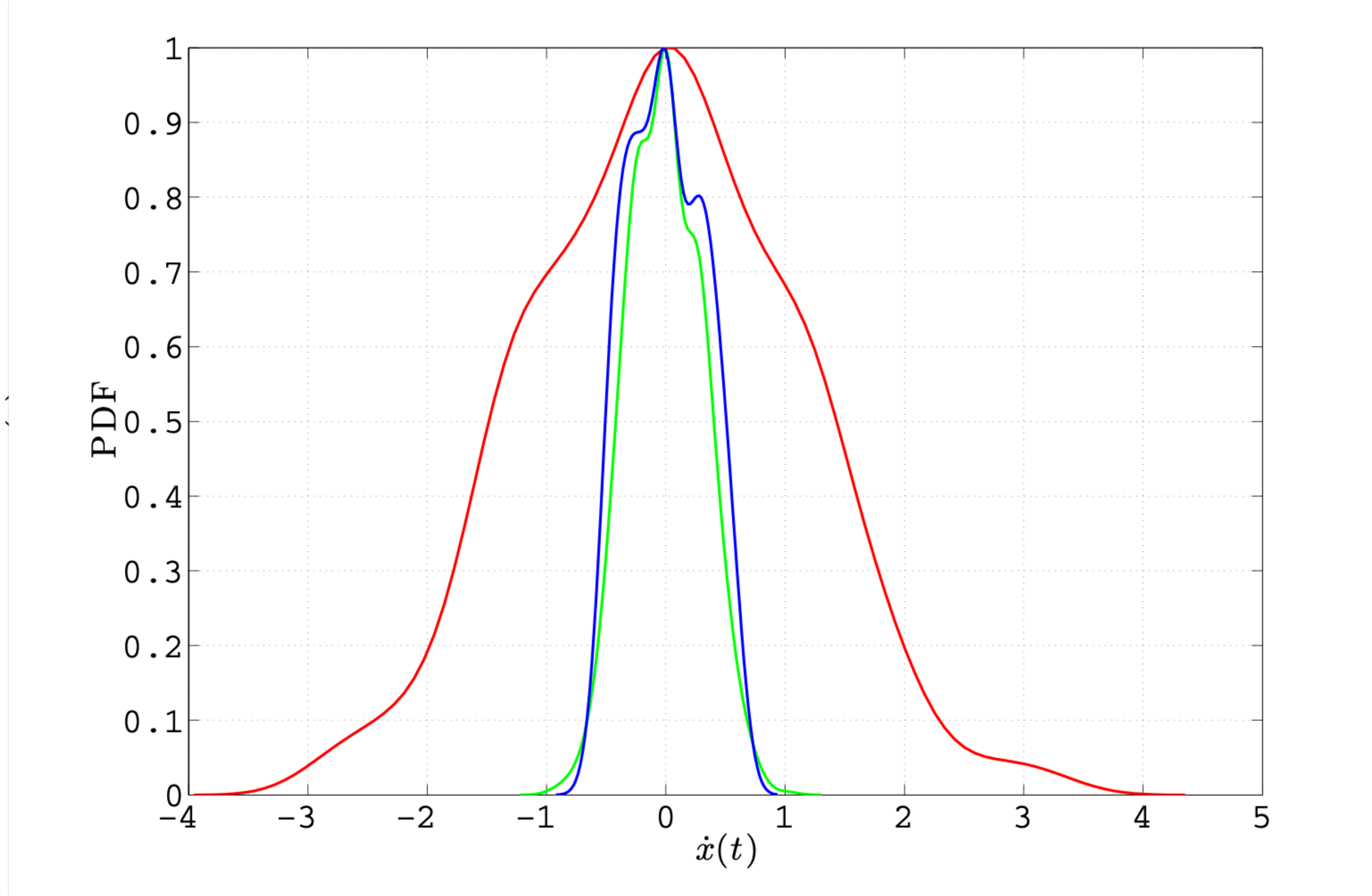
Leader: HP (green), Follower: VP (blue)

Experimental validation (Montpellier, France)

Leader: HP,   Follower: VP (avatar)

Leader (HP) - Follower (VP)

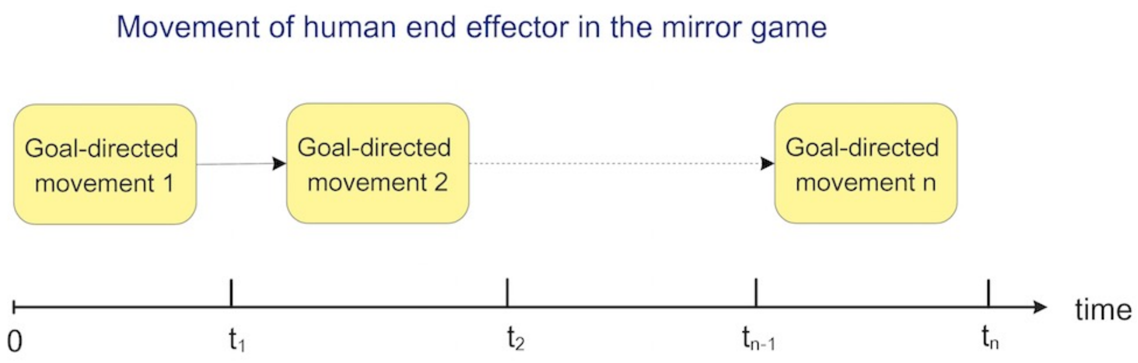
Temporal correspondence
Kinematic similarity

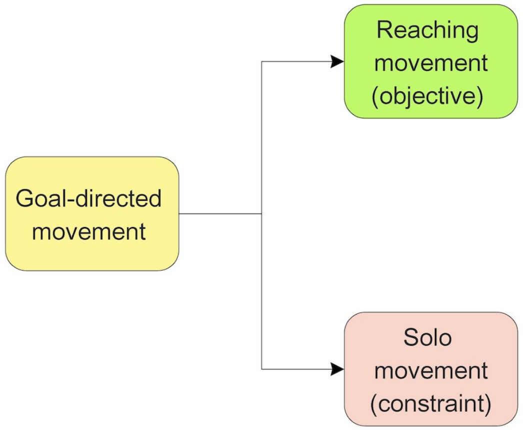


Blue: AFC, Red: RPC, Green: HP (leader)

An alternative strategy

- Adaptive control performs well but no control of the motor signature is possible and the VP cannot improvise its motion with a HP.
- To solve this problem we moved to a different control algorithm based on **optimal feedback control (OFC).**
- We consider finite time intervals and assume that on each of them the player tries to *minimise the relative position error with the other player…*
- … *while being constrained by the kinematic features of its own motor signature*





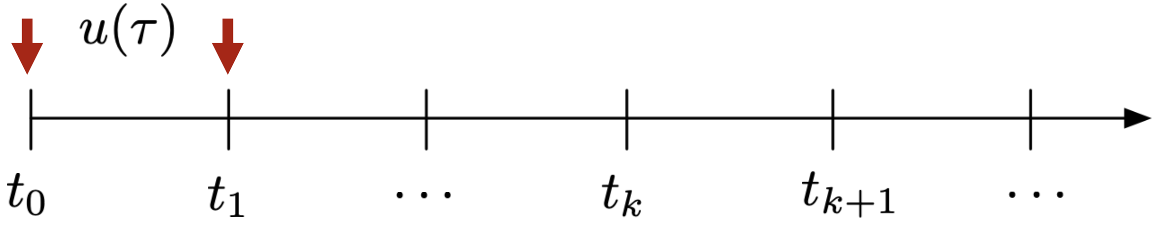
Optimal control

- We formulate the problem as an **optimal control problem** over a finite time horizon.
- Namely, on each subinterval, we look for the optimal control input that minimises

$$J = \frac{1}{2}\left[\underbrace{\theta_p \left(x(t_{k+1}) - \hat{r}_p(t_{k+1}) \right)^2}_{\text{Temporal correspondence}} + \int_{t_k}^{t_{k+1}} \underbrace{\left(1-\theta_p\right)\left(\dot{x}(t) - \sigma(t)\right)^2}_{\text{Signature control}} + \underbrace{\eta u(t)^2}_{\text{Control effort}} \, dt \right]$$

where $\sigma(t)$ is the time series associated to the desired signature (velocity profile), the position of the HP is estimated as $\hat{r}_p(t_{k+1}) = r_p(t_k) + \hat{r}_v(t_k)(t_{k+1} - tk)$ and $x, \ \dot{x}$ are predicted by the following model (dynamic constraint):

$$\ddot{x} + (\alpha x^2 + \beta \dot{x}^2 - \gamma) + \omega^2 x = u, \quad x(t_k) = x_k, \dot{x}(t_k) = \dot{x}_k$$

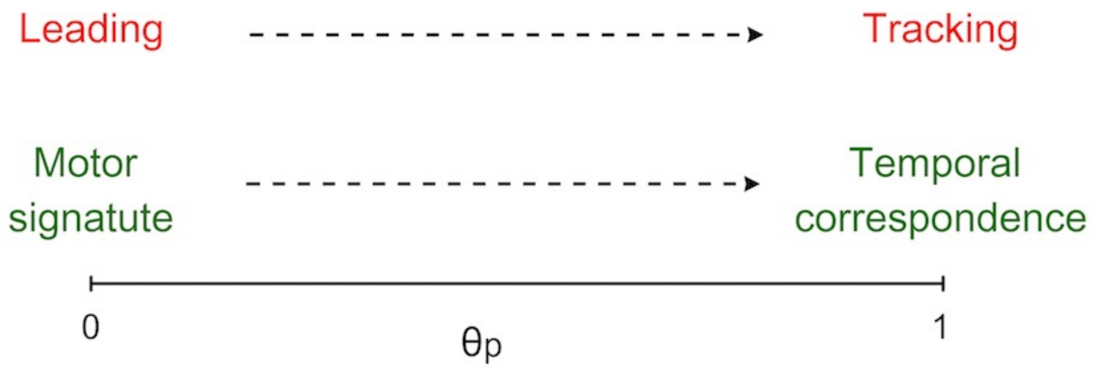


Different game configurations

- Note that by tuning the parameter $\theta_p \in [0,1]$ we can change the behaviour of the VP by making it more or less sensitive to the movement of the HP.

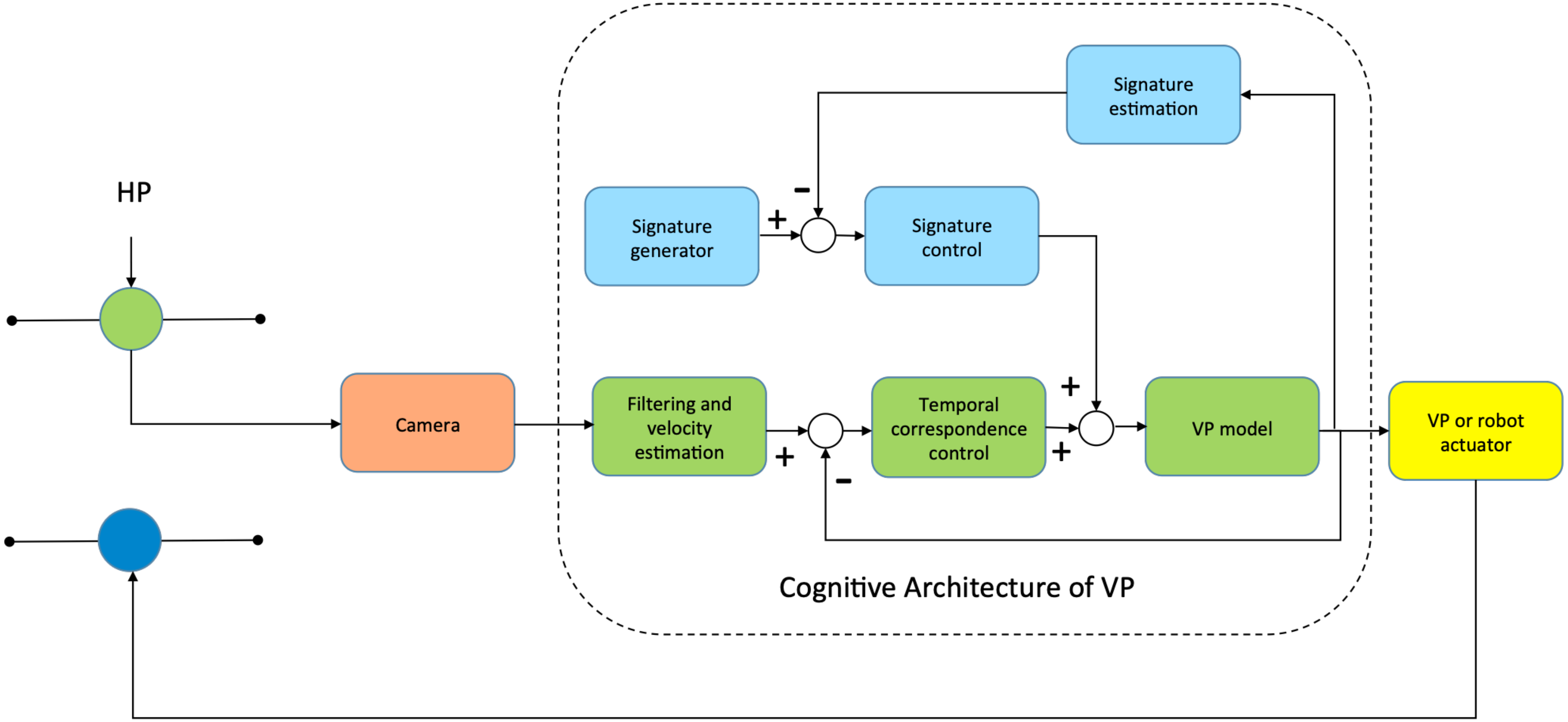
$$J = \frac{1}{2}[\theta_p \left(x(t_{k+1}) - \hat{r}_p(t_{k+1})\right)^2 + \int_{t_k}^{t_{k+1}} \theta_\sigma \left(\dot{x}(t) - \sigma(t)\right)^2 + \eta u(t)^2 + \underbrace{\theta_v \left(\dot{x}(t) - r_v(t)\right)^2}_{\text{Additional term}} \, dt]$$

- In so doing the VP can act both as a leader ($\theta_p \ll 1$) or as a follower ($\theta_p \approx 1$).



- For Joint imporvisation we add an extra term to the cost function.

Cognitive architecture



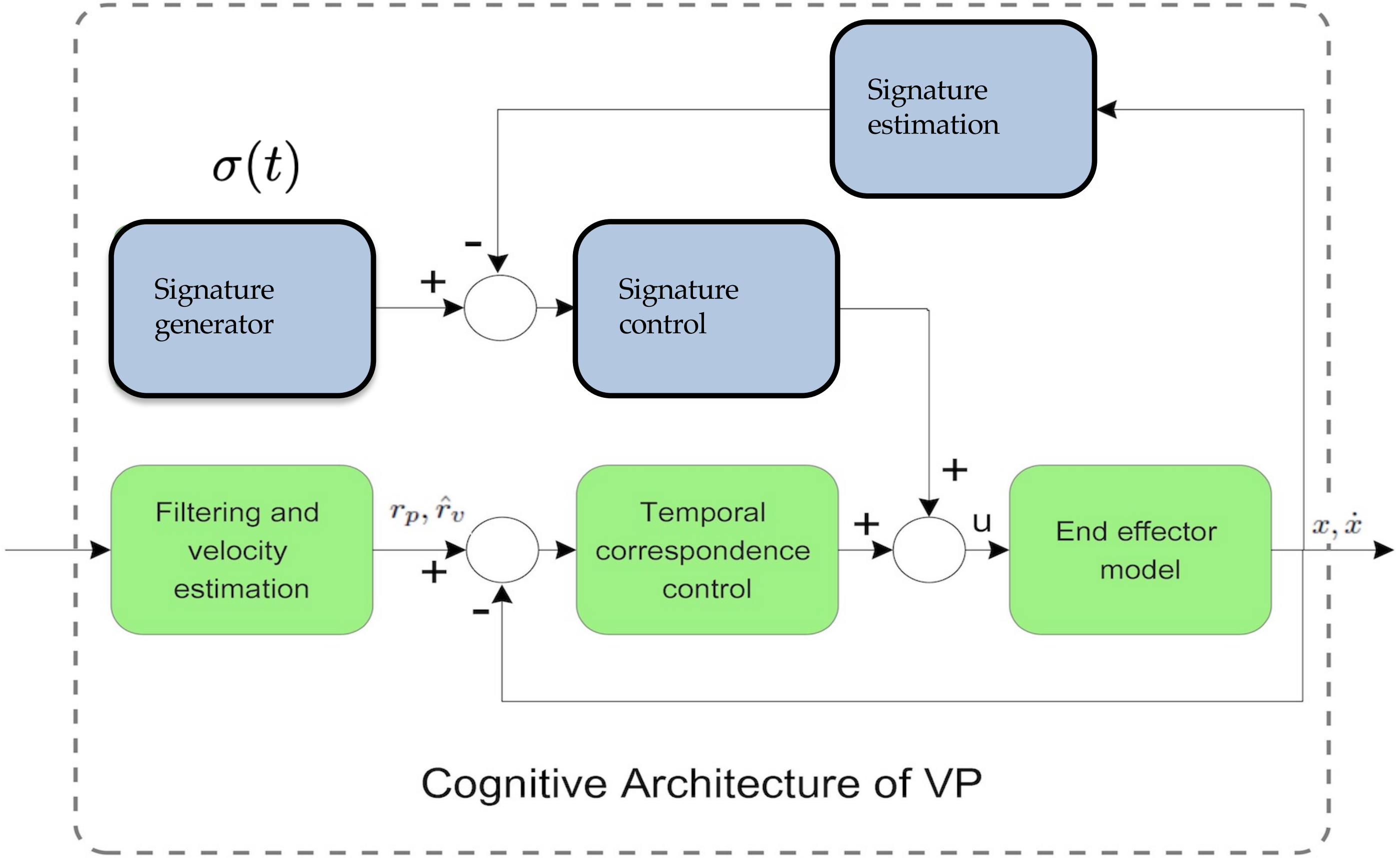
Zhai, C., Alderisio, F., Tsaneva-Atanasova, K. and di Bernardo, M. "A model predictive approach to control the motion of a virtual player in the mirror game," Proc. IEEE Conference on Decision and Control, 2015, pp. 3175-3180.

Signature generation and estimation

- In order to implement the controller we need a *signature generator* able to generate a velocity time series associated to the desired signature velocity (pdf).

- We started by using pre-recorded velocity time series of real human players collected during solo trials.

- A *signature estimator* is used to evaluate the signature of the VP in real time.

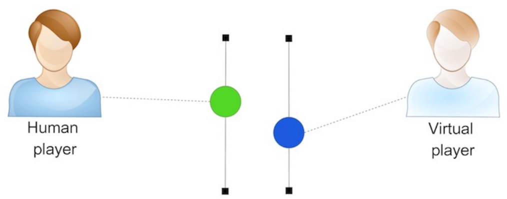


- At the moment we use simply the velocity of the VP during the game but other solutions are possible.

Outline

- Introduction and motivation
- The mirror game and the need for a virtual player
- Previous approaches
  - Reactive Predictive models [Noy et al, 2011]
  - Human Dynamic Clamp [Dumas et al, 2009; 2014]
- A feedback control approach
  - adaptive control
  - optimal control
- Validation and performance evaluation
- Movement coordination in larger human ensembles
- Conclusions

Experimental validation



- We validate our approach in several scenarios.
- To evaluate the control performance we need to define appropriate metrics
- To assess temporal correspondence we use the root mean square of the position Error (RMS) computed as:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(x_i - r_{p,i}\right)^2}$$

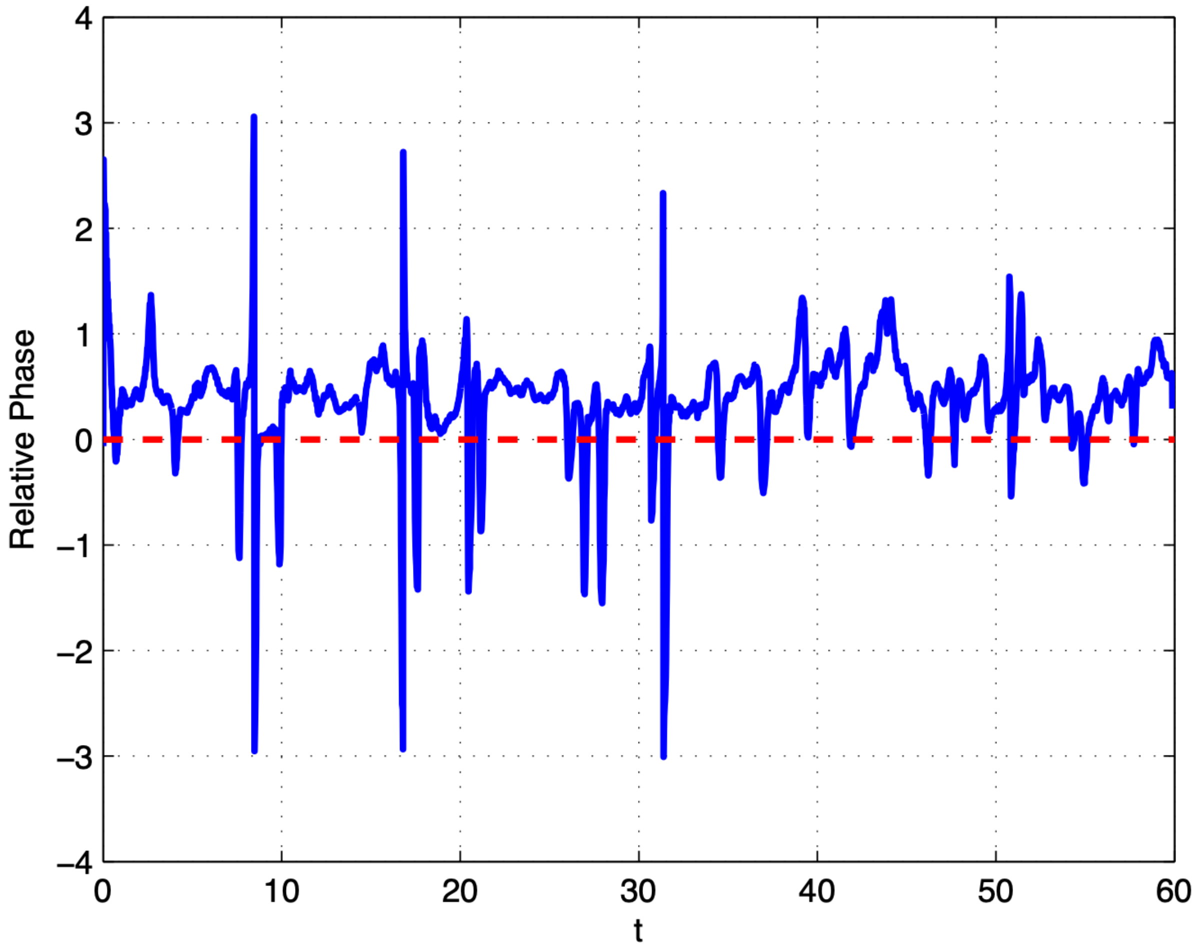
- To assess the similarity/dissimilarity between motor signatures we use the EMD between their distributions:

$$EMD\left(p_1, p_2\right) = \int_Z \left|CDF_{p_1}(z) - CDF_{p_2}(z)\right| dz$$

- We also keep track of the control energy:

$$A_u = \frac{1}{n}\sum_{i=1}^{n}\left|u_i\right|$$

Virtual follower configuration



Control parameters

$$T_p = 0.03, \theta_p = 0.9$$

Temporal correspondence

$$\mathrm{RMS} = 0.0918$$
$$\mathrm{CV} = 0.09190$$
$$\text{Time Lag} = 0.1869$$

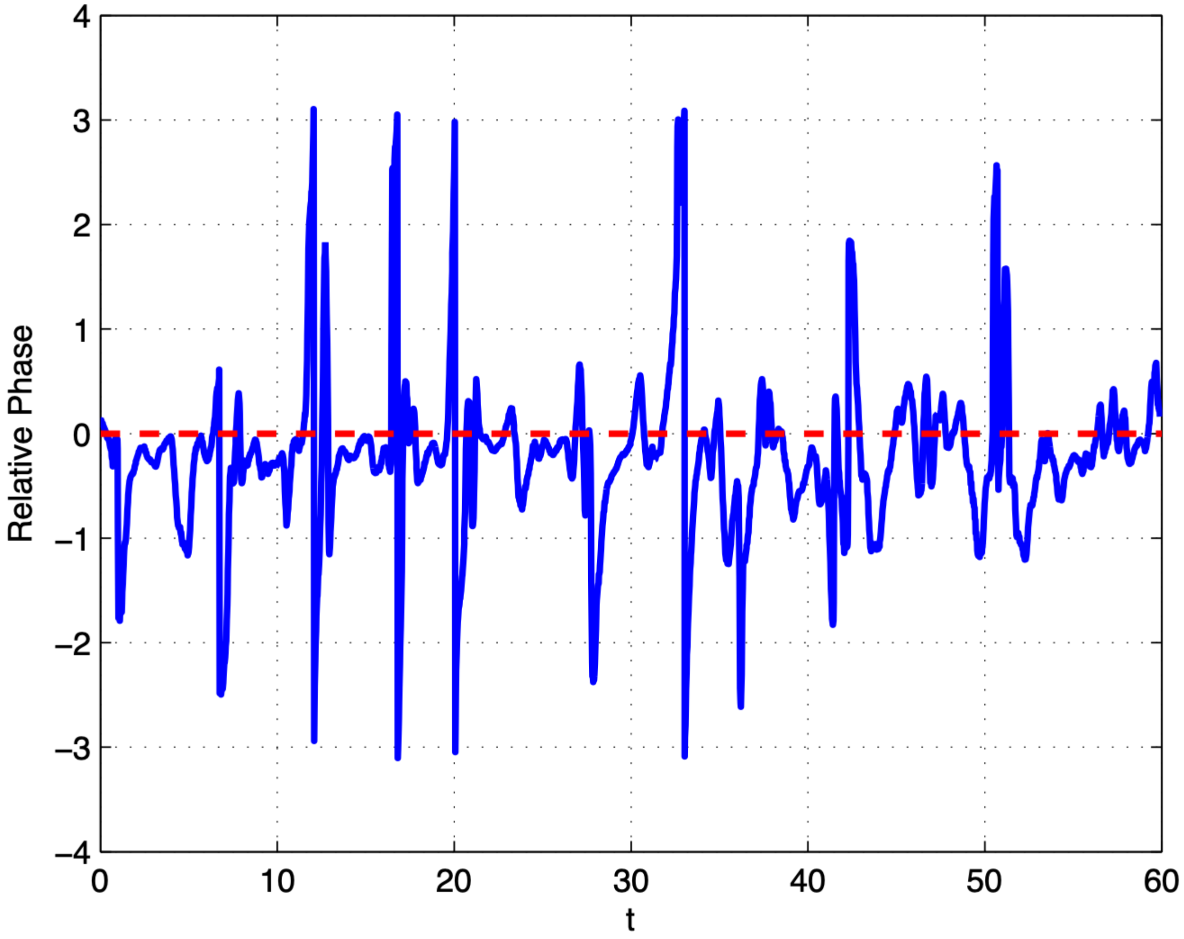
Signature difference

$$EMD(VP, r_\sigma) = 0.1552$$
$$EMD(VP, HP) = 0.0972$$
$$EMD(HP, r_\sigma) = 0.1320$$

Control effort

$$A_u = 3.5309$$

Virtual leader configuration



Control parameters

$T_p = 0.03, \theta_p = 0.1$

Temporal correspondence

$\mathrm{RMS} = 0.0981$

$\mathrm{CV} = 0.8129$

$\mathrm{Time\ Lag} = -0.1280$

Signature difference

$EMD(VP, r_\sigma) = 0.0630$

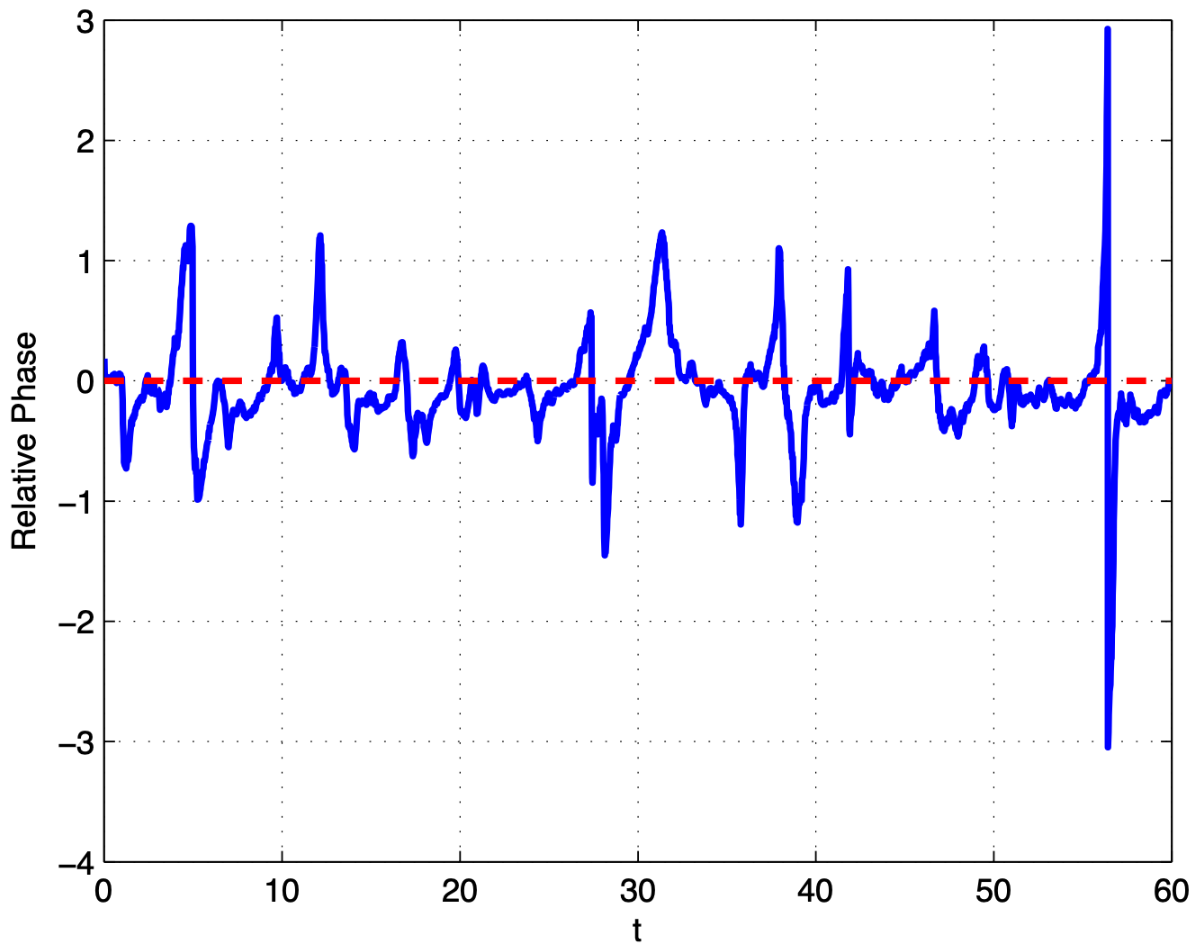
$EMD(VP, HP) = 0.0341$

$EMD(HP, r_\sigma) = 0.0758$

Control effort

$A_u = 1.4294$

Joint improvisation configuration



Control parameters

$T_p = 0.03,\ \theta_p = 0.1,$

$\theta_\sigma = 0.3,\ \theta_v = 0.6$

Temporal correspondence

$\mathrm{RMS} = 0.0623$

$\mathrm{CV} = 0.9334$

$\text{Time Lag} \approx 0$

Signature difference

$EMD(VP, r_\sigma) = 0.1127$

$EMD(VP, HP) = 0.0764$

$EMD(HP, r_\sigma) = 0.0659$

Control effort

$A_u = 3.1143$

Comparison

VP mode	RMS	Time Lag	EMD(VP, sig)
Follower	0.0918	0.1869	0.1522
Leader	0.0981	-0.1280	0.0630
JI	0.0623	0	0.1127

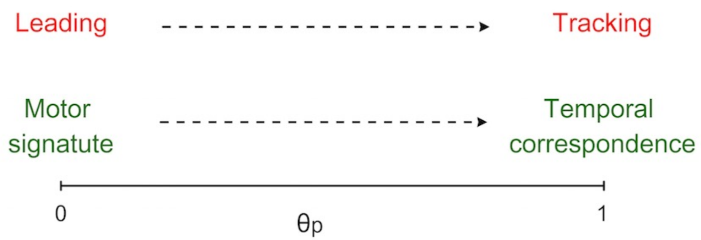
HP leading

HP following

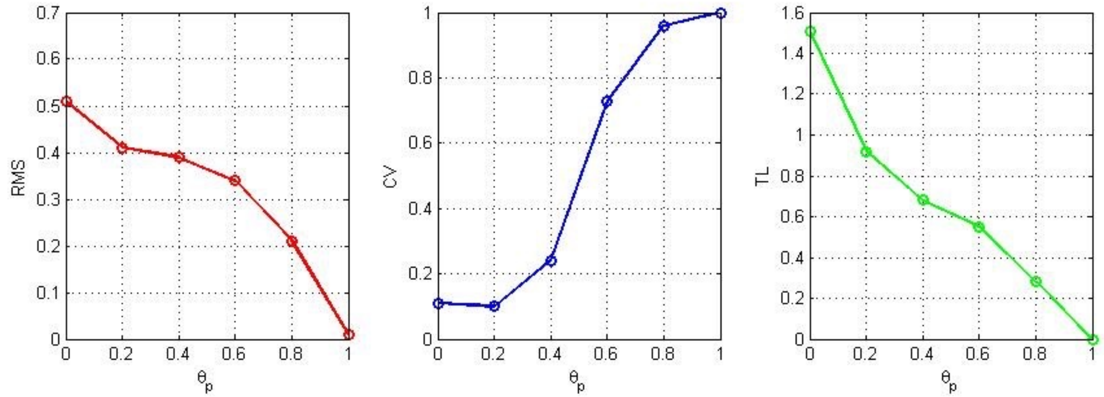
no roles

Effects of tuning θ_p in a LF configuration

- To test the effect of tuning the weight θ_p , we asked the VP to track a simple reference signal and computed how some key parameters are affected by its variation



Effects of tuning parameter θp on the temporal correspondence



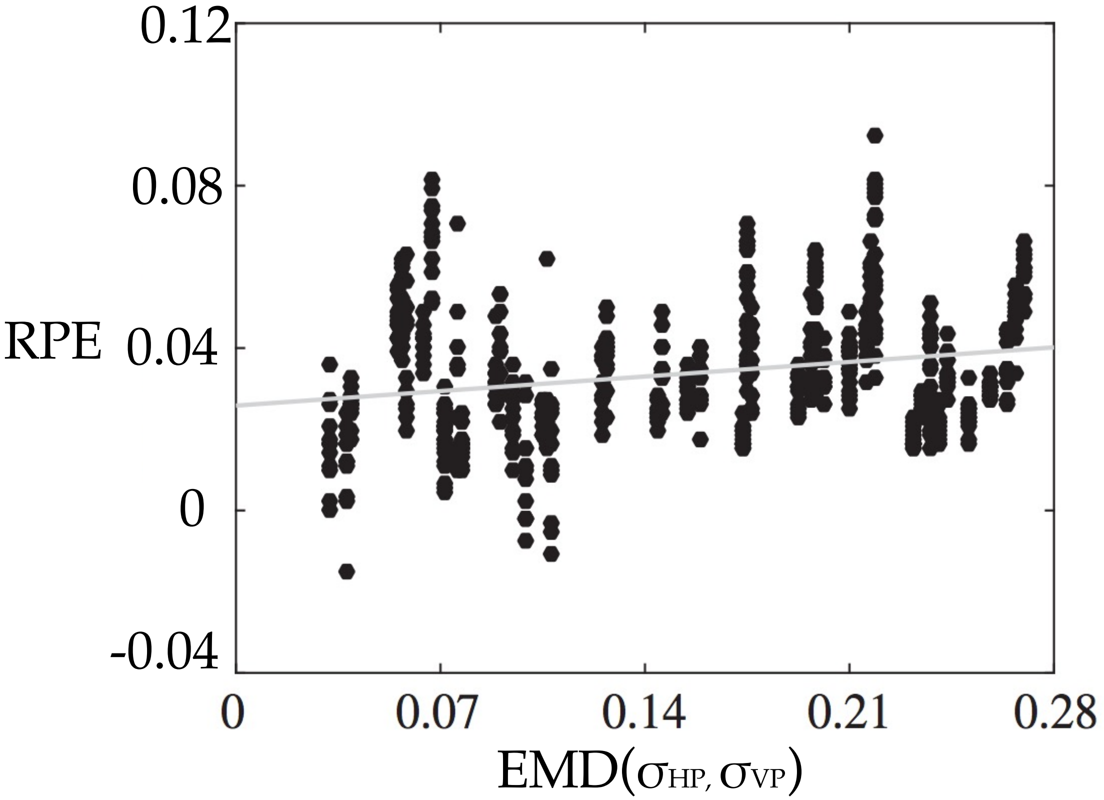
Effects of tuning parameter θp on the similarity

Reference signal: r=0.5sin(2t)

Effects of kinematic similarity in a LF configuration

- Relative position error (RPE):

$$\begin{cases} (x_1(t) - x_2(t))\mathrm{sgn}(v_1(t)), & \mathrm{sgn}(v_1(t)) = \mathrm{sgn}(v_2(t)) \neq 0, \\ |x_1(t) - x_2(t)|, & \text{otherwise.} \end{cases}$$



Lower values of EMD between the signature assigned to the VP (leader) and that of the HP (follower) correspond to lower position mismatches (R=0.48>0, Pearson's coefficient).

kinematic similarity promotes coordination

Słowiński, Piotr, et al. "Dynamic similarity promotes interpersonal coordination in joint action." Journal of The Royal Society Interface 13.116 (2016): 20151093.

Comparison with RPC and HDC

- We carried out some tests to compare our approach with previous ones
  1. the reactive predictive controller proposed by Noy et al;
  2. the HDC model using both an HKB and a Jirsa-Kelso excitatory model.
- We first asked a human to follow a pre-recorded leading trajectory.
- We then used our OFC approach, the RPC and HDC to track the same trajectory (for the OFC we use as a signature that of the human player).

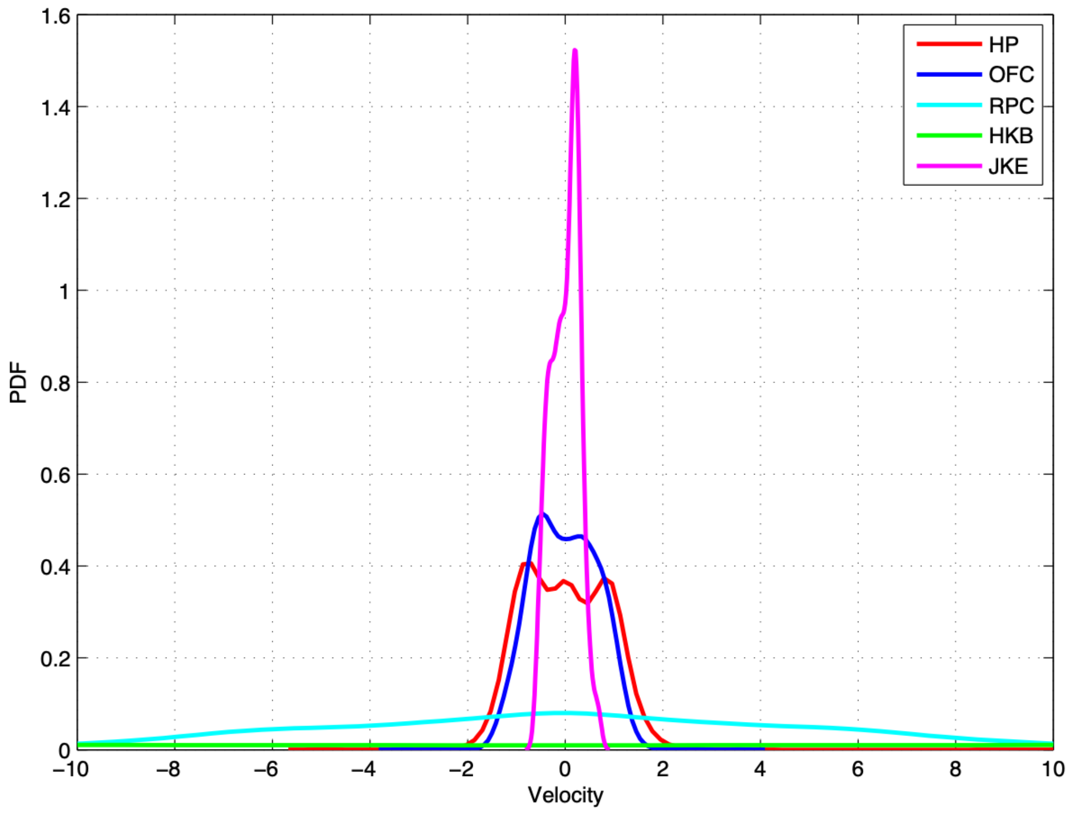
TC index	HP	OFC	RPC	HDC-HKB	HDC-JKE
RMS	*0.16*	*0.1*	*0.98*	*0.46*	*4.2*
CV	*0.66*	*0.87*	*0.18*	*0.21*	*0.02*
TL	*0.2*	*0.13*	*0.04*	*-0.94*	*-0.69*

Noy, Lior, Erez Dekel, and Uri Alon. "The mirror game as a paradigm for studying the dynamics of two people improvising motion together." Proceedings of the National Academy of Sciences 108.52 (2011): 20947-20952.

G. Dumas, G. C. de Guzman, E. Tognoli, and J. A. S. Kelso, "The human dynamic clamp as a paradigm for social interaction". Proceedings of the National Academy of Sciences of the United States of America, vol. 111, no. 35, pp. E3726–E3734, Sep. 2014.

Signature control performance

- Note that our OFC matches best the behaviour of the HP when playing the same game both in terms of temporal correspondence and motor signature.

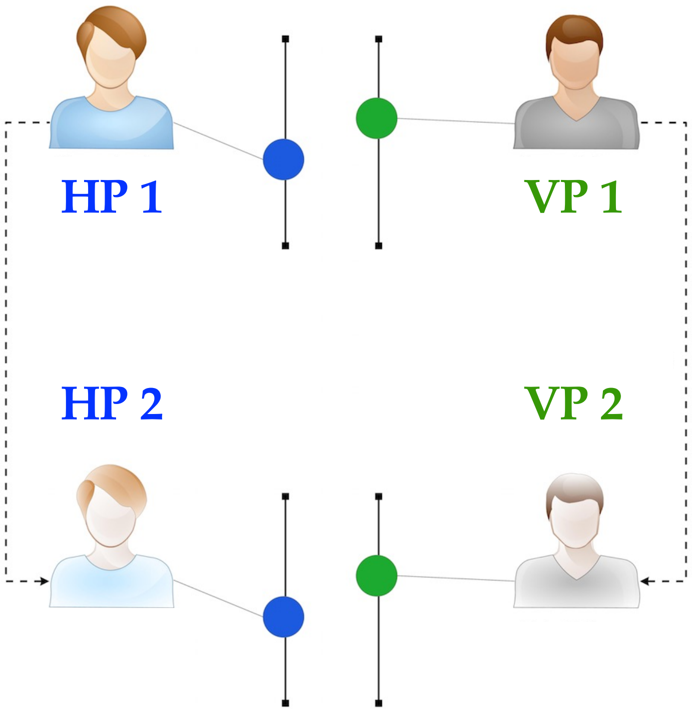


EMD(HP, OFC)	0.1554
EMD(HP, RPC)	2.4822
EMD(HP, HDC-HKB)	*3.9858*
EMD(HP, HDC-JKE)	*0.4752*

Virtual players

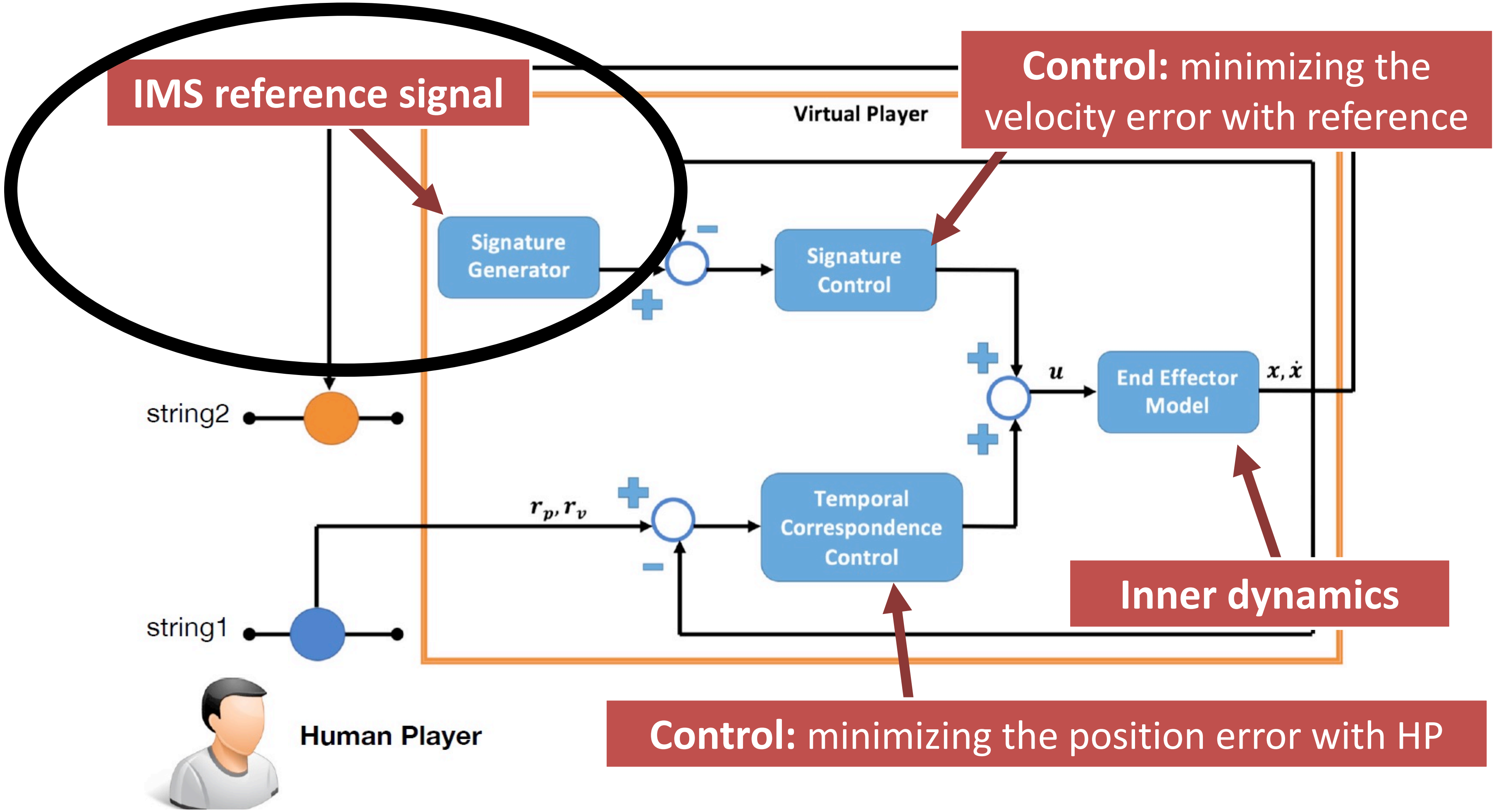
- Using our approach it is also possible to run *"in-silico"* simulations of virtual players characterised by different motor signatures.
- It can be useful for experimental design and quick testing of different hypotheses:

1. Each VP is fed the signature of a given HP to generate its movement effectively mirroring the motor signature of that player;
2. Two VPs can then be made to play against each other in silico;
3. The parameters of the MPC can be tuned to make the two VPs play any type of game configuration.

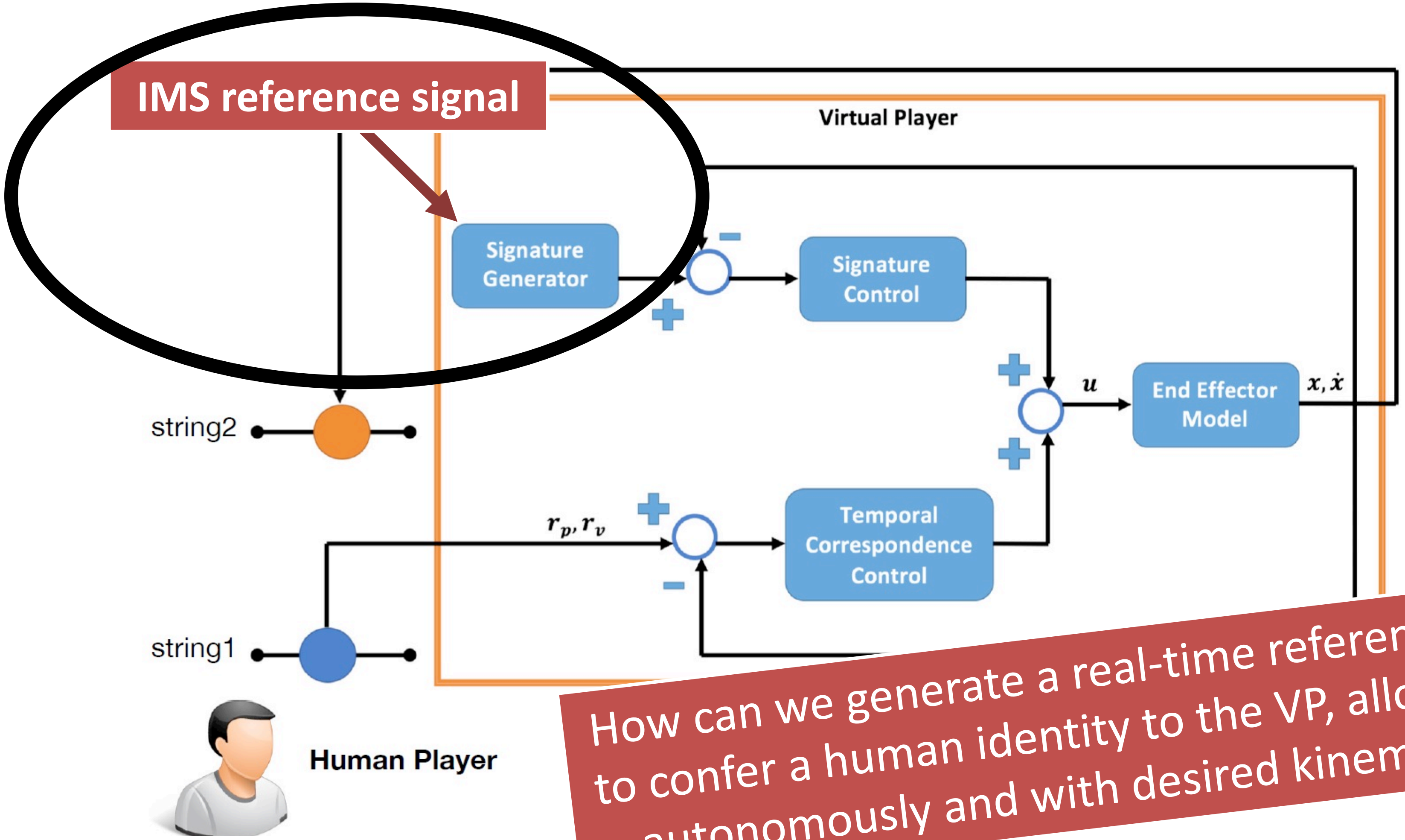


- Still there is a big problem. We are using pre-recorded human velocity signals to generate the avatar kinematic signature

Generating reference signatures for the avatar



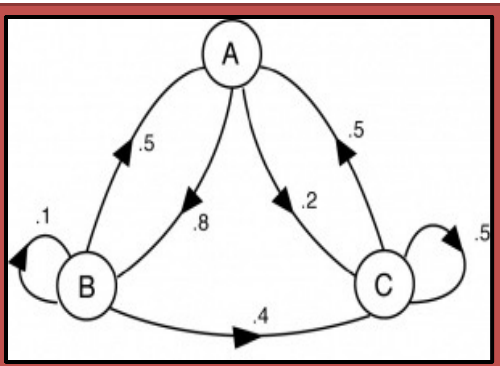
Control Architecture: block diagram



How can we generate a real-time reference signal in order to confer a human identity to the VP, allowing it to behave autonomously and with desired kinematic properties?

Markov Chain and Modelling

Markov Chain



Finite state stochastic model, characterized by:

- Initial state s_0
- Transition matrix $A := [a_{ij}]$ where $a_{ij} := P(s_{t+1} = j \mid s_t = i)$

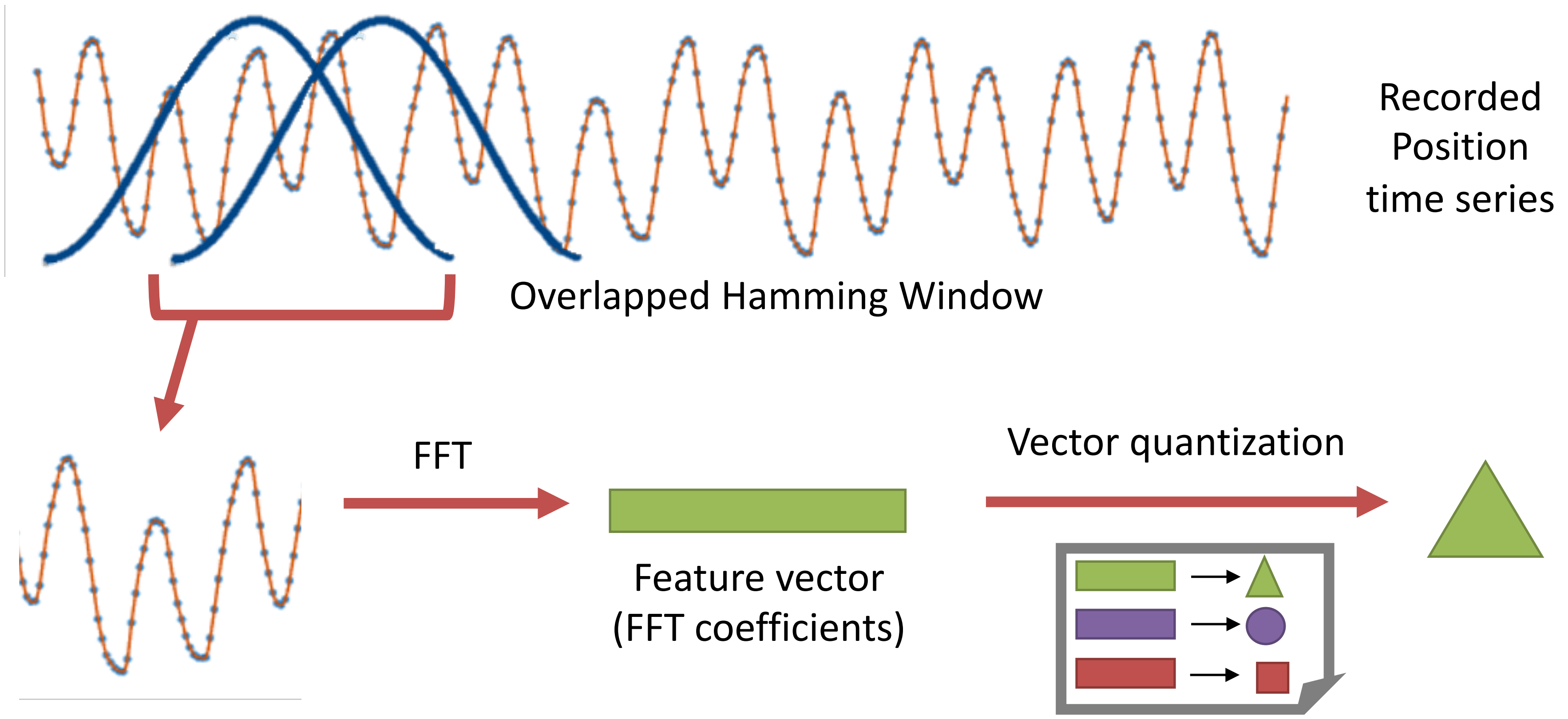
- Based on Markov Chain, we model the IMS Generator via the following three steps:

1. Data collection and pre-processing
2. Markov model training
3. Data generation

Modelling of IMS Generator

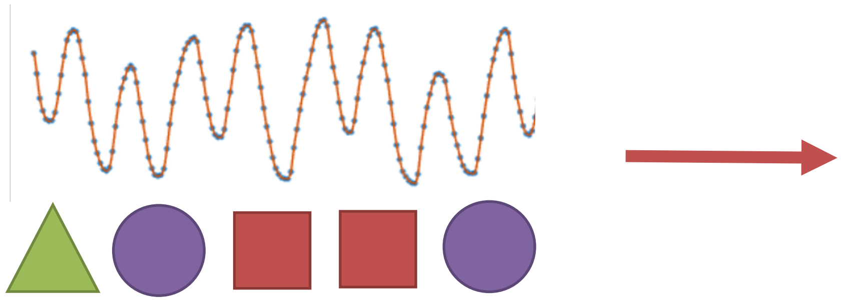
1. Data collection and pre-processing

Convert the continuous measurements in a finite set of symbols

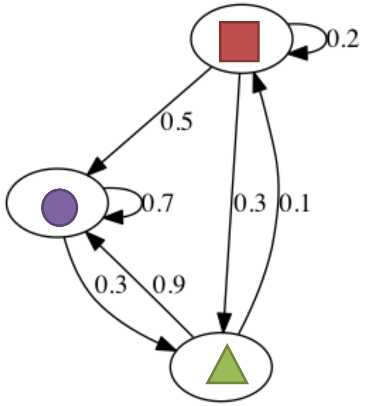


Modelling of IMS Generator

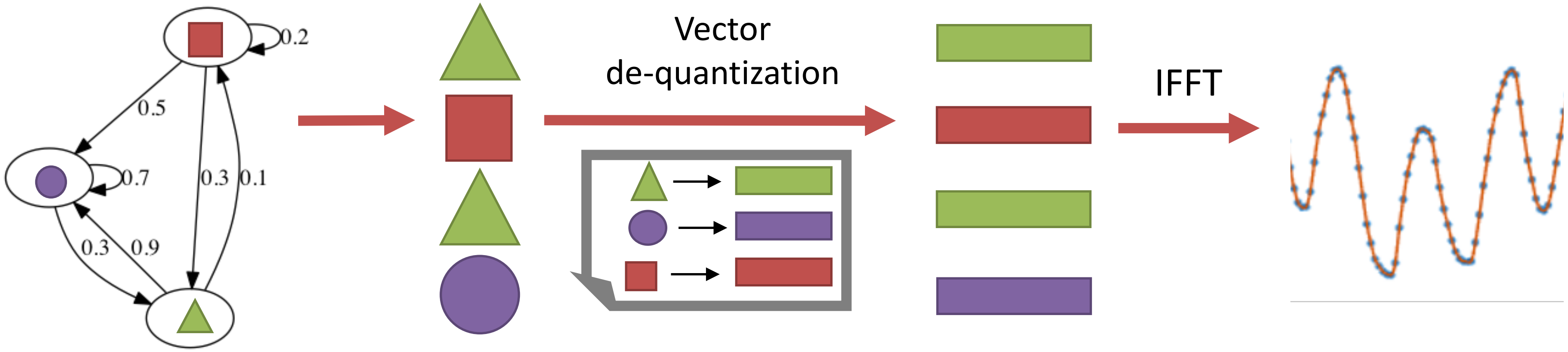
2. Markov model training



$$A = \begin{pmatrix} a_{11} & \cdots & a_{1N} \\ \vdots & \ddots & \vdots \\ a_{N1} & \cdots & a_{NN} \end{pmatrix}$$



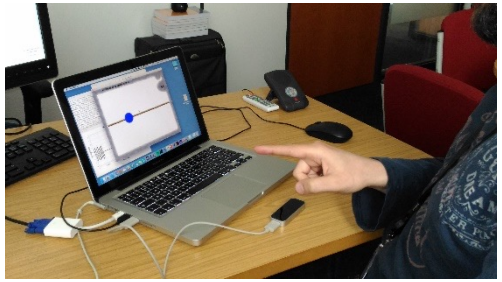
3. Data generation

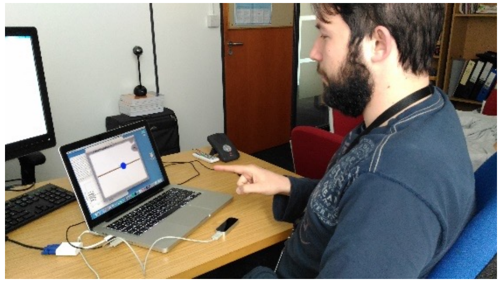


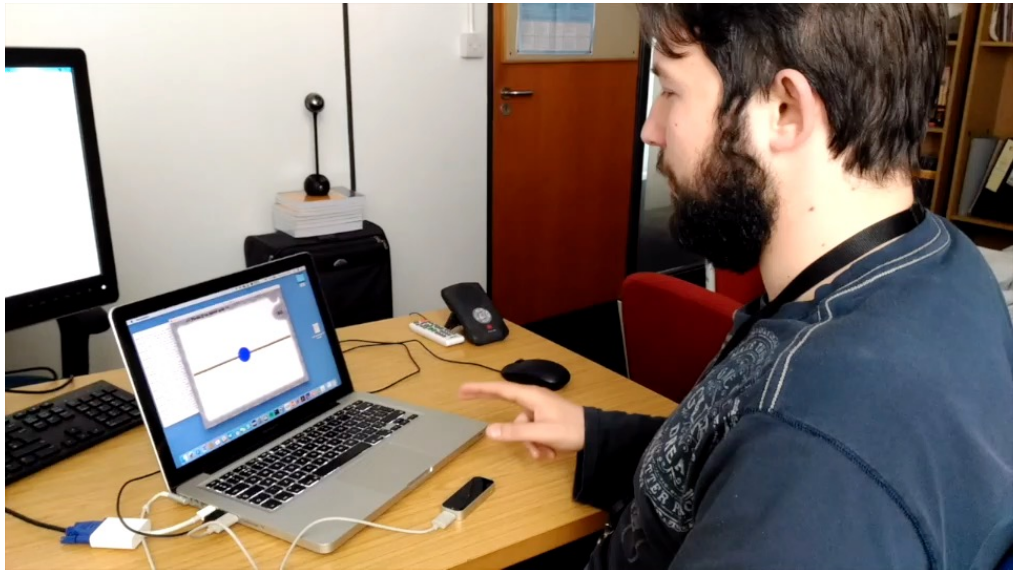
Experiments

- To validate our methodology based on Markov Chain, experiments were performed to acquire some human IMS:

  - 6 participants
  - Each participant was asked to move his/her index of preferred hand in a spontaneous way from left to right in order that the his/her individual motor signature could emerge







Metrics

Different analysis tools have been considered to assess quality of IMS generation based on Markov chain

- **Velocity Probability Density Function** (PDF) of the virtual agent (IMS)

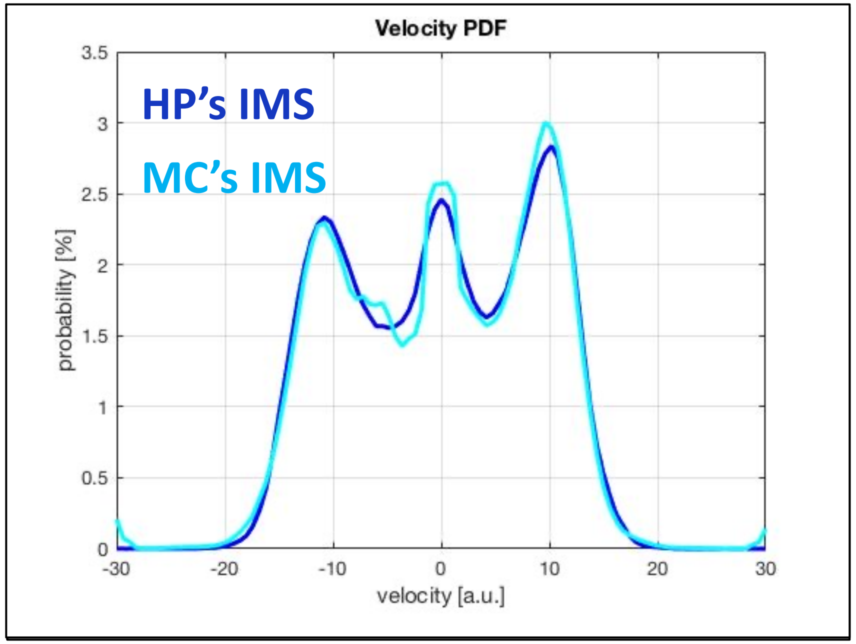
- **Earth mover distance:** to assess difference between IMS of the reference human and that generated by our approach

$$EMD(PDF_{VP}(z), PDF_{HP}(z)) = \int_Z |CDF_{VP}(z) - CDF_{HP}(z)|\, dz$$

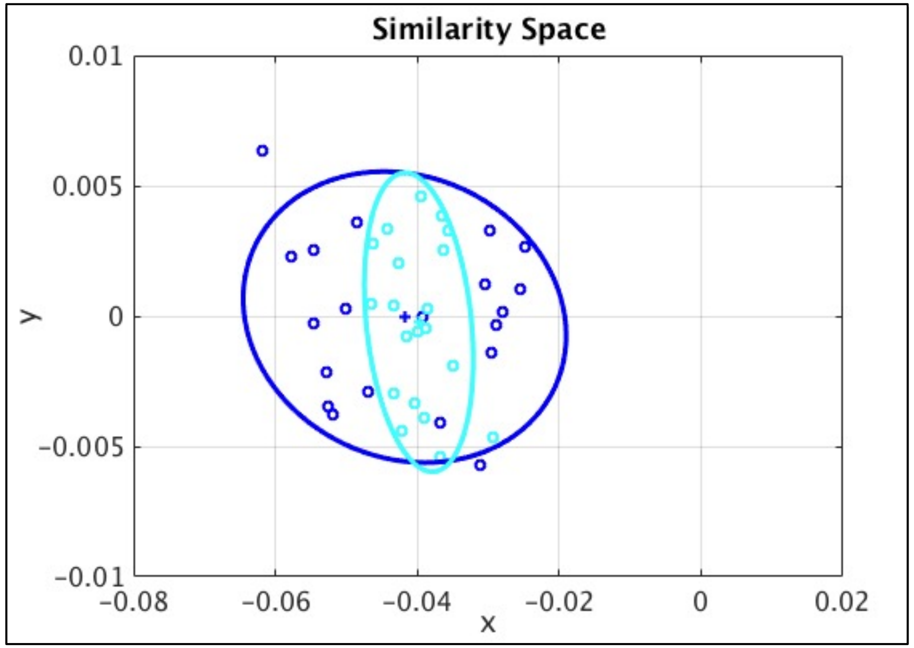
- Multidimension scaling (MDS) allows to map IMSs as points in an abstract geometric space known as **similarity space** where the Euclidean distance between two points is related to that between the corresponding IMSs.

Validation

The PDF is well approximated

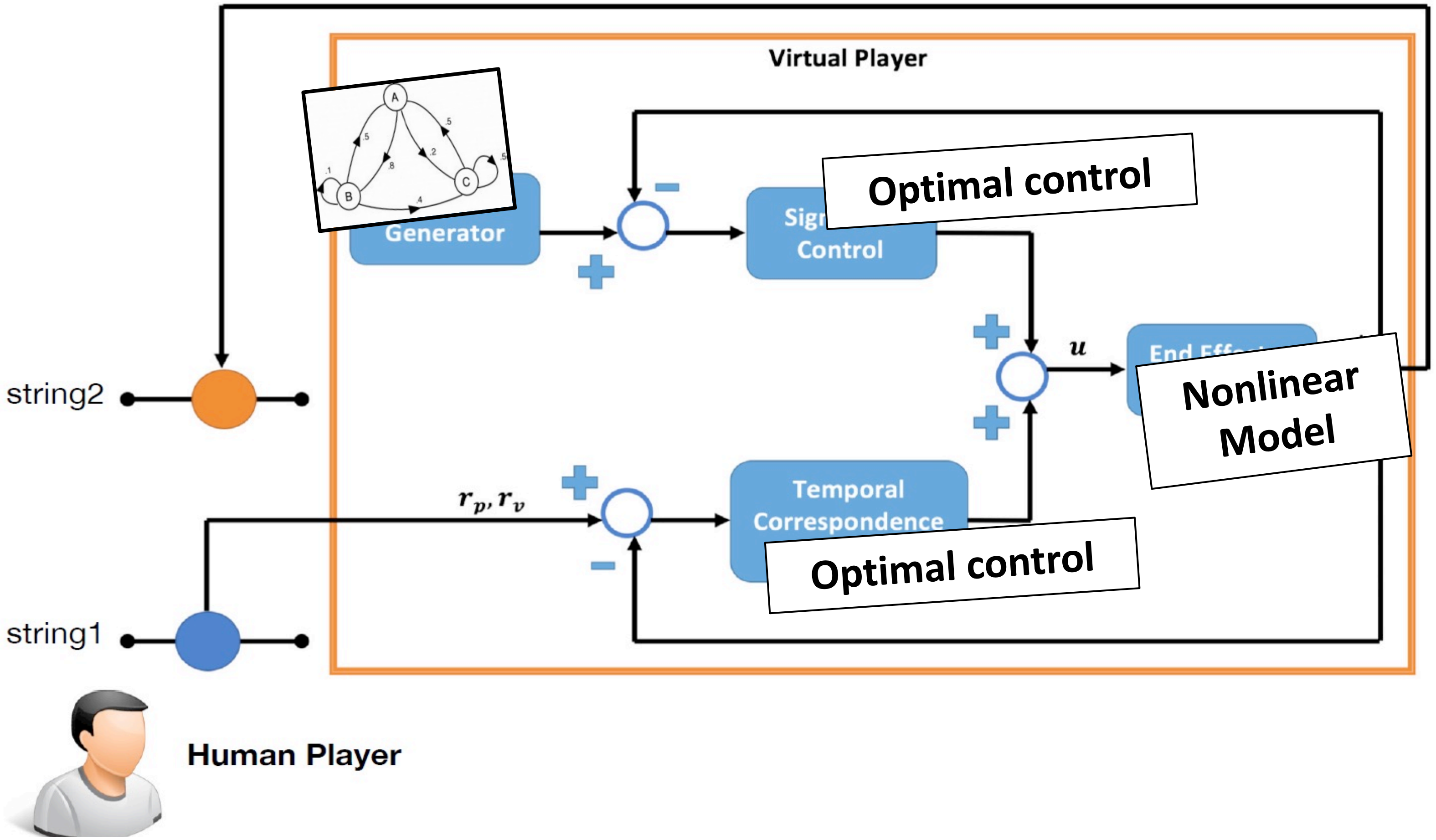


The characteristic region of the IMS generator is included in the region of the real human player



Validation

Putting all together…



Zhai, C., Alderisio, F., Slowinski, P., Tsaneva-Atanasova, K., & di Bernardo, M. (2017). Design and Validation of a Virtual Player for Studying Interpersonal Coordination in the Mirror Game. *IEEE Transactions on Cybernetics*, 1–30.

Details on Cognitive Architecture: dynamics and control

- **Inner dynamics**: Haken – Kelso – Bunz oscillator

$$\ddot{x} + (\alpha\dot{x}^2 + \beta x^2 - \gamma)\dot{x} + \omega^2 x = u$$

  - $x, \dot{x}, \ddot{x}$ are the position, velocity and acceleration of the VP
  - ω is the frequency; α, β, γ characterize the damping

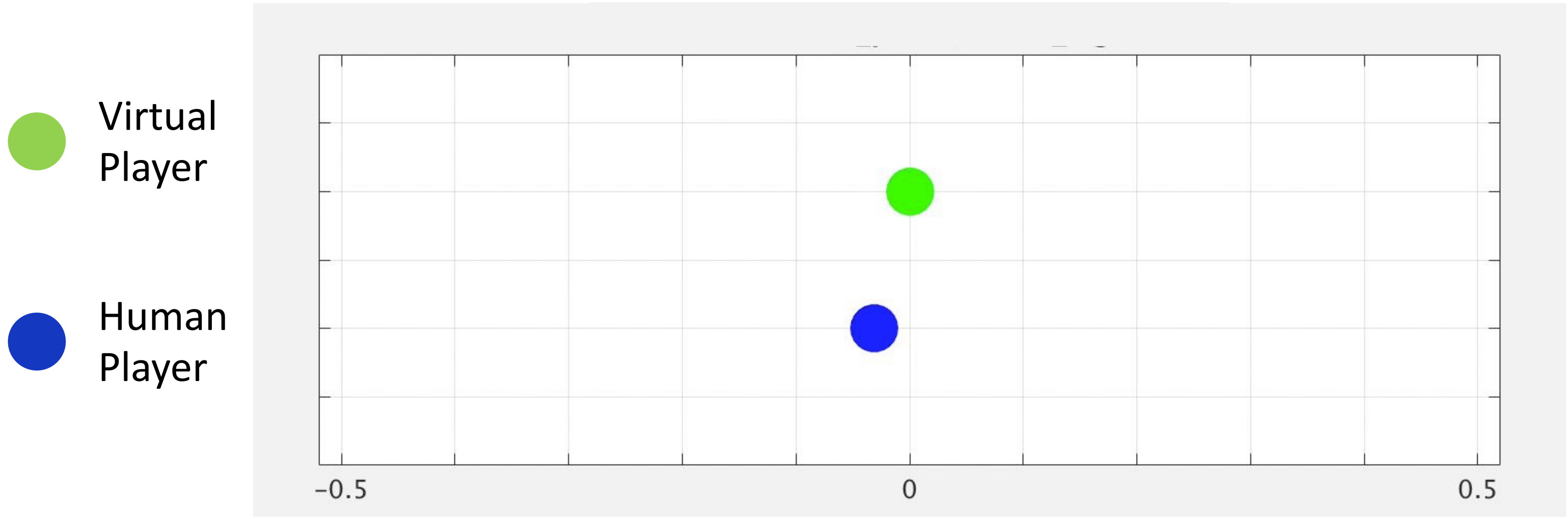
- **Optimal Control**

$$\min_u \; J = \frac{1}{2}\left[\underbrace{\theta_p \left(x(t_{k+1}) - \hat{r}_p(t_{k+1})\right)^2}_{\text{Temporal correspondence}} + \int_{t_k}^{t_{k+1}} \underbrace{\theta_s(\dot{x}(\tau) - \dot{r}_\sigma(\tau))^2}_{\text{Signature control}} + \underbrace{\eta u(\tau)^2}_{\text{Control effort}} \, d\tau\right]$$

  - $\hat{r}_p$ is the measured position of the HP
  - $\dot{r}_\sigma$ is the reference velocity
  - η, θ_p, θ_s positive weights to tune the control energy

Validation

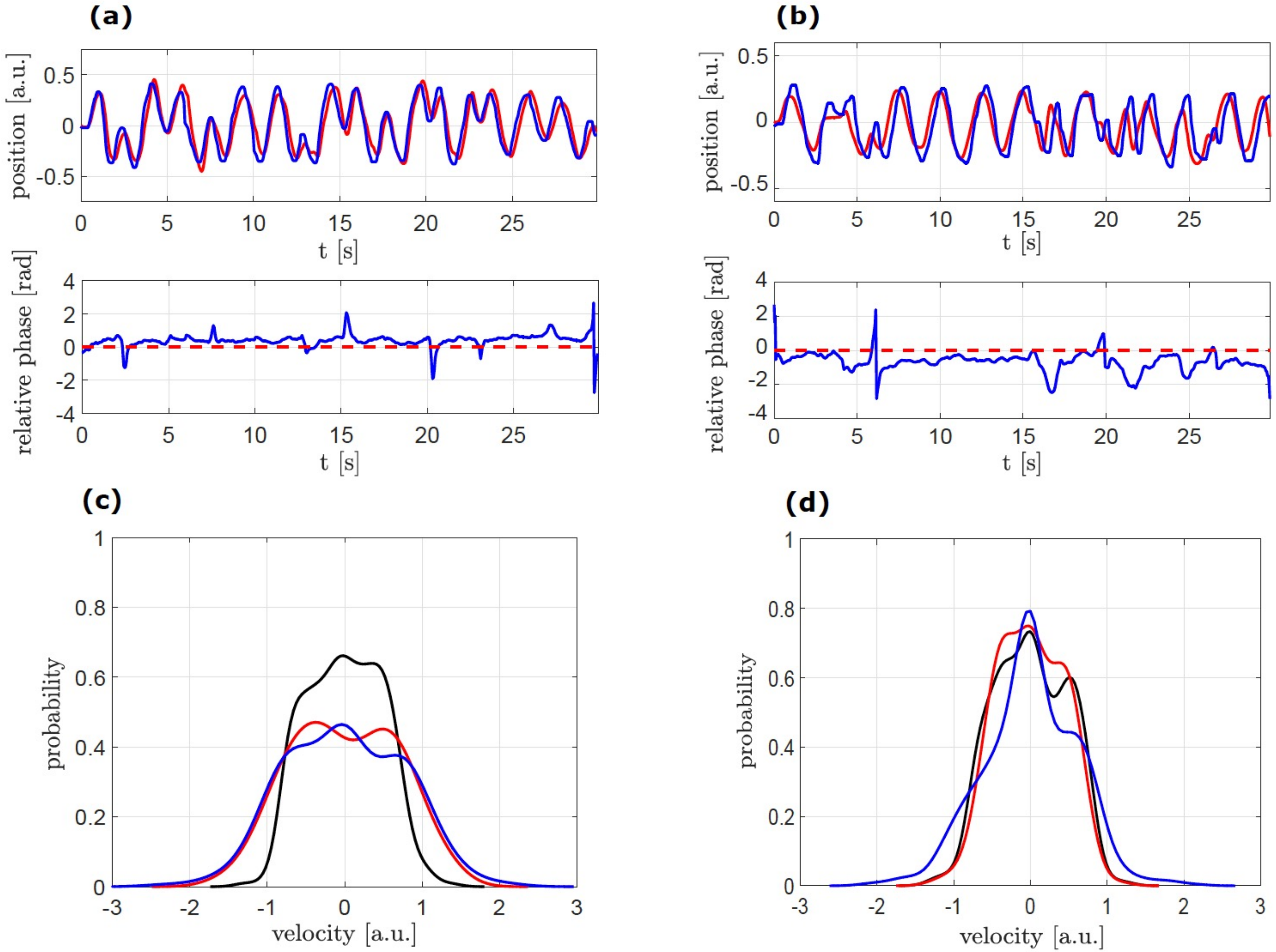
The Virtual Player is able to play the Mirror Game with a Human Player exhibiting a desired human IMS



Leader – Follower Session with Virtual Player as Leader

Validation

VP as follower | VP as leader



Human player
Virtual player
IMS reference

Some numerical value…

VP as follower

CV = 0.933
RMS = 0.112
Relative phase = 0.394 ± 0.408
EMD(Ref, VP) = 0.006
EMD(HP, VP) = 0.018

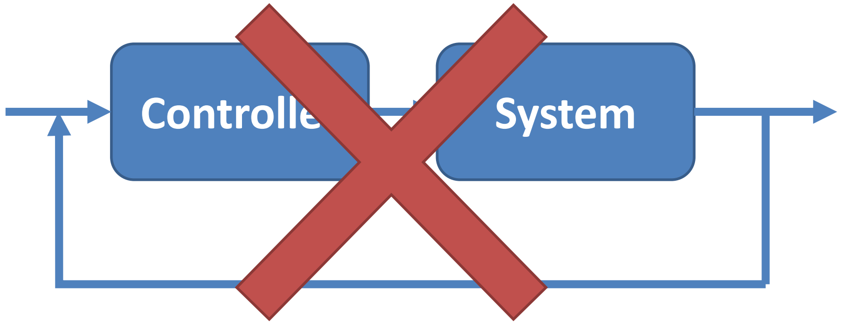
VP as leader

CV = 0.868
RMS = 0.122
Relative phase = -0.664 ± 0.574
EMD(Ref, VP) = 0.0263
EMD(HP, VP) = 0.011

Another approach

- Are traditional control approaches fit for the purpose?
- How can we render the avatar *truly* autonomous and able to observe and *learn* humans how to coordinate with each other?
- The answer is to move towards machine-learning based control algorithms

Nonlinear control approach



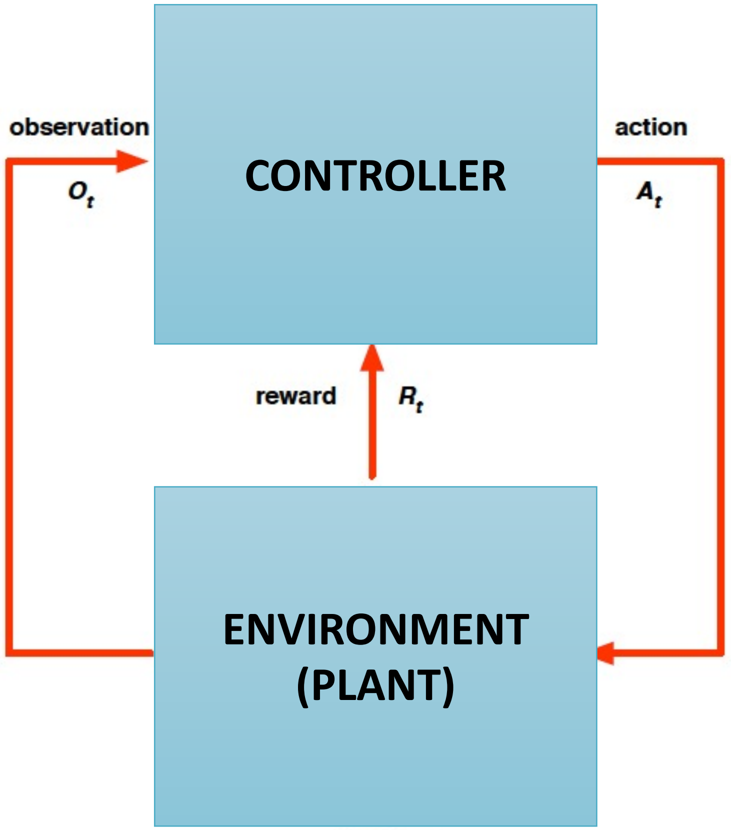
- Human model not known
- Deterministic nature of the controller
- Fine tuning of control parameters

We propose a **data-driven** architecture based on **reinforcement learning**

(Q-learning)

Basic concept:

- The agent interacts with the environment taking an action a_t from the set of all possible actions



- The agent chooses the action following a *"policy"* $\pi : S \to A$
- The agent can observe the state s_t of the environment following its action
- The agent receives a **reward** r_t that measure the "goodness" of the current state s_t

Reinforcement Learning

Solving a reinforcement learning problem means solving a system of NxA non linear equations, Bellman optimal equations, (one for NxA states) in NxA unknowns

where N are the number of states, A the number of possible actions

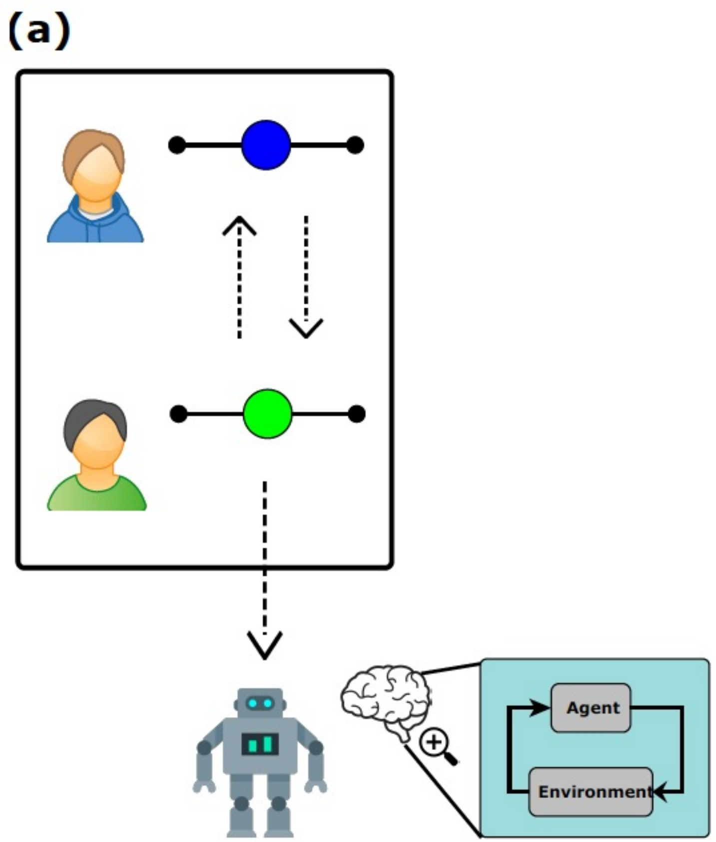
Iterative approach:

Q-learning (Temporal Difference Learning)

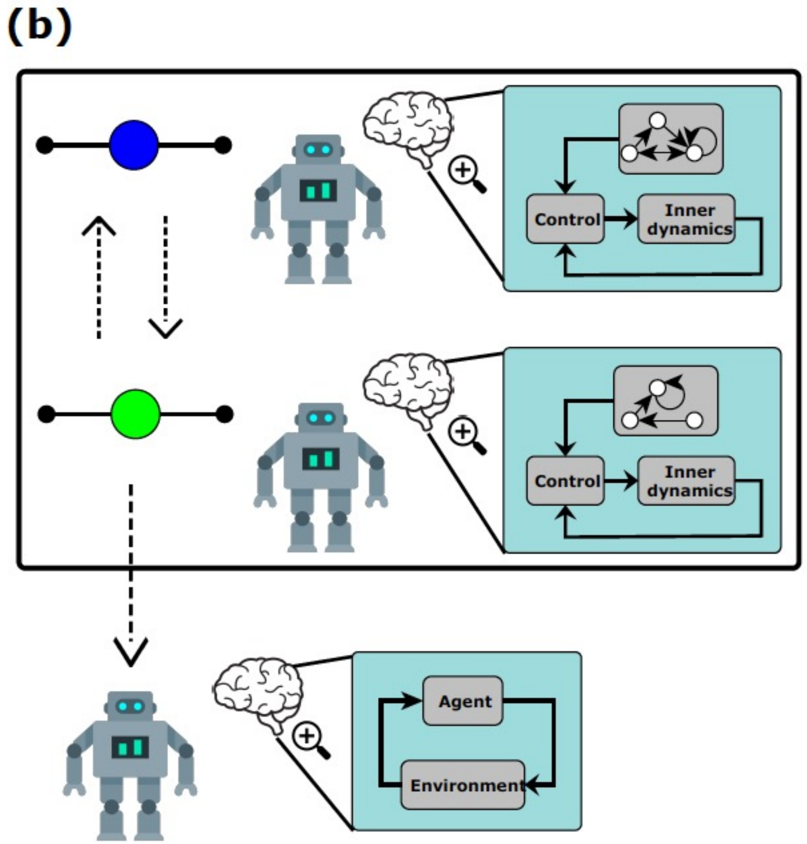
- No knowledge on the environment
- Online estimation of the state value using the observed rewards and the estimated future rewards

Learning phase: our approach

Ideally

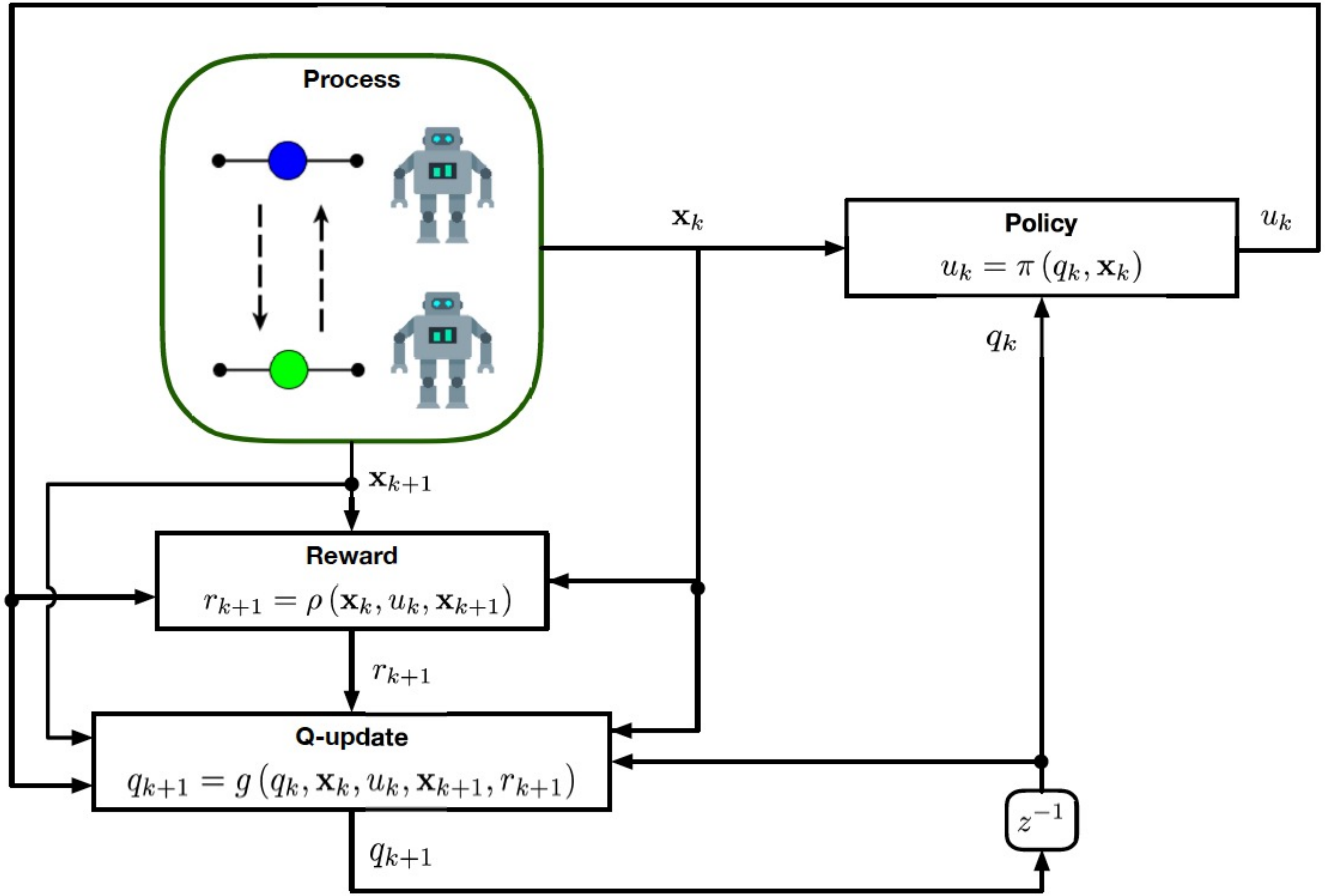


In practice



To avoid a large amount of data directly from humans, we propose first to learn the cyber player with synthetic data generated via a nonlinear stochastic model of human behaviour (called Virtual Trainer)

Learning process in detail



The cyber player:

1. observes its state and the partner' positions and velocity
   $x, \dot{x}, x_p, \dot{x}_p$

2. takes a control action according to its policy
   ε-greedy policy

3. receives a reward
   $\rho = -(x - x_t) - 0.1(\dot{x} - \dot{x}_t)^2 - \eta u$

4. updates the q-table and consequently updates the policy

Qualitatively results

- Player target = VT_5
- Training set =
- VT_1, VT_2, VT_3, VT_4
- Further VT_6 used as validation
- The cyber player has been trained both to play as leader and as follower

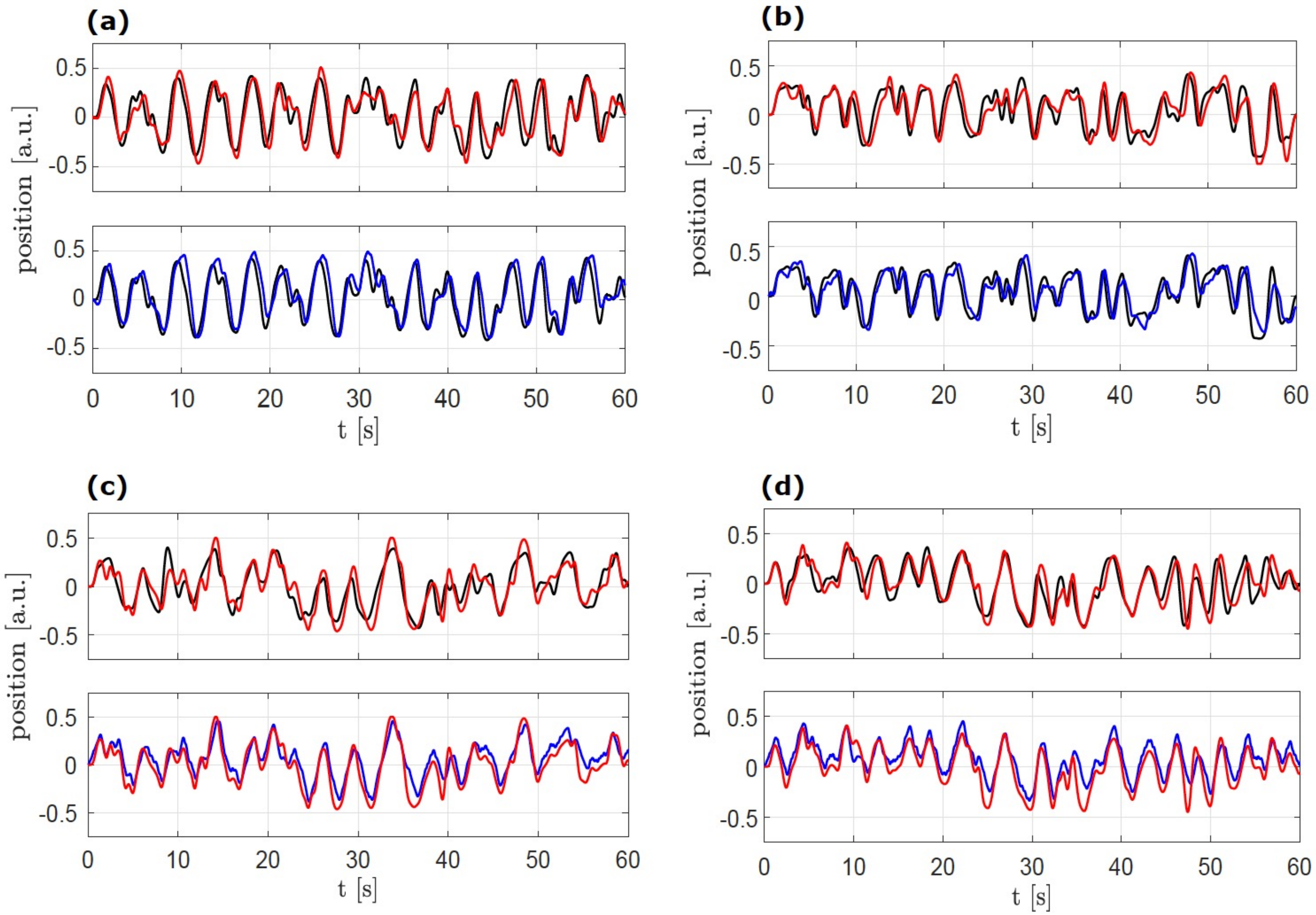
Cyber player
VT follower
VT leader

Against VT_2
(included in the train set)

Against VT_6
(not included in the train set)

CP as follower

CP as leader



Quantitative results

	Following	EMD	CV	RMS
VT_1	VT_5	0.002	0.76 ± 0.06	0.11 ± 0.01
	CP	0.008	0.80 ± 0.05	0.11 ± 0.01
VT_2	VT_5	0.003	0.86 ± 0.06	0.11 ± 0.01
	CP	0.004	0.86 ± 0.06	0.12 ± 0.01
VT_3	VT_5	0.003	0.85 ± 0.04	0.12 ± 0.01
	CP	0.007	0.88 ± 0.04	0.12 ± 0.01
VT_4	VT_5	0.004	0.74 ± 0.07	0.10 ± 0.01
	CP	0.004	0.79 ± 0.07	0.10 ± 0.01
VT_6	VT_5	0.003	0.83 ± 0.05	0.11 ± 0.01
	CP	0.002	0.86 ± 0.04	0.11 ± 0.01

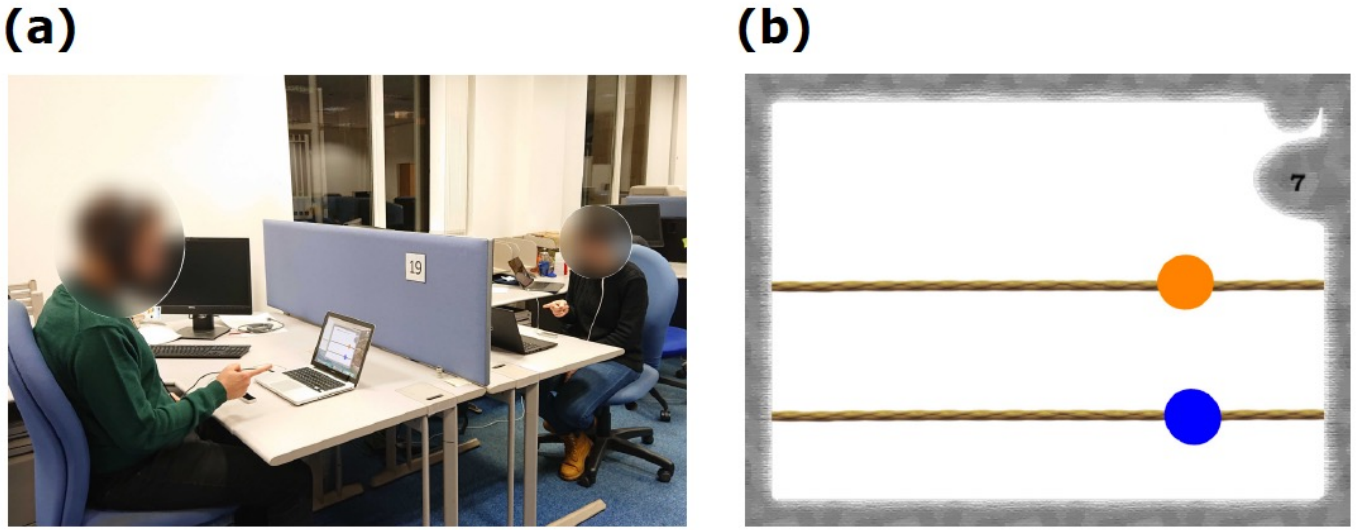
	Leading	EMD	CV	RMS
VT_1	VT_5	0.003	0.83 ± 0.04	0.11 ± 0.01
	CP	0.007	0.88 ± 0.03	0.12 ± 0.01
VT_2	VT_5	0.003	0.82 ± 0.03	0.12 ± 0.01
	CP	0.007	0.90 ± 0.03	0.11 ± 0.01
VT_3	VT_5	0.003	0.81 ± 0.05	0.12 ± 0.01
	CP	0.007	0.90 ± 0.03	0.12 ± 0.01
VT_4	VT_5	0.003	0.86 ± 0.05	0.10 ± 0.01
	CP	0.007	0.89 ± 0.03	0.11 ± 0.01
VT_6	VT_5	0.003	0.84 ± 0.04	0.10 ± 0.01
	CP	0.007	0.90 ± 0.03	0.11 ± 0.01

Paired t-test (95% of confidence) has been performed for each pairs of players. No statistically significant difference has been revealed.

Cyber player playing with real human players

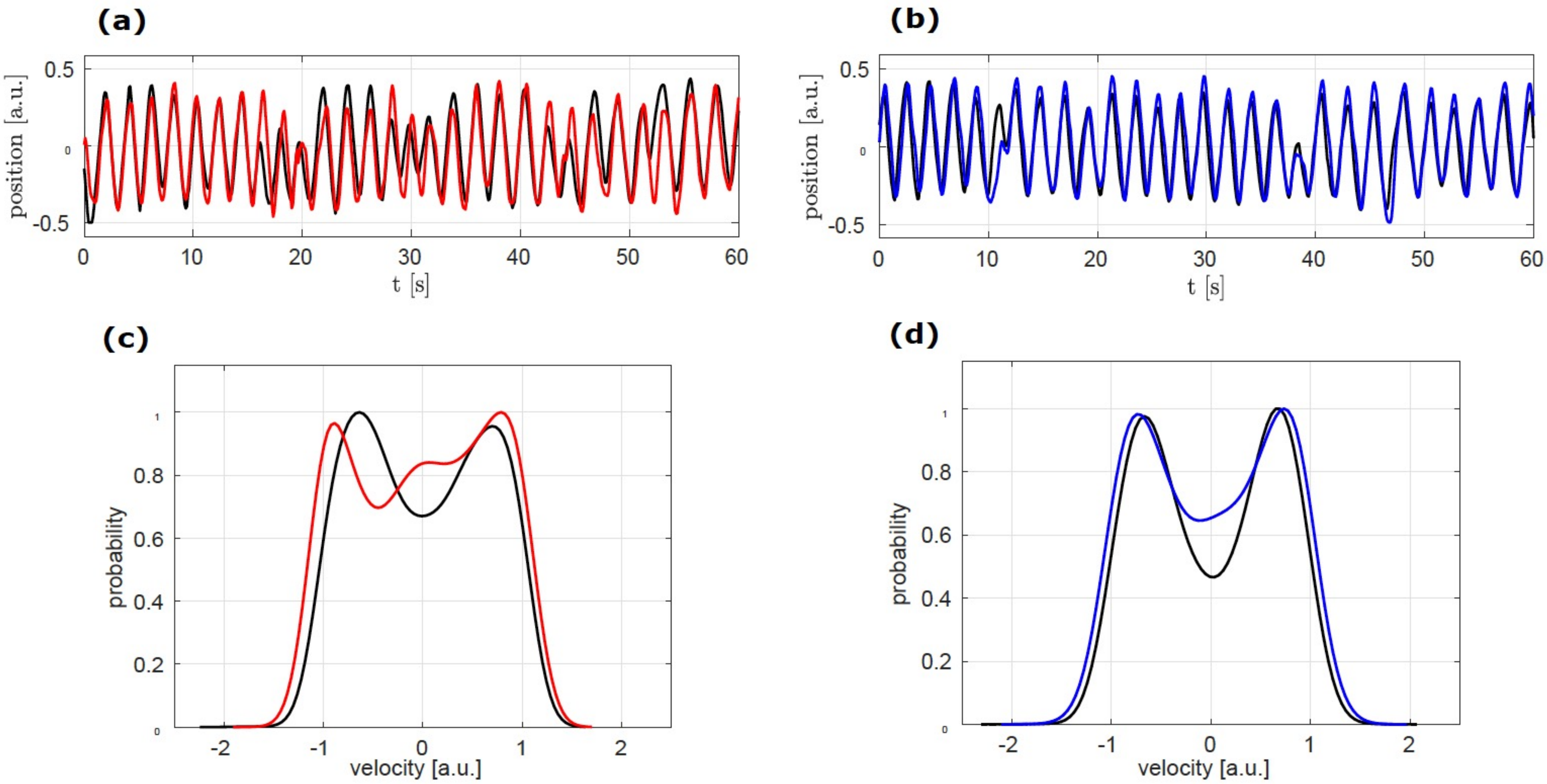
Cyber player and HP_5 was made to play with other 4 different human players
(NB. The cyber player was trained on VT_5, emulating HP_5)

Experiments were performed through CHRONOS. We performed 8 trials for each pair of players lasting 60 seconds.



F. Alderisio, M. Lombardi, G. Fiore, and M. di Bernardo, "A novel computer-based set-up to study movement coordination in human ensembles," Frontiers in Psychology, vol. 8, p. 967, 2017.

Qualitative results



Quantitative results

	Following	EMD	CV	RMS
HP_1	HP_5	0.01	0.9 ± 0.05	0.18 ± 0.03
	CP	0.01	0.9 ± 0.06	0.14 ± 0.06
HP_2	HP_5	0.007	0.84 ± 0.07	0.15 ± 0.04
	CP	0.006	0.89 ± 0.05	0.15 ± 0.05
HP_3	HP_5	0.006	0.92 ± 0.01	0.17 ± 0.03
	CP	0.005	0.93 ± 0.06	0.15 ± 0.05
HP_4	HP_5	0.009	0.86 ± 0.06	0.16 ± 0.03
	CP	0.004	0.87 ± 0.03	0.12 ± 0.02

Pair	CV	RMS
$HP_1 - HP_5$ $HP_1 - CP$	$t(7) = -0.081$, $p = 0.938$	$t(7) = 1.562$, $p = 0.162$
$HP_2 - HP_5$ $HP_2 - CP$	$t(7) = -2.105$, $p = 0.073$	$t(7) = -0.347$, $p = 0.739$
$HP_3 - HP_5$ $HP_3 - CP$	$t(7) = -0.496$, $p = 0.635$	$t(7) = 1.25$, $p = 0.251$
$HP_4 - HP_5$ $HP_4 - CP$	$t(7) = 0.933$, $p = 0.382$	$t(7) = 2.340$, $p = 0.052$

Paired t-test (95% of confidence) has been performed for each pairs of players. No statistically significant difference has been revealed.

Outline

- Introduction and motivation
- The mirror game and the need for a virtual player
- Previous approaches
  - Reactive Predictive models [Noy et al, 2011]
  - Human Dynamic Clamp [Dumas et al, 2009; 2014]
- A feedback control approach
  - adaptive control
  - optimal control
- Validation and performance evaluation
- Movement coordination in larger human ensembles
- Conclusions

Background

- Man is by nature a *social animal* (Aristotle, “Politics”).

- Understanding how and why human beings interact in groups are key research questions across different scientific fields.

- Answering these paramount questions is challenging as interpersonal cooperation involves different levels of interactions.

Movement coordination in larger human ensembles

- Groups of people spontaneously coordinate their movements in several daily activities.

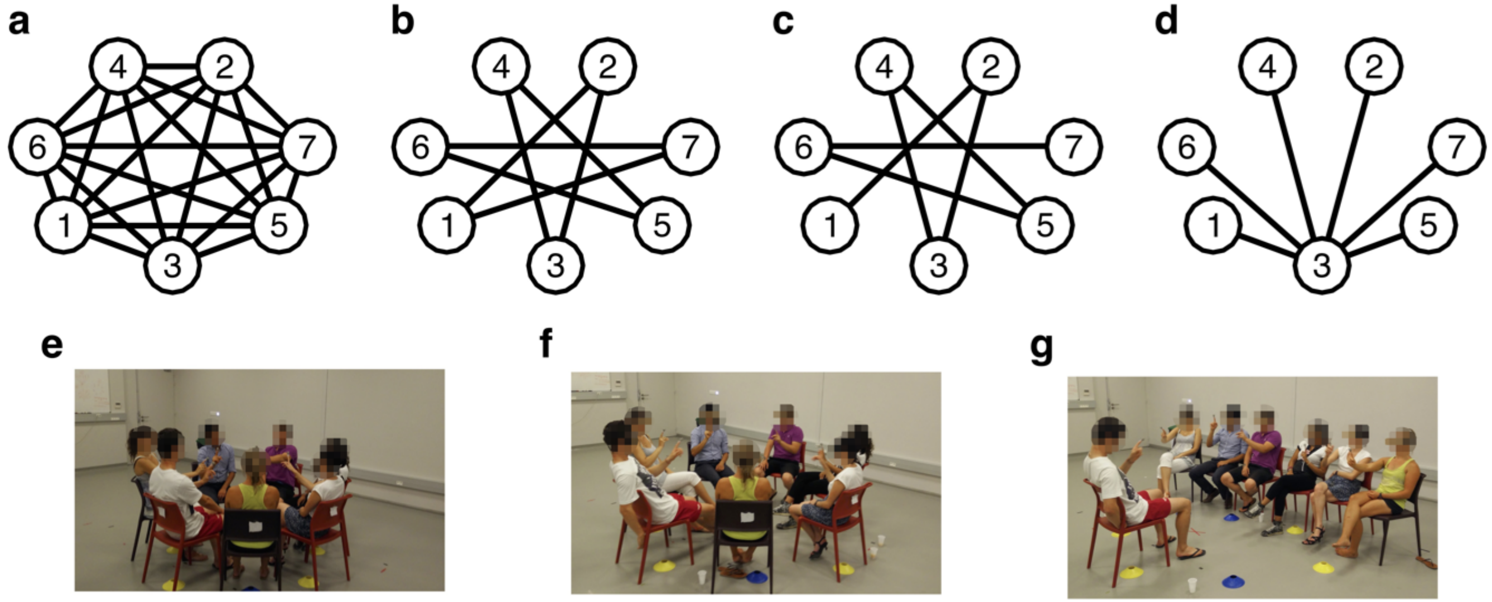
- Some big questions:
  - What are the mechanisms that underlie synchronization in a group of people?
  - How do the topologies of social interactions and the individual dynamics of the players affect the level of synchronization?
  - Does a leader spontaneously emerge when a group of people synchronise?

- How can we engineer avatars or robots able to merge within human groups?

Extension of the mirror game to a multiplayer scenario

- We take as a paradigmatic example the case where participants are asked to generate an oscillatory hand motion and coordinate it with that of the others.

- Participants are connected over different interaction patterns implemented through visual coupling, meaning that they are able to see the movements of only a designated subset of the others.



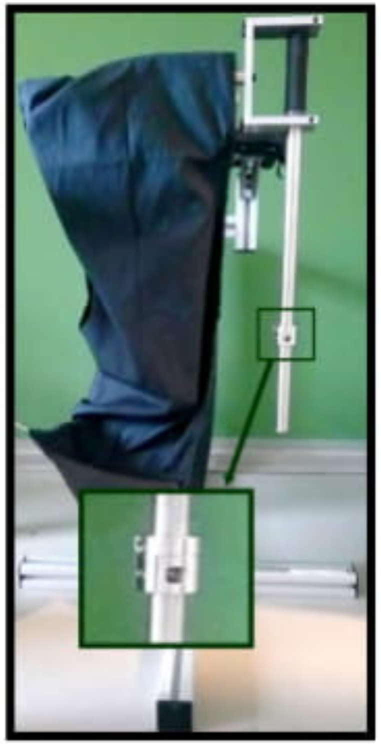
Alderisio, F., Fiore, G., Salesse, R. N., Bardy, B. G., & di Bernardo, M. (2016). Interaction patterns and individual dynamics shape the way we move in synchrony. Nature Scientific Reports, 2017

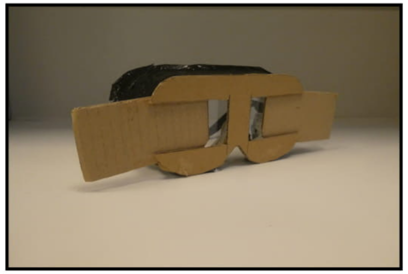
Experiments - all to all network

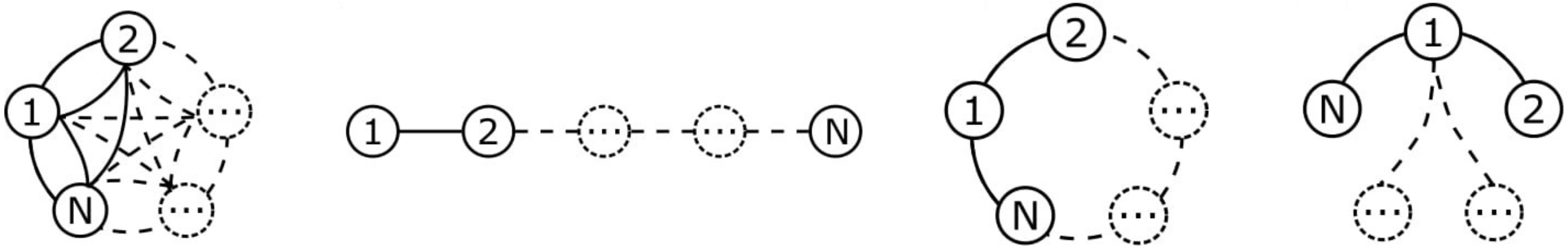
Alderisio, F., Fiore, G., Salesse, R. N., Bardy, B. G., & di Bernardo, M. (2016). Interaction patterns and individual dynamics shape the way we move in synchrony. arXiv preprint arXiv:1607.02175.

Mirror game- setups

- **Pendula**
  - Manipulating natural frequency
  - Social feedback



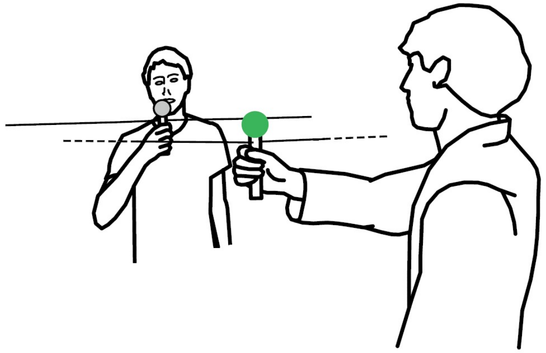


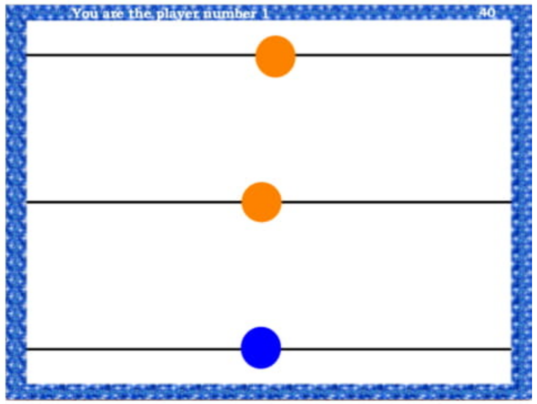


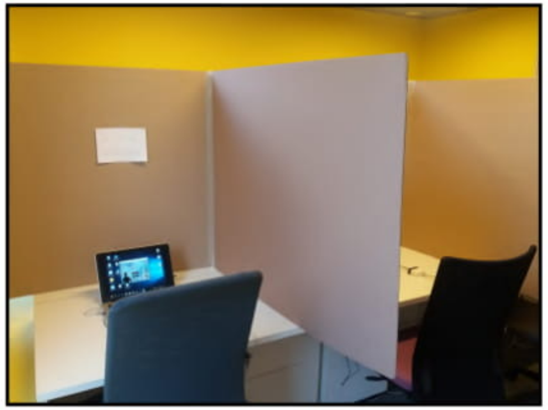
[2] Alderisio, F., Fiore, G., Salesse, R. N., Bardy, B. G., & di Bernardo, M. (2017). Interaction patterns and individual dynamics shape the way we move in synchrony. Scientific reports, 7(1), 1-10.

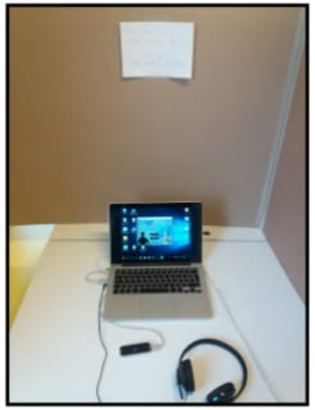
Mirror game- setups

- **Setup 2- Chronos**
  - Possible use of virtual agent
  - No social feedback







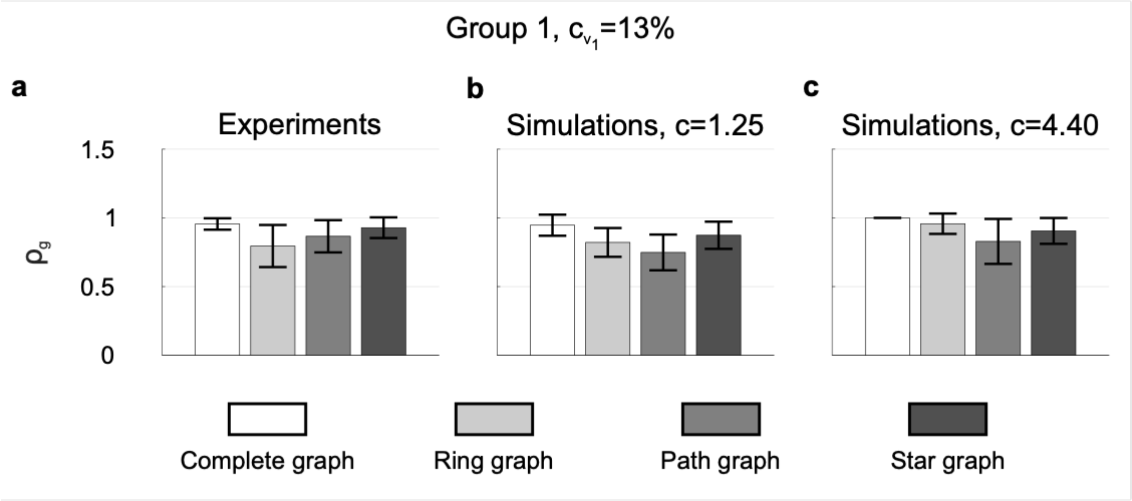


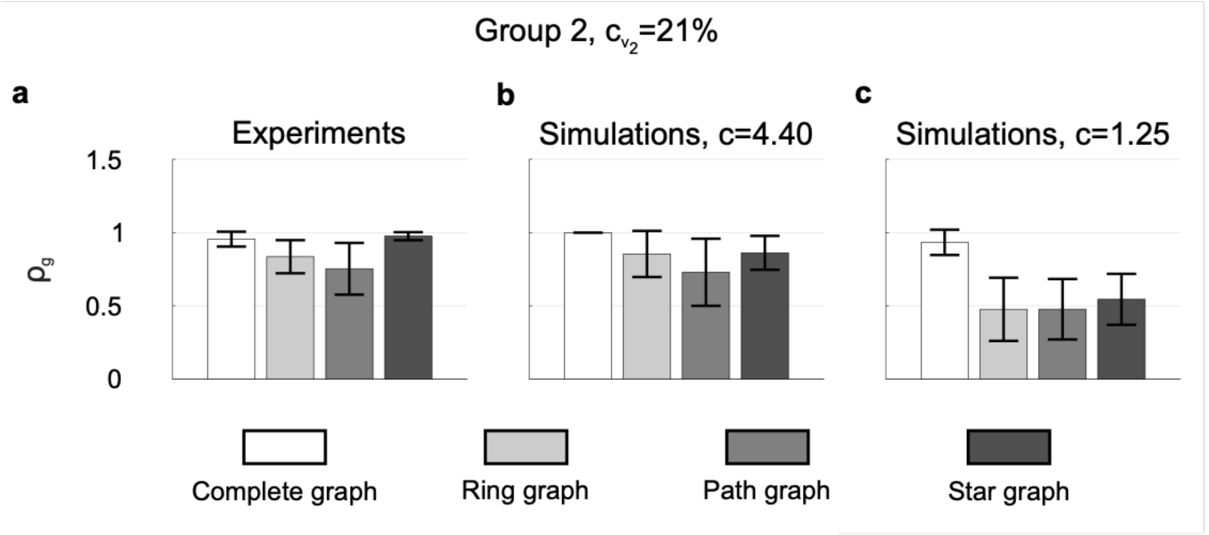
[3] Alderisio, F., Lombardi, M., Fiore, G., & di Bernardo, M. (2017). A novel computer-based set-up to study movement coordination in human ensembles. Frontiers in Psychology, 8, 967.

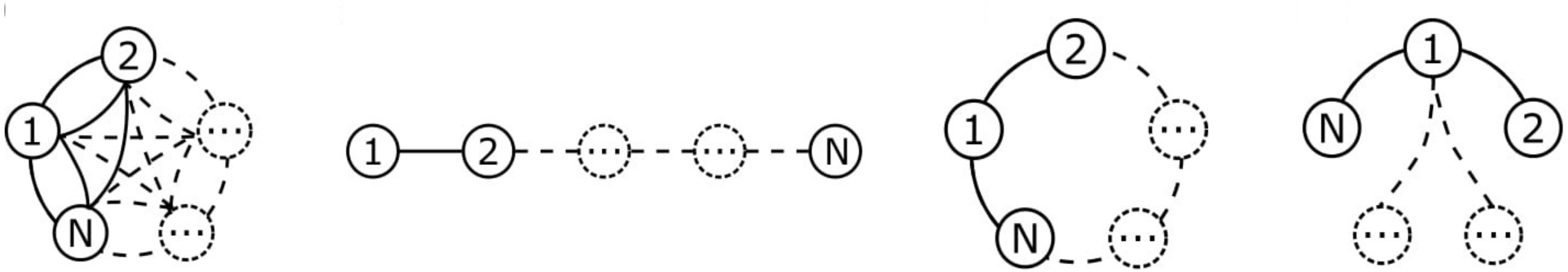
Modeling and effects of graph structure

- We can use nonlinear Kuramoto oscillators to characterize the motion of the group

$$\dot{\theta}_i = \omega_i + \frac{c}{N}\sum_{j=1}^{N} a_{ij}\sin\left(\theta_j - \theta_i\right)$$



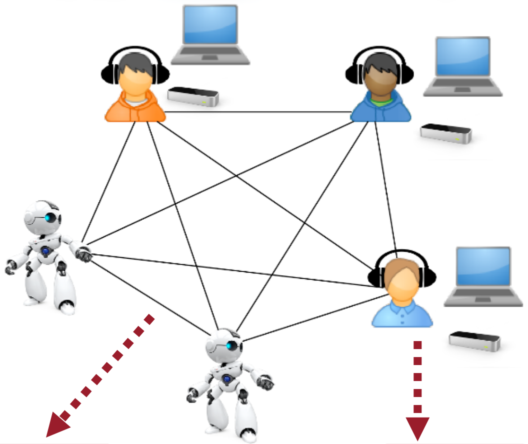




Introducing an artificial agent in the group

- We are interested in merging a virtual agent with the group

Chronos



topology

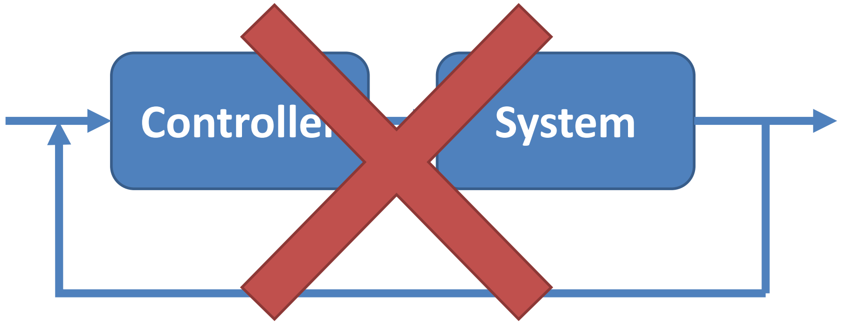
node

- Mathematically, group of agents performing a joint task can be modelled as a **complex network** of dynamical systems

Control problem

We want to design a cognitive architecture, based on real time feedback control, able to drive an artificial avatar in performing joint oscillatory motor task with a group of people while exhibiting human-like kinematic features

Nonlinear control approach



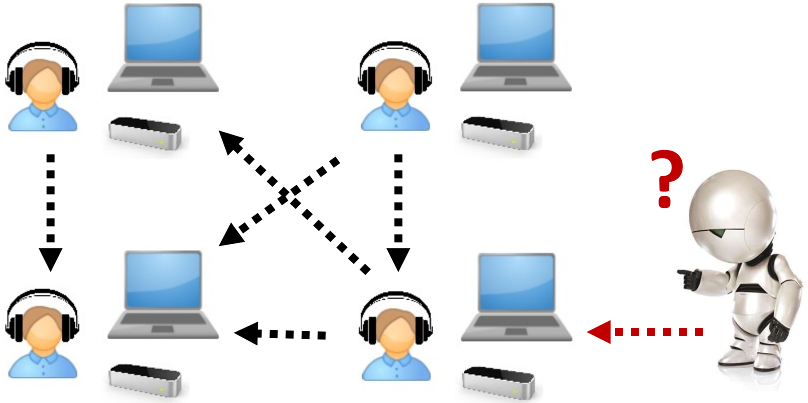
- Human model not known
- Deterministic nature of the controller
- Fine tuning of control parameters

We propose a **data-driven** architecture based on **deep learning**

(Deep Q-network)

Our approach

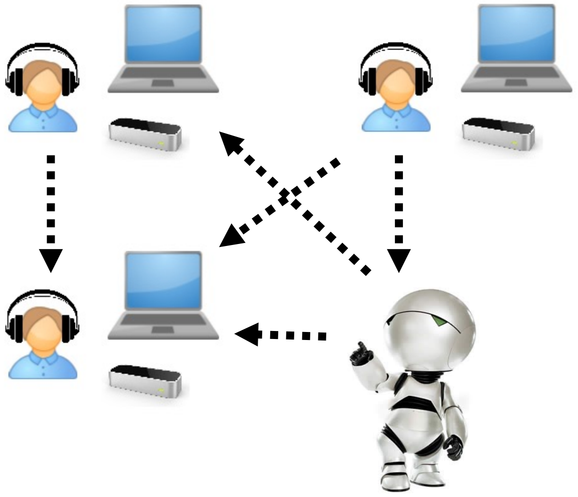
Phase 1:
Learning from humans



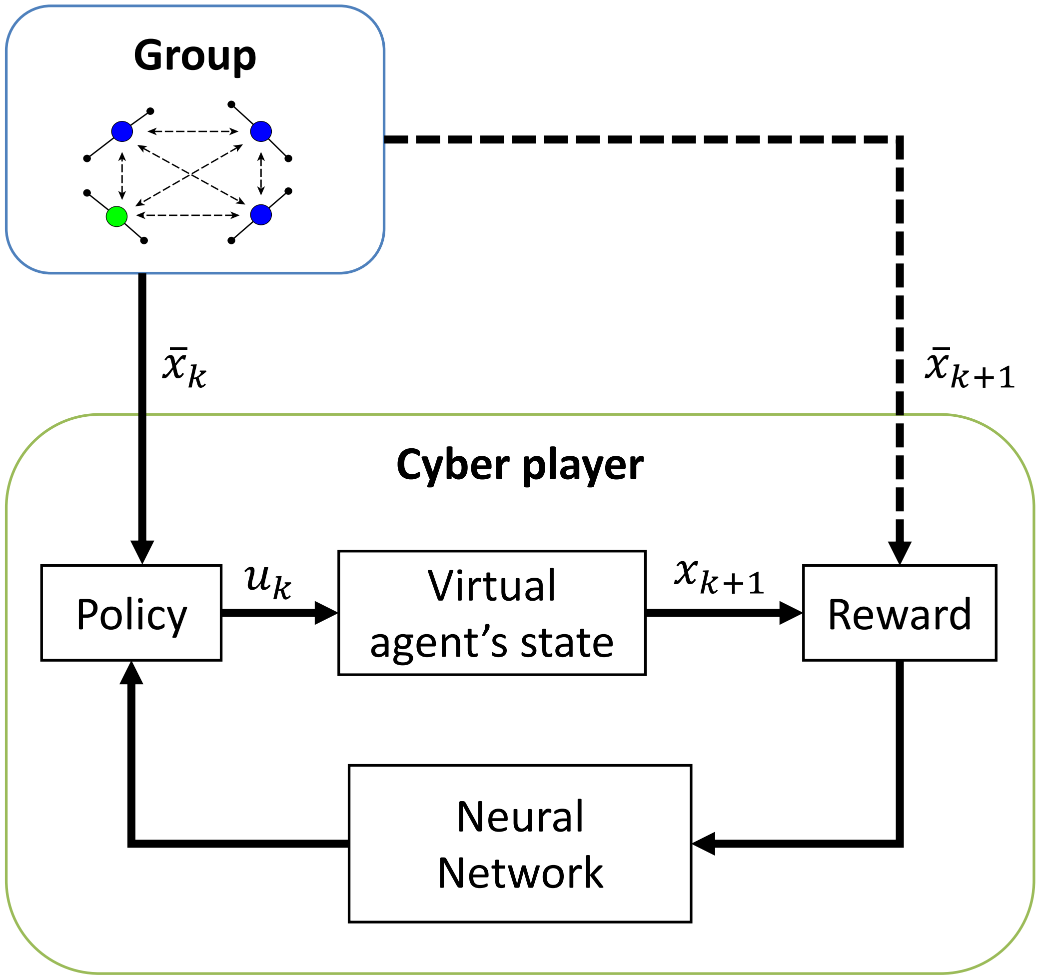
Group performing the oscillatory task
with a specific interaction pattern

replace

Phase 2:
Playing with humans



Phase 1: training the cyber player



The cyber player:

1. observes the vector of agents' positions and velocity

$\bar{x}, \dot{\bar{x}}$

2. takes a control action according to its policy

ε-greedy policy

3. receives a reward

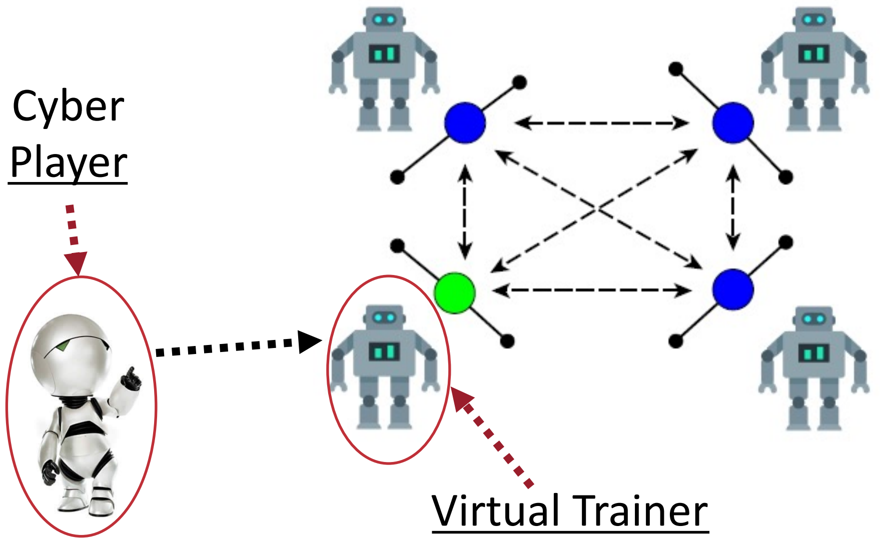
$$\rho = -(x - x_t) - 0.1(\dot{x} - \dot{x}_t)^2 - \eta u$$

4. trains the neural network that updates the policy

Phase 1: training the cyber player

- How can we get enough data for the artificial agent?
- To avoid a large amount of data directly from humans, we propose first to learn the cyber player with synthetic data generated via a nonlinear stochastic model of human behaviour

VT_1, VT_2, VT_3 have been used for the training VT_4 has been used as target player

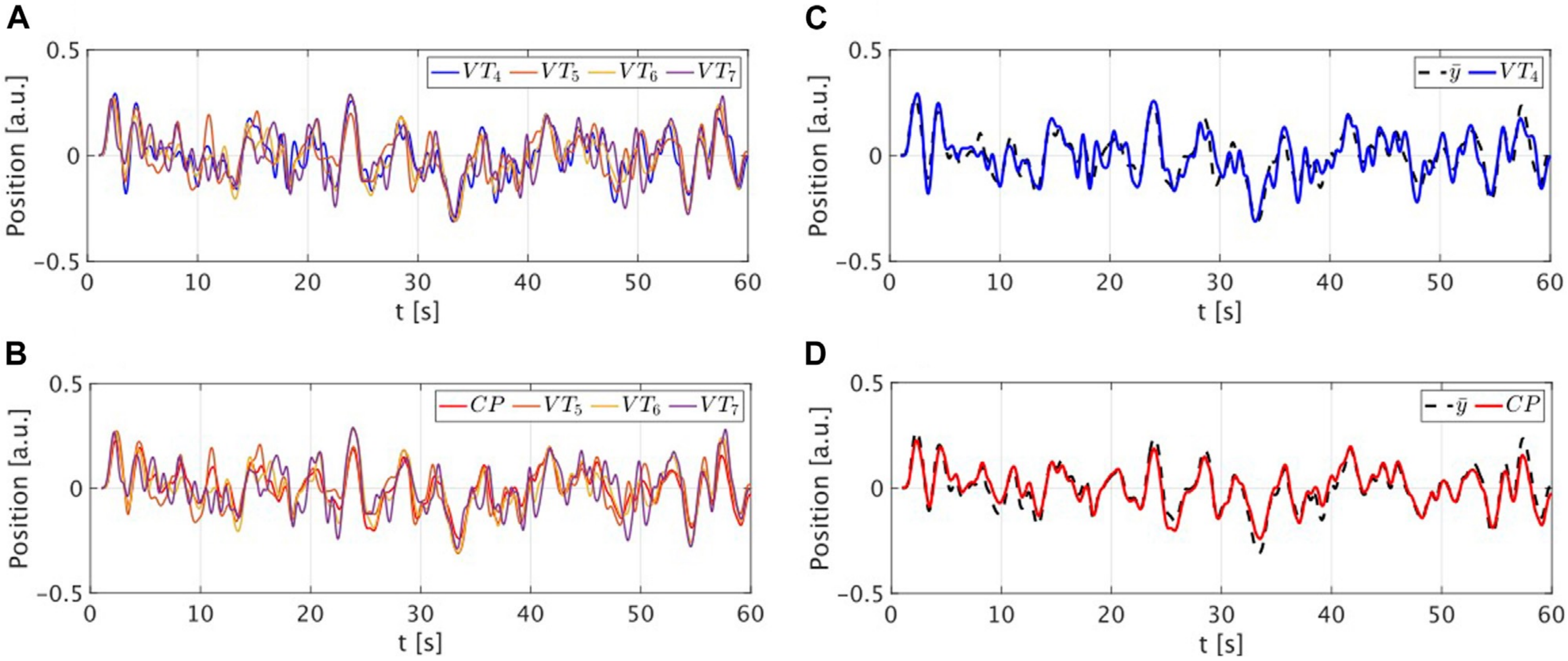


Nonlinear virtual agent based on Markov Chains

Zhai, C., Alderisio, F., Slowinski, P., Tsaneva-Atanasova, K., & di Bernardo, M. (2017). Design and Validation of a Virtual Player for Studying Interpersonal Coordination in the Mirror Game. IEEE Transactions on Cybernetics, 1–30.

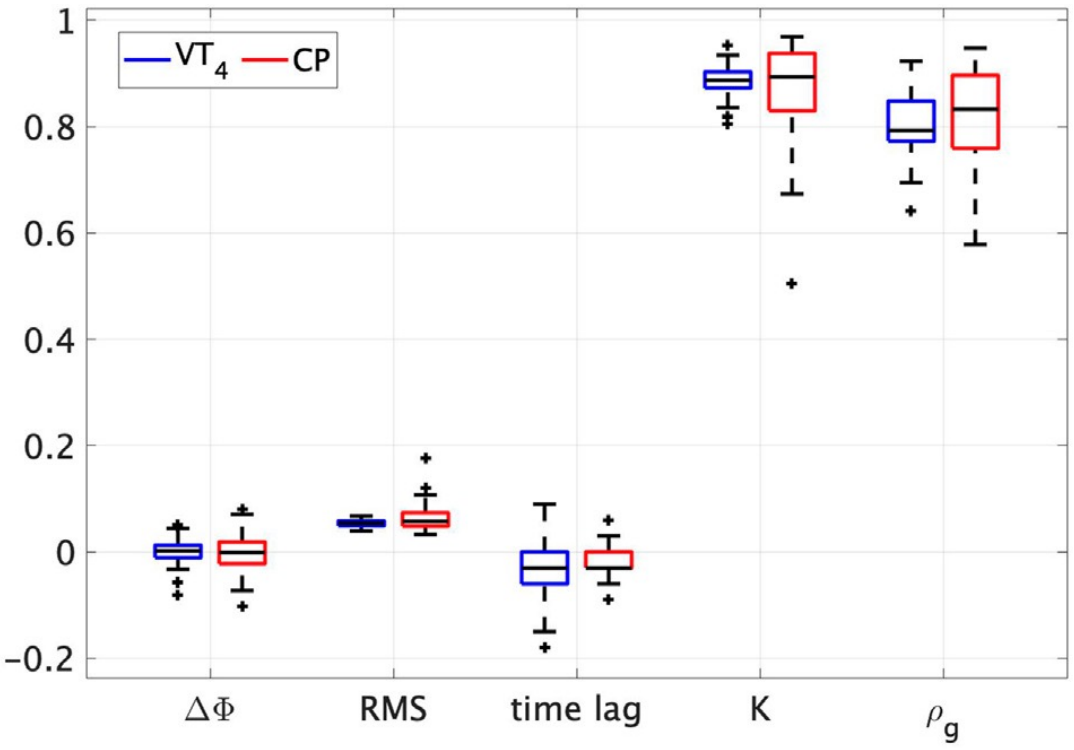
Phase 2: playing with group

Temporal correspondence on a random topology



Phase 2: playing with group

Human-like features on a random topology



Metric	CP	Human-like	T-test
Relative phase	-5.127e^-4±0.032	-2.506e^-4±0.023	W(54)=732, p=0.753, effect size=-0.059
RMS position error	0.062±0.018	0.054±0.006	W(54)=606, p=0.171, effect size=-0.213
Reaction time	-0.021±0.031	-0.034±0.051	W(54)=469.5, p=0.096, effect size=-0.264
Max cross-covariance	0.881±0.064	0.887±0.024	W(54)=801, p=0.788, effect size=-0.040
Group synch index	0.821±0.086	0.804±0.046	W(54)=593, p=0.139, effect size=-0.230

Since the data were not normally distributed, we performed the Wilcoxon t-test as a non-parametric test. All metrics reports a p-value > 0.05

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Conclusions

- We have discussed the problem of **designing a virtual player** able to play the mirror game in different configurations.
- The virtual player has to lead, follow the human player or improvise with him/her.
- This problem can be seen as **a nonlinear feedback control problem** (a solution based on optimal feedback control was proposed).
- The virtual player is then able to guarantee *temporal correspondence* and also to exhibit a *motor signature* that can be chosen at will.
- Once parameterised, the *VPs can be made to play against each other* opening the possibility of carrying out "in-silico" experiments even in multiplayer configurations.
- We explored methods based on machine learning to render the avatar truly autonomous
- We introduced the problem of looking at the emergence of coordination in Human groups and designing avatars in that context

Lots still to be done

- Great area at the edge between engineering and computational psychology and social sciences
- Many possible applications to rehabilitation and medicine
- The design of better cognitive architectures is essential in many areas of science and engineering, e.g. social robotics
- Many open problems and challenges remain:
  - What if the tasks are more complicated (assembling something together, playing sports etc)?
  - What if the group includes patients with social disorders (autism, schizophrenia etc)?
  - What if the motion is not 1D but becomes fully 3D?
  - How does leadership emerges? Can VPs assume leadership roles? How?

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  - **Carmela Calabrese** (now postdoc in Marseille)
  - **Chao Zhai** (Postdoc, Singapore-ETH center).
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  - **Piotr Slowinski** (Postdoc, Exeter).
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