Electrocardiogram classification using Reservoir Computing

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An adapted state-of-the-art method of processing information known as Reservoir Computing (RC) is used to show its utility on the open and time consuming problem of heartbeat classification. RC mimics brain neural networks by processing information that generates patterns of transient neural activity as a response to a sensory signal[1] and is composed of layers for processing the information. It has been used for classification tasks, time series prediction and modeling[2,3]. We use a kind of reservoir consisting of a nonlinear dynamical element subject to delayed feedback. Nonlinear systems with delayed feedback and/or coupling, also known as delay systems, arise in a variety of real live contexts[4]. These systems can exhibit a wide range of dynamics ranging from stable operation to periodic oscillations and deterministic chaos[5]. At least three layers are needed for the classification task, an input layer to feed the information, the reservoir layer that transforms the input through the nonlinearity and an output layer collecting the results of the processing and adapting the classifier through the learning process. Our approach includes a minimum pre-processing consisting on expanding the dimmension of the input using a mask. The reservoir layer consists in a single node with a nonlinearity known as Mackey-Glass oscillator[6]. The model contains a delayed feedback term and has been extended to include an external input $I(t)$. Appeltant et al.[2] presented the extended model as:

$$\dot{X}(t) = -X(t) + \frac{\eta \cdot [X(t-\tau) + \gamma \cdot I(t)]}{1 + [X(t-\tau) + \gamma \cdot I(t)]^p}, \qquad (1)$$

with X denoting the dynamical variable, $\dot{X}$ being its derivative with respect to a dimensionless time t, and τ denoting the normalized delay in the feedback loop. Parameters η and γ represent feedback strength and input scaling, respectively. Without an external input ($\gamma = 0$) the system is chosen to operate in a stable fix point. However, under external inputs the system can exhibit complex dynamics. In particular, we are interested in a dynamical regime that produces consistent transient responses. The exponent p can be used to tune the nonlinearity. Although we have chosen the Mackey-Glass nonlinearity, it is expected that other nonlinear functions perform similarly well. For instance, a semiconductor laser has been used to perform similar tasks[3,7]. Finally, the learning process is a logistic regression method. The logistic regression (LR)[8] is a widely used learning technique in biostatistical applications in which binary responses occur quite frequently, in questions such as a condition is present or absent. LR uses logit transformation in order to give the probability that a input belongs to a particular class. We use the MIT-BIH Arrhythmia Database[9] available at Physionet which contains 48 ambulatory ECG recordings of half hour each, obtained from 47 subjects. The recordings were digitized at 360 samples per second with 11-bit resolution over a $10mV$ range. Two or more cardiologists independently annotated every heart beat in each record. We followed the guidelines of the Association for the Advancement of Medical Instrumentation (AAMI)[10] for the definition of classes and measures of performance. Comparing performance with other published results is a difficult task due to the different parameters and criteria used in this field. Our multi-class classification results indicate an average specificity of 92.24% with an average accuracy of 86.99% showing an improvement on previously reported results. Recall and precision show an average of 80.01% and 78.65%, respectively, what makes our approach significant for its use in a clinical context.

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