Inference of contractility evolution on planar worm locomotion

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EXTENDED ABSTRACT

1 Introduction

Small slender organisms have the ability to propel autonomously in a very efficient manner. By using their lateral muscles, they bend their longitudinal body, and due to their distinct tangential and lateral friction, the body is subjected to propulsive forces [1]. The set of bending modes (eigenworms) [2] and friction coefficients has been measured computationally and experimentally [3, 4]. However, a full mechanical explanation and simulation reproducing the worm locomotion is still missing.

We here present a worm model composed of straight segments, which have associated longitudinal and bending elastic potential. By adding the worm active bending through a set of self-equilibrated forces, and the non-isotropic friction, we are able to reproduce worm locomotion. From a set of simulations and experimental images, and resorting to machine learning techniques, we also aim to infer the set of bending moments that best match the observed the worm dynamics. We comment on the different strategies employed and their suitability for solving the inverse dynamics problem at hand.

2 Worm Mechanics

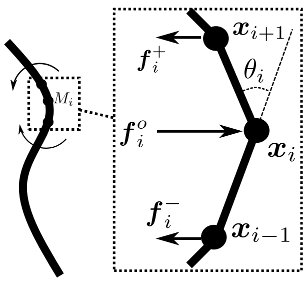
The worm backbone is modelled as an elastic slender body made of N segments with longitudinal and bending elastic energy given by,

$$W_l^{el} = \frac{1}{2}\sum_{i=1}^{n} k_l (l_i - l_0)^2 \quad , \quad W_\theta^{el} = \frac{1}{2}\sum_{i=1}^{n-1} k_\theta \theta_i^2$$

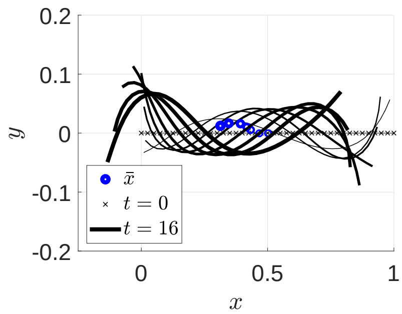
with θ_i the relative angle between segment $i+1$ and i, $l_i = ||\boldsymbol{x}_{i+1} - \boldsymbol{x}_i||$, and (k_l, k_θ) the stretching and bending stiffness, respectively. The body is subjected to a non-isotropic friction which is given by longitudinal and normal friction coefficients $(\mu_\tau, \mu_n$, and a frictional tensor $\boldsymbol{\nu} = \mu_\tau \boldsymbol{\tau} \otimes \boldsymbol{\tau} + \mu_n \boldsymbol{n} \otimes \boldsymbol{n}$. After neglecting inertial forces, the equations of motion can be written as

$$\nabla_{\boldsymbol{x}_i}(W_l^{el} + W_\theta^{el}) + \boldsymbol{\mu}\dot{\boldsymbol{x}}_i = \boldsymbol{m}_i, i = 1, \ldots, N \tag{1}$$

The external forces $\boldsymbol{m}_i$ are a set of self-equilibrated forces that mimic the effect of the bending moment M_i at the interior nodes $i = 2, \ldots, N-1$. See Figure 1a and [5] for further details. Figure 1b shows an illustrative set of deformations that result in the motion of the centre of mass $\bar{\boldsymbol{x}}$. These are obtained by solving the non-linear ordinary differential equations in 1 with an implicit algorithm.



(a)



(b)

Figure 1: (a) Scheme of mechanical model. (b) Simulation of worm locomotion from mechanical model and using a wave of bending moments. Extracted from [5].

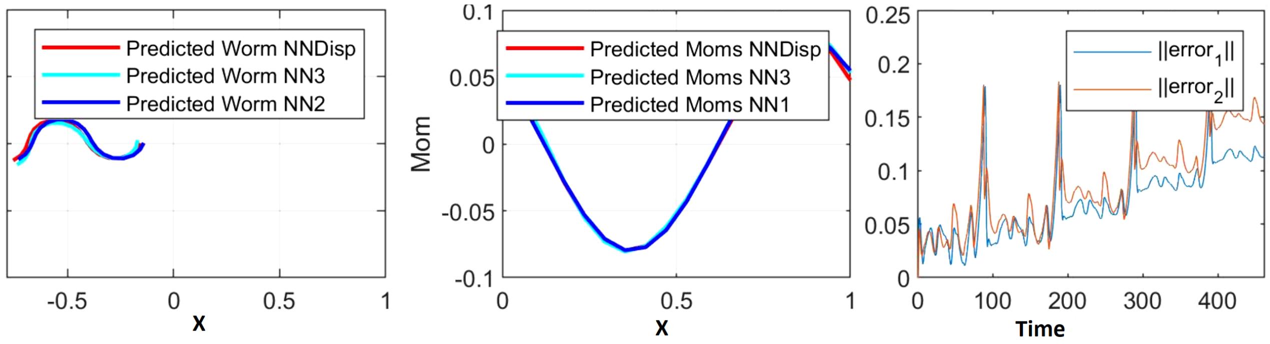
3 Moment inference

Through a set of simulations, we aim to infer the nodal moments $M_i(t_n)$ at each time-step t_n that best match a sequence of worm motions. This inverse problem is solved resorting to machine learning techniques and the training of a neural network with a sufficiently large set of simulations. In order to reduce the training data, we pull back the worm configuration $\boldsymbol{x} = \{\boldsymbol{x}_1, \ldots, \boldsymbol{x}_N\}$ onto the position $\bar{\boldsymbol{x}} = \boldsymbol{0}$, and rotate the worm such that the vector $\boldsymbol{x}_n - \boldsymbol{x}_1$ is aligned with the $x - axis$. We also test different training and fitting strategies, depending on the variables employed (total or incremental displacements $\boldsymbol{u}$ and moment $\boldsymbol{M}$), which are summarised in Table 1.

Name	Input	Output
NNDisp	$\Delta u^{exp}, \boldsymbol{u}_n^{exp}, M_n$	ΔM
NN1	$\boldsymbol{u}^{exp}$	M_{n+1}
NN2	$\boldsymbol{u}^{exp}, \boldsymbol{u}_{n+1}^{exp}$	M_{n+1}
NN3	$\Delta \boldsymbol{u}^{exp}, \boldsymbol{u}_n^{exp}, M_n$	M_{n+1}

Table 1: Different strategies employed in the training of the neural network. $\boldsymbol{u}_n^{exp}$ denotes "experimental" displacements at time t_n. Operator $\Delta(\bullet) = (\bullet)_{n+1} - (\bullet)_n$ denotes incremental quantities.

The performance of each strategy is given in Figure 2, where we have applied the inference techniques to a synthetically generated set of worm motions. The Figure shows the reproduced configuration (a), the evolution of the moments (b) and the error with respect to the synthetically generated deformations (denoted as "experimental" in Table 1).



(a) (b) (c)

Figure 2: (a) Snapshot of worm deformation. (b) Extracted moments along worm backbone. (c) Evolution of error E between inferred worm positions and synthetically generated positions.

4 Conclusions

In this work we show that ML techniques can be employed to derive the worm activity. So far the methodology has been applied to a simulated worm locomotion. In future work we will apply the techniques to experimentally measured worm configurations.

Acknowledgments

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