Representing and Combining Dynamics in Biologically Plausible Neurons

Sean R. Aubin

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Abstract

Conceptors, although biologically implausible, admirably capture high dimensional dynamical patterns. This report describes how, with the use of the Neural Engineering Framework to compute Rhythmic Dynamic Movement Primitives using spiking neurons, the same dynamical pattern approximation can be achieved in a biologically plausible manner.

1 Introduction

The intent of this project was to replicate the results of Conceptors in the domain of representing dynamics in a neural population [6], but instead doing so in a biologically plausible manner. The Conceptor approach to representing dynamics is inspired by Reservoir Computing, where a randomly connected population of neurons are fed back on themselves to create a dynamic system. This dynamic system can then create specific dynamic patterns by the modification of the recurrent weight matrix. This constant dramatic modification of the recurrent weights, which are mapped onto synaptic weights, makes this approach biologically implausible, since synaptic weights generally undergo gradual changes.

The results from Conceptors in approximating complex dynamic systems is impressive. In particular, they have been demonstrated to approximate human motion signals, as shown in Figure 1.

The results from Conceptors is a laudable demonstration of full-body control of a humanoid form, even if there are no external forces acting on it. The ability to reliably create these signals in a biologically plausible manner is a valuable goal and is necessary for a complete cognitive system. This report describes how this aforementioned goal was achieved using the Neural Engineering Framework (NEF). All code used in this report is available at `https://github.com/Seanny123/nef-conceptors`.

2 Methods

The rhythmic core of the model is a speed controlled oscillator following a path along the unit circle, as shown in Figure 2 in the plot titled “osc”. A variety of methods were attempted to decode meaningful behaviour off this oscillator.

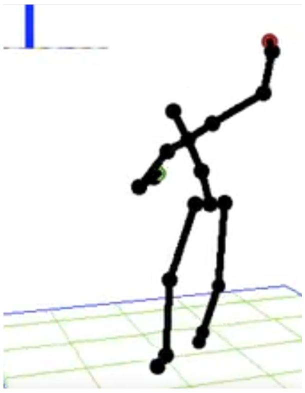

Figure 1: Dynamic signals represented by Conceptors being output to create a humanoid figure dancing. Screenshot taken from `https://www.youtube.com/watch?v=DkS_Yw1ldD4`.

2.1 Decoding Directly From An Oscillator

The first naive attempt was to decode a signal directly off the output of the oscillator. Although it is simple to map the output of arctan to an arbitrary output signal using a NEF ensemble, due to the discontinuous nature of arctan, no signal could be approximated noiselessly, as shown in Figure 2.

The ideal alternative would be an ever-increasing ramp function, however this is biologically implausible, so the idea of decoding directly was abandoned.

2.2 Rhythmic Dynamic Movement Primitives

The alternative to decoding directly was to work in the domain of dynamic systems.

Dynamic Movement Primitives (DMPs) are a way of planning movement using dynamics. To achieve this, weighted basis functions approximating a path dictate the forces on a point as it goes from the starting point to the finish point attractor [3]. In a neural implementation, the basis functions are leaky-integrate-fire neuron tuning curves and the weights are the decoding weights that correspond to the aforementioned neurons. This neural implementation already been used to create a fully neural implementation of arm control in REACH [5]. An example of an arm's path being dictated by point attractor dynamics is shown in Figure 3.

Rhythmic Dynamic Movement Primitives (rDMPs) are a variation of DMPs, where instead of having a discrete goal, a repeating path is followed [4]. The path is decoded from an oscillator, however, instead of directly decoding, the decoding weights are determined by taking the force of a point attractor in the center of the pattern into account. Compensating for this force overcomes the discontinuity problem described in the previous section, as shown in Figure 4

Moderate amounts of distortion between target movements and the reproduced signals are still visible, as shown in Figure 5. However, this is considered a minor concern and potential approaches for solving this problem are described in Section 3.

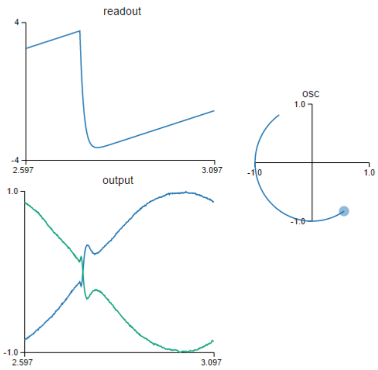

Figure 2: Plots showing how distortions in the sinusoid, the “output” plot, are due to the discontinuity in the decoded oscillator readout. For the plots “readout” and “output” the horizontal axis represents time in seconds, while the Y axis represents the magnitude of the signal, while the “osc” plot traces the oscillator activity over time.

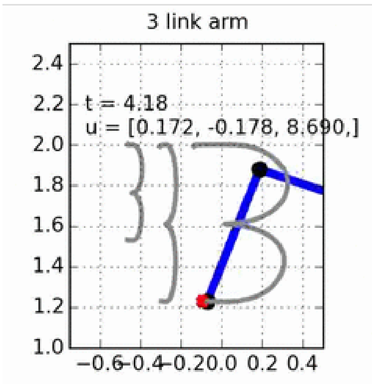

Figure 3: A robotic arm following various trajectories using DMPs. Taken from DeWolf’s blog post on the subject [3].

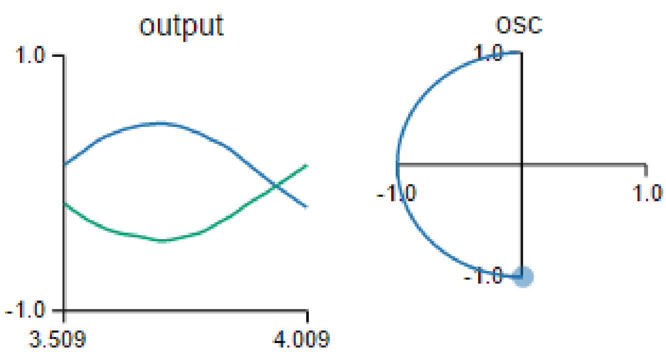

Figure 4: Plots showing replicated sinusoid without any discontinuity.

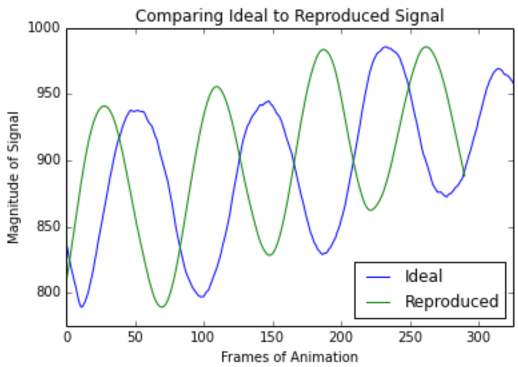

Figure 5: Plot showing the replicated signal lagging in a non-consistent manner behind the intended, ideal signal.

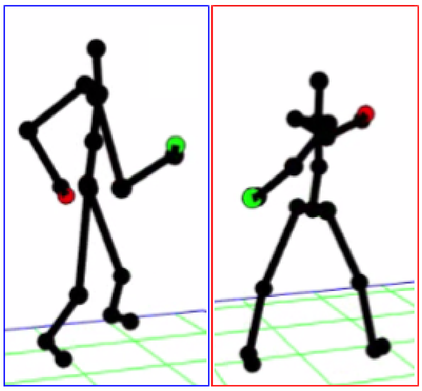

Figure 6: Screenshots of both the jogging (blue frame) and exaggerated stride (red frame) movements patterns. Videos available at `https://youtu.be/CVHnGuS4U9Y` and `https://www.youtube.com/watch?v=0rVH0Q48raM`.

2.3 Post-Processing

The Mocap Toolbox written in Matlab [1] was used to create the Conceptor demo in Figure 1. The signals are 61 dimensional with a predefined time-step and wildly varying ranges. This provided an additional challenge for neural simulation.

The basic pipeline for processing was compression of the original signal into a range of $[-1, 1]$, simulation, amplification back into the original range and finally additional smoothing with a low-pass filter, due to the noise being amplified with the rest of the signal. The successful results of this pipeline are shown in Figure 6.

2.4 Creating New Actions

In the previous section, only a single ensemble was used at a time. However, it is possible to combine the output of multiple ensembles by doing a weighted linear combination of the signals to make new signals, as show in Figure 7.

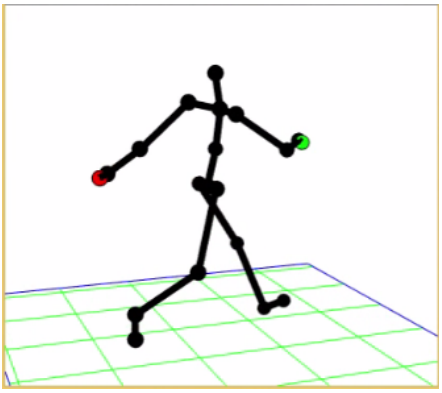

Figure 7: Plot showing a combination the jogging and exaggerated stride pattern, creating an exaggerated, almost skip-like, jog. Video available at `https://youtu.be/okht5fB4oPQ`.

3 Discussion

This report demonstrated that the dynamic signal representation exhibited in Conceptors could be replicated using the NEF. Human movements, animated using the MoCap toolbox, were replicated after being represented as rDMPs in neural ensembles. However, this is still room for improvement in terms of temporal lag and representational quality.

Temporal lag, as shown in Figure 5, is most likely a result of poorly choosing parameters, such as evaluation points and gains, which should be adapted depending on the signal being approximated.

Various options exist to increase the accuracy of the representation, if a better temporal representation is achieved via better DMPs. Using rate neurons instead of spiking neurons, greatly improved the representation quality. Alternatively, another option to further improve the representation quality of the signals would be to increase the number of neurons and switch to simulating on neuromorphic hardware, such as Spinnaker [7]. Finally, a better understanding of the actual range of possible value of the MoCap toolbox would help better determine the radius of the neuron populations, instead of awkwardly scaling them via post-processing.

In terms of neuroanatomical mapping, the rDMP populations of this model map onto the Central Pattern Generators [2], which are neural circuits in the human spinal chord that assist with the creation of rhythmic movements. The action selection via inhibition is analogous to the inhibition created by the thalamus. Obviously, to match neurological data exactly and to store the patterns more realistically, a more sophisticated model of human movement needs to be used.

3.1 Future Work

To expand on this model to make it suitable for publication, there are two avenues of expansion possible: integration with a visual system and internal visualization.

It would be interesting to integrate the visual system to first imitate the actions of recorded human being and then to refine the imitation with feedback. This could be accomplished by developing a skeletal model from the video and then mapping onto a high dimensional vector of patterns.

Given a model of the human body, one possible experiment would be to generate new patterns of movement in a manner similar to internal visualization and see if this internal exploration of a problem space translates into better performance on an actual problem.

References

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