Dynamic sensorimotor graphs

Some Guy, Random Stranger and Anonymous Dude

***Abstract*— Regularities present in the sensorimotor signals of a robotic agent can reflect its embodiment, as well as the associations resulting from the active control policy. In this work, we analyze the functional connectivity of the sensorimotor signals based on pairwise mutual information. As the robot performs exploratory motions based on motor babbling we capture and study the time-varying changes in the relationships. We provide analysis of the instantaneous and average sharing of information and extrapolate the meaning in relation to the physical properties of the robot's body. Results from a simulated planar system validate the use of mutual information as a tool not only for the analysis of the relationships between the sensorimotor signals but also to drive exploratory motions.**

TODO

I. Introduction

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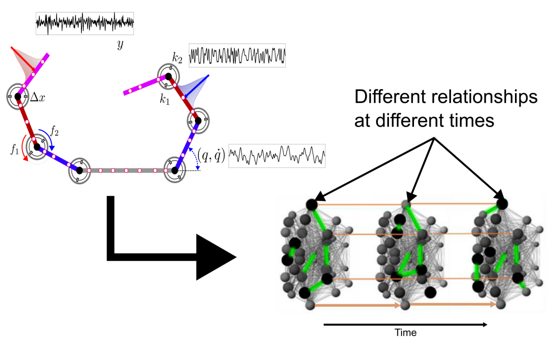

Fig. 1: General overview.

A. Background

Dynamical functional connectivity (DFC) has has mainly being used to study functional networks in the brain. For instance, in [1], it was used to show states of lower functional connectivity during onsets of epilepsy.

The work in [2] used NNMF on EEG signals to to identify potentially abnormal connectivity patterns in brains affected by illness.

B. Related works

Refer to Mannella, Gama, Marcel, Kanazawa, Husbands, Hoffmann (puppy).

C. Contributions

In this work we present an analysis based on the dynamic relationships existing among the sensorimotor signals of a embodied agent. In the analysis we show how the state of information sharing in the system is related to the motion of the robot and the tactile events that stem from its movement.

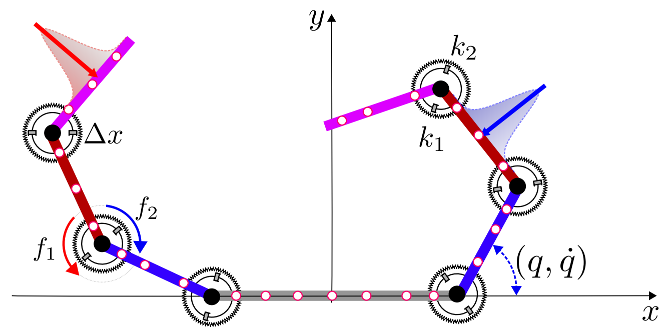

Fig. 2: The planar dual arm robot.

Using non-negative matrix factorization we identify different information sharing states and classify them according to their information content. In a case study we demonstrate how after a motor babbling phase, by only focusing on the mutual information and without having knowledge about the morphology of the robot, an excitation trajectory for both the robot arms can be devised that avoids self contact. A comparison of this trajectory against conventional trajectory design methods is presented.

II. The embodied agent

The robot model in this work is based on the planar dual arm system with six degrees of freedom (DoF) used previously in [3], [4]. The robot is equipped with a set of tactile sensors modeled as Gaussian receptive fields distributed along the robot's body. Motion of the robot was originally based on reference joint angle commands. We, however, have extended the model to instantiate its dynamics by assigning inertial properties to the robot's composing bodies. Furthermore, we changed the actuation mechanism inspired by simple muscle-inspired antagonistic joint model **REF** where the muscle activation controls spring stiffness. The extended model is depicted on Fig. 2.

The tactile sensors were modified too to account for the strength of touch. Essentially, the previously distance-based activation of the Gaussian receptive fields in now scaled by the contact force.

A. Population coding

TODO The proprioceptive signals were encoded using proprioceptive coding (five receptive fields per signal), see Fig. 3

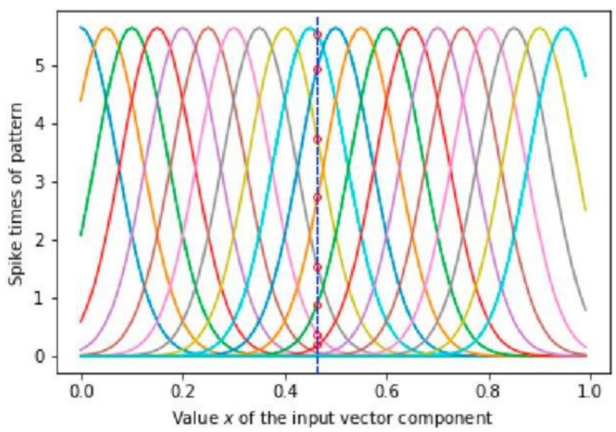

Fig. 3: The receptive fields used in population coding.

III. The sensorimotor dynamic functional connectivity

A. Functional connectivity

Functional connectivity (FC) is a method for network topology inference that characterizes the dependencies of the observed signals from a system based on their probability distributions[5]. It can be subdivided into undirected and directed; the latter being related to the analysis of statistical causation from the data [6]. By studying the FC it is possible to reveal a structure that aids in the analysis of the interaction among the entities.

Based on the connection between embodiment and information structure [7], our hypothesis is that properties of the sensorimotor interactions can be made apparent by studying the FC among the somatosensory signals $\boldsymbol{x}(t)$. From the various metrics that have been proposed to evaluate such relationships, we in particular leverage those based on information theory [8], [9], as their *model-free* nature can capture linear and nonlinear relationships between signals. Particularly, we use the *mutual information* (MI), a quantity that has been applied in different contexts to quantify the relationships between variables [10]. The MI between two signals $I\left(X,Y\right)$ can be interpreted as the amount by which a random signal Y reduces the uncertainty about a random signal X [11]. It is a symmetric measure of the information sharing by both signals and is computed as:

$$I\left(X;Y\right) = I\left(Y;X\right) = H(X) + H(Y) - H(X,Y) \quad (1)$$

with the Shannon's entropy of a variable X defined by

$$H(X) = -\sum_{i=1}^{n} p(x_i)\log_2\left(p\left(x_i\right)\right) \quad (2)$$

and the joint entropy between X and Y expressed as

$$H(X,Y) = -\sum_{i=1}^{n}\sum_{j=1}^{n} p(x_i,y_j)\log_2\big(p\left(x_i,y_j\right)\big). \quad (3)$$

By extension, the mutual information matrix $\hat{\boldsymbol{W}}_{MI} \in \mathbb{R}^{m\times m}$[1] can be constructed by computing the pairwise MI between the $\{x_i\}_{i=1}^{m}$ somatosensory signals. Its (i,j) entries are given by

$$(\hat{\boldsymbol{W}}_{MI})_{i,j} = I(x_i,x_j). \quad (4)$$

In practice, computing (4) for a pair $(x_i(t),x_j(t))$ of time series from the data matrix $\boldsymbol{X}$, centering their samples (to zero mean and unit standard deviation) and using either binning, kernel, or nearest neighbor methods [12] to compute their mutual information.

In this work, for the computation of $\hat{\boldsymbol{W}}_{MI}$ we use the the open-source MATLAB package *Mutual information computation*[13].

B. Dynamic functional connectivity

When analizing FC it might be interesting to look not only at the aggregated effect of a complete dataset of recordings but also at the instantaneous changes that occur in the relationships. Indeed, the relationships between sensorimotor signals might change rapidly depending on the motion policy. To capture these time-varying functional connectivity with mutual information, the most common approach involves the usage of a sliding time window [14]. In particular, tactile events might have a short time scale, the nutual information was computed for a time window of length T, that is to say $x_i(t,t-1,\ldots,t-T)$, we called this term the *instantaneous mutual information*.

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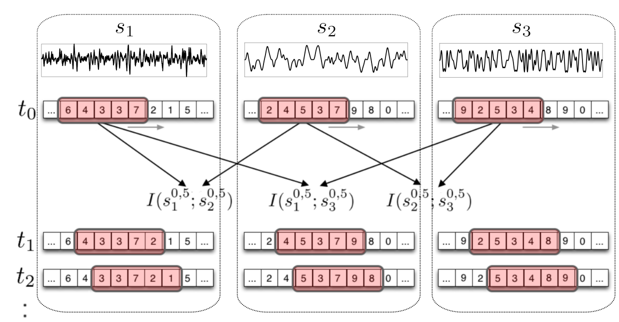

Fig. 4: Sliding window strategy to compute the instantaneous mutual information.

C. Analyzing patterns

Other methods to detect repeating patterns in DFC include the cosine similarity [15]

Non-negative matrix factorization (NNMF) [16] was employed to extract data from the connectivity graphs defines by the instantaneous mutual information. NNMF is an unsupervised machine learning algorithm that can be used to split an input matrix $\boldsymbol{V}$ into two parts: a matrix $\boldsymbol{W}$ of bases, or subgraphs, and a matrix $\boldsymbol{H}$ of their corresponding

[1]We use the *hat* notation to emphasize that this matrix is an estimate and there is no actual ground truth.

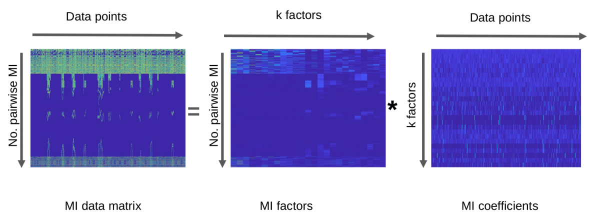

Fig. 5: Decomposition of the mutual information data matrix using non negative matrix factorization.

contributions to the input matrix $\boldsymbol{V}$. The input matrix (A) for the NMF, which produced the subgraphs (W) and associated time series of contributions (H), which were assumed to represent the relative temporal activation of each of these networks, was created by combining connectivity graphs.

NNMF has also being used to detect communities in networks [17], [18]

There are various methods to select an adequate number of factors [19]. To choose the number of factors we followed as in [20] and "which was chosen by performing NMF iteratively for increasing values of k and selecting the inflection point, or elbow, in the reconstruction residual sum of squares error curve"

In [21] it is shown how the basis graph change their expressing during learning of a ask

To show graphically how the different factors cluster naturally depending on the touched regions we used the PaCMAP dimensionality reduction method [22] given its properties to preserve aspects of the global and local structure when reducing into the latent space [23].

IV. Simulation Results

TODOFor the computation of the instantaneous mutual information we used sensors signals sampled at 100 Hz and a sliding window of $T = 0.1$ seconds; i.e., the previously seen 10 samples. With this short memory which is stored in a buffer, we can capture (fast) touch events.

V. Case study: robot excitation trajectories

TODOIn this section we use the instantaneous mutual information to generate trajectories for the left and right arms avoiding potential collisions. This is done agnostic to the actual morphology of the robot. In contrast we use a standard method for the design of excitation trajectories and compare the results.

VI. Beyond robotics

TODO

VII. Conclusions

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