Pattern Modules of Cuttlefish Coloration

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Introduction

Cuttlefish (Sepiidae) belong to the cephalopods family, known for their ability to change coloration, and have a remarkable range of coloration patterns. The components of chromatic patterning are chromatophore organs, divided in three main color classes of yellow, orange and dark brown, and reflective elements. The chromatophore organs are dominant in patterning due to their transformation ability.

Most of the coloration patterns in cuttlefish are directed towards camouflage, either to avoid predators or to capture prey. But in contrast to other animals, the rich repertoire of patterns in cuttlefish is not restricted to camouflage but also used for communication purposes [1], such as intraspecific behavior (sexual display or antagonistic behavior) especially in adult cuttlefish. Thus, understanding patterning could lead to understanding their behavior.

Research in the field of cuttlefish patterning has indicated that these patterns might be generated by a small amount of pattern modules [2]. Hence, identification of these modules could admit the communicational units of cuttlefish. To this end, what is needed is an effective mathematical/computational tool that could be able to find these modules or provide some insight into the patterning system of cuttlefish. Independent Component Analysis (ICA) might be that tool.



Fig 1: Vivid stripe-like coloration patterns in Cuttlefish. Cuttlefish express a remarkable range of different patterns depending on the situation.

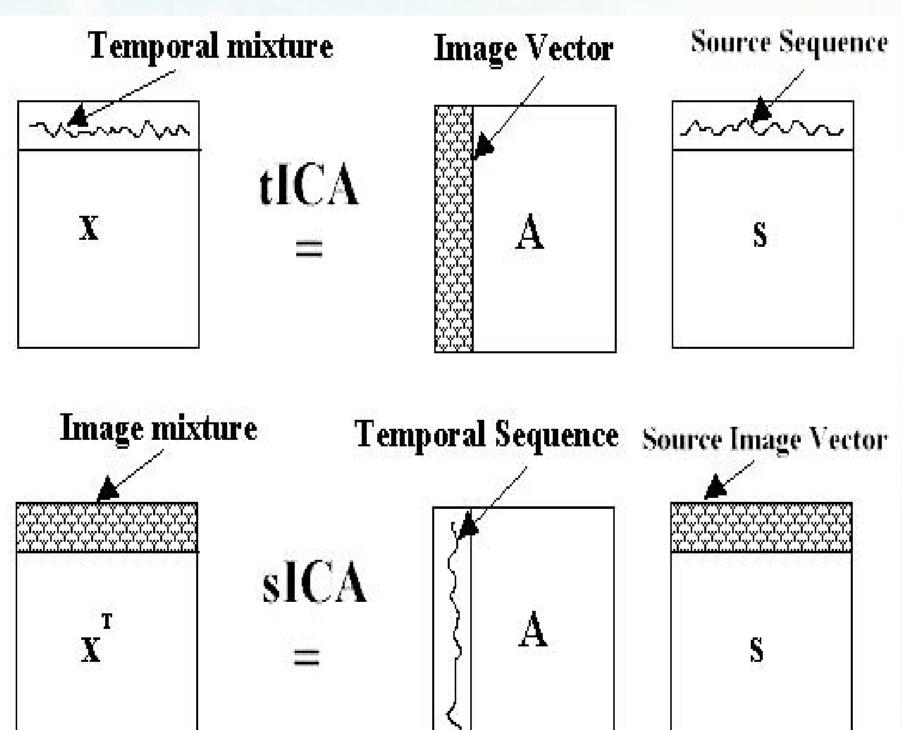
[1] Hanlon, R. T., & Messenger, J. B. (1988). Adaptive coloration in young cuttlefish (Sepia officinalis L.): the morphology and development of body patterns and their relation to behaviour. Philosophical Transactions of the Royal Society of London. B, Biological Sciences, 320(1200), 437-487. [2] Anderson, J. C., Baddeley, R. J., Osorio, D., Shashar, N., Tyler, C. W., Ramachandran, V. S., ... & Hanlon, R. T. (2003). Modular organization of adaptive colouration in flounder and cuttlefish revealed by independent component analysis. Network: Computation in Neural Systems, 14(2), 321-333. James, V. S. (2004). [3] Independent component analysis a tutorial introduction. [4] Comon, P. (1994). Independent component analysis, a new concept?. Signal processing, 36(3), 287-314.

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Independent Component Analysis

ICA is a computational method used for separating a multivariate signal in its sources (images, sounds, e.t.c.) without the need for many assumptions about the sources of these components. The only necessity for ICA to work effectively is that the sources must statistically independent. A common example of ICA is its use in the differentiation of different voices in a mixture signal, but it can also be used for images.

Consider x as a set of signal mixtures. The independent sources are given by y = M x. Where, M is the unmixing matrix. Hence in order to find the sources we need to find the unmixing matrix and thus we need a measure of the independence. This is given by the statistical entropy where maximum entropy means maximum independence. So, ICA works by finding the unmixing matrix **M** that maximized the entropy.



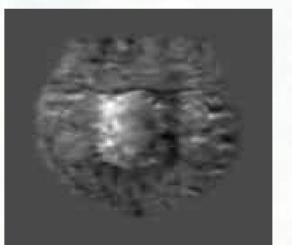
ICA is separated into two main approaches, temporal ICA (tICA) or spatial ICA (sICA) depending on whether the data are independent over time (speech) or over space. In the context of images, a single image is considered a mixture of source images (components) for a single point in time, in the case of sICA, in contrast to tICA where the gray-level of a pixel (single point in space) is considered a mixture of temporal source signals [3].

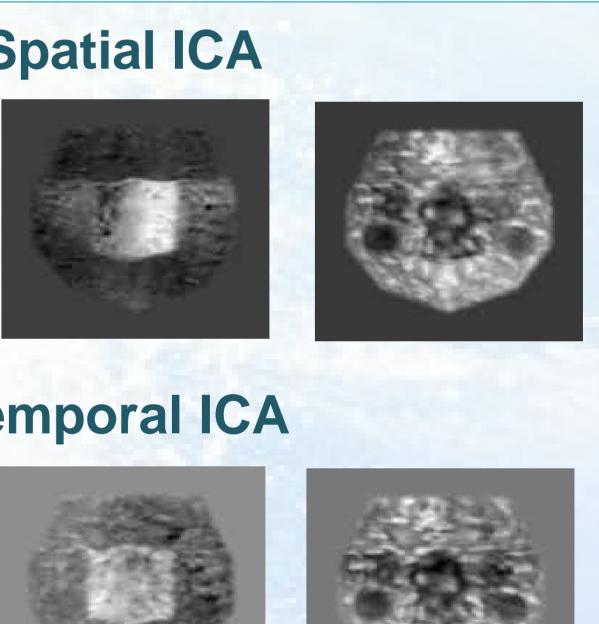
Fig 2 [3]: tICA: Using tICA, the set of observed signal mixtures x is a set into lecomposed temporal source ndependent signals and a corresponding set of unconstrained image vectors. Each ndependent temporal source how the signal determines contribution of one image vector (column of A) to the observed image sequence varies over time.

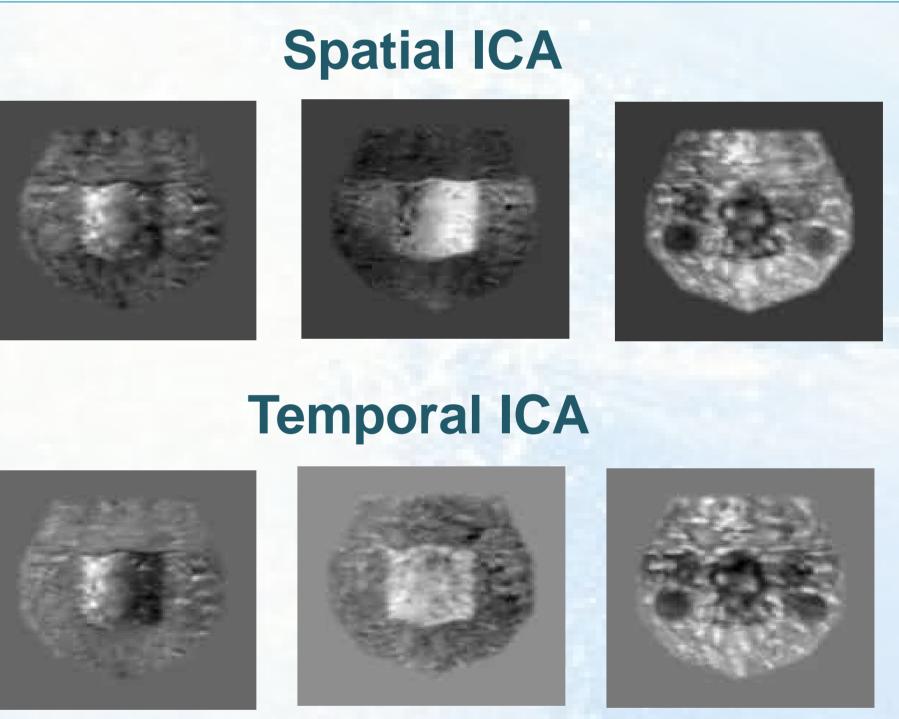
sICA: Using sICA, the set of observed image mixtures \mathbf{x}^{T} is decomposed into a set of independent source images and a corresponding set of unconstrained temporal signals. Each temporal sequence determines how one independent source image vector contributes to the observed image sequence over time

ICA of Cuttlefish Coloration Patterns

Anderson et al. applied both temporal and spatial ICA on a total of 30 images of a single cuttlefish in order to try and identify pattern modules (units). Initially ICA was used on a series of synthetic cuttlefish pattern images, made completely from a linear combination of individual units (squares, lines, e.t.c.). ICA was successful in recovering all the independent modules. Regarding the realistic photos, both methods identified 3 pattern modules accounting for 86-80% of the variation across the images [2]. Although sICA was able to find more spatial components due to the nature of the method, most of them were considered noise apart from the main three. The fact that both methods identified the same three modules indicated that they might be true pattern modules and ICA could provide an effective means of analyzing patterns in animals.







Conclusion

In conclusion, on the one hand ICA seems to provide a viable technique for extracting animal pattern modules. These patterns can be useful in behavioral research (identifying generators, neural control centers) and they need to be observed in a wide range of different behavioral setting to assign a meaning to them. On the other hand what was found from this work is the need for large image datasets as, in the case of tICA, the number of spatial components is severely limited by the number of available photographs.





Spatial Fig component extracted from the 30 images using sICA and tICA respectively. The same three pattern modules are indentified in both methods.



