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Biologically-Inspired Control for a Planetary Exploration Tensegrity Robot

Marc Leroy – marc.leroy@epfl.ch

USRA NAMS Student R&D Program and École Polytechnique Fédérale de Lausanne, Switzerland

Introduction

Tensegrity structures are becoming increasingly popular as mechanical structures for robots. Their inherent compliance makes them extremely robust to environmental disturbances, and their design allows them to have a high strength-to-weight ratio whilst being lightweight compared to traditional robots. For these reasons they would be of interest to the aerospace industry, particularly for planetary exploration.

However, being such compliant structures thanks to their network of elastic elements also means that their control is not an easy task. Relying solely on traditional control strategies to generate efficient locomotion would surely be near impossible due to the complex oscillatory motions and nonlinear interactions of its members.

The goal of this project was to use bio-inspired control techniques to generate locomotion for a tensegrity icosahedron, namely the SUPERball project of the Intelligent Robotics Group of NASA Ames Research Center, shown in Figure 1.

Figure 1. SUPERball v1.0 (left) with 12 actuated cables and 12 passive ones; and SUPERball v2.0 (right) with 24 actuated cables

Methods

Many living creatures are capable of handling a multitude of environments, whether they're in a flat or rough or even sloped terrains. Central Pattern Generators (CPGs) are neural networks capable of driving signals from the brain into the spine, thus generating a feedforward component for the animal's locomotion. These, along with other signals coming from sensory feedback (e.g. reflexes when the feet are touching or not the ground), can generate efficient, distributed and reliable locomotion. They can indeed be activated by simple electrical signals and can produce different types of gaits.

However, there is no general methodology as to how these CPGs should be implemented. Still, the models generally rely on phase oscillators, as CPGs want to reproduce periodic gaits. Different approaches were explored in the scope of this project.

Firstly, a chain of phase oscillators can be used. This model is mainly described by the following equation, where depending on the coupling functions/factors all oscillators will phase-lock/synchronize:

$$\frac{d\phi_i}{dt} = \omega_i + h(\phi_{i-1}, \phi_i, \phi_{i+1})$$

The second model relies on Arbitrary Waveform Oscillators (AWOs). This model can be used if the mathematical functions for the desired signals and their derivatives are already known. The equations governing this model are as follows:

$$\frac{d\phi_i}{dt} = \omega_i + \sum_j \mathrm{a_{ij}} \cdot \sin(\phi_j - \phi_i - \phi_{ij})$$

$$\frac{dx_i}{dt} = \frac{df_i(\phi_i)}{d\phi_i} \cdot \frac{d\phi_i}{dt} + \gamma_i \cdot (f_i(\phi_i) - x_i) + K_i$$

Finally, the last approach is a model more closely related to true animal locomotion, as it mimics input driving signals coming from the brain's Mesencephalic Locomotor Region (MLR). The equations in this case are:

$$\frac{d\phi_i}{dt} = \omega_i + \sum_j \mathrm{r_j} \cdot \mathrm{a_{ij}} \cdot \sin(\phi_j - \phi_i - \phi_{ij})$$

$$\ddot{r}_i = c_i \cdot \left(\frac{c_i}{4} \cdot (R_i - r_i) - \dot{r}_i\right)$$

$$x_i = f(r_i, \phi_i)$$

In this respect, only the mathematical functions of the desired signals are required. There is no need to have an analytical description of their derivatives. This final model is particularly interesting, as smooth frequency modulation of the signal can be achieved online and saturation can also be programmed.

These models were specifically for the CPGs per se, so the feedforward component of the controller. Feedback can be integrated in the set of equations as follows:

$$\frac{d\phi_i}{dt} = \omega_i + \sum_j \mathrm{r_j} \cdot \mathrm{a_{ij}} \cdot \sin(\phi_j - \phi_i - \phi_{ij}) - \sigma \cdot N_i \cdot \cos(\phi_i)$$

It can be shown that this modification allows for signal inhibition, and phase resetting, which can be useful in rough terrain.

Results

The project started with the implementation of the chain of oscillators. Physical simulation was achieved thanks to the NASA Tensegrity Robotics Toolkit (NTRT), which is built on top of the Bullet Physics Engine v2.82. Early results before tuning the couplings were promising, as SUPERball could achieve rolling in a single general trajectory overall, as it can be seen in Figure 2.

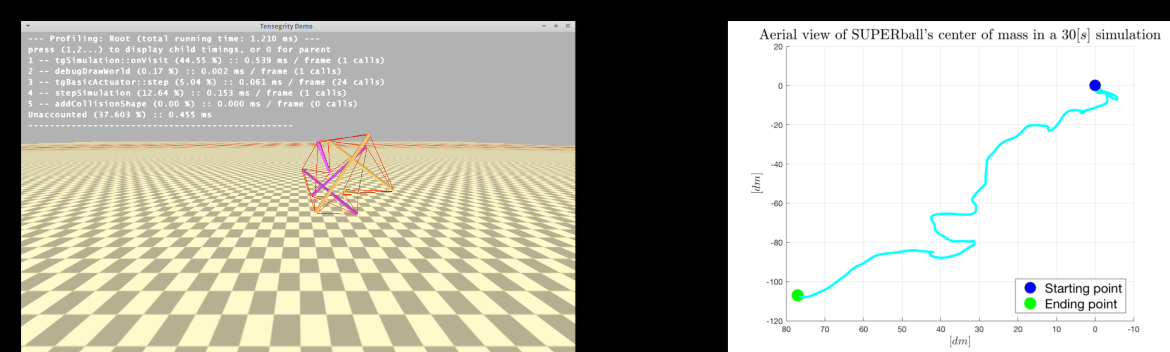

Figure 2. NTRT (left) and results with chain of phase oscillators (right)

Problems arose however when trying to use machine learning techniques and genetic algorithms. It was discovered that NTRT has some reset issues, which have not yet been fully corrected. The framework can be found in the project's GitHub repository, such that when NTRT's reset is made deterministic, the controller may be correctly tuned.

The AWOs were able to correctly learn desired signals as it can be seen in Figure 3. They were implemented using the codyn framework, a general modeling and simulating tool for coupled dynamical systems. They could also be used to learn more complex signals in the future.

The method more closely related to the MLR inputs is the one being further explored. The signals that allowed the SUPERball's first prototype (12 actuators version) to roll were used as an input. These had been obtained thanks to reinforcement learning algorithms, and validated thanks to ROS.

Adding the feedback component is also working to reset phases, and Figure 4 illustrates that. This property shall be further explored in future works.

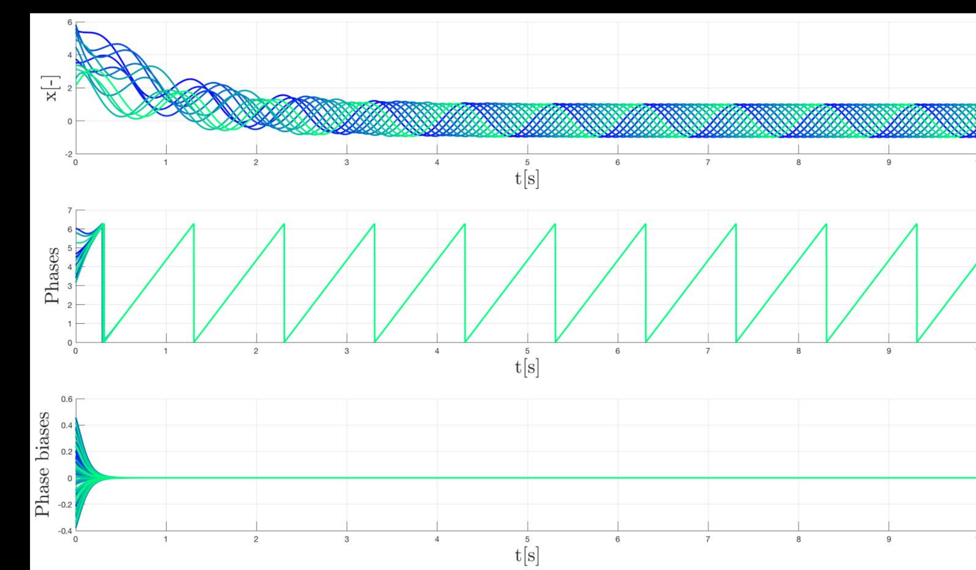

Figure 3. AWOs learning equally-spaced cosine functions

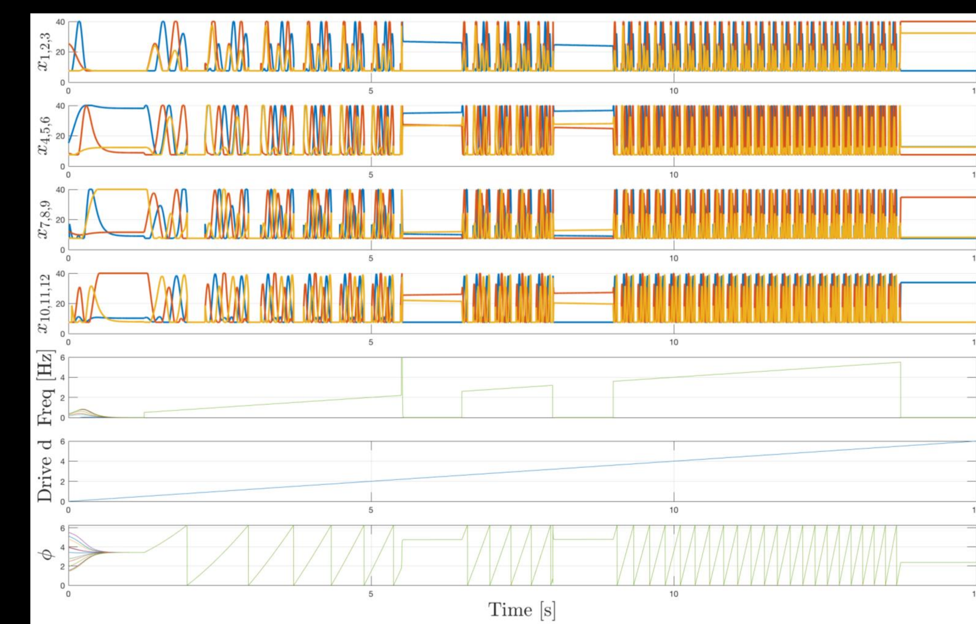

Figure 4. Current CPG implementation showcasing the smooth frequency modulation and saturation above or below given thresholds (MLR similarity). The learning signal was interpolated thanks to 8-component Fourier series. Two simulated force feedbacks are also present to show that they stop the signals' evolution until their disappearance.

Future Works and Conclusion

Though NTRT is an efficient simulation environment for tensegrity systems, the reset issues make it unproductive to try to tune the controller in it with learning algorithms before it is made sure that they have been taken care of. Experiments are in current development to correct those issues.

The AWOs were able to correctly learn desired signals for a single frequency. Further research is required to be able to achieve online modulation.

The final method seems to be correctly reproducing SUPERball's earlier gait, so frequency modulation and robustness to different terrains shall be explored in the near future along with the force feedback.

Future works can also include reusing the reinforcement learning techniques to find new motor primitives for SUPERball with 24 actuators, and then using these new signals as trainers for the CPGs.

With this done, it will be possible to evaluate the algorithm's capabilities of achieving ground locomotion.

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Biorobotics Laboratory EPFL

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE