

# Sensing Through the Body\*

E. Judd, G. Soter, H. Hauser, and J. Rossiter

**Abstract**— The goal of the project is to develop a novel approach for proprioceptive sensors in robotics based on the principle of morphological computation, i.e. the use of morphological features for computational tasks. In the presented work we use the body dynamics of a moving octopus inspired robot arm to classify the position of objects in its vicinity. Proprioceptive strain sensors were emulated by employing computer vision techniques on recorded videos of the experiments to estimate the amount of bending along the arm. Simple linear regression on these proprioceptive signals was sufficient to classify different position of an object. Preliminary results suggest that arm was able to “feel” the position through its body without touching.

## I. INTRODUCTION

The theory of embodied intelligence, which is inspired by biological systems, suggests that behaviour is an emergent property of the interaction between a system’s controller, body and environment [1]. A crucial part for intelligent behaviour is sensing. While in nature sensors are cheap and plenty, robotic systems typically lack this richness and have to rely on a few and expensive sensors. Another issue in robotics is that sensors and controllers are artificially separated leading to very static systems. On the other hand, we can observe in Nature a distribution of sensing capabilities throughout the body and a tight coupling between body and environment, resulting in seemingly much more robust and adaptive solutions. To enable the next generation of embodied robots, we need to develop novel sensor technology that brings us closer to the performance of biological systems. This will potentially even help us to build bodily aware soft robots as suggested in [3]. One of the biggest obstacles to use a high number of sensors, besides the price, is the incorporating of the sensor data. However, reservoir computing [2] seems to provide a promising solution for this problem. It allows us to combine linearly all available signals without having to know the actual meaning of the value. As a result, it enables us to exploit the sensory structure and dynamics with a highly reduced computational burden (i.e., we can use linear regression for incorporating information to carry out complex, nonlinear computational task, see e.g. [2]). Furthermore, we can expect robustness and improved learning capabilities from such structures [4].

## II. EXPERIMENT AND RESULTS

An EcoFlex 10 octopus inspired silicone arm with 32 markers was submerged vertically in water and attached to a linear slider with a sinusoidal input signal (Fig. 1). A



Figure 1. EcoFlex 10 octopus inspired, passive silicone arm submerged in water. The proximal end was attached to a linear slider with a sinusoidal input signal that excited the arm without touching the object. The object was moved to different locations. Simple linear regression was sufficient to learn to classify different positions of the object by simply observing the bending of the arm (proprioceptive sensing).

cylindrical object was attached to a linear slider along the y axis. 30 strain measurements were obtained between successive markers, 15 on either side of the arm, using OpenCV’s Blob Detector to identify and track the corresponding markers between frames. These positions were used to estimate the local bending and orientation of the arm. A preliminary data set of 8 object positions were recorded for 30 seconds at 60 frames per second. The object was situated far enough away from the arm to avoid contact. A linear regression model was trained using data from 7 of the 8 times series labelled with the object positions. The time series for the 8<sup>th</sup> object position was left out for testing.

The linear regression model was trained with object positions of  $y = 8.5$  through  $22.5$  cm in steps of  $2$  cm, excluding  $16.5$  cm which was used for testing. Testing results showed a prediction of  $y = 16.11$  cm. Future experiments will explore the use of the presented methodology across multiple actuation frequencies and amplitudes for classification of object positions in both x and y axes.

## REFERENCES

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Euan Judd is with the Department of Engineering Mathematics, University of Bristol, Merchant Venturers Building, Woodland Road, Bristol BS8 1UB, UK (corresponding author: e-mail: euan.judd@brl.ac.uk).

Gabor Soter is with the Department of Engineering Mathematics, University of Bristol, Merchant Venturers Building, Woodland Road, Bristol BS8 1UB, UK (e-mail: gabor.soter@bristol.ac.uk).

Helmut Hauser is with the Department of Engineering Mathematics, University of Bristol, Merchant Venturers Building, Woodland Road, Bristol BS8 1UB, UK (e-mail: helmut.hauser@bristol.ac.uk).

Jonathan Rossiter is with Department of Engineering Mathematics, University of Bristol, Merchant Venturers Building, Woodland Road, Bristol BS8 1UB, UK (e-mail: Jonathan.Rossiter@bristol.ac.uk).