DENOISING SOURCE SEPARATION: FROM TEMPORAL TO CONTEXTUAL INVARIANCE

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We have developed a general framework that allows the guidance of source separation by prior knowledge of the source characteristics. This framework is called denoising source separation (DSS) [2]. The prior knowledge can vary from very detailed knowledge to general principles resulting in blind source separation (BSS). In DSS, the source separation is achieved by decorrelating the input, projecting the input to the source level, denoising and adapting the projection according to the denoised source estimates in a Hebbian way. Additionally, DSS can be realised using online learning. Until now, we have only considered linear projections. However, DSS should generalize to nonlinear projections quite easily.

We have shown that certain independent component analysis (ICA) algorithms, such as FastICA or nonlinear PCA, can be seen as special cases of DSS. In addition, DSS allows for building of the denoising in a procedural way. This is especially useful when the prior knowledge is best described hierarchically. We have, for instance, contemplated the use of speech recognition models to guide auditive source separation.

Neurons actually carry out computations similar to DSS: The decorrelation in DSS implements competition between the elements resembling the lateral inhibitory connections of neurons. Furthermore, neurons learn in a Hebbian way and connect to other neurons forming projections. Finally, denoising can be seen as the central goal of neural information processing.

For this reason, it does not seem unnatural that source separation type of approaches have been successful in reproducing certain features of the cells of the visual cortex. For example, when exposed to natural image data, ICA has been shown to mimic the simple cells of primary visual cortex V1. Even more important has been the reproduction of some constances of the complex cells such as translational and scaling invariance. These have been successfully implemented in slow feature analysis (SFA) [3] and bubble-ICA [1].

The acting principle in these algorithms is the slowness of the stimuli (in bubble-ICA this is called temporal coherence). To us, slowness seems to be one way of achieving context dependency. However, there are examples where stimulus does not change slowly, but the context can aid in making sense of it nevertheless. Such a case is presented in recognition of written characters. Though different characters do not have any visual similarities, the context can be used to determine whether a character is capital 'O' or number zero. In context of other letters, the character would more likely be a letter than a number and vice versa. We speculate that, in addition to slowness, it is possible to account for other types of context invariance as well in DSS framework.

References

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