[https://arxiv.org/pdf/1012.0269.pdf](https://arxiv.org/pdf/1012.0269.pdf%20)

(a) one may consider that the data consist in the realization of tl random variables, each one measured (sampled) on vl voxels. This results in tl 3D spatial maps of activation. Each 3D map is then unrolled (in an arbitrary order) to get a matrix X of size vl × tl . The mixing matrix A is in this case of size tl × tl .

(b) one may consider that the data consist in the realization of vl random variables, each one measured at tl time points. This results in vl time courses each one of length tl , collected into a matrix X of size tl × vl (here again, the order of the vl time courses in the resulting matrix is arbitrary). The mixing matrix A is in this case of size vl × vl .

Case (a) corresponds to spatial ICA (sICA) and the rows of matrix S T contain spatially independent source signals of length n = vl (unrolled source spatial maps).

Case (b) corresponds to temporal ICA (tICA) and the rows of matrix S T contain here temporally independent source signals of length n = tl (source time courses).

Now, due to the large number of voxels in fMRI experiments, it is not computationally tractable to fully diagonalize the correlation matrix in the temporal case (which is in this case of size vl ×vl). So tICA, as far as we know, has never been applied on the entire brain volume but only on a small portion of it

To identify a number of unknown sources of signal, ICA assumes that these sources are mutually and statistically independent in space (sICA) or time C´ecile Bordier, Michel Dojat, Pierre Lafaye de Micheaux 3 (tICA). This assumption is particularly relevant to biological time-series (Friston (1998)). For fMRI data set analyses, sICA is preferred because temporal points (few hundreds, corresponding to each occurrence of a functional image acquisition) are small compared to spatial ones (more than 105 , corresponding to the number of voxels contained in a functional image) leading for tICA to a computationnaly intractable mixing matrix (McKeown, Makeig, Brown, Jung, Jindermann, Bell, and Sejnowski (1998)). However, temporal ICA could be relevant for some neuroscientific applications where temporal independence of sources can be assumed (Calhoun, Adali, Pearlson, and Pekar (2001)). In this context, these authors wrote “... Note that tICA is typically much more computationally demanding than sICA for functional MRI applications because of a higher spatial than temporal dimension and can grow quickly beyond practical feasibility. Thus a covariance matrix on the order of N2 (where N is the number of spatial voxels of interest) must be calculated.

<http://research.ics.aalto.fi/events/ica2000/proceedings/0543.pdf>

It seems that neither spatial nor temporal ICA are a priori superior over the other

<http://ieeexplore.ieee.org.ezlibrary.technion.ac.il/stamp/stamp.jsp?tp=&arnumber=6098493>

sICA can find a set of mutually IC images and a corresponding set of unconstrained time course, whereas tICA can find a set of IC time course and a corresponding set of unconstrained images. From the above analysis, we can draw a conclusion that tICA can be used to detect a desired signal overlapping with some physiological signals in spatial position, which is useful in small signal detection for brain functional connectivity.

<http://www.nrc-iol.org/cores/mialab/publications/2001_HBM_ICA_reprint.pdf>

Note that TICA is typically much more computationally demanding than SICA for functional MRI applications because of a higher spatial than temporal dimension and can grow quickly beyond practical feasibility. Thus a covariance matrix on the order of N2 (where N is the number of spatial voxels of interest) must be calculated. A combination of increased hardware capacity as well as more advanced methods for calculating and storing the covariance matrix may provide a solution in the future.

Independent component analysis can be applied to fMRI data in two different ways, spatial ICA or temporal ICA. To date, spatial ICA has dominated fMRI analysis even though initially temporal ICA was introduced to the field. We have provided data demonstrating that SICA and TICA can have diverging results, depending upon the characteristics of the underlying signals to be estimated. In particular, when the assumption of spatial or temporal independence is strongly violated (e.g., the signals are highly dependent spatially or temporally, respectively), then ICA results do not agree with regression.

Note that spatial ICA has only previously been shown to produce similar results to temporal ICA when there is a single task-related waveform. We find that they also produce similar results in the case of two components only where the components are uncorrelated in both the spatial and the temporal dimensions. Additional considerations are needed when attempting to apply ICA to an experiment in which two waveforms induced by the researcher are involved. Of primary consideration should be whether the waveforms (or hypothesized activated areas) are heavily dependent either in time or space. If such is the case, then temporal ICA or spatial ICA, respectively, should not be applied or, if applied, the results should be interpreted carefully. Future studies are needed to further elucidate the application and interpretation of ICA analyses