Plastic CPG-based Robot Controllers for Human-Robot Rhythmic Interactions

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I. Introduction

In the last few years, social robotics has been widely developed with the problematic of making robots more acceptable. An aspect which should not be neglected is the social adequacy and especially the synchronization phenomena which tend to emerge consciously, or unconsciously when humans interact with each other ([1]). Humans require their interaction partner to behave in an appropriate way in order to connect, that is, a socially acceptable response in accord with the social and human context is expected.

Waving is an important part of the gestural communication, creating a synchronous state where both partners wave simultaneously. The rhythmic nature of this gesture leads us to believe that it induces the same synchronization and locking phenomena as other rhythmic movements.

Intrinsically rhythmic bio-inspired robot controllers, such as Central Pattern Generators (CPGs), which also incorporate synchronization learning abilities, are able to produce rhythmic movements and trigger the emergence of a synchronization in the interaction.

In this work, plastic CPGs are implemented, i.e. CPGs endowed with neural and synaptic Hebbian plasticity, in the joints of the Pepper robot in order to achieve synchronization with a human partner waving with a changing frequency.

II. The robot controller

For the CPG we use the half-center model proposed by [2]. The CPG architecture and principle are represented on Figure 1. For the rhythm generator neurons, Rowat-Selverston (RS) cells are used:

$$\dot{V} = y \tag{1}$$

$$\dot{y} = \left(\sigma_f - \frac{\tau_m}{\tau_s} - 1 - \sigma_f \tanh^2\left(\frac{\sigma_f}{A_f}V\right)\right)\frac{y}{\tau_m} - \frac{1+\sigma_s}{\tau_s\tau_m}V + \frac{A_f}{\tau_s\tau_m}\tanh\left(\frac{\sigma_f V}{A_f}\right) \tag{2}$$

with V the membrane potential and τ_m and τ_s time constants, A_f influences the output amplitude, while σ_f determines whether the neuron is able to oscillate or not. σ_s is a gain. For more details, refer to [3].

Since the RS model is a generalized Van der Pol oscillator, Hebbian mechanisms designed to learn the frequency, input and output amplitudes and inspired by ([4]) can be integrated, enabling it to synchronize with an external signal:

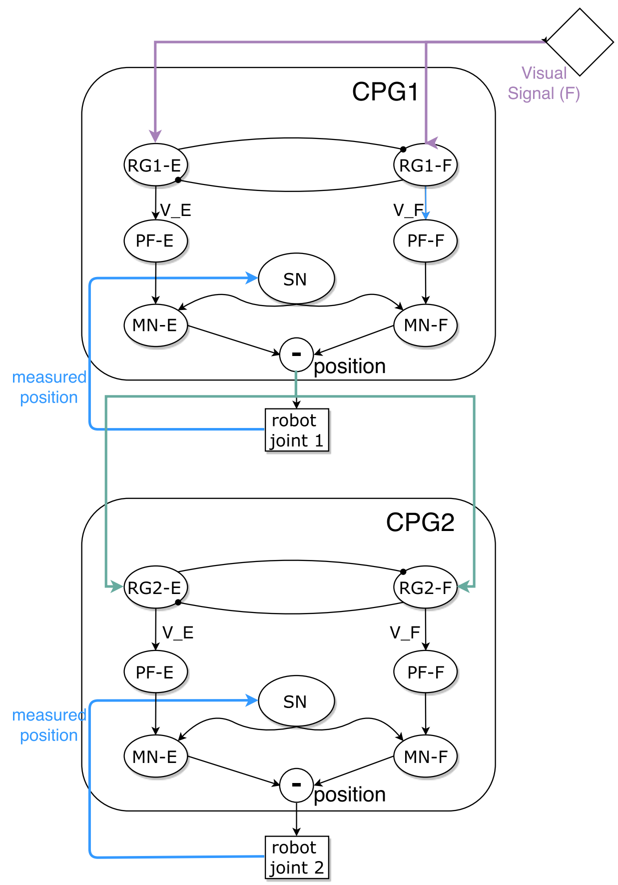

Fig. 1. CPG architecture employed. The input of the first CPG is the optical flow detected, while the input of the second CPG is the output of the first.

$$\dot{\sigma}_{s_{i_{\{E,F\}}}} = 2\epsilon F_i \sqrt{\tau_m\tau_s(1+\sigma_{s_{i_{\{E,F\}}}} - \sigma_f)}\frac{y_{i_{\{E,F\}}}}{\sqrt{V^2_{i_{\{E,F\}}} + y^2_{i_{\{E,F\}}}}} \tag{3}$$

$$\dot{A}_{f_{i_{\{E,F\}}}} = -\mu\left(\left(\frac{\nu\sigma_f V_{i_{\{E,F\}}}}{A_{f_{i_{\{E,F\}}}}}\right)^2 - {F_i}^2\right) \tag{4}$$

$$\dot{\epsilon}_{i_{\{E,F\}}} = \lambda tanh^2(\xi F)\left(1 - (\epsilon_{i_{\{E,F\}}}F_i)^2\right) \tag{5}$$

with μ and λ, learning steps and ν and ξ, scaling factors.

*This work was not supported by any organization

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III. RESULTS

The experiment can be divided into four observed main phases (see Figure 2, the different phases are delimited).

Learning phase (from t = 1.7 s to t = 7 s): The human starts waving slowly and the σ_s instantly decrease.

Slow waving - permanent phase (from t = 7.5 s to t = 21 s): The human partner is still waving slowly, σ_s is stable around 12 which corresponds to an intrinsic frequency of 0.5 Hz for the CPG. Both CPG outputs are also in phase with the optical flow detected.

Fast waving (from t = 21 s to t = 41 s): The human partner accelerates the waving. The σ_s adapt and start increasing. The new stability value is around 40 (intrinsic frequency of 1 Hz for the CPG).

No waving (from t = 41 s to t = 50 s): The waving has ceased. Both σ_S remain stable, showing that the CPG retains the new frequency learned.

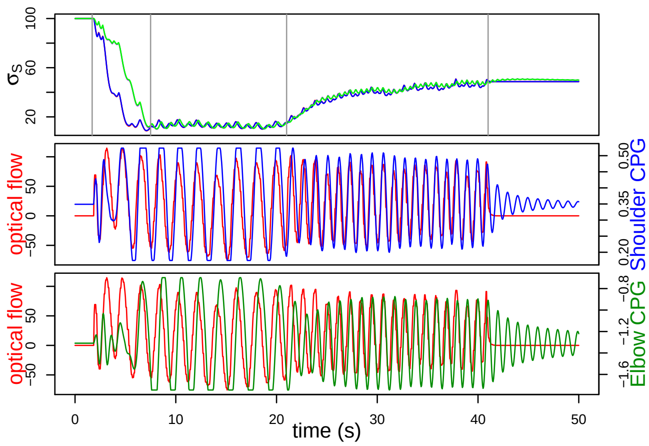

Fig. 2. Above, evolution of σ_S: in red and blue for the shoulder CPG; in green and purple for the elbow CPG. Note that the extensor and flexor curves are merged for both CPGs. Below, in red, the optical flow detected. In blue, the position command sent to the shoulder joint. In green, the position command sent to the elbow joint.

A. Evaluation of Coordination

The Phase Locking Value (PLV) has been introduced by [5] to measure coordination in brain signals.

Figure 3 represents the superimposed PLV for the ten interactions. It can be plainly observed that though the shoulder joint quickly coordinates with the optical flow (t = 7 s), the elbow joint experiences a longer transition phase before achieving coordination (t = 9.7 s). Similarly, at t = 20 s, when the waving frequency changes, the transition is more distinct for the elbow joint than for the shoulder joint. Waving in the higher frequency appears less stable and with more variability than for the lower frequency, especially for the elbow joint.

IV. CONCLUSION

CPG-based controllers endowed with plasticity mechanisms are able to synchronize with an external visual signal. This synchronization property enables motor synchronization

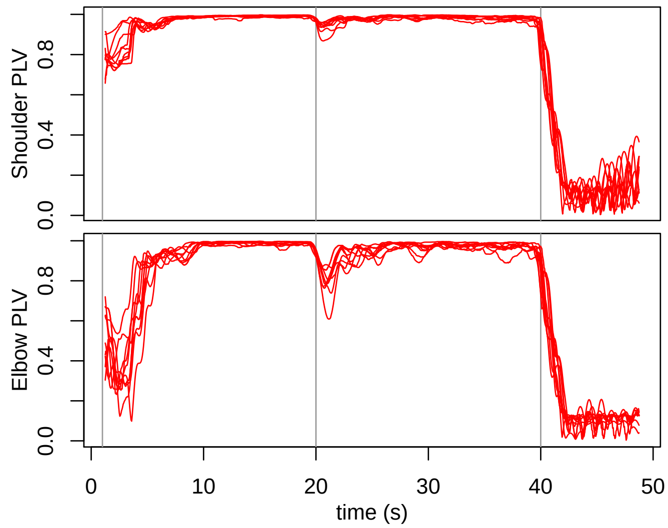

Figure 3. Top, PLV for the shoulder joint and the optical flow; Bottom, PLV for the elbow joint and the optical flow. The PLV for ten interactions are superimposed.

which in turn, triggers the emergence of social synchronization between the robot and the human. This was achieved by analyzing the synchronization between the optical flow and articular command values across ten different interactions thanks to the PLV. Despite the obvious human variability in the different interactions, results show an interesting coherence with signals often overlapping. Thus, the coordination observed previously is not merely due to chance but the controller indeed triggers the emergence of coordination (the PLV tends to reach 1.0) after a transitory phase where the system adapts to the new input information.

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