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ORIGINAL RESEARCH PAPER

New automated learning CPG for rhythmic patterns

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Abstract In this paper, we suggest a new supervised learning method called Fourier based automated learning central pattern generators (FAL-CPG), for learning rhythmic signals. The rhythmic signal is analyzed with Fourier analysis and fitted with a finite Fourier series. CPG parameters are selected by direct comparison with the Fourier series. It is shown that the desired rhythmic signal is learned and reproduced with high accuracy. The resulting CPG network offers several advantages such as, modulation and robustness against perturbation. The proposed learning method is simple, straightforward and efficient. Furthermore, it is suitable for on-line applications. The effectiveness of the proposed method is shown by comparison with four other supervised learning methods as well as an industrial robotic trajectory following application.

Keywords Supervised learning · Central pattern generators (CPG) · Nonlinear oscillators · Rhythmic motion · On-line trajectory generation

1 Introduction

The basic locomotor patterns of most biological systems, such as breathing, are generated by the central pattern generator (CPG). Central pattern generators are neuronal circuits situated in the spinal cord of vertebrates and the segmental ganglia of invertebrates. When activated, CPG can produce a variety of rhythmic motor patterns such as walking, breathing, chewing, flying, and swimming in the absence of sensory or descending inputs that carry specific timing information. CPG is composed of collective neural oscillators, which individually provide the required signals for controlling the movement of each limb or movement of the body [1,2]. Recently, CPG based trajectory generation approaches have gained popularity in the field of biological inspired robotics. CPG has several advantages such as demonstrating limit cycle behavior, which means the effect of temporary perturbations is quickly diminished; analytical solution with explicit frequency, amplitude, and phase lag parameters do exist for a number of CPGs; its parameters can be used as control parameters; it produces smooth trajectories even when the control parameters are abruptly changed, and it is computationally efficient. There are two generic methods for designing CPG to produce a rhythmic pattern, namely, supervised learning and unsupervised learning.

Techniques involving unsupervised learning are used when the periodic signal that needs to be generated by the CPG is not known in advance. There are usually performance criterions that help generate the desired trajectory. For instance, stable locomotion and/or minimum energy consumption that should be met. Among such techniques, evolutionary algorithms are extensively used to design CPG models. Hasanzadeh and Akbarzadeh Tootoonchi [3] presented a novel gait, forward head serpentine (FHS), for a snake robot. A fitness function covering robot speed and head link angular changes is defined. Genetic Algorithm (GA) is used to find gait parameters resulting in maximum speed while the head link angular changes remain in an acceptable range. Kim et al. [4] proposed a nonparametric

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estimation based PSO (NEPSO) to search for the parameters of CPG needed for bipedal walking. Shrivastava et al. [5] used Genetic Algorithm to construct a trajectory generation method for an 8 DOF robot that climbs stairs and walks on flat terrain.

Techniques involving supervised learning are used when the periodic signal that needs to be generated by the CPG is known in advance. Using the desired periodic signal, an explicit error function is defined and minimized. Examples of such techniques include statistical learning algorithms for dynamical systems [6], gradient-descent learning algorithms for recurrent neural networks [7,8], learning for vector fields [9] and programmable central pattern generators (PCPG) where learning is implanted into the dynamical system. The PCPGs use a number of frequency adaptive oscillators to learn a desired periodic signal [10]. A. J. Ijspeert used PCPG to learn rhythmic trajectories for biped locomotion with a simulated humanoid robot. The system is used as an on-line trajectory generation method for the humanoid robot. The main drawback of this approach is its excessive time for learning. It takes more than 1000 s for learning a specific pattern. Moreover, the return to the limit cycle after a perturbation is relatively slow due to the time needed to converge to the right phase lags between the multiple oscillators. Furthermore, for complex signals, the required numbers of oscillators are increased rapidly, leading to a complex system structure. Another on-line learning approach is based on encoding trajectories as a limit cycle produced by a two layered dynamical system. Gams et al. used this system to learn periodic tasks of a HOAP-2 humanoid robot [11]. The shortcoming of this approach is its complex structure and many numbers of constant parameters which must be tuned by hand. Furthermore, some of the constant parameters are sensitive and must be carefully determined.

In this paper, a new supervised learning method called Fourier based automated learning CPG (FAL-CPG), is presented and utilized to learn a periodic signal used for trajectory planning of robotic systems. A network of coupled nonlinear oscillator, as a CPG model, is then used to generate the learned signal. Compared with existing supervised learning methods, the proposed approach has several advantages; it is simple, efficient and computationally inexpensive. Required time for regenerating the desired signal is very low which potentially makes the FAL-CPG suitable for on-line applications. Trajectory planning is executed in two steps. In the first step, a finite Fourier series is fitted to the desired periodic signal. In the second step, based on the Fourier series, the main parameters of the coupled oscillators are determined.

In the next sections, the main idea of the proposed system is presented, Sect. 2, followed by the illustrative examples to show its effectiveness. And finally, discussion and concluding remarks are presented in the last sections.

2 Main idea

Generally, CPGs are realized with nonlinear oscillators. Harmonic oscillators are widely used in CPGs as the main oscillator model [12]. It is known that steady state or limit cycle solution of a harmonic oscillator is sinusoidal. The main idea of this paper originates from this simple concept. It is well known that a cyclic pattern, desired rhythmic pattern, can be approximated by a finite Fourier series. There is also a relation between a sinusoidal function and the main parameters of a harmonic oscillator. Therefore, by direct comparison of the steady-state solutions for each of the harmonic oscillators with the corresponding terms in the approximated Fourier series, the main parameters of the oscillators can be determined.

2.1 Oscillator model

The harmonic oscillator selected in this paper is an amplitude-controlled phase oscillator [12]. This oscillator is governed by the following equation.

$$\begin{aligned}\dot{\theta}_i &= 2\pi \nu_i \\ \ddot{r}_i &= a_i\left[\frac{a_i}{4}(R_i - r_i) - \dot{r}_i\right]\end{aligned} \tag{1}$$

The two linear differential equations determine the phase (θ_i) and amplitude (r_i) of the ith oscillator. The constant parameters υ_i and R_i determines the intrinsic frequency and amplitude. Additionally, a_i is a positive constant that determines the speed of the convergent to the limit cycle. The solutions of the Eq. 1 are represented in Eq. 2.

$$\begin{aligned}\theta_i(t) &= 2\pi \nu_i t + \theta_i(0) \\ r_i(t) &= R_i + \frac{1}{2}e^{-\frac{at}{2}}[2r_i(0) - 2R_i + (a_i r_i(0) + 2\dot{r}_i(0) - a_i R_i)t] \\ &\quad \{\text{Steady-State response}\} r_i(t) = R_i\end{aligned} \tag{2}$$

The output signal of the ith oscillator is defined by the following equation.

$$x_i(t) = r_i(t)\cos(\theta_i(t) - \theta_{0i}) \tag{3}$$

where θ_{0i} introduces a constant phase lag. Equation 3 is the output signal extracted from the ith oscillator and is periodic. It therefore, allows direct comparison with the terms in the Fourier series.

2.2 Determination of CPG parameters

The parameters υ_i and R_i are the main oscillator parameters. The most difficult part of designing a CPG model is to specify these parameters to result in a desired signal. In this paper, we introduce a simple and efficient method for identifying the main oscillator parameters. Assume a desired rhythmic signal is provided. In the first step of the proposed method, a finite Fourier series is fitted to the desired rhythmic pattern (Eq. 4).

$$\tilde{x}(t) = a_0 + \sum_{n=1}^{m} (a_n \cos(n\omega t) + b_n \sin(n\omega t)) \quad (4)$$

Clearly, as the number of terms in the Fourier series increase the desired signal is better reproduced. The complexity of the rhythmic pattern as well as the accuracy in which the desired signal is reproduced determines the number of terms in the Fourier series. The required accuracy depends on the applications. For example, consider walking of a humanoid robot. There are a number of joints such as hip, knee, ankle that must be coordinated in order to result in a human-like motion. Each joint has a rhythmic signal. However, the rhythmic patterns of certain joints are more complicated and therefore, require more Fourier series terms for their estimation.

The Fourier series is shown in Eq. 3 may be written in terms of cosine terms. To do this, the sine terms are transferred to the cosine by subtracting $\pi/2$.

$$\tilde{x} = a_0 + \sum_{n=1}^{m} \left(a_n \cos(n\omega t) + b_n \cos\left(n\omega t - \frac{\pi}{2}\right)\right) \quad (5)$$

This form of the series is in the same format as the output of the oscillator (Eq. 3). For each cosine term in the series, we need a corresponding amplitude-controlled phase oscillator (Eqs. 1, 3). By direct comparison of Eqs. 1–3 with Eq. 5, it can be seen that the parameters a_n and b_n in Eq. 5 are the steady-state value for R_i and R_{i+1} in the oscillator. The parameter $n\omega$ is equal to $2\pi\nu_i$ and represents the frequency in the oscillator output. The parameter θ_{0i} is equal to zero and $\pi/2$ for the cosine and sine terms, respectively. Furthermore, the output of the CPG must be produced from time zero. Therefore, the initial conditions of the oscillators are selected in a manner to initiate the output of the oscillator from its steady-state solution (Eq. 6).

$$\theta_i(0) = 0; \quad r_i(0) = R_i; \quad \dot{r}_i(0) = 0; \quad (6)$$

2.3 Coupling

One of the main advantages of the CPG is its synergy properties. Coupling between oscillators makes them work with each other to produce a specific phase relation. If a perturbation is presented in any one of the oscillators, the phase relation will be disturbed. However, the coupling between oscillators will return the dynamic system to a stable state and will continue to produce the desired phase relation. The coupling method adopted in the present paper is the Kuramoto coupling scheme [13]. The overall nonlinear oscillator

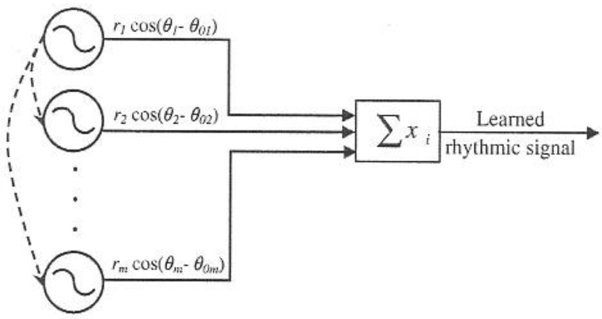

Fig. 1 Overall structure of the oscillators network

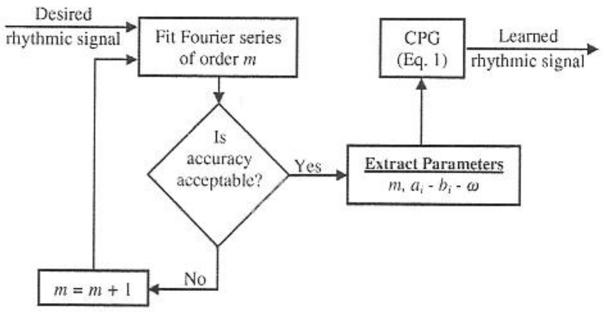

Fig. 2 Flowchart of the learning process

model with coupling is represented in Eq. 7.

$$\dot{\theta}_i = 2\pi\nu_i + \omega_{ij} \sin\left(\theta_j - \frac{\nu_i}{\nu_j}\theta_i - \phi_{ij}\right)$$
$$\ddot{r}_i = a_i \left[\frac{a_i}{4}(R_i - r_i) - \dot{r}_i\right] \quad (7)$$

where ω_{ij} is coupling strength and ϕ_{ij} is the desired phase difference between ith and jth oscillators. The role of ϕ_{ij} is similar to the θ_{0i} used in Eq. 3. Any of these two parameters can induce a phase difference between oscillators. Therefore in Eq. 7, ϕ_{ij} is selected to be zero and therefore, the desired phase difference is applied to θ_{0i} in Eq. 3. Phase difference for the applications presented in this paper is $\pi/2$ as indicated in Eq. 5. All the oscillators are coupled with the first oscillator. The overall structure of the oscillator network is illustrated in Fig. 1.

The proposed FAL-CPG method is summarized in the following flowchart (Fig. 2).

As shown in Fig. 2, the learning process is straightforward and the error of the learned signal depends on the accuracy of the Fourier fit. In applications where the desired signal is complex or the desired accuracy is high, the number of Fourier terms may be large. Consequently, the number of oscillators in the network grows as each term of the Fourier is modeled with one oscillator. Other learning methods also exhibit similar characteristics. In other words, as the complexity of the desired signal increases so does the number of required oscillators. In the next section, effectiveness of the

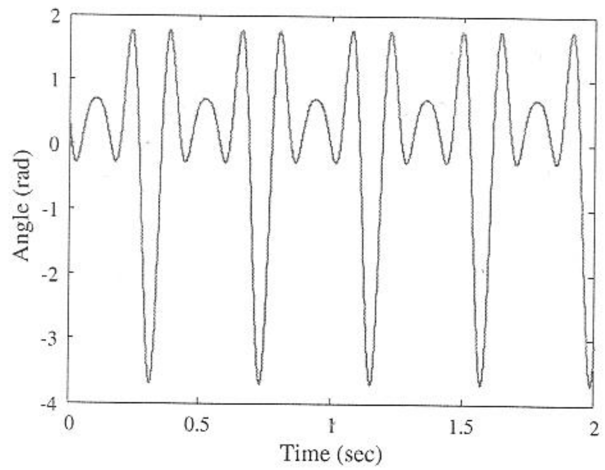

Fig. 3 Desired rhythmic pattern

Table 1 Main CPG parameters and initial conditions

	R	ν	θ_0	$r(0)$	$\dot{r}(0)$	$\theta(0)$
Oscillator 1	0.8	$\frac{15}{2\pi}$	$\frac{\pi}{2}$	0.8	0	0
Oscillator 2	1	$\frac{30}{2\pi}$	0	1	0	0
Oscillator 3	−1.4	$\frac{45}{2\pi}$	$\frac{\pi}{2}$	−1.4	0	0
Oscillator 4	−0.5	$\frac{60}{2\pi}$	0	−0.5	0	0

FAL-CPG method is demonstrated and compared with four other supervised learning methods.

3 Illustrative examples

The goal is to design a CPG network to learn a desired rhythmic pattern. The rhythmic pattern may then be used for trajectory planning of robotic systems. Using CPG as a trajectory planning method has several advantages compared to other conventional methods like polynomial trajectory planning. CPG is robust to perturbation. It can modulate between trajectories by changing a few parameters. This makes it suitable for some on-line robotic trajectory planning applications. Assume the following desired rhythmic pattern (Fig. 3).

Fourier analysis is applied to the rhythmic pattern. This results into the following finite Fourier series (Eq. 8).

$$P(t) = 0.8\sin(15t) + \cos(2\times 15t) - 1.4\sin(3\times 15t) - 0.5\cos(4\times 15t) \tag{8}$$

The sine terms are transferred to cosine terms.

$$P(t) = 0.8\cos(15t - \pi/2) + \cos(30t) - 1.4\cos(45t - \pi/2) - 0.5\cos(60t) \tag{9}$$

The series above has four terms and therefore four oscillators are selected. As discussed in the previous section, the CPG parameters are also readily obtained from the Eq. 9. The initial conditions are selected in a manner to initiate the pattern from the limit cycle of the oscillators. This selection insures that the desired pattern is reproduced from the time zero. The CPG parameters and the initial conditions for the oscillators are listed in Table 1.

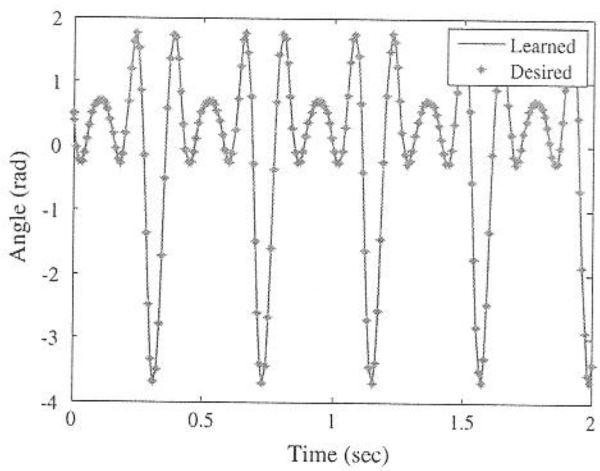

Fig. 4 Desired versus learned rhythmic pattern

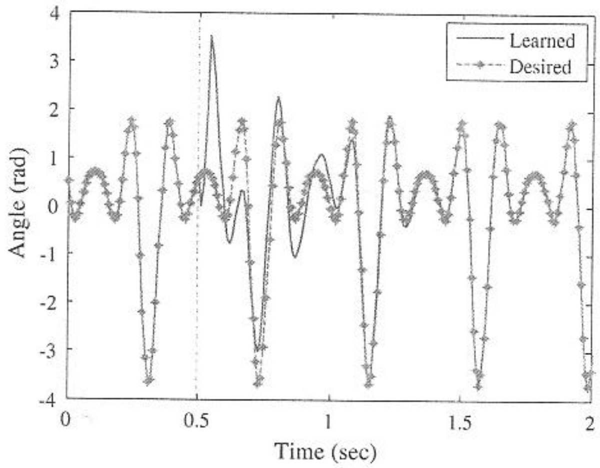

Fig. 5 Perturbation of the pattern

Results are shown in Fig. 4.

As shown in Fig. 4, the desired pattern is reproduced with CPG from the time zero. The learning time is near zero and negligible. This is because only one period of the rhythmic signal is needed for learning. Therefore, the learning time is the time required to fit the Fourier. The negligible learning time is one of the key advantages of the proposed method.

The couplings between oscillators make it robust to perturbation. To examine the robustness of the CPG network to perturbations, a number between 0 and 100 is randomly added to all states $(r, \dot{r}, \theta)$ of oscillator number two at time 0.5 s. See Fig. 5.

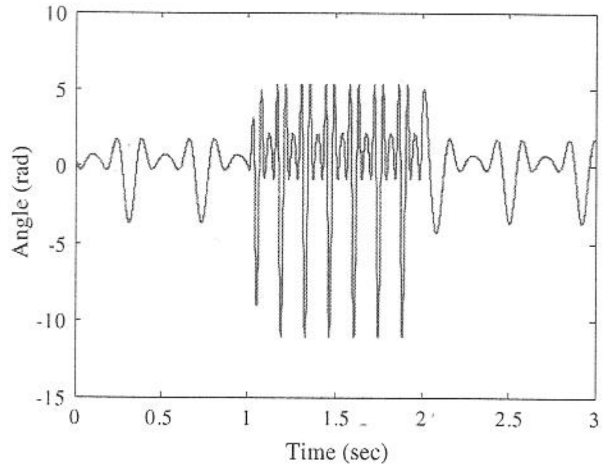

Fig. 6 Modulation of the CPG parameters

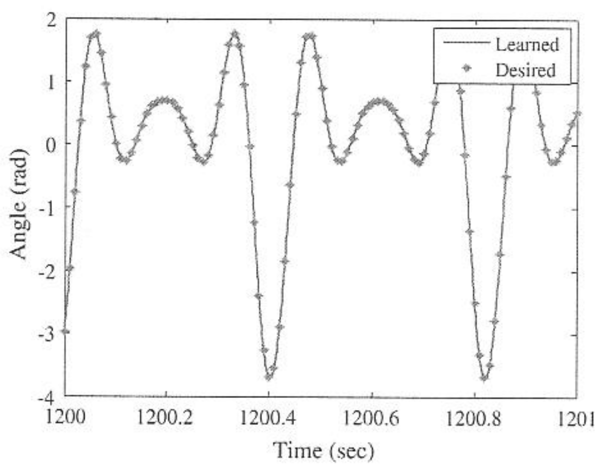

Fig. 7 Actual and desired signal [10]

After perturbation, the desired signal is quickly recovered to its original behavior. Modulation is another important property of a CPG. Modulation is necessary when the desired pattern is needed to change to another rhythmic pattern in an on-line manner. To examine this property, both frequencies and amplitudes (υ_i and R_i) of all oscillators are multiplied by number 3 during a 1 s interval, during 1–2 s of the simulation time. See Fig. 6.

As shown in Fig. 6, during 1–2 s of the simulation, the output signal is modulated. Furthermore, at the start and end of the modulation, the signal is changed in a smooth manner. In the following subsections, comparison between the proposed FAL-CPG methods with four other recently published supervisory learning methods is presented. All the simulations are performed in Matlab software using a computer with 3-GHz CPU and 2-GB RAM memory.

3.1 Righetti and Ijspeert [10] scheme

Righetti and Ijspeert [10] presented an architecture for building Programmable Central Pattern Generators, PCPG. Their PCPG encodes arbitrary periodic trajectories as limit cycles in a network of coupled oscillators and can be used for online trajectory generation in autonomous robots. The same signal as earlier shown in Fig. 3 is used. Figure 7 illustrates the results of the learning process.

As it can be seen the learning time is about 1200 s. This time poses a challenge for the learning process to occur in an on-line manner. However, similar to the FAL-CPG method, the PCPG offers on-line modulation of the signal is possible. Furthermore, in comparison, the learning time of the FAL-CPG method is quite insignificant as the desired signal could be produced right after the Fourier analysis (Fig. 4). The required time to fit the Fourier series and learn the CPG parameters for this signal is 0.0135 s. This time is rather low and potentially negligible for some on-line applications.

3.2 Gams et al. [11] scheme

Gams et al. [11] presented a two-layered system for learning and encoding a rhythmic signal without any knowledge on its frequency and waveform, as well as modulating the learned rhythmic signal. They used several examples to demonstrate the applicability of the proposed method. One of their complex desired signals, Eq. 10, is considered for comparison in the present paper

$$P(t) = 3 + 2\sin(\pi t) + \sin(2\pi t) + 2sin(4\pi t + \pi/3) + 0.5\sin(6\pi t) + \cos(8\pi t) \quad (10)$$

The signal is simulated and Fourier analysis is applied. See Eq. 11.

$$P(t) = 3 + 2\sin(3.142t) + \sin(2\times 3.142t) + 0.866\cos(4\times 3.142t) + 0.5\sin(4\times 3.142t) + 0.5\sin(6\times 3.142t) + \cos(8\times 3.142t) \quad (11)$$

Six oscillators are used to simulate the signal. Results are shown in Fig. 8. As shown in Fig. 8, there is a slight frequency oscillation of the learned pattern used by Gams et al. method. It should be noted that, this error is because they used fewer oscillators than the frequency components of the desired signal. The FAL-CPG method is also applied and desired signal is reproduced immediately after the Fourier analysis with negligible error. Required time to fit the Fourier series and learn the CPG parameters for this signal is 0.019 sec.

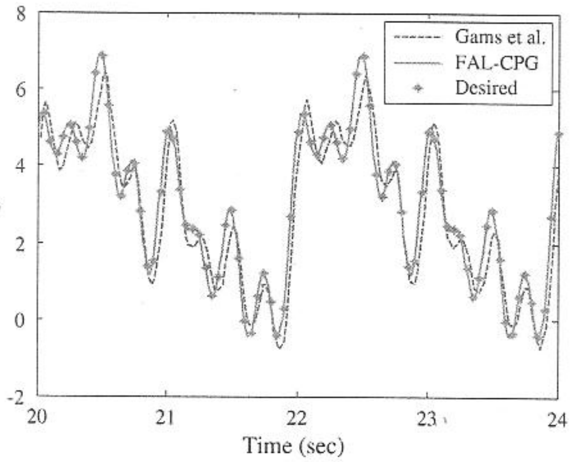

Fig. 8 Desired and reproduced pattern

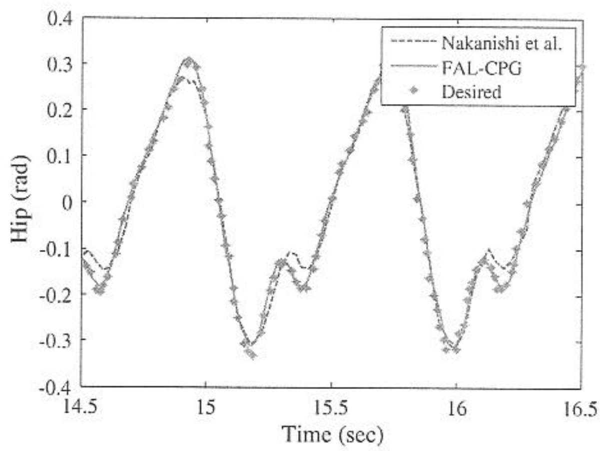

Fig. 9 Joint trajectory for hip

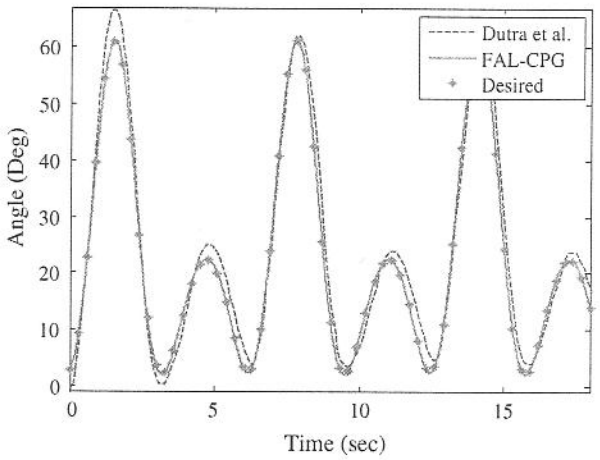

Fig. 10 Joint trajectory for hip

3.3 Nakanishi et al. [6] scheme

Their scheme encodes periodic patterns as an output of a set of non-linear dynamical systems. The system is composed of a canonical dynamical system with a phase oscillator. The system also includes a dynamical transformation system and a non-linear function approximator. The scheme is used to encode a reference trajectory for joints of a biped robot. To compare the performance of this scheme with the proposed method in this paper, hip trajectory is considered. To do this, data for the desired hip trajectory is obtained from the original paper [6]. Next, the Fourier fit is applied with $m = 6$ (Eq. 12).

$$\begin{aligned} P(t) = & -0.0129 - 0.2538\cos(7.811t) + 0.02839\sin(7.811t) \\ & + 0.066\cos(2\times 7.811t) + 0.05937\sin(2\times 7.811t) \\ & + 0.03964\cos(3\times 7.811t) - 0.01793\sin(3\times 7.811t) \\ & + 0.01786\cos(4\times 7.811t) + 0.009265\sin(4\times 7.811t) \\ & + 0.01092\cos(5\times 7.811t) + 0.001734\sin(5\times 7.811t) \\ & + 0.0001978\cos(6\times 7.811t) \end{aligned} \tag{12}$$

The CPG parameters are next determined using steps outlined in Sect. 2.2. Results are shown in Fig. 9. Required time to fit the Fourier series and learn the CPG parameters for this signal is 0.0187 s. As shown in Fig. 9, the FAL-CPG method reproduces the desired pattern. It should also be noted that oscillator output by [6], shown in Fig 9, includes the body dynamics such as the inertia. This is perhaps the main reason for the difference in actual and desired oscillator output.

3.4 Dutra et al. [14] scheme

Another learning scheme is suggested by Dutra et al. [14] where bipedal locomotion is simulated by using mutually coupled Van der Pol nonlinear oscillators as a CPG model. Fourier analysis is first applied to a set of experimental data for human locomotion. Next, harmonic balance method is used to compute the fundamental parameters of the oscillators. Other parameters are determined manually. To compare the performance of this scheme with the proposed FAL-CPG method in this paper, hip trajectory is again considered. To do this, data for the desired hip trajectory is obtained from the original paper [14]. Next, the Fourier fit is applied with $m = 3$ (Eq. 13).

$$\begin{aligned} P(t) = & \ 22.06 + 0.8085\cos(1.001t) + 16.11\sin(1.001t) \\ & -19.6\cos(2\times 1.001t) + 0.8905\sin(2\times 1.001t) \\ & -0.5001\cos(3\times 1.001t) - 3.159\sin(3\times 1.001t) \end{aligned} \tag{13}$$

Six oscillators are selected to simulate the desired trajectory. Results are shown in Fig. 10.

As shown in Fig. 10, the error of the van der Pol method is much larger than the FAL-CPG method. Moreover, to find the fundamental frequencies of the oscillators a set of nonlinear equations with harmonic balance method must be analytically solved. In comparison, the FAL-CPG method

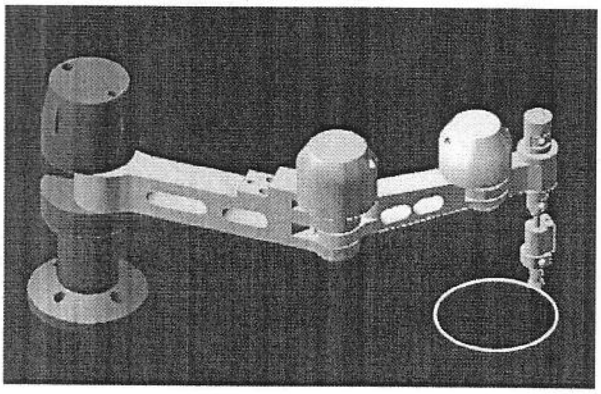

Fig. 11 Three DOF planar robot modeled in SolidWorks and imported into ADAMS

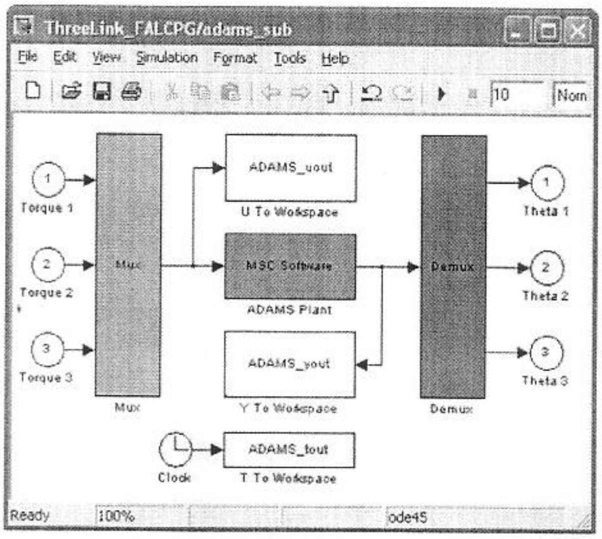

Fig. 12 Link Matlab with Adams

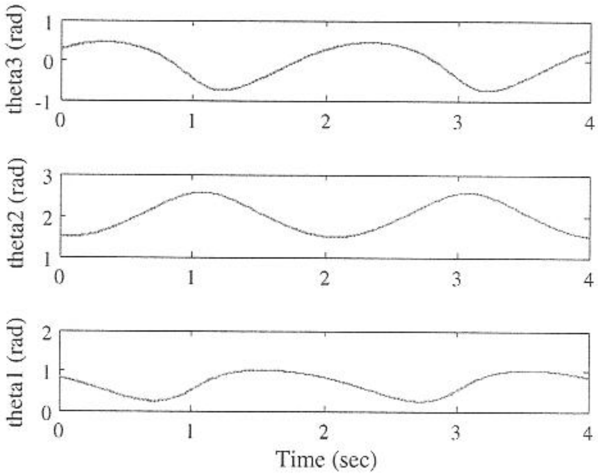

Fig. 13 Desired angels from inverse kinematics (-) and FAL-CPG method angels (–)

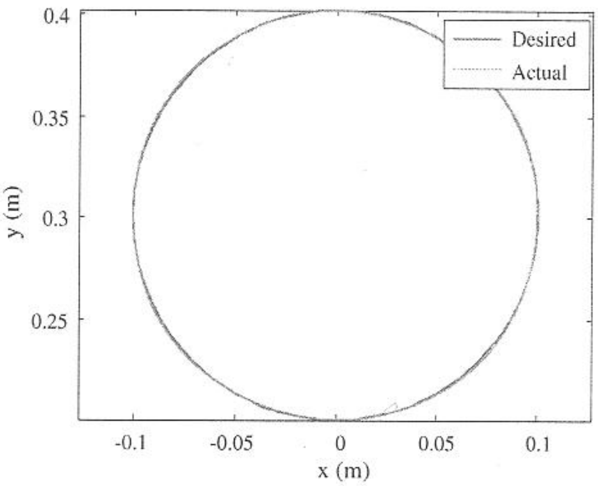

Fig. 14 Desired versus actual path

computes the fundamental parameters without the need to analytically solve any linear or non-linear equations. The computation time for learning the CPG parameters for this signal is 0.0134 s. It should also be noted that, unlike the previous study by [6], the oscillator output, shown in Fig 10, does not include effects of body dynamics such as the inertia.

3.5 Industrial application

As a final example, an industrial application of CPG for trajectory planning is considered. For more detailed information about path planning with CPG, see [15]. A three DOF planer robot is used to follow a periodical circular path. The mechanical structure is modeled in SolidWorks and imported into ADAMS software (Fig. 11).

The CPG model and control is performed using Matlab software. To do the control, Matlab and ADAMS are linked (Fig. 12).

First, the inverse kinematics is solved to obtain the required joint angles to pass through the circular path. Next, the Fourier analysis is applied to each of the three joint angles to find the main CPG parameters. Figure 13 shows the desired joints obtained from inverse kinematics and results of Fourier series with $m = 4$. Required time to fit the Fourier series and learn the CPG parameters for this signal is 0.0165 s.

As it can be seen from Fig. 13, the Fourier series closely fit the desired trajectory. The desired and actual circular path generated by the robot in ADAMS software is shown in Fig. 14.

With the controller using the CPG to generate the desired trajectory, the robotic system can benefit from all the features of CPG as briefly outlined in Sect. 3. This is an approach we have previously proposed for control of industrial robots [15].

Table 2 Comparison between different learning methods

	Error of learning	Time to learn	On-line learning	On-line modulation	Computation cost	Need for Fourier analysis
Righetti and Ijspeert [10]	Very low	Very high	No	Yes	High	No
Nakanishi et al. [6]	High	Medium	Yes	Yes	Medium	No
Dutra et al. [14]	High	High	No	Yes	Medium	Yes
Gams et al. [11]	low	Low	Yes	Yes	Low	No
Proposed method (FAL-CPG)	Very low	Very Low (0.0161 s)	Yes	Yes	Low	Yes

4 Discussion

In this section, overall performance of the proposed FAL-CPG method is compared with the four other methods used for comparison.

The performance ranking shown in Table 2 should be considered with great care. The stated ranking is authors' best knowledge and opinion. The rankings are also relative and not absolute. As shown in Table 2, in comparison with the other methods, the FAL-CPG method performs better than the other methods except the need for the Fourier analysis. Among the four methods compared, the performance of the FAL-CPG and Gams et al. methods are most similar. The advantage of the FAL-CPG method is its small error, the difference between desired and actual, which depends on the accuracy of the Fourier fit. The number of the oscillators can be increased to reach the desired accuracy. Its other advantage is rather low learning time. The average learning time between the four examples is 0.0161 s, which potentially enables the FAL-CPG to be used in on-line applications [16, 17]. The advantage of the Gams et al. [11] method is that the process of frequency extraction and adaptation is embedded into its dynamics. However, it requires more time for learning the desired signal compared to the FAL-CPG. The method proposed by Nakanishi et al. [6] has the advantage of including the robot body dynamics in the learning process. The ability of including the dynamic effect offers certain advantages. However, in many applications the desired trajectory based on system dynamic can be generated in advance and next learned by the CPG. Therefore, the learned trajectory incorporates the body dynamics. This potentially eliminates the need to simultaneously include the dynamics with the learning process. Furthermore in the FAL-CPG method, after learning the desired signal, the body dynamics effects may be applied to the CPG as external feedbacks. Once a signal is learned the FAL-CPG offers all the traditional advantages for its CPG. It can be modulated to adapt with a dynamic environment and trajectories are robust to perturbations. In authors' opinion, the process of Fourier analysis is not complex and could easily be applied to rhythmic patterns. Therefore, authors believe the FAL-CPG continues to offer its advantage. It is not the purpose of this paper to claim that the FAL-CPG is advantageous over all the other presented CPGs. Instead, the authors wish to present a new method and offer some of its advantages like simplicity and low learning time, which makes it suitable for a wide range of applications.

5 Conclusion

A supervised learning method, Fourier based automated learning CPG (FAL-CPG) for learning rhythmic signals is presented. The method automatically fits a finite Fourier series to the desired rhythmic signal and determines the CPG parameters. The learning time for a typical trajectory is rather low, about 0.0161 s, and can therefore be potentially used as an on-line learning method. It should be noted that the computation time can be significantly reduced with higher power computers as the reported time is collected using a lower end PC. It is also shown that the resulting CPG network contains all the basic characteristics, modulation and robustness to perturbation, of a traditional CPG. Applicability of the FAL-CPG method is demonstrated by learning various periodic signals. The usefulness of the proposed method is illustrated by comparing with four recently published learning methods. Finally, an industrial robotic trajectory planning application is also provided.

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