Synchrony as a Tool to Establish Focus of Attention for Autonomous Robots

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Abstract— **With technology and artificial intelligence advancements, the notion of professional service robots has emerged. Consequently, robots must share their physical and social space with human beings. How can robots select a partner among many interactants and how can they focus their attention on regions of interest? As psychologists consider synchrony as an important parameter for social interaction, we hypothesize that in the case of social interaction, people focus their attention on regions of interest where the visual stimuli are synchronized with their inner dynamics. Then, we assume that a mechanism able to detect synchrony between internal dynamics of a robot and external visual stimuli (optical flow) can be used as a starting point for human robot interaction. This kind of mechanism can also be involved in more complex tasks of interaction such as partner selection. Inspired by human psychological and neurobiological data, we propose a synchrony-based neural network architecture capable of selecting the robot partner and of locating focus of attention.**

I. INTRODUCTION

Human verbal interaction is not only speech dependent, in fact, many non-verbal behaviors such as facial expressions, pauses during discussion, hand movements and some other gestures are also involved. In other words, when two humans interact, they generate interpersonal interactions which synchronizes naturally between the two agents watching each other [1]. Studies of dyadic interactions show that synchrony is a necessary condition for interaction between an infant and its mother. An infant stops interacting with its mother when she stops synchronizing with it [2]. Condon and Ogston also described that when two persons are engaged in a discussion their behaviors are temporally correlated [3]. In addition, Rochat [4] has underlined the self-imitiation where an infant reproduce their own actions, he proposed that the systematic repetition of self produced actions could serves as a primary source of knowledge about the self and basic process by which infants gain self-reflective capabilities. Trevarthen and Hubley [5] suggested that imitation by mothers can be assumed as a tactic to get the attention of their babies.

In physics, the earliest known scientific discussion of synchronization started in 1657 when the famous Dutch physicist Christiaan Huygens observed and described the synchronization phenomenon working with pendulum clocks [6]. Blekhman [7] did similar experiments and observed two stable synchronization states (anti-phase and in-phase). Flashing of fireflies, Cricket chirping, pacemaker cells in the heart circadian rhythm and people's clapping show the synchronization is a quite general property in living systems [6] [8].

Michalowski et al. developped a dancing robot to analyse the properties and significance of synchronized movement in general social interaction [9]. Murtaza et al. [10] proposed a tracking method to synchronize the robot (steps) with musical beats. Crick et al. programmed a robot for drumming (with human drummers) by integrating multiple sensors input (oscillatory). They showed that precise synchronization between humans and robot can be achieved by fusing multiple sensors input although incoming data is imperfect [11]. Ikegami and Iizuka [12] used the genetic algorithm technique and showed that coupling and turn-taking between two agents are sensitive to the dynamics of interaction.

One of the major concerns of interactive robotics is how to focus on salient features among various visual stumuli. In fact, focusing attention and discriminating useful data from the others reduce significantly the big amount of incoming information from sensors and keep computational resources available for other important tasks. A good example of Focus of Attention (FOA) is the cocktail party where humans are able to focus their attention on one interesting voice in a noisy room.

From the above discussion, it is clear that synchrony is a crucial parameter for social interaction as well as largely witnessed in natural (dynamical) systems. In this paper, we use immediate synchronous imitation (adaptation of other's synchronous behavior) as a communication tool. In other words, robot imitates the other agent, if it detects synchrony between its internal dynamics and the interactant's movements. This approach addresses the question "who to imitate" discussed by Dautenhahn and Nehaniv [13]. The paper is organized as follows: In section 2, materials and methods are defined. Section 3 describes a model of dynamical interaction (for two agents). In section 4, the architecture to select an interacting partner among various interacting agents using synchrony information is presented. Section 5 explains the concept and the architecture of focus of attention (FOA) by predicting synchrony informationand finally, before concluding, section 6 details the experimental results.

II. MATERIALS AND METHODS

We used a minimal setup for our experiments as shown in fig. 1. Components of our experiment includes Nao robot, basic automata (1 degree of freedom), human and cameras. To avoid the limitation of the Nao's camera which is limited

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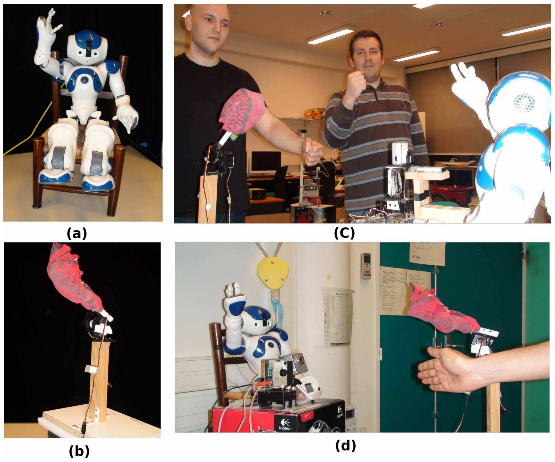

Fig. 1. Setup for our experiments. (a) basic automata (1 degree of freedom, assembled in the lab) (b) Nao robot (c) & (d) Overall setup for human-robot and robot-robot interaction.

to 10 Hz (frame rate) through the ethernet connection, a new camera has been added. The frame rate for our experiments is 30 Hz. Robot's head is used to show where the robot focuses its attention.

Phase locking value (PLV) is used to investigate the interaction dynamics between two signals. PLV is a practical method presented by Lachaux et al [14] for detecting EEG synchrony in a band of frequencies. The phase locking value for the two signals is defined as $PLV_{n,r} = \frac{1}{T}|\sum_{t=1}^{T} exp(i(\phi_n - \phi_r))|$. Where T is the number of samples in each window and $\phi_n - \phi_r$ is the phase difference between two signals. Synchronization leads the PLV value at 1 and on the contrary close to zero. The videos of our experiments based on proposed architectures can be found on the following web site: http://www.etis.ensea.fr/neurocyber/Videos/synchro/

III. HUMAN ROBOT INTERACTION USING OPTICAL FLOW

Here, we propose a model based on dynamical interactions of two agents. Agent 1 (Nao robot) dynamically adopts or imitates the behavior of agent 2 (either human or basic automata). Our aim is to provide minimal capabilities to Nao to interact with other agents by dynamically adopting the frequency and phase of the other agents. Optical flow represents the visual stimuli and it is input for our architecture.

A. Oscillator Model

The oscillator model shown in the fig. 2 is similar to [15]. It is made of two neurons $N1$ and $N2$, fed by a constant signal and multiplied by the parameter $\alpha1$ and $\alpha2$. These two neurons inhibit each other proportionality to the parameter β. The frequency of the oscillator depends on the parameters $\alpha1$, $\alpha2$ and β.

$$N_1(n+1) = N_1(n) - \beta N_2(n) + \alpha 1 \quad (1)$$

$$N_2(n+1) = N_1(n) + \beta N_2(n) + \alpha 2 \quad (2)$$

In addition, reservoir of oscillators (echo state network) could be used to work with a larger range of frequencies.

B. Dynamical Interaction Model

As shows in fig. 2, the oscillator is connected with Nao (robot's arm) and oscillates normally at its own frequency and amplitude. Motion in the visual field of Nao (we restrict our motion up-down only) is estimated by an optical flow algorithm, velocity vectors are then converted into positive and negative activities. If the perceived movements are in the upward direction, the oscillator gets the positive activity and its amplitude increases on the positive side depending on the quantity of energy induced. Similarly, if the negative activity is perceived, the amplitude goes down. Fig. 3(e) is a snapshot taken during an experiment illustrating the optical flow functioning. There are two moving objects in the field of view of Nao. One moves upward and it is transformed to positive activities by the optical flow (shown by black color) while the other moves downward and transformed into negative activities (gray and unfilled).

These positive and negative activities will be learnt by the robot and modifies the oscillator accordingly. When an agent interacts with Nao, Nao's oscillator can be modified within certain limits otherwise it continues to its default frequency. Mathematical equation of the oscillator can be rephrased as

$$N_1(n+1) = N_1(n) - \beta N_2(n) + \alpha 1 + \gamma f' \quad (3)$$

Where f' is the induced energy, f' may be either positive or negative. γ is the coupling scaling factor

Fig. 3 (column 1) shows an agent (human) comeing in the visual field of Nao and trying to interact by imitating NAO. Initially, both are unsynchronized (see fig. 3(b) (column 1)). PLV (indicator of synchrony) has its lowest value. Fig. 3(a) and 3(b), column (2) shows after some time of interaction both Nao and human are synchronizing little by little similar to pendulum coupling. Their increasing PLV value also shows the emerging synchrony. In the column 3 of fig. 3(a) and 3(b), it is clearly shown that both agents are completely synchronized and the corresponding PLV value has its highest possible range. Fig. 3(c) shows Lissajous curve between $N(t)$ (Nao's oscillation) and $H(t)$ (human's movements). The shape of the curve is an ellipse indicating that both signals are almost identical.

Interesting facts are observed during experiments. Some of these observations were also made by Pantaleone in his study on analysis of metronomes synchronization [17]. First, if the natural frequency of the two agents (in his case two pendulums) differs by more than a certain limit, synchronization will not occur but the range of interacting frequency (that can be synchronized with Nao) can be augmented by increasing the coupling energy (f') that feeds to the Nao's oscillator. With low coupling scaling factor (γ) both agents can be synchronized if their natural frequency differs by more than few percents. Similarly, higher scaling factor (γ) leads to higher range of frequencies. For this human-robot interaction the default frequency of Nao's oscillator was 0.428 Hz

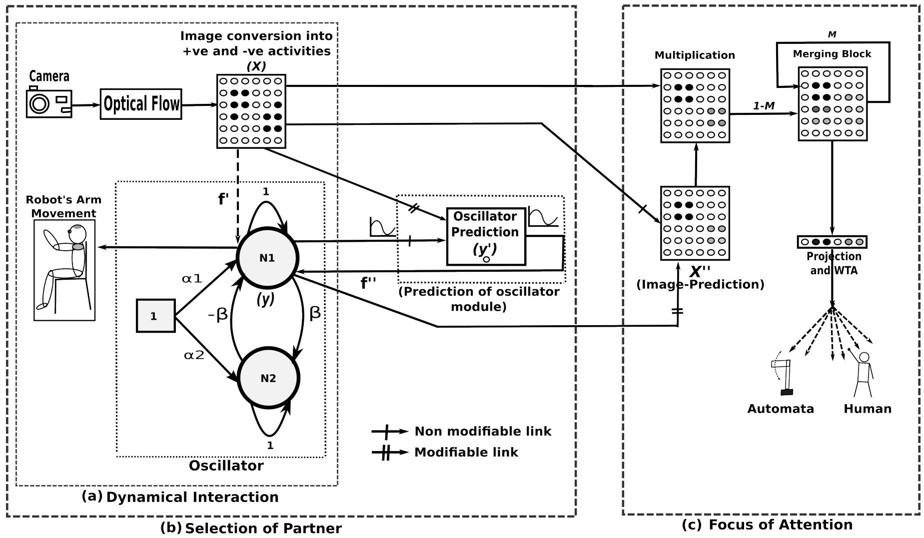

Fig. 2. (a) Oscillator model made of two neurons $N1$ and $N2$ (b) Selection of Partner: select a interacting partner on the basis of synchrony detection among various interacting agents. (c) Shows attentional mechanism architecture.

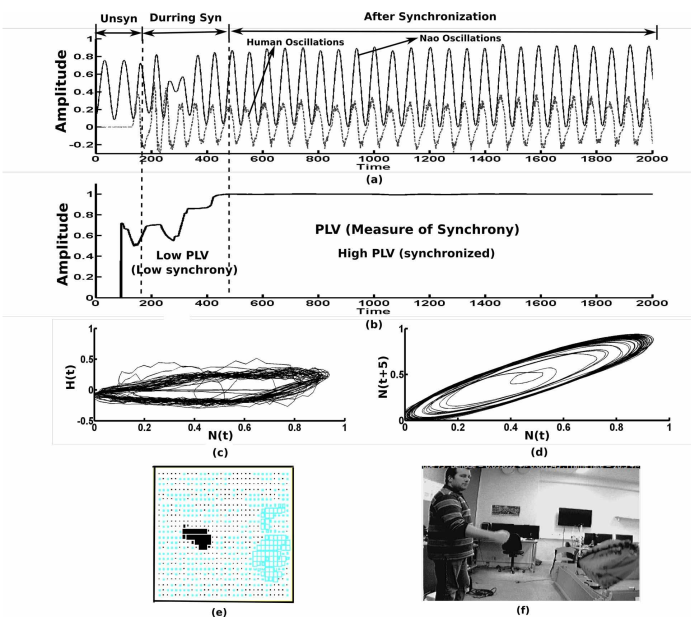

Fig. 3. Describes how the two agents are synchronized. (a) Shows two signals (human and Nao's modifiable oscillator). (b) PLV measurement. (c) Lissajous curve $N(t)$ (Nao' oscillation) and $H(t)$ (Human's movements), curve's ellipse shape indicates that both signals are identical (d) Lissajous curve between two different time values of Nao ($N(t)$ and $N(t+5)$). (e) Optical flow function: Upward movements shows as black and realized by $+ve$ activities while downward motion perceived as $-ve$ activities and shown by black color. (f) Real image seen by camera that corresponds to the optical flow shown in (e)

while human's interacting frequency (measured by adding the active pixels of motion estimation) was between 0.4615 Hz to 0.476 Hz (7.8% to 11% higher to the Nao's frequency) with the scaling factor of γ=0.15 and the corresponding Δf (largest possible difference in frequencies that can still lead to synchronization) is about 15%, 0.3 coupling scaling factor leads to $\Delta f = 29\%$ with little varying amplitude and γ=0.5 scaling factor results to $\Delta f = 72\%$ but this higher coupling introduces saturation of amplitude. Second, for the same parametric conditions, if the natural frequencies of both agents are the same no phase lag was observed but as the Δf increases to a certain limit phase lag increases too and beyond the limit (Δf) stated above it ends up with asynchronous state. We experienced 0^0 to 90^0 of phase shift in our experiments. Better performances and control can be obtained using Rowat-Selverston CPG (Central Pattern Generator) but for sake of simplicity, we will not present it in this paper.

IV. Selection of Partner

We proposed a neural network architecture (Fig. 2(b)) that selects an interacting partner on the basis of synchrony detection among various interacting agents. The architecture can be divided into two parts. One part is related to the dynamical interaction illustrated before. Previously, the modifiable Nao's oscillator controlling the arm movement was directly connected to the optical flow. Now, the coupling is made through oscillator-prediction module (f''). The reason of this indirect coupling is to make sure that the architecture will entertain the visual stimuli (optical flow) that are similar to its own motion (learnt in oscillator-prediction module). Equation of modifiable oscillator can be rewritten as

$$N_1(n+1) = N_1(n) - \beta N_2(n) + \alpha 1 + +\gamma f'' \qquad (4)$$

Where f'' is the energy induced by the Oscillator-prediction module to the modifiable oscillator. Other variables remains the same.

The Oscillator-prediction block (represented by y') is linked to the robot's oscillator (represented by y) with a non modifiable link and the image (represented by X) with a modifiable link. The Oscillator-prediction (y') module learns the robot's oscillation as a weighted sum of image pixels.

The neuron activity in the Oscillator-prediction (y') can be computed using $X \rightarrow y'$ synapses by equation 5 that corresponds to the predicted future value.

$$x_i^{y'}(t) = \sum_{k \epsilon X} W_{ik}^{X \rightarrow y'} x_k^X \tag{5}$$

The learning of $X \rightarrow y'$ synaptic weights can be computed (equation 6) by a Normalized Least Mean Square (NLMS) algorithm [19].

$$W_{ij}^{X \rightarrow y'}(t+dt) = W_{ij}^{X \rightarrow y'}(t) + \alpha\eta . \frac{x_i^{y}(t) - x_i^{y'}(t)}{\sum_{k \epsilon X} x_k^X(t)^2 + \sigma 1} . x_j^X(t) \tag{6}$$

η is synaptic learning modulation, α is the learning rate and $W_{ij}^{X \rightarrow y'}$ represents the synaptic weights from Image neuron j to $Oscillator - prediction$ neuron i, x_i^y is the activity transmitted to neuron i by the oscillator, it is a target signal for Normalized Least Mean Square (NLMS) algorithm. In online learning case, the introduction of η is necessary for convergence. It modulates randomly the learning speed by introducing a randomization effect that suppresses the negative effects of the temporal regularities of input data. The normalization term $\sum_{k \epsilon X} x_k^X(t)^2 + \sigma 1$ is specific to the NLMS. To avoid the divergence of the weights (if the image value is too small), $\sigma 1$ is a constant having small value.

Now we consider the complete scenario. For the selection of partner, the architecture works in two phases: learning phase and testing phase. During the learning phase, NAO oscillates according to its standard frequency (no visual stimulus). NAO looks at its own hand. This initiates two processes. First the oscillator prediction module which was zero due to non availability of visual stimuli starts now predicting robot's modifiable oscillator as a weighted sum of its own visual stimuli. The oscillator-predication module learns the optical flow associated to its motion. As a consequence, it modifies the oscillator (as described in the dynamical interaction section) and this process of learning and adaptation to each other works continuously and settle down after some time. This process of adjustment can be assumed as a basic process by which infants gain self reflective abilities as underlined by Rochat [4]. Once the learning is over, the architecture can be tested for multiple agents. When an agent interacts with a similar frequency, weights (that are already learnt on modifiable links) are associated with the visual activities induced by the human movements and Nao's modifiable oscillator adopts the interacting frequency and phase. If the interacting frequency is different from the learnt one, the weights (modifiable links) can not be associated with the visual stimuli and NAO continues to move at its default frequency. The same is true for multiple agents case. Among two interactants only the agent having a similar frequency as Nao is selected.

In this experiment, three agents are involved, in addition to NAO and human, a basic automata is introduced (Figure 1(d)). The coupling scaling factor (γ) was 0.07, Naos default frequency was 0.407 Hz, automata's synchronized frequency was 0.4318 (6% higher) and human synchronized frequency was 0.36 (11% low) to 0.38 (6% less than default frequency). When a subject interacts with a frequency close to the learnt one, the network selects this agent as a good interacting partner and NAO modifiable oscillator synchronizes with it. Initially, both agents move with close frequencies (within an allowable range) but after some time of interaction NAO adopts human movements and both oscillate with exactly the same frequency corresponding to the human motion. Good results are obtained with this architecture, these are collectively shown in the next sections.

V. ATTENTIONAL MECHANISM

In this section, we used prediction of synchrony as a parameter to attract the attention (FOA) of a robot. If two visual stimuli are present at the same time and only one of them has the same frequency as Nao, Nao will synchronize with the "interacting" partner (the one oscillating almost at the same frequency as Nao) but NAO will not be able to locate the good interacting partner in its visual field, because this algorithm works on the perceived energy irrespective of the agent location. The proposed FOA algorithm dynamically learns and locates the selected interacting agent using spatial predictions.

Fig. 2(c) shows the architecture of FOA. During interaction, the selection of partner algorithm selects a good interacting partner and synchronize NAO's movements, the image-prediction module (X'') learns the spatial location of these movements as a weighted sum of Nao's synchronized frequency and able to predict the corresponding movements. After a short while, an other agent comes and moves with a different frequency (lower or higher than Nao), X'' which already learnt synchronized rhythmic motion of optical flow predicts strongly the first agent even in the presence (in the visual field) of the unsynchronized one (because the prediction is made by the weighted sum of the learnt frequency).

To determine the correct interacting partner and to discriminate between multiple stimuli, our algorithm modulates the current visual stimuli with the image-prediction X''. A merging block is used to compute a weighted average of these current results (modulation) and results of the previous iteration (see Fig. 2). The higher values of this merging block are then correlated to the location of synchronous movements. All the pixels of the merging block are projected on the x axis (i.e all pixels in each column are added). Then a Winner Takes All (WTA) selects the highest activated column. This selected column indicates the location of the synchronized movement and the robot can point to the synchronized region to show the current Focus of Attention (FOA). The robot always focus with the synchronized posture even if the partner changes his location. For this experiment the resolution of the predicted image of optical flow is $32\times$ 24 (32 columns or location), these 32 possible locations are realized in 60^0 (-30^0 to 30^0) circular angles which are fed to the motor according to corresponding columns (column zero refers to -30^0 while 32^{th} column

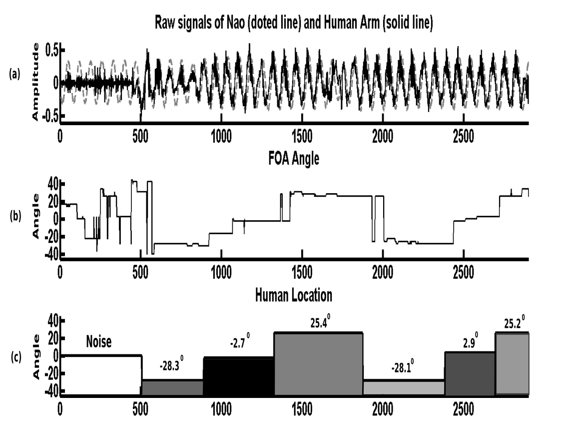

Fig. 4. (a) Nao's oscillations along with interacting agent (b) Fluctuating angle of FOA according to the rhythmic motion (c) It describes the interactant's location in front of Nao.

corresponds to 30^0) and 0^0 when the agent stands in front of Nao.

The learning rule for movement-prediction (X'') module is almost the same and the weights are normalized to smoothing the learning processes. The activity of neurons in (X'') can be computed using $y \rightarrow X''$ synapses by (7). The learning of $y \rightarrow X''$ synaptic weights can be computed by :

$$x_j^{X''}(t) = \sum_{i \epsilon y} x_i^y W_{ij}^{y \rightarrow X''} \quad (7)$$

$$W_{ij}^{y \rightarrow X''}(t + dt) = W_{ij}^{y \rightarrow X''}(t) + \epsilon . x_i^y(t) . U_j^X(t) \quad (8)$$

Where x_j is the activity of neuron in X'' group, x_i is the neuron of conditional group (Oscillator) and U_j is inconditional stimulus (Image) and defined as ($U_j = \sum_{i\ \text{inconditional}} X_i . W_{ij}$), weights are normalized as $[W_{ij} = \frac{W_{ij}}{\sum_i W_{ij}}]$.

VI. RESULTS

The focus of attention mechanism is tested in a simple way and results are shown in fig. 4, where in (a) Nao's oscillations along with the interacting agent are shown. Fig.4(b) indicates the angle of FOA according to the rhythmic motion and finally fig.4(c) describes the interactant's location in front of Nao. At start, no visual stimuli is presented to Nao, the FOA moves randomly between -30^0 and 30^0. After 500 time units (16.6 sec.), a synchronized motion is introduced from the left side (-28.3^0) of Nao. This interaction results in turning the FOA to the synchronized location as shown in fig. 4. As the interacting agent moves a little to right side -2.7^0 consequently our architecture force the FOA to relocate itself in the direction of the correct motion. Next, the agent moves to the left side 25.4^0 of the Nao and FOA again follows the agent. The same sequence is repeated again to verify that FOA always followed the interactant. Fig. 4 corresponds to the experiment shown on the video available on our website.

After this simple experiment, we examine our selection of partner algorithm along with FOA architecture by extending the experiment to the case of two agents : an Automata (one DoF) and a human (only one of them is synchronized at a time). Results show that when the Automata moves similarly to Nao's movements while human oscillates with a different frequency, Nao synchronizes with the Automata (by selection of partner algorithm) and FOA mechanisms turns towards Automata but if the human adapts his frequency close to Nao, Nao aligness itself with the human and FOA moves towards human.

These results of both algorithms are shown in fig. 5 by two sets of graphs. Fig. 5(a) shows the onset of the experiment, where the Automata enters in the visual field of Nao from the left side (about -20^0) and imitates it. Consequently, both become synchronized with each other using our selection of partner algorithm. Fig. 5(a1) sketches the signals of Nao modifiable oscillator, and Automata illustrating how they become synchronized. Fig. 5(a3) shows the PLV value (measure of synchrony) of the two agents. Initially, PLV is low but as the interaction gets longer it increases to maximum. Fig. 5(a4) depicts FOA mechanisms during interaction with the Automata. Fig. 5(a2) shows signals of Nao and human illustrating that initially there is no interaction by human from the right side of the robot. After 700 time units ($23sec$)human comes with a different frequency. He does not succeed in disturbing the selection of partner (PLV remains high for robotic arm) and FOA remains towards the Automata.

In continuation of this experiment, the automata is tuned to a low frequency and human instructed to imitate Nao (fig. 5(b1 & b2)). As a result, Nao switches the synchronized region, from left (-20.3^0) to right side (about 40^0). The PLV related to human increases to the highest value while the Automata PLV shifts to a low value (fig. 5(c3)) while FOA shifts from the automata to the human (fig. 5(c4)). After 2650 time units (88.3 sec), the Automata is tuned to its previous frequency again and human instructed to make different oscillations. Consequently, this induces a switch of the recognized interacting partner (again) as well as FOA (fig. 5(b)).

VII. CONCLUSIONS

In this paper, we proposed a novel approach for building autonomous robots that can interact with multiple agents and select an interacting partner among several agents on the basis of synchrony detection. We applied our neural network model on a humanoid robot (Nao), where experiments showed that when multiple agents interact with Nao and only one of them is synchronized, Nao selects the synchronized one as an interacting partner. We also showed that synchrony prediction could be used as a way to establish focus of attention. The idea to use synchrony can be assumed as a robust way of interaction because in contrast to the verbal communication where all the information directly related to words (that can be wrongly understood) here the robot extracts information not by a single word but by the way of

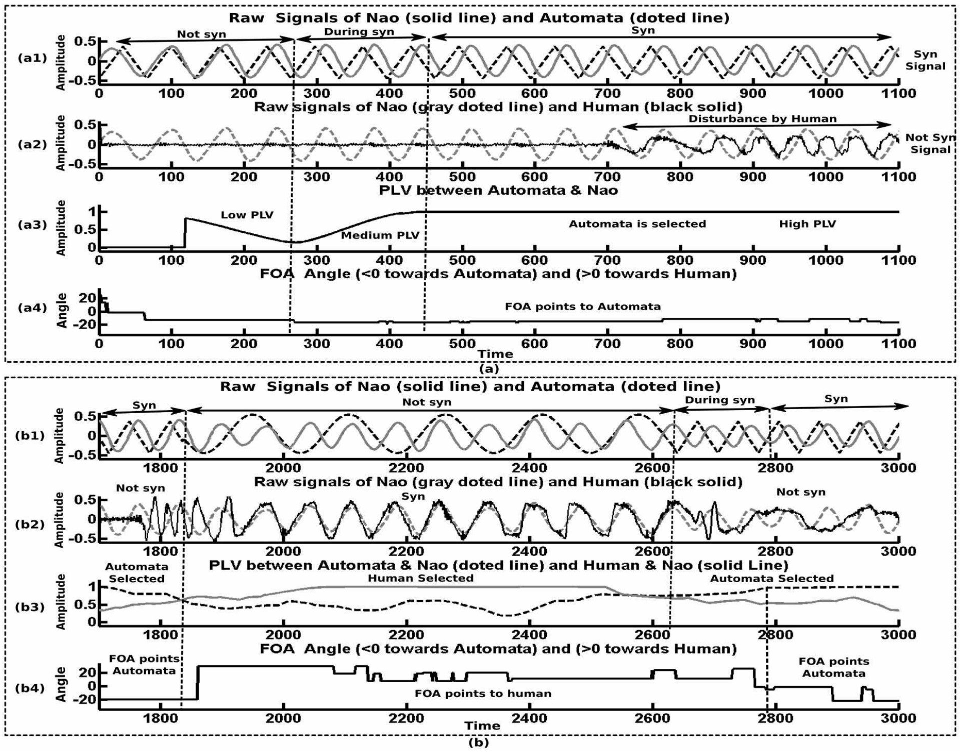

Fig. 5. Results: Every set has 4 graphs with same sequence where first time series of every set shows the raw signals of Nao oscillations along with robotic arm while second contains raw signals of Nao along with human and third time series shows the PLV (quality of synchrony) for the pairs of interacting agents and finally, forth shows the FOA angle of Nao which follows the synchronized region. (a) shows start of experiment with single agent and then disturbed by the other agent. (b) Multiple agent having different frequencies interact (one of them with same as Nao) and Nao always selects similar frequency partner.

interacting. In other words, the way of interacting could be more important then the transmitted information. The only way to interact with robot is not only to show something but also to repeat it and correct it and to be truly engaged in interaction with it. In future works, we are planing to implement our algorithm on mobile robots to test its impact on the interactive teaching of complex tasks.

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