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Adaptive Neural Control for Efficient Rhythmic Movement Generation and Online Frequency Adaptation of a Compliant Robot Arm

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Abstract. In this paper, we propose an adaptive and simple neural control approach for a robot arm with soft/compliant materials, called GummiArm. The control approach is based on a minimal two-neuron oscillator network (acting as a central pattern generator) and an error-based dual integral learning (DIL) method for efficient rhythmic movement generation and frequency adaptation, respectively. By using this approach, we can precisely generate rhythmic motion for GummiArm and allow it to quickly adapt its motion to handle physical and environmental changes as well as interacting with a human safely. Experimental results for GummiArm in different scenarios (e.g., dealing with different joint stiffnesses, working against elastic loads, and interacting with a human) are provided to illustrate the effectiveness of the proposed adaptive neural control approach.

Keywords: Adaptive robot behavior · Soft robot · Human-machine interaction · Artificial intelligence.

1 Introduction

Since robots are being used more extensively for service duties, exploring inaccessible areas and handling emergency and security tasks, the field of robotics is moving toward more autonomous and intelligent systems. As a result, easy and flexible cooperation between humans and robots is becoming increasingly important and must be considered during development of modern robots [10].

Trajectory tracking for traditional robot arms works well for determined tasks due to stiff joints without passive compliance. While the use of stiff joints avoids the coupling effect between joints [1], this conventional approach does not permit humans to interact with the robot safely.

To address this problem, Stoelen et al. (2016) [5] have developed a new type of robot arm with soft/compliant materials, called GummiArm. To mimic human-like muscle compliance, GummiArm is designed in such a way that it inherently involves passive compliance and in turn increases the coupling effects, which require a more sophisticated control approach in order to move efficiently and in an adaptable manner.

In this work, we propose a simple and adaptive neural control approach for GummiArm. The control approach is based on 1) a minimal two-neuron oscillator network (acting as a central pattern generator (CPG)) for efficient rhythmic movement generation and 2) an error-based dual integral learning (DIL) mechanism for online frequency adaptation. The DIL makes sure the arm is able to follow the entire given trajectory, generated by the CPG, by adapting the frequency. As a result, we reduce the loss of precision, avoid unwanted movement, and in the worst-case scenario, motor collapse in various manipulation tasks.

The adaptive neural control approach uses only motor positions as sensory feedback and does not require the kinematic or dynamic model of the arm as is often needed in classical arm control techniques [8]. This approach allows us to treat the coupling effects between the compliant robot joints as unknown while achieving good shock tolerance, low reflected inertia, little damage during inadvertent contact, and automatic frequency adaptation of the arm. Recent related works in the field of rhythmic movement generation and frequency adaptation include the use of the Rowat-Selverston oscillating neuron model (CPG) with dynamic Hebbian learning for human-robot handshaking [2]. However, this work evaluates the control method on a simulated Kinova Mico robot with stiff joints. Another work proposes a new framework based on a combination of several components, including the Matsuoka neural model (CPG), feature processing, neural networks, and signal filtering, for adaptive locomotion of the NAO humanoid robot with stiff joints [9]. While these recent works are impressive in their own right, they do not deal with the control of compliant joints and real-time adaption with uncertainty of arm properties, loads and external disturbances as proposed here.

This study is a continuation of our previous works [7,6] which proposed the control method and mainly applied it to control legged robots with stiff joints and one of the works briefly introduced compliant arm control. Here, we present the complete technical details, analysis, and experimental results of compliant arm control in various scenarios which have not been previously published. Furthermore, compared to related works in the field of rhythmic movement generation and frequency adaptation, the work goes beyond the existing works [2,9] by demonstrating real-time online adaptation in the real compliant robot arm system with uncertainty of arm properties, loads, and external disturbance which has not been shown by others.

2 Bio-inspired compliant robot arm (GummiArm)

2.1 Technical specification of GummiArm

To mimic the compliant property of a human arm, each joint of GummiArm is driven indirectly through tendons by two or three motors. The tendons are made of FilaFlex filament, which is an elastic material, and provides the arm with passive compliance. The robot has seven degrees of freedom (DOFs) and is equivalent to a 50th percentile female right arm (see [5] for more details). Each motor in GummiArm is a digital DC servo of the AX-12A or AX-18A type, from Dynamixel, equipped with a PID controller for position control.

2.2 Simulation of GummiArm

We simulated GummiArm using the robot simulation framework V-REP and used the Robot Operating System (ROS) to interface between our adaptive neural control and the real and simulated GummiArm robots. This makes it possible to have direct communication between both real-world and simulated entities. These two communicating entities are depicted in Fig. 1.

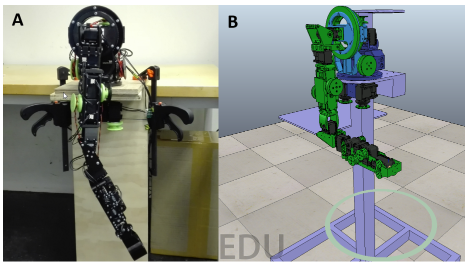

Fig. 1. A) Real GummiArm robot in a resting position. **B)** Simulated arm in V-REP.

3 Adaptive neural control

In this study, an artificial neural network is used to develop the adaptive neural control of GummiArm. It consists of two main mechanisms, as shown in Fig. 2A. The first mechanism is a recurrent neural network which is formed as the SO(2)-oscillator [4]. The oscillator, which functions as a CPG, is used to generate the rhythmic movements of GummiArm. The second mechanism is an error-based DIL method. It is used for quickly adapting the frequency of the generated rhythmic movements to match the performance of GummiArm.

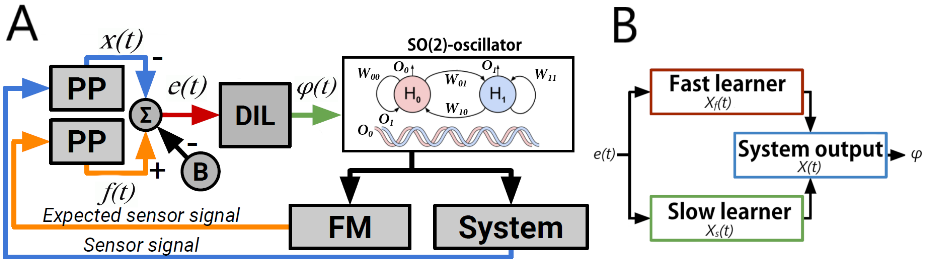

Fig. 2. A) The combination of the DIL [6] and the SO(2)-oscillator [4] based CPG model for robot control (modified from [6]), which outputs the motor commands as periodic patterns for both the shoulder roll joint motor and the elbow joint motor. The error feedback $e(t)$ is the subtraction of the (preprocessed/PP) low-pass filtered measured joint angle amplitude (x(t), sensor signal) and the (preprocessed/PP) low-pass filtered expected joint angle amplitude (f(t), expected sensor signal). The expected joint angle is obtained from the transformation of a CPG output through a forward model (FM). $\varphi(t)$ is a frequency control parameter (Eq. 3) of the SO(2)-oscillator. B denotes a bias term. The system refers to the GummiArm robot. **B)** Schematic representation of the DIL. $x(t)$ denotes the system output and is the sum of the outputs from the slow and fast learners ($x_f(t)$ and $x_s(t)$, respectively). $e(t)$ denotes the error and is the difference between the preprocessed signals from the forward model and the system. The DIL's output φ is fed to the CPG.

3.1 SO(2)-Oscillator (CPG)

The oscillator has two fully interconnected neurons with four synapses w_{00}, w_{01}, w_{10}, and w_{11} (see Fig. 2A). The activity in each neuron evolves as:

$$a_i(t+1) = \sum_{j=1}^{N} w_{ij} o_j(t) \; ; \; i = 1, ..., N, \tag{1}$$

where N denotes the number of units and w_{ij} is the synaptic strength of the connection from neuron j to neuron i. Equation 2 shows the neuron output o_i, given by a hyperbolic tangent (tanh) transfer function:

$$o_i = tanh(a_i) = \frac{2}{1 + e^{-2a_i}} - 1. \tag{2}$$

The network can act as a CPG if the weights are set according to the special orthogonal group SO(2) as:

$$\begin{pmatrix} w_{00}(t) & w_{01}(t) \\ w_{10}(t) & w_{11}(t) \end{pmatrix} = \alpha . \begin{pmatrix} \cos(\varphi(t)) & \sin(\varphi(t)) \\ -\sin(\varphi(t)) & \cos(\varphi(t)) \end{pmatrix}, \tag{3}$$

with $-\pi < \varphi < \pi$ and $\alpha = 1.01$, the CPG generates periodic outputs $o_{\{0,1\}}$ of the neurons $H_{\{0,1\}}$, shown in Fig. 2A, where φ defines the frequency of the output signals. The outputs (i.e., o_0 and o_1) are linearly translated to the position motor commands of the shoulder roll joint and the elbow joint of GummiArm. Only the shoulder roll joint angle information is used as feedback in this study. This is to show that using only one feedback is enough for adaption. More feedback (e.g., position errors from other joints) can be included and might result in better error calculation and in turn reduce the adaption times.

3.2 Error-based dual integral learning (DIL)

In order to adapt the frequency of the CPG during runtime such that GummiArm can efficiently perform its movements with a low tracking error under different conditions, the error based DIL from [6] is used as a plug-in to the CPG. In principle, the DIL relies on error feedback, given as the difference between the low-pass filtered motor command amplitude for the shoulder roll joint of the CPG and the measured low-pass filtered motor position amplitude of the shoulder roll joint of GummiArm. The DIL combines slow and fast learners in parallel for fast and stable error reduction [6], as depicted in Fig. 2B.

Each learner receives exactly the same error and assimilates part of it using the rules in Equation 4 to alter the estimate of the perturbation.

$$\begin{aligned} x_f(t) &= A_f.x_f(t-1) + B_f.e(t) + C_f.\int e(t), \\ x_s(t) &= A_s.x_s(t-1) + B_s.e(t) + C_s.\int e(t), \\ x(t) &= x_s(t) + x_f(t)\ ,\ e(t) = f(t) - x(t), \end{aligned} \tag{4}$$

where $x_s(t)$ and $x_f(t)$ are the outputs of the slow and fast learners, respectively. $x(t)$ denotes the sum of the two outputs, $e(t)$ denotes the error feedback given as the tracking error between the low-pass filtered expected joint angle amplitude $f(t)$ and the low-pass filtered actual joint angle amplitude of GummiArm $x(t)$.

The expected joint angle amplitude is calculated from a CPG output through a forward model (FM). The FM here is modeled as a simple gain. This makes it possible to compare the CPG output with the actual joint angle sensory feedback from GummiArm. B_f and B_s are the learning rates, and A_f and A_s are the retention factors. The selection of the parameters is constrained so that $B_f > B_s$ and $A_f < A_s$. The last part of the equation also takes the accumulated error into account under the constraint that $C_f > C_s$. This term thrusts the learning process to minimize any constant error. The slow learner consequently learns more slowly as indicated by the lower learning rates of B_s and C_s but remembers for longer as indicated by a higher retention factor A_s. B is a small threshold bias term which allows for increasing and decreasing the frequency of the CPG during the learning process to find a proper level. In this study, we empirically tuned the parameters based on the mentioned assumption as such we can almost guarantee the stability. However, we will further investigate the parameter analysis for the adaptation stability in future work. For implementation, the DIL directly changes the frequency of the CPG (i.e., $\varphi(t) = x(t)$) based on error feedback. The advantage of implementing the DIL is that the CPG is coupled with the physical world via sensory feedback from the joint angle of the shoulder roll joint. This means that the DIL offers the possibility that the tracking error can be minimized by enabeling GummiArm to quickly adapt its movements and stabilize itself. The use of two learners in parallel has several desirable properties such as fast and stable learning, savings in relearning, tracking error reduction, and spontaneous recovery of previously learned parameters (see [6] for more details of the learning mechanism).

4 Experimental results

In this section, we present the performance of the proposed adaptive neural control for efficient rhythmic movement generation and online frequency adaptation of GummiArm. Only feedback from the real-world shoulder joint motor was provided to the DIL. The parameters of the DIL were $A_s = 0.992$, $A_f = 0.59$, $B_s = 0.0036$, $B_f = 0.1$, $C_s = 0.00018$, $C_f = 0.007$, and $B = 0.05$.

Four main experiments were conducted to show the online adaptation of the control to deal with different joint stiffnesses, elastic loads, and human-robot interaction. In each experiment, real-world circumstances were altered, and the robot arm was set to perform a rhythmic back and forth horizontal end effector movement. As mentioned before, this motion is fundamental for sawing and cutting applications as well as pick and place conveyor belt operations.

In each experiment, the DIL was activated after a short period of time because GummiArm needs to come from a resting position to its moving state. GummiArm was also initialized with a value of the SO(2)-oscillator parameter φ to generate initial high frequency movements. An arbitrary frequency of 0.64 Hz was chosen for the first two experiments and GummiArm's stable frequency of 0.265 Hz was chosen for the last two experiments.

Figure 3A shows the result of the first experiment. The control automatically adapted its frequency to GummiArm to minimize tracking error and as a result, GummiArm could follow the generated rhythmic movement. The stable working frequency of 0.265Hz was reached after 90 seconds For applications such as sawing wood or cutting objects, traction results in an opposing force to the rhythmic motion. In the following experiments, we show that GummiArm is able to stabilize itself in such conditions. Figure 3B shows the result of the second experiment where the control automatically adapted its frequency to deal with a high shoulder joint stiffness in GummiArm. The tension was altered by changing the offset positions of the two motors in the shoulder joint (see red arrows in Fig. 3B). In this case, the steady-state stability frequency was approached after 70 seconds; about 20 seconds earlier in comparison to the original state adaptation time. Another test with a lower tension applied to the shoulder roll joint can be seen at vimeo.com/362777822 (password is QCNXngC0YQ).

Figure 4A shows the result of the third experiment in which the arm started with an initial frequency of 0.265 Hz. In this experiment, the end effector of GummiArm was connected to an elastic load (i.e., elastic rubber band) having a pulling force of 3 N. This elastic rubber bands has a stiffness of 0.7 N/cm. The

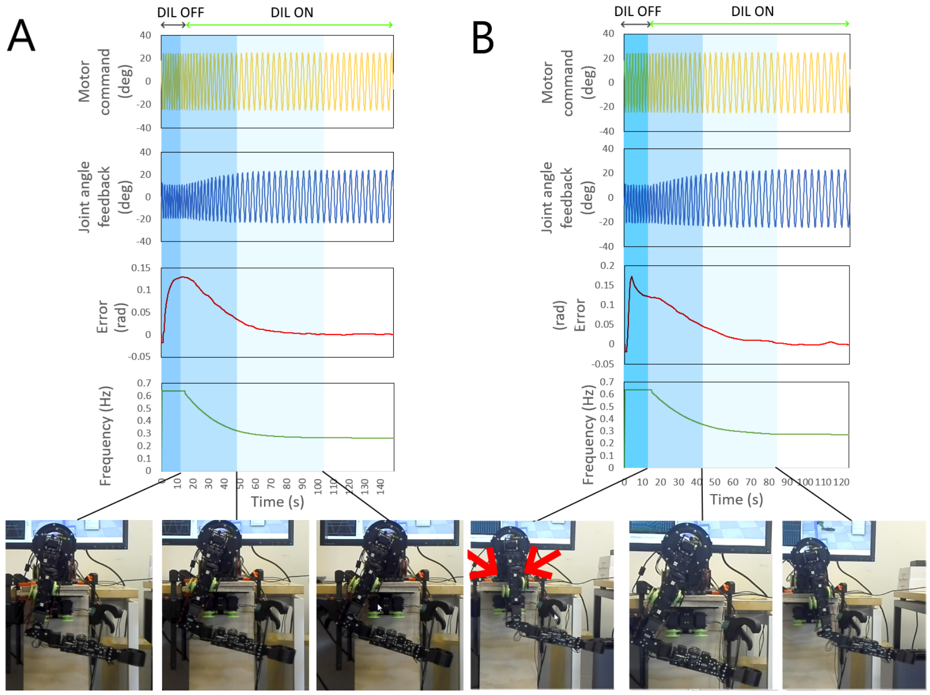

Fig. 3. A) First experiment: starting point configuration (normal joint stiffness). The supplementary video of this experiment can be seen at `vimeo.com/362777732`. **B)** Second experiment (high joint stiffness). The supplementary video of this experiment can be seen at `vimeo.com/362777903`. The password for the videos is QCNXngC0YQ.

working frequency in this case was lower at 0.240 Hz, compared to the stable frequency. Another test with an elastic load of up to 5 N attached to the end-effector can be seen at vimeo.com/362778130 (password is QCNXngC0YQ). The experimental result shows that the control automatically adapted its frequency to deal with different elastic loads attached to GummiArm and that stiffness is negatively correlated with the working frequency.

Figure 4B shows the result of the last experiment in which the control automatically adapted its frequency to deal with a variety of external human perturbations to see how GummiArm reacts to human intervention. These perturbations include encumbering and encouraging GummiArm's movement twice after having reached a zero steady-state error (see 1 and 3), and once while reaching zero steady-state error (see 2). It takes around 100 seconds to recover from a 4.7 second lasting total obstruction (see 1), around 35 seconds to recover from a forced frequency of 0.343 Hz (see 2) and around 80 seconds to recover from a semi obstruction lasting 9.3 seconds (see 3). This experiment shows that dealing with perturbations is time-invariant and that GummiArm adapts at a moderate speed, which might be suitable for maintenance or non-critical intervention applications.

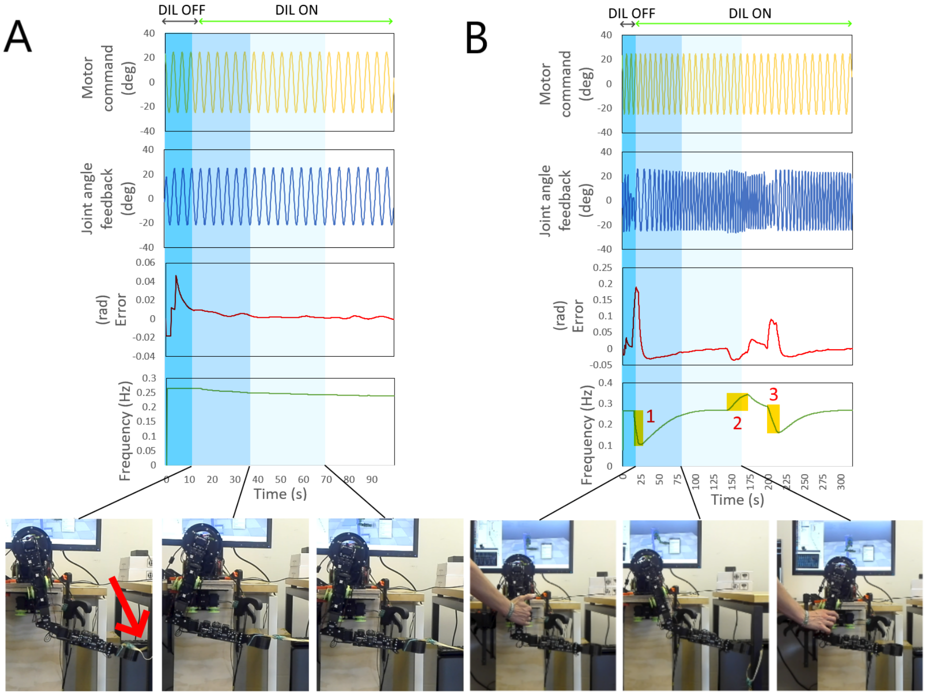

Fig. 4. A) Third experiment: an elastic load of up to 3 N is attached to the end-effector. The supplementary video of this experiment can be seen at `vimeo.com/362778000`. **B)** Fourth experiment: a human subject interacting with the robot three times (see (1), (2), and (3)). The supplementary video of this experiment can be seen at `vimeo.com/362778423`. The password for the videos is QCNXngC0YQ.

5 Conclusions

In this paper, we used an adaptive neural control mechanism consisting of a CPG and DIL to let a robot arm, called GummiArm, perform the rhythmic end effector movements necessary for pick-and-place tasks, sawing wood, cutting objects, etc. We showed that the control entity effectively curtails the tracking error between desired and actual joint movementss. It is also important to emphasize that the adaptive neural control works online and can achieve multiple adaptations (including adapting the arm property with different joint stiffnesses, elastic loads, and unexpected human interaction) by relying only on a tracking error feedback-based objective function which is more simple than using multiple complex objective functions or robot kinematic control. The proposed mechanism makes sure that the CPG frequency stabilizes and matches the performance of GummiArm, in real-time.

This adaptive neural control is well suited to enable a robot to operate safely around humans and can be potentially applied to other robotic systems. Future extensions of this work include 1) introducing a motor pattern shaping mechanism

[3] to transform the primitive rhythmic CPG signals into complex motor signals for complicated manipulation tasks, 2) using more sensory feedback for better error calculation to speed up the adaption time, and 3) applying the control framework as a basis for soft/compliant robot control in terms of "closed-loop control with online adaptation" which remains one of the challenges in soft robotics research.

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