THREE-STEP-APPROACH FOR THE ANALYSIS OF INFORMATION TRANSMISSION VIA NEURAL SYSTEMS WITH MULTIPLE INPUTS AND OUTPUTS

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Goal. Development of a method for assessing the transinformation via dynamic neuronal systems with multiple inputs and outputs. We want to yield a lower bound of transinformation for both, continuous and discrete input signals with correlated temporal or frequency representations. In particular, the method should be applicable for the development of a retinal prosthesis where we aim to optimize electrical retina stimuli with respect to high resolutions in the spatial, temporal, and intensity domains while minimizing stimulation energy.

Methods. A three step approach is developed using *indirect methods* of calculating transinformation. Its estimation is affected by three separate factors: the model performance, the coordinate system, and the precision of the entropy estimation. Our steps are:

(1) The *deterministic response* of the system is estimated by correlational averaging on the basis of linear kernels to isolate the components carrying stimulus information from those unrelated to the stimulus (defined here as *noise*). Thus, deviations of single-trial *original responses* from the *deterministic response model* comprise *noise*.

(2) Corresponding epochs of original and deterministic responses are transformed to the space of principal components to obtain a linearly independent representation. This is a fundamental requirement for applying the formula for transinformation requiring the additivity of partial information values [1].

(3) Partial transinformation values are calculated for each coefficient either by means of Shannon's information capacity formula [1] assuming normality of the distributions, or by using a density estimation procedure, not depending on the type of distribution [2]. Our method is not restricted to Gaussian stimulus distributions. In addition, it can handle several outputs (e.g., neural recording channels) due to the comprehensive decorrelation achieved by the Principal Component Analysis [3]. Additional to the calculation of overall transinformation our approach allows to relate conditional values of transinformation to individual stimulus features, due to adjustable model properties. This is achieved by optionally including stimulus features into the response model and implicitly utilizing a code related to the currently included features. Our approach is illustrated by calculations of retino-cortical transinformation for Gamma-interval impulse trains as electrical (input) stimuli and multiple μ-electrode recordings from striate cortex in anesthetized cats as output signals.

Results & Conclusions. First we investigated the performance of the algorithms on the basis of simulated data for a variety of parameter settings. We found that a lower bound of transinformation results if nonlinear correlations in the original data can be neglected and the principal component coefficients are approximately normal. The use of a weak deteterministic response model, i.e., one that does not accurately explain the deterministic fraction of the response, only leads to information loss and thus transinformation is underestimated. The data epochs should be chosen just long enough to fully capture the serial correlations inherent in the data.

In a second step we tested the approach on the cat primary visual pathway with electrical stimuli in the retina. Transinformation in the experimental data depended strongly on stimulus parameters such as the mean stimulus impulse rate, the retinal position of the stimulus electrode, and on stimulus intensity (current amplitude).

For systems with relevant nonlinear properties, the calculation of the deterministic response model can be extended by including higher-order (non-linear) kernels [4,5] and by replacing the linear principal component coordinate transformation by an equivalent transformation based on Independent Component Analysis [6]. Thereby, non-Gaussian signal properties and nonlinear correlations can be included in their influence on the transinformation. Finally, we want to encourage the use of artificially generated test data as an objective benchmark for testing the precision of algorithms calculating transinformation.

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