2018 European Control Conference (ECC)
June 12-15, 2018. Limassol, Cyprus

Generation and classification of individual behaviours for virtual players control in motor coordination tasks

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Abstract— **The interaction of robots or physical/virtual avatars with humans will be increasingly common in a number of different scenarios intended to improve the quality of human life. For example, in the domain of healthcare, they can support therapists aiding patients in need of motor rehabilitation and so on. In this context, a fundamental control problem is to synthesize strategies to make the artificial agents interact with humans in a "natural" and human-like fashion. This is particularly relevant when artificial agents are required to coordinate their motion with humans performing joint tasks. It has been shown that for rehabilitation purposes, virtual agents in motor coordination tasks must exhibit certain kinematic properties (or Individual Motor Signature) that are characteristic of human motion. In this paper we discuss a method based on the use of Markov chain to generate artificial individual motor signatures that can be used to provide online reference signals for the control of virtual agents. The methodology is also used to classify and identify individual motor signatures belonging to individuals affected by social disorders.**

I. INTRODUCTION

Having robots or physical/virtual avatars interacting with humans will be an increasingly common scenario in the near future. The trend is to have more robots and agents assisting people in daily activities to improve their quality of life. An open problem and a clear challenge from a control perspective is to design an autonomous artificial agent able to interact with individuals in real time and in a "human-like way". An interesting application where the use of autonomous artificial agents may have a crucial role is in the health-care context, promoting innovative rehabilitation therapies for patients suffering from social or motor disorders [1]. In this context, for example, the human patient may be asked to coordinate the motion of a limb or a finger with that of an artificial agent. The use of such agents can have many advantages. For example, it can allow the development of home therapies, reduce costs and guarantee better working conditions for medical doctors and therapists [2]. To achieve this goal, it is important to study human motor coordination and investigate control strategies to make the artificial agents best interact with people.

Human motion has been studied for decades, raising the interest of different research areas, spanning from psychology to neuroscience [3], [4]. More recently, this problem has also attracted the attention of control theorists and applied mathematicians, and some dynamical models describing human movement have been derived [4], [5]. It has been shown that the motion of each person is characterized by specific individual kinematic properties defining "Individual Motor Signature" (IMS) [6]. Such IMS has been defined in terms of the Probability Density Function (PDF) of velocity profile of a human performing a paradigmatic motor task called the Mirror Game (see later). The authors in [6] also showed that IMS does not change over time and is, in principle, unique for every individual, thus making it possible to distinguish one person from another. It is also proved in the literature that people with social disorders such as schizophrenia have personal abnormal movements that influence the peculiarity of their IMS [7].

The Mirror Game [8] has been recently proposed as a simple, yet powerful paradigm for studying human motion and interpersonal human coordination. In the Mirror Game, two players imitate each others movements by moving two handles back and forth horizontally. Three different conditions can be implemented:

1) leader-follower (LF), in which one player is designated as the leader, while the other (follower) has to track the leader's motion;
2) joint-improvisation (JI), in which the players have to imitate each others motion without any designation of leader and follower;
3) solo condition (SC), in which one player plays alone and records his/her IMS.

In [9], it was suggested that designing a Virtual Player (VP) or avatar able to play the Mirror Game and coordinate its motion with that of Human Player (HP) can be extremely useful to provide new clinical interventions for rehabilitation of social disorders. From a control viewpoint, the key challenge in this context is to design the architecture of the VP so as to make it track or lead the motion of the HP while exhibiting an healthy reference IMS of choice, and interacting with the patient so as to maintain a feeling of engagement with her/him.

The aim of this paper is to propose a method based on the use of Markov Chains (MC) to identify, classify and generate IMS to provide a real-time reference for control purposes. In particular, after giving the background in Sec. II, in Sec. III we derive data-driven Markov models able to solve this problem. The models are informed by real data collected during the course of the European project ALTEREGO [18]

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and are validated in Sec. IV showing their effectiveness. Conclusions are drawn in Sec. V.

II. BACKGROUND AND MOTIVATION

In the few papers available in the literature on the problem, the synthesis of a control strategy for the VP consists of two main parts:

1) the inner dynamics, representing how the VP moves when moving in the absence of a human player. This was previously modelled using a nonlinear Haken-Kelso-Bunz (HKB) oscillator [5], [10], [11];
2) the control algorithm, that drives the motor interaction of the VP with a HP while exhibiting desired kinematic properties. In [10], [11] three different controllers have been proposed based on the use of optimal, adaptive or classical (PD) control approaches.

In this paper, we model the position, velocity and acceleration of the VP as those given by a nonlinear HKB model of the form:

$$\ddot{x}+\left(\alpha x^2+\beta\dot{x}^2-\gamma\right)\dot{x}+\omega^2 x=u, \tag{1}$$

where x is the terminal position of the VP, u is the control term that will be chosen as a function of the movement of the HP, and α,β,γ are parameters characterizing the damping, while ω is related to the movement frequency.

The control input u is chosen following an optimal control approach as the strategy that minimizes the cost function:

$$J(t_k)=\frac{1}{2}\theta_p\left(x(t_{k+1})-\hat{r}_p(t_{k+1})\right)^2+ \\ \frac{1}{2}\int_{t_k}^{t_{k+1}}(1-\theta_p)\left(\dot{x}(\tau)-\dot{r}_\sigma(\tau)\right)^2+\eta u(\tau)^2\,d\tau, \tag{2}$$

where $\hat{r}_p$ is the measured HP position, $\dot{r}_\sigma$ is the reference velocity corresponding to the desired motor signature of the VP, η is a positive weight used to tune the control energy, t_k and t_{k+1} represent the current and the next optimization time instants, and finally θ_p is a constant parameter in $[0,1]$ that makes the VP more responsive to the position mismatch with the human or not determining whether it plays in a leader or follower configuration. For more details see [11].

Notice that the current control architecture as shown in Figure 1 requires two reference signals, one being the position of the HP the other the velocity profile describing the desired IMS the VP has to exhibit. In the existing solution presented in the literature [9], such latter reference signal is extracted off-line from a pre-recorded human IMS. The use of pre-recorded signature makes the VP's behaviour less natural, since such signature is always the same and generated a priori. A crucial aim of this paper is to provide an alternative modelling approach based on MCs to generate online an original IMS reference signal to be used within the control scheme described above.

The model we develop can also be used to classify IMS from human players. This is particularly relevant as IMS anomalies are exploited to diagnose patients affected by schizophrenia providing new biomarkers for this mental disorder. In particular, a classification methodology is presented in [12] which is based on the characterization of neuromotor markers extracted from the recordings of participants spontaneous hand motion. Specifically, three different features are extracted from the collected data and, a posteriori, a majority rule is applied by the classifier to take its diagnostic decision. Even though this proposed scheme is innovative for the use of biomarkers in comparison with the previous literature [13], it still suffers from several limitations, such as the possibility of a providing reliable online classification.

The contribution of this paper is twofold since we adopt a methodology that, at the same time, allows us to both generate in real-time human-like motion in the context of the mirror game and solve the classification problem of IMS, applying it to both group classification of players into patients or healthy individuals and to classification of individual players.

The generation of human-like trajectories is crucial to overcome the limitations of the control architecture proposed in [9] where the controller uses as a reference signal the pre-recorded motion of a HP. By using learning techniques [14] the models presented in this paper allow to generate such reference in real-time during the game with a HP allowing the VP to behave autonomously and in a controlled manner with desired kinematic properties (IMS). To do so, our model exploits the theory of stochastic processes and observational learning, in particular Markov processes, suitable to model dynamical systems with a discrete set of states. Our goal is to derive from the observations of a person playing the mirror game, a general internal description model of the motion, capturing the key features from the collected player's IMS. Also, it is possible to use our methodology to design a classifier, alternative to that in [12], to distinguish between different individuals by analysing their IMS and then, recognize and so diagnose if an individual suffers from mental disorders such as schizophrenia. We show that the classifier derived in this paper is able to reach and overcome the accuracy presented in [12] using a simpler scheme which extracts from the signal only one feature based on the frequency spectrum of the position time series. As also done in [12], for our study we consider motion data collected from human players performing the mirror game in the Solo Condition.

III. MODELLING

A Markov model is a finite state stochastic model used to describe randomly changing systems. For any given system, a Markov model consists of a finite set of all possible states in which the system can be, the possible transition paths between those states, the probability rate parameters of those transitions, and a list of possible observations as output associated to each state. If the states are observable, they correspond to the model output. This particular Markov model is called a Markov Chain (MC) [14]. A Markov chain is fully characterized by:

- its transition matrix $A:=[a_{ij}]$ where $a_{ij}:=P(s_{t+1}=j|s_t=i)$ is the probability of being in state j at time $t+1$ given that the state at time t is i;

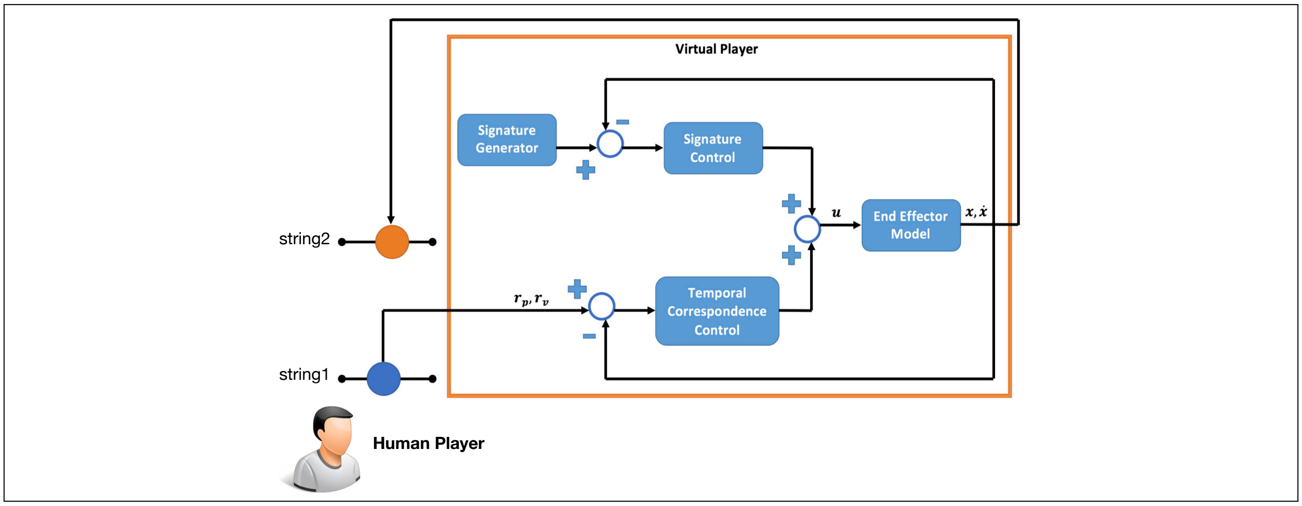

Fig. 1: Cognitive architecture (in blue) that allows the VP to follow two main objectives: temporal correspondence, that is the minimization of the position error between HP and VP; similarity to a desired motor signature, in order to guarantee a kinematic behaviour similar to that of a HP. The HP plays the mirror game moving a spherical handle (blue ball), his/her position r_p and velocity r_v are recorded and used as input to the control strategy that generates the position x and the velocity $\dot{x}$ of the VP's handle (orange ball).

- its initial state s_0.

Through MCs we aim at capturing the essence of the motion of a HP in the mirror game so as to be able to generate artificially realistic human-like motion and classify the associated IMS. To do so, we designed a modelling process consisting of the following 4 steps.

A) *Data collection and preprocessing*: it is essential that the data is represented in a homogeneous and invariant form before they are used to train the MCs. Here, as preprocessing we consider the short-time Fourier transform and vector quantization techniques;

B) *Markov model training*: preprocessed data are encoded into a MC in order to find the right parameters for the transition matrix A;

C) *Data generation*: new data is generated by the MC model defined in the previous step and then validated through appropriate analysis tools;

D) *Classifier design*: a classifier is designed using the MC model. In this step, the MC model is stored in the classifier knowledge base and, through it, the system is able to take a classification decision.

A) *Data collection and preprocessing*

In order to characterize human IMS by MC, the first step is to convert the continuous measurements of the human positions into a finite set of symbols. In this paper, the preprocessing has been conducted in two stages: feature selection and symbol generation, as illustrated in Figure 2a.

To extract the main features, the Fast Fourier Transform (FFT) algorithm was selected as a viable preprocessing tool for the following reasons:

- the Fourier transform and its inverse establish a one-to-one mapping between the time domain and the frequency domain;
- FFT algorithm can be implemented efficiently;
- the Fourier transform preserves the information of the original signal, ensuring that its important features are not lost during the transformation.

However, the Fourier transform has the drawback of not explicitly displaying the time localization of the frequency components. To overcome this problem, in our scheme we adopted a suitable pre-windowing partition of the signal's time domain (Short Time Fourier Transform). Roughly speaking, the STFT can be viewed as a "local spectrum" of the signal $x(t)$ in an "analysis window" centered around t.

So, for the input signal, a Hamming window ("signal windowing") of a certain width is first used to decompose the signal into frames. To prevent loss of information, the windows are overlapped by $3/4$ of the window's width. In this way, the sum of the sequence of the windows is a resulting flat-top window.

The FFT analysis has then been performed for every window. Finally, a set of feature vectors is obtained from the FFT coefficients. Such vectors will feed the Vector Quantizer (VQ) in the next step of the preprocessing. A VQ is completely defined by a codebook, which consists of a set of N fixed prototype vectors generated by an appropriate algorithm. Here Lloyd's algorithm was used to produce the VQ codebook [15]. Also known as Voronoi iteration, the algorithm at the first step partitions the Euclidean space into well-shaped and uniformly sized convex cells, then iteratively finds the centroid of each partition and re-partitions the space according to which of these centroids the inputs are closest. Since the operation of quantization inevitably causes distortion between the original data and the quantized data, the VQ has to map each feature vector in one of the prototype vectors of the codebook that minimizes the squared error distortion between the vector data and prototype vector. The indexes of the N prototype vectors, integers from 0 to $N-1$, are used as symbols in the output of the discrete MC.

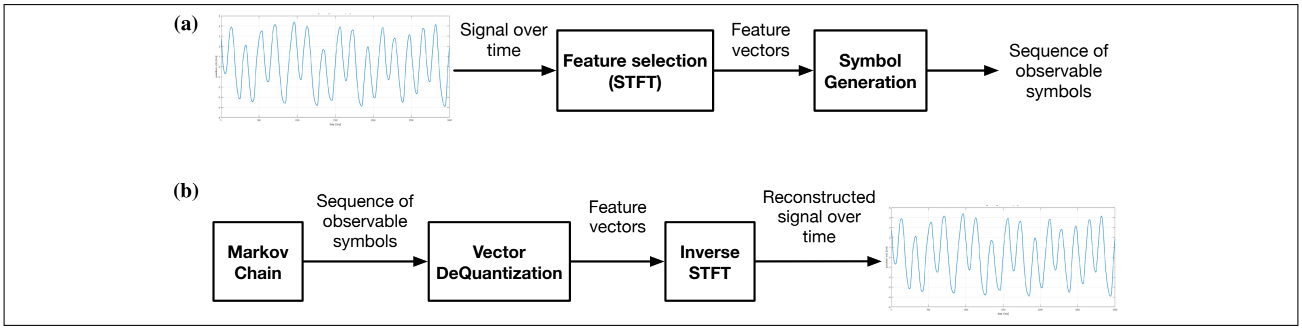

Fig. 2: **(a)** Block diagram representing the preprocessing phase. The position time series is processed by the first block of feature selection, having as output a set of feature vectors. The symbol generation block further processes this set and produces a sequence of finite symbols. **(b)** Block diagram representing the reverse preprocessing. The sequence of symbols is sent back through a vector dequantizer in order to generate for each symbol the corresponding vector of FFT coefficients.

B) *Markov model training*

The features, encoded in the symbols, are used to build a Markov model that represents the IMS to which those features belong. Building a MC means deciding the elements of the transition matrix A, whose elements are the transition probabilities from one state to another. The states of our MC model will correspond to the codebooks symbol set, i.e., the model has as many states as symbols. The estimation of the model parameters has been done using Baum-Welch algorithm [15], which is essentially based on a frequentist approach. In its general form, it uses the Expectation-Maximization algorithm (EM) [15] to find the maximum likelihood estimate of the parameters given a set of observed feature vectors.

C) *Data generation*

The MC model synthesized as in the previous section includes the stochastic features of the data that have been acquired and processed.

Since the MC itself generates a sequence of symbols according to the probabilities encoded in the transition matrix A, a reverse preprocessing is needed to reconvert the sequence of symbols into a function of time, as illustrated in Figure 2b. First of all, the generated sequence of symbols has to be processed by a vector dequantizer with the same codebook used for the forward preprocessing. In this way, each symbol is mapped into a prototype vector of FFT coefficients. The inverse STFT is applied to each single vector and, after an appropriate concatenating operation, it is possible to reconstruct a human-like position time series over time.

D) *Classifier design*

Given a dataset, it is possible to divide it into different classes based on some measures of inherent similarity or distance. The classification procedure of a new observation, implemented by a *classifier*, is the problem of identifying to which of these classes it belongs, based on "how similar" this new observation is with respect to the members of different classes. In this paper, we decided to build a IMS classifier by assigning and tuning a dedicated MC model to each class we are interested in or we evaluated as significant for the human motion generation/classification problem. The set of all models corresponding to all considered classes constitutes the base of knowledge of the classifier. Specifically the classifier has been designed both for single mirror-game players recognition and healthy/schizophrenic players. For the sake of brevity, only the healthy/schizophrenic players recognition will be detailed in Sec. IV-B.

The classifier takes as input one or more position time series of a certain player. For each of them, it consults its base of knowledge and takes a decision. More specifically the classifier evaluates the probability of having the sequence in input as output of each MC and chooses the class as the one corresponding to the model that maximises the probability.

Formally, we can compute the probability of having a specific sequence of states $\vec{s}$ belonging to a MC λ_i as

$$P(\vec{s},\lambda_i) = \prod_{t=1}^{T} P(s_t|s_{t-1};A_i) = \prod_{t=1}^{T} a^{(i)}_{s_{t-1}s_t}, \qquad (3)$$

where $\vec{s}$ is the sequence of the states, T is the length of the sequence, s_t is the current state at time instant t and $A_i := [a^{(i)}_{ij}]$ is the transition matrix for the model λ_i. Evaluating the maximum of all the probabilities as $max_{\lambda_i}(P(\vec{s}|\lambda_i))$, where N is the number of the models λ_i in the classifier's base of knowledge, allows to assign the time series to the most probable class it belongs. If more than one time-series belongs to the same class, a second level of classification takes the final decision according to a majority rule.

As also mentioned in Sec. II, a great advantage of our approach with respect to [12], is that the classifier is also able to work completely online while the HP is performing the mirror game in Solo Condition. In real time the classifier acquires the samples of the position signal, buffers a minimal window of samples needed to evaluate a meaningful FFT, and then starts evaluating the classification probability of the data. Note that although during a game the length of the position time-series being acquired increases, the computational complexity of the classification exercise remains constant ($O(N)$ where N is the constant number of buffered samples).

IV. VALIDATION

In this section, we present the validation of our methodology for the two cases of generation and classification. All the participants took part in the experiments voluntarily, signing an informed consent in accordance with the Declaration of Helsinki. Any information obtained in this study remained confidential and participants' identity is kept anonymous.

A. Generation of new signatures

Specifically, regarding the generation of IMS among different players, we have carried out the experiments with the following setup:

- *participants*: a total of 6 people participated: 1 female and 5 male. All the participants were right handed and none of them had physical or mental disabilities.
- *experiments*: each participant carried out 30 different trials, 30 seconds long each, playing the Mirror Game in Solo Condition mode trough Chronos, a software tool developed to study movement coordination [16]. Each player was asked to move his/her index of preferred hand in a spontaneous way in order that his/her individual motor signature could emerge.

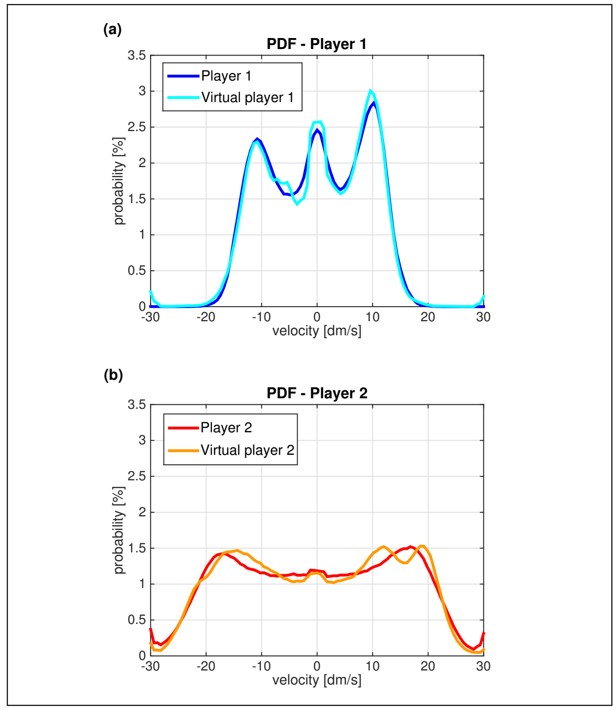

Fig. 3: **(a)** velocity PDF of the first player (in dark blue) and of the corresponding VP (in light blue). **(b)** velocity PDF of the second player (in red) and of corresponding VP (in orange).

Our methodology based on MC allows us to generate meaningful position signals for an autonomous virtual agent, that in this way acquires a signature identity. To build such MCs, we conducted experiments collecting the motor signature of six different players, as described before. Each trial (position time series) has an original sampling rate at 10 Hz, interpolated to 100 Hz during the preprocessing. The interpolated signal is windowed with a Hamming window of 60 samples with an overlapping of 45 samples. The signal is quantized with a codebook of 256 levels/symbols and so the trained MC is made up of 256 states (one per symbol). At the end of the training, six different MCs have been derived, one per player. In this section we compare different motion signals generated by the MC with the motion signals belonging to the HPs, with which the MC was trained. A total of 20 new motion signals were generated. For a better graphic visualisation, our results are shown for just 2 players out of the 6 involved. In Figure 3, we can see that the velocity PDF of the VP well approximates the velocity PDF of the real player for both the players.

Other metrics have been evaluated (e.g. skewness and kurtosis, EMD and similarity space defined in [12]) confirming the same impressive performances highlighted by the PDF in Figure 3. The analysis with these other metrics is not reported here for the sake of brevity and will appear in an extended journal version of this work.

B. Classification patient/control

To test the classification ability of our approach, we validate the methodology classifying patients from healthy individuals, as done in [12]. With the aim of making a good comparison, we use the same data adopted in [12] and collected with the collaboration of the patients from the University Department of Adult Psychiatry (CHRU Montpellier, France) (for details see [12]). The dataset is obtained as follows:

- *participants*: 29 controls and 30 patients.
- *experiments*: each participant carried out 4 trials 60 seconds long each. Each participant was asked to move the ball left to right in a spontaneous way, in order that his/her individual motor signature could emerge.

As described in Sec. III, our methodology is made up of different steps. After an interpolation to 100 Hz, each position time series is windowed with a Hamming window of 200 samples with an overlapping of 150 samples. The signal is quantized with a codebook of 256 levels/symbols and so the trained MC is made up of 256 states (one per symbol). The two modelled MCs represent one the class "patient" and the other the class "control". To evaluate the performance of the classifier, we used the following four sets: true negative (TN) are controls classified as controls; false negative (FN) are the patients classified as controls; true positive (TP) are patients classified as patients; false positive (FP) are controls classified as patients. The metrics are: *i*) Accuracy $:= (TP+TN)/N$, *ii*) Sensitivity $:= TP/(TP+FN)$, *iii*) Specificity $:= TN/(TN+FP)$, *iv*) Precision $:= TP/(TP+FP)$).
Table I shows the comparison between our results and the ones in [12]. The main difference between the two methodologies lies in the number of features adopted. Indeed, our method exploits only one feature, based on the FFT as described in Sec. III, whereas [12] uses a total of three features, combines them and chooses according to the

Results of classification based on SFTF									
Feature	**Ctrls/Pts**	**TN**	**FP**	**TP**	**FN**	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**
STFT-MC	29/30	30	0	30	0	1	1	1	1
Existing results of classification based on biomarkers									
(c_4, c_2)	29/30	25	4	21	9	0.7797	0.7000	0.8621	0.8400
ΔP_0	29/30	21	8	24	6	0.7627	0.8000	0.7251	0.7500
GWS	29/30	23	6	21	9	0.7458	0.7000	0.7931	0.7777
Majority	29/30	28	1	27	3	0.9322	0.9000	0.9655	0.9642

TABLE I: Comparison between our STFT-MC methodology and the existing results in [12] regarding the classification of people suffering from social disorders or not. Data are extracted from solo condition experiments of 29 controls (Ctrls) and 30 patients (Pts).

majority. The three features are: the global wavelet spectrum (GWS), the ΔP_0 distribution of the lengths of movement segments (lengths between two turning points) and the distribution of $(c_1, c_2, c_3, c_4, c_5)$, polynomial coefficients of the stochastic model used to describe hand motion. Furthermore, the method in [12] requires to acquire the whole signal before processing it, while our method works intrinsically online. Experiments conducted to identify individual single players have been also conducted showing the same promising performances here reported for the classification case patients/controls. We do not report here this case for the sake of brevity and we remind the reader to an extended journal version of our work.

V. CONCLUSIONS

Motivated by the human-in-the-loop challenges for futuristic control systems, and in particular focusing our attention on healthcare applications, in this paper we addressed the problem of synthesizing realistic artificial individual motor signatures and devising a classifier able to recognise and classify players by analysing their IMS. Specifically, we presented a new methodology based on action learning techniques and MCs. The methodology was evaluated on preliminary experimental results for classifying patients suffering from Schizophrenia. It was shown that it overcomes some of the limitations of previous approaches and can be used to generate realistic human-like motion in real time.

The next step is to embed the MC based approach we presented in the control scheme shown in Figure 1 to implement the missing signature generation block. The availability of such a block will allow the synthesis of fully autonomous VPs able to interact with HPs while observing and classifying their behaviour for diagnostic purposes in serious rehabilitation games. This is the scope of current research which will be presented elsewhere.

ACKNOWLEDGMENT

The authors wish to thank Dr. Piotr Słowiński at the University of Exeter for his support and for providing the data used to test classification of patients. We also wish to thank all the people who took part in the experiments and Mr. Alberto Ingenito who carried out some of the simulations for the validation of the approach described in this paper as part of his M.Sc. thesis work at University of Naples Federico II.

REFERENCES

[1] C.J. Winstein, D.K. Rose, S.M. Tan, et al., "A randomized controlled comparison of upper-extremity rehabilitation strategies in acute stroke: a pilot study of immediate and long-term outcomes". In Physical Medicine and Rehabilitation, 85(4), pp 620-628, 2004.

[2] M. Pirovano, R. Mainetti, G. Baud-Bovy, P.L. Lanzi, and N.A. Borghese, "Intelligent Game Engine for Rehabilitation (IGER)". In IEEE Transactions on Computational Intelligence and AI in Games, 8(1), pp. 43-55, 2016.

[3] R.C. Schmidt, and M.T. Turvey, "Phase-entrainment dynamics of visually coupled rhythmic movements". In Biological cybernetics, 70(4), pp. 369-376, 1994.

[4] G. Dumas, G.C. de Guzman, E. Tognoli, and J.S. Kelso, "The human dynamic clamp as a paradigm for social interaction". In Proceedings of the National Academy of Sciences, 111(35), pp. E3726-E3734, 2014.

[5] H. Haken, J.S. Kelso, and H. Bunz, "A theoretical model of phase transitions in human hand movements". In Biological Cybernetics, 51(5), pp.347-356, 1985.

[6] P. Słowiński, E. Rooke, M. di Bernardo, and K. Tanaseva-Atanasova, "Kinematic characteristics of motion in the mirror game". In IEEE International Conference on Systems, Man and Cybernetics (SMC), pp. 748-753, 2014.

[7] M. Varlet, L. Marin, S. Raffard, R.C. Schmidt, et al., "Impairments of social motor coordination in schizophrenia". PloS one, 7(1), 2012.

[8] L. Noy, E. Dekel, and U. Alon, "The mirror game as a paradigm for studying the dynamics of two people improvising motion together". In Proceedings of the National Academy of Sciences, 108(52), pp. 20947-20952, 2011.

[9] C. Zhai, F. Alderisio, P. Słowiński, K. Tsaneva-Atanasova, and M. di Bernardo, "Design and validation of a virtual player for studying interpersonal coordination in the mirror game". In IEEE Transactions on Cybernetics, 2017.

[10] C. Zhai, F. Alderisio, K. Tsaneva-Atanasova, and M. di Bernardo, "Adaptive tracking control of a virtual player in the mirror game". In IEEE 53rd Annual Conference on Decision and Control (CDC), pp. 7005-7010, 2014.

[11] C. Zhai, F. Alderisio, K. Tsaneva-Atanasova, and M. di Bernardo, "A model predictive approach to control the motion of a virtual player in the mirror game". In IEEE 54th Annual Conference on Decision and Control (CDC), pp. 3175-3180, 2015.

[12] P. Słowiński, F. Alderisio, C. Zhai, Y. Shen, P. Tino, C. Bortolon, D. Capdevielle, et al., "Unravelling socio-motor biomarkers in schizophrenia". In npj Schizophrenia, 3(1), p. 8, 2017.

[13] D.C. Goff, K. Romero, J. Paul, et all., "Biomarkers for drug development in early psychosis: current issues and promising directions". In European Neuropsychopharmacology, 26(6), pp. 923-937, 2016.

[14] N. Privault, "Understanding Markov chains: examples and applications". Springer Science & Business Media, 2013.

[15] S.J. Russell, and P. Norvig, "Artificial intelligence: a modern approach". Pearson Higher Education, 3rd edition, 2010.

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

[17] P. Słowiński, C. Zhai, F. Alderisio, et al., "Dynamic similarity promotes interpersonal coordination in joint action". In Journal of The Royal Society Interface, 13(116), p. 20151093, 2016.

[18] Available from: http://www.euromov.eu/alterego/project.