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Measuring motion significance and motion complexity

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ABSTRACT

In this paper, we propose two novel measures to specify motion significance and motion complexity from human motion trajectories. *Motion significance* indicates the relative meaningfulness of every motion frame which is defined as a set of data points acquired at a time index from multiple motion trajectories. *Motion complexity* indicates the number of meaningful motion frames involved in a set of such human motions. For this, we first show that motion significance can be measured by considering both temporal entropy and spatial entropy of a motion frame, based on the analysis of Gaussian mixtures learned from human motions. Motion complexity is then calculated by measuring the averaged amount of motion significance involved in all time indexes of motion trajectories. These two measures are devised to satisfy the requirement of neural complexity measure proposed to attain small values for totally random or totally regular activities. To show that the proposed measures are consistent with our intuitive notion of motion significance and motion complexity, several human motions for drawing and pouring are analyzed by means of motion significance and motion complexity. Furthermore, our complexity measure is compared with three existing complexity measures to analyze their similarity and dissimilarity.

1. Introduction

Motion significance indicates the relative meaningfulness of each motion frame at every time index of multiple human motion trajectories. Here, a motion frame denotes a set of data points captured by a time index of motion trajectories acquired from multiple trials. *Motion complexity* indicates the number of meaningful motion frames involved in a set of human motions. For this, these two measures are devised to satisfy the requirement of neural complexity measure proposed to attain small values for totally random or totally regular activities [38].

In this section, we will first present several related works of our proposed measures. Specifically, we will further elaborate neural complexity measure which is a motive of our measures to grasp its characteristics. Next, our contributions and the organization of this paper will be presented to help readers understand two measures.

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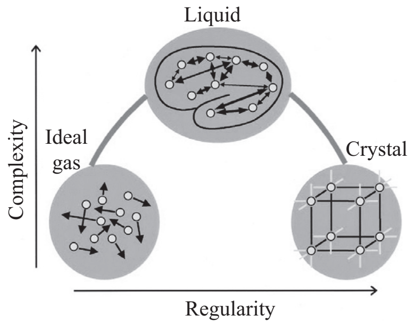

Fig. 1. Illustration of relation between regularity of activities and their complexity extracted in [38]. Here, random activities of elements (e.g., activities of gas molecules) or completely regular activities (e.g., activities of molecules in crystal lattices) are not complex. However, a mixture of random and regular activities (e.g., activities of molecules in liquid) is obviously complex compared with the others.

1.1. Related works

Before introducing our two measures, let us first consider some existing complexity measures. Over the last decades, a variety of complexity measures have been proposed to analyze the systems or their datasets. Some of those complexity measures include the popular Kolmogorov complexity [39], logical depth [7], and dimensional complexity [18], which were proposed to measure both randomness and regularity values from various datasets types. Those randomness and regularity factors have recently been used as key criteria even to measure complexity from human motions. For example, Peng et al. [32] evaluated the effectiveness of five well-known complexity measures in calculating motion complexity from symbolic motion sequences. However, those authors did not consider temporal changes of datasets at continuous time intervals.

Many researchers did attempt to measure complexity from datasets with the aforementioned temporal changes. Pincus et al., [33] and Doğanaksoy et al., [14] have proposed methods to measure complexity from temporal changes at continuous time intervals. Sample entropy [34], approximate entropy [35], Shannon spectral entropy [8], and Higuchi's fractal dimension [1] are well-known measures to obtain randomness and regularity from continuous trajectories. Yang et al., [43] also tried to measure randomness and regularity of motions by considering both correlations and smoothness factors between all joint motion trajectories. The complexity measure devised by Grassberger [17] is a famous measure of the amount of information needed for optimal prediction to indicate the extent to which an observation of passed time is related to an observation of future time. This has been used with different terminologies such as predictive information [9], excess entropy [16], stored information [36], and so on [2,3,25,26]. Recently, the permutation entropy proposed by Bandt et al., [4] has frequently been adopted to measure temporal changes of complexity from continuous motion trajectories. However, those measures were all designed to attain large values for only single side of totally random or totally regular activities. In Section 3.3, the result obtained by the permutation entropy will be presented to be compared with our proposed measures.

Unlike all the measures mentioned in the previous paragraph, the complexity measure proposed in [38] shows bell-shaped relations between regularity of activities and their complexity, as shown in Fig. 1. To elaborate further, a mixture of random and regular activities is more complex when compared with totally random or totally regular activities. A number of complexity measures have been proposed so far, as noted in [38], but very few measures (e.g., neural complexity [38] and LMC (Lopez–Ruiz, Mancini and Calbet) complexity [27]) can satisfy the requirement of attaining small values for totally random or totally regular activities. Here, it is not trivial to measure temporal aspect of complexity in multidimensional continuous trajectories using the neural complexity because of its computational complexity [5]. The reason will further be presented in Section 1.2. Unlike the neural complexity measure, the LMC complexity tends to show low computational complexity while satisfying *the requirement of neural complexity* (hereafter, to convey the characteristics of our complexity measure, the requirement of our complexity measure is designated as *the requirement of neural complexity* to represent complexity characteristics of both neural complexity and LMC complexity) [12]. However, the LMC complexity is also different with our proposed measures in terms of not considering temporal information of human motions. In Section 3.3, their similarity and dissimilarity are evaluated using several experiments. Furthermore, those all measures did not consider to measure motion complexity at every time index of motion trajectories such as our motion significance. To show the advantage of our proposed measures, the applicable areas and the discussion of our two measures will be presented in Sections 4.1 and 4.2, respectively.

1.2. What is neural complexity?

To help readers understand our proposed measures, let us consider neural complexity. In [38], the complexity measure was devised to find intrinsic neuronal activities by analyzing EEG signals captured from human brains and was thus referred to as neural complexity. That neural complexity measure was larger when activities from an EEG system included a mixture of random and regular ones vs. when its activities were totally random or totally regular. The neural complexity is