Quantifying Self-Organizing Behavior of Autonomous Robots

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\begin{abstract}
Introduction
In recent years research in autonomous robots has been more and more successful in developing algorithms for generating behavior from a generic task-independent objective. Examples are intrinsic motivations for artificial curiosity, empowerment, homeokinesis, and maximizing predictive information. Independently of its origin, it would be useful to quantify behavior, in order to objectively compare algorithms with each other or even with human or animal movements. We investigate different methods for extracting characteristic measures based on information theoretic quantities.

Example Behaviors
We consider behaviors from a hexapod robot with \textit{18} DoF and from a snake robot with \textit{14} DoF when controlled by a simplified predictive information maximizing controller (Der and Martius, 2013). The behavior is generated by an adaptive coupling between sensors and motors in a purely reactive manner – without a central pattern generator nor internal recurrences. In Fig 1 two example behaviors of the snake are shown which we use here as a brief illustration. The data consists of \textit{10}\textsuperscript{6} steps of joint position sensors.

![Figure 1: Side-rolling and crawling of the SNAKE. The segments are linked with 2-way hinge joints.](image)

\begin{itemize}
\item \textbf{Attractor Dimension and Core Complexity} In case of a periodic or quasi-periodic behavior the \textit{attractor dimension} can be considered as a descriptive quantity. For a simple limit cycle the dimension would be one, for a torus it would be two and so on. In addition we want to quantify the complexity of the time series, where the excess entropy (Shaw, 1984) is a natural choice. We study for the first time the resolution-dependence of the excess entropy and propose a decomposition of it into: the attractor dimension, the length-scale of the behavior and the remaining \textit{core complexity}. We find that the excess entropy diverges as \( E = c - D \log(\varepsilon) \) for deterministic behavior, where \( D \) is the attractor dimension, \( c \) is a constant and \( \varepsilon \) is the resolution (think of a grid size). The constant \( c \) contains the overall scale (e.g. amplitudes) of the data. If this is subtracted we obtain the \textit{core complexity} \( \hat{c} \) measuring the long term memory of the system: \( \hat{c} = c - D \log(\varepsilon) \). The scale can be estimated with different methods, e.g. the variance or more elaborate methods. But how to estimate the excess entropy? We compared estimators based on the continuous mutual information and the correlation integral (Kantz and Schreiber, 2004) with the latter turned out to be more appropriate. Figure 2 shows the excess entropy and respective fits for the behaviors of the SNAKE – both have dimension \( 1.05 \) on the coarse (macroscopic) scale (\( \varepsilon \in [0.08, 0.8] \)). However the constant \( c \) would suggest that “side rolling” has a higher complexity (0.75 vs. 0.7), but the new core complexity tells that the “crawling” behavior is more complex. Besides, the “crawling” behavior is 2.5-dimensional on the small (microscopic) scales (\( \varepsilon \in [0.0001, 0.01] \)).

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