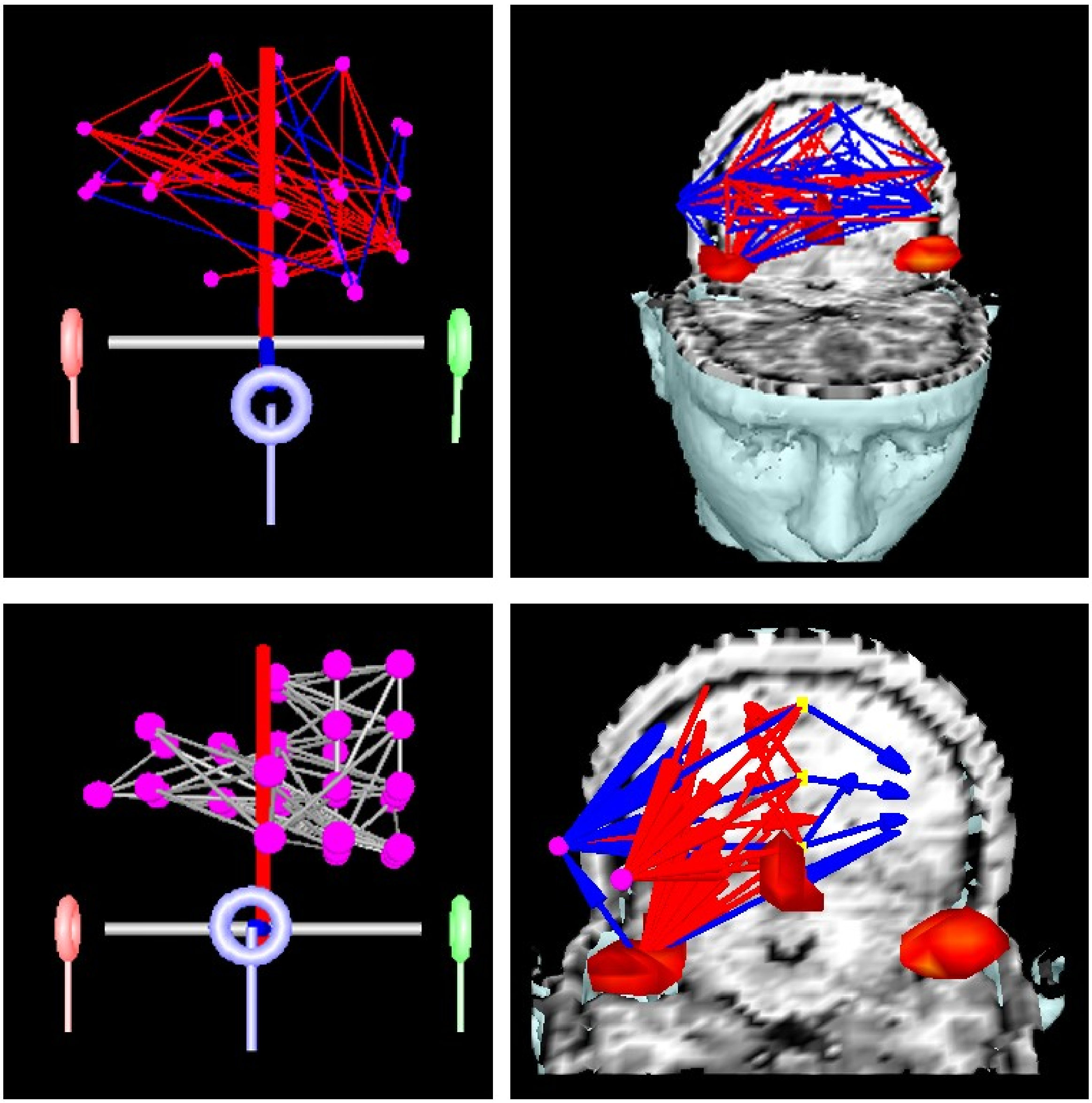
Neural Network at Source Levels

Software Guide (EEG/MEG Data)



DISCLAIMER

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Features and specifications of this software program are subject to change without notice. This manual contains information and images about our software and its user interface, GUI and its other signal processing algorithms, publications that may be protected by copyright. The software is designed to analyze source coherence, correlation and association.

Sending Your Comments and Critiques: We would like to hear from you. Your comments and suggestions for improving this document are welcome and appreciated. Please e-mail your feedback to BrainX@live.com

Thank you.

Contents

Warnings and Cautions

The correlation or association between signals from two sources in the brain can be analyzed in several ways. The coherence of a two-source pair has been frequently used in the study of brain function. The study of the oscillatory synchrony between two sources can be done by computing the coherence, correlation and covariance. This can be performed in the frequency domain by normalizing the magnitude of the summed cross-spectral density between two signals by their respective power. For each frequency bin the coherence value is a number between 0 and 1. The coherence values reflect the consistency of the phase difference between the two signals at a given frequency. The correlation or association between two sources can also be analyzed in “source waveforms”, which are typically termed as “virtual sensor” waveforms.

By changing or delaying the time-points in the “virtual sensor” spectrograms or waveforms, the correlation/coherence/covariance can also be used to describe the “causality of two sources”. Of notes, the “source coherence” is a general name for a set of functions that were designed for analyzing the relationship of two-source pairs.

This program is optimized for computing source coherence for all possible pair in volumetric source images, for example, all voxel pairs in a set of time-slices in volumetric source images. If there are N voxel points for computing source coherence, the results will be a matrix with size of N by N. Consequently, the results can be systematically analyzed with matrix operations.

Preface

This guide describes the operation applying to the source waveforms from two areas in the brain. The source coherence module is one of the core functions in MEG/EEG data analysis. It is used as the primary tool to determine if the signals from two brain areas are correlated. The source coherence module provides graphic user interface (GUI) for access the functions.

Intended Audience

This guide is intended for persons responsible for analyzing the correlation of source pairs in the brain. This reference is useful to anyone who performs analysis techniques for MEG/EEG data. Operations of correlation and covariance analysis require some expertise to satisfy requirements of accuracy and fitness for use of the results. Technicians may use the application under review by highly trained analytical staff. The guide assumes the reader is familiar with standard MEG/EEG procedures and is familiar with the Windows operating systems.

The volumetric data generated by source coherence operation can be used in causality analysis.
We typically use “virtual sensors” to refer to the waveforms or spectrograms from sources in the brain, at source levels.
We typically use “virtual channels” to refer to the waveforms or spectrograms generated by two or more physical channels, at sensor levels.

References

This document assumes familiarity with many terms related to computer operations and physiology. This document also assumes you are familiar with the principles of correlation coefficients, covariance and virtual sensors as well as the data collection and recording process. It also assumes some knowledge of MEG/EEG analysis. The document uses terms related to computer operations and physiology as well as many acronyms.

Document Structure

Documents are generally provided in both Microsoft Word® format and Adobe® Acrobat® PDF (Portable Document Format). All editions are distributed on Flash Driver, CD or websites with the related software, and include bookmarks and hyperlinks to assist navigating the document. Please feel free to send your critiques, corrections, suggestions and comments to: BrainX@live.com.

Conventions

Numeric: Numeric values are generally presented in decimal but in special circumstances may also be expressed in hexadecimal or binary. Hexadecimal values are shown with a prefix of 0x, in the form 0x3D. Binary values are shown with a prefix of 0b, in the form 0b00111101. Otherwise, values are presumed decimal.

Units: Units of measure are given in metric. Where measure is provided in imperial units, they are typically shown in parenthesis after the metric units. Magnetic signal strength is given in Teslas (T), the SI unit of flux density (or field intensity) for magnetic fields, also known as the magnetic induction. Typical signal strengths in MEG measurements are in the order of pT (picoteslas = 10^{-12}) or fT (femtoteslas = 10^{-15}).

Changes from Previous Releases

If you used the software before, please read the ReadMeFirst.doc file for late changes that did not make it into this manual and for a list of new functions or options, changes, additions, bug fixes, and known bugs for the application. In comparison with previous version of the software, this version of the software only provides volumetric image for coherent sources (VICS). The main reason for this change is to provide better user experience and minimize the use of "manually selected sources", which are subjective, error-prone and time-consuming. However, virtual sensor waveforms and spectrograms can still be computed in the "virtual" sensor software module.

Introduction

This manual describes the various graphical elements that make up source coherence analysis module and defines the source coherence data throughout the software applications. There are several ways to analyze the correlations of source waveforms or source spectrograms. In this guide, the source coherence operations will be discussed according to the computing of source coherent data and the visualization of source coherent data. The mathematic algorithms will be explained briefly.

Graph Theory

Graph theory (GT) concerns the relationship among lines and points. It gives a language for networks. In mathematics and computer science, graph theory is the study of graphs, which are mathematical structures used to model pairwise relations between objects. It allows us to define networks exactly and to quantify network properties at all different levels. This quantification is likely to improve further since new graph measures are described regularly. The real challenge of modern network theory is to come up with models that combine mathematical elegance with explanatory power.

In graph theory, a graph is a mathematical representation of a network. A graph, usually indicated by the letter G, consists of a set of nodes or vertices (V) or points and a set of connections or edges (E) or links between these vertices: G(V,E). Two vertices are called neighbors if they are connected by an edge. In an unweighted or binary network edges are absent (0) or present (1); in a weighted network a weight w can be assigned to each edge. The weight can represent the strength of the connection, or some physical distance between the two connected vertices.

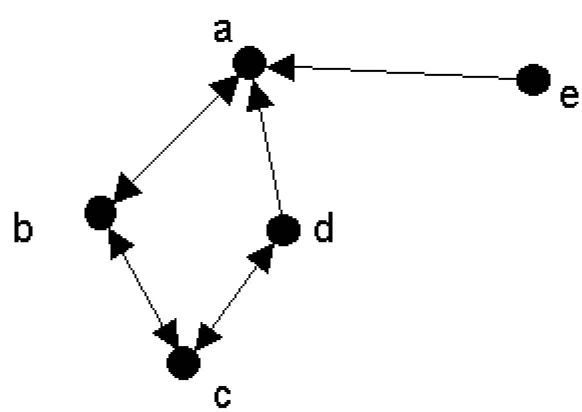
Edges connecting vertices can be undirected or directed. Directed edges represent the fact that one vertex exerts some influence on its neighbor but not the other way around. A graph can also be represented by a square matrix where the number of rows and columns is equal to the number of vertices. This matrix is called the adjacency matrix of the graph and is often referred to by a capital A. In an undirected graph the matrix A is symmetrical; in a directed graph A does not have to be symmetrical. In an unweighted graph the cells of A have a value of 0 if no edge exists between the two vertices and a value of 1 if two vertices are connected by and edge. In a weighted graph a weight can be assigned to each edge. The size of a graph is equal to the number of vertices of the graph. A graph is connected if any vertex can be reached from any other vertex. In a complete graph all possible edges exist.

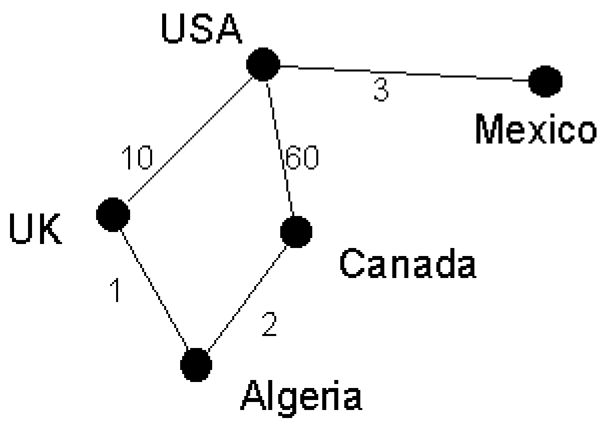
Adjacent: if a line connects two points, they are said to be adjacent;

Incident: two edges that share a point are said to be incident;

There are many synonyms for the terms "node" and "line":

Node	**Line**
• vertex	• edge
• point	• link
• actor	• tie





Measurements in graph theory

A graph G consisting of a set of vertices V and a set of edges E can be characterized by several measures, some relatively simple, others quite complex. Here we describe measures for unweighted networks. For most of these measures weighted versions have now been described as well.

Degree

One of the most important and elementary measures is the degree, often indicated by k. The degree of a vertex is the number of connections or edges it has. The probability that a randomly chosen vertex will have degree k is given by the degree distribution, indicated by P(k). The form of the degree distribution provides important information about the structure of the network. As described below, different types of graphs have their own characteristic degree distribution.

The degree of a point is defined as the number of lines incident upon that node. In Figure 3, the degree of USA is 3 because it has 3 ties. If a point has degree 0 it is called an isolate. If it has degree 1 it is called a pendant.

In a directed graph, a point has both indegree and outdegree. The outdegree is the number of arcs from that point to other points. In Figure 2, the outdegree of node a is 1. The indegree is the number of arcs coming in to the point from other points. The indegree of node a in Figure 2 is 3.

Clustering coefficient

The clustering coefficient of a vertex is the probability that the neighors of this vertex (all other vertices to which it is connected by an edge) are also connected to each other. The clustering coefficient of a vertex ranges between 0 and 1. The average clustering coefficient C of the whole network is the average of the clustering coefficients of all individual vertices. The clustering coefficient is considered to be a measure of the local connectivity or "cliqueness" of a graph. High clustering is associated with robustness of a network, which is resilience against random network damage.

Motifs

The clustering coefficient is a special case of a more general graph property referred to as motifs. The clustering coefficient depends upon the presence of the triangle motif, consisting of three vertices fully connected by edges. Other more complex motifs exists as well, and their presence in graphs can be quantified.

Modules

Subgraphs that consist of sets of vertices that are more strongly connected to each other than to the rest of the network are called modules. Identification of modules within complex networks is important, since modules often correspond to different functional aspects of the networks, and modules may also be important for the way normal and abnormal activity can spread through the network. It is also possible to define modules within modules. Networks with such a structure are said to have a hierarchical modularity. The concept of a module is a statistical one. Different definitions of modularity exist, the most well-known being the modularity as defined by Newman. Alternatively, modularity can also be defined in terms of the eigenvalues and eigenvectors of the graphs matrix.

The clustering coefficient, motifs and modules are descriptions of network structure at increasingly larger scales.

Path length and efficiency

Whereas clustering reflects local network structure, the shortest path length reflects the level of global integration in the network. A shortest path between two nodes A and B is the path between A and B with the smallest number of edges. The average shortest path L of a network is the average of all shortest paths between all pairs of vertices. The diameter of a graph is the longest of all shortest paths. Related to the idea of the average shortest path is that of global efficiency, which is the inverse of the average shortest path. The local efficiency of a particular vertex is the inverse of the average shortest path connecting all neighbors of that vertex.

A path is an alternating sequence of points and lines, beginning at a point and ending at a point, and which does not visit any point more than once. Two (or more) paths are point-disjoint (also known as vertex-independent) if they don't share any nodes. Two paths are edge-disjoint (edge independent) if they don't share any edges. If they are point-disjoint, then they are definitely edge-disjoint. But if they are edge disjoint, they might not be point-disjoint.

A walk is like a path except that there is no restriction on the number of times a point can be visited. A path is a kind of walk.

A cycle is just like a path except that it starts and ends at the same point.

The length of a path or walk (or cycle) is defined as the number of edges in it.

The shortest path between two points is called a geodesic. It is not always unique (that is, there may be several paths between the same two points that are equally short). The graph-theoretic distance between two points is defined as the length of the shortest path between them.

If something is flowing through a network (such as gossip, or a disease), the time that it takes to get from one point to another is partly a function of the graph-theoretic distance between them. Nodes that are not far, on average, from all other nodes, tend to receive what's flowing through the network sooner than other nodes.

A graph is connected if there exists a path (of any length) from every node to every other node. The longest possible path between any two points in a connected graph is n-1, where n is the number of nodes in the graph.

A node is reachable from another node if there exists a path of any length from one to the other.

A connected component is a maximal subgraph in which all nodes are reachable from every other. Maximal means that it is the largest possible subgraph: you could not find another node anywhere in the graph such that it could be added to the subgraph and all the nodes in the subgraph would still be connected.

For directed graphs, there strong components and weak components. A strong component is a maximal subgraph in which there is a path from every point to every point following all the arcs in the direction they are pointing. A weak component is a maximal subgraph which would be connected if we ignored the direction of the arcs.

A cutpoint is a vertex whose removal from the graph increases the number of components. That is, it makes some points unreachable from some others. It disconnects the graph.

A cutset is a collection of points whose removal increases the number of components in a graph. A minimum weight cutset consists of the smallest set of points that must be removed to disconnect a graph. The number of points in a minimum weight cutset is called the point connectivity of a graph. If a graph has a cutpoint, the connectivity of the graph is 1. The minimum number of points separating two nonadjacent points s and t is also the maximum number of point-disjoint paths between s and t.

A bridge is an edge whose removal from a graph increases the number of components (disconnects the graph). An edge cutset is a collection of edges whose removal disconnects a graph. A local bridge of degree k is an edge whose removal causes the distance between the endpoints of the edge to be at least k. The edge-connectivity of a graph is the minimum number of lines whose removal would disconnect the graph. The minimum number of edges separating two nonadjacent points's and t is also the maximum number of edge-disjoint paths between s and t.

Assortativity

Related to the notion of degree is the concept of mixing or assortativity. If vertices with a high degree tend to be connected to other vertices with a high degree, and vertices with a low degree to other low degree vertices, the graph is said to be assortative. An assortative graph has a positive degree correlation. In a disassortative graph, the degree correlation is negative, and high degree vertices tend to connect to low degree vertices and vice versa.

Centrality and hubs

Another important concept related to that of node degree is centrality. Centrality refers to the relative importance of a node or vertex within the network. Node degree is in fact one, relatively simple measure of centrality. A more sophisticated measure of centrality is betweenness. The betweenness centrality of a particular vertex is the fraction of shortest paths in the network that pass through this vertex. In a similar way, betweenness centrality can also be defined for edges (edge centrality). Another concept of centrality is based upon graph spectral analysis. Eigenvector centrality of a vertex is the value of the vector component, where the vector is vector that corresponds to the largest eigenvalue (spectral radius) of the adjacency matrix. If the notion of hub centrality is combined with the definition of modules it becomes possible to classify hubs. Hubs that are mainly connected to other vertices in the same module are referred to as provincial hubs; hubs that are mainly connected to vertices in other modules are called connector hubs. Provincial and connector hubs may play different functional roles within a network.

Graph spectral analysis

Graph spectral analysis is an interesting alternative way to characterize the adjacency matrix of a graph and its related Laplacian matrix. The Laplacian matrix contains the node degree as diagonal elements, and -1 for all cells corresponding to existing edges and 0 for cells corresponding to absent edges. If the adjacency and Laplacian matrix are symmetrical, and eigenvalue / eigenvector analysis can be performed, resulting in a series of eigenvalues and corresponding eigenvectors. It is assumed that the series of eigenvalues and eigenvectors represent all information present in the graph. Some graph spectral measures have special significance. The largest eigenvalue of the adjacency matrix is called the spectral radius and is inversely related to the synchronization threshold of dynamical processes on the graph. In addition, the values of its corresponding vector are a measure of centrality. The spectral gap (the difference between the largest and the second largest eigenvalue) provides information on how rapid the synchronous state is reached. The second smallest eigenvalue of the Laplacian matrix is called the algebraic connectivity. It is a measure of network robustness. If the algebraic connectivity is 0, the network consists of at least two disconnected components. The ratio of the largest and the second smallest eigenvalues of the Laplacian matrix is a measure of the stability of the synchronous state of a dynamical process on the network. The information contained in graph spectral analysis can also be used to identify modules within the network.

Models of complex networks

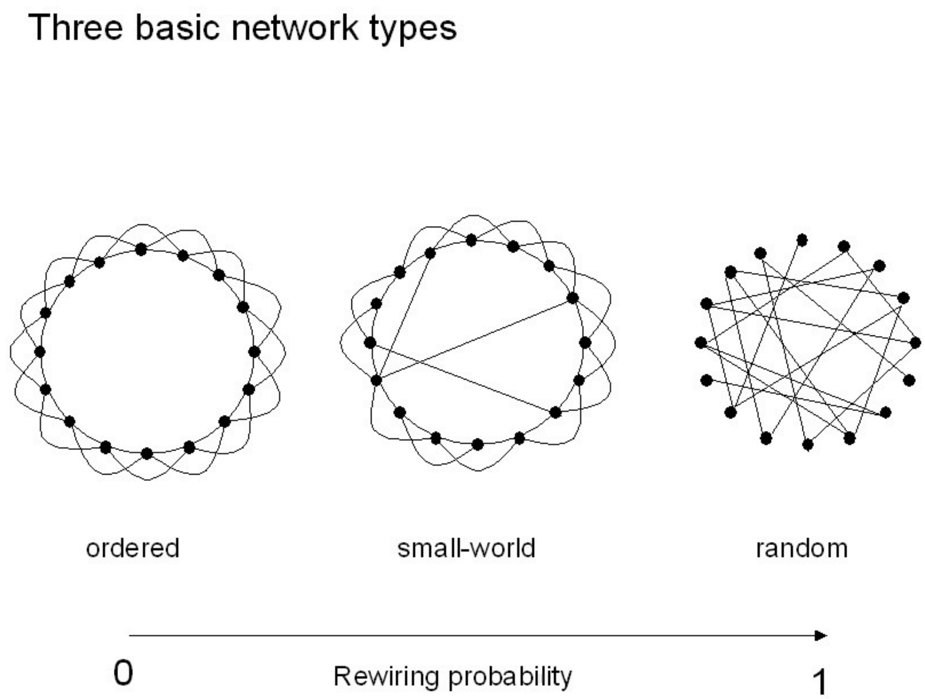
Models are extremely important in modern network theory. It can be argued that the discovery of models for very large networks with a mixture of randomness and order lies at the heart of the transition from conventional graph theory to the modern science of networks. Here we describe three prototype models that illustrate many of the key principles.

Random network (graph)

The oldest model of complex networks is that of random graphs as introduced by Rapoport and analyzed in detail by Erdos and Renyi. In a random graph G(V,E) edges between any pair of vertices exist with a probability p. The properties of the random graph have been studies extensively and many important mathematical results have been obtained. For instance, if p is increased from 0 to 1, the size of the largest connected component in the graph will undergo a phase transition at p=0.5. Random graphs have a low clustering coefficient, a small average shortest path length, no assortativity, a narrow degree distribution and not real hubs. While random graphs can explain some properties of real complex networks, notably the short distances between any two nodes, they fail in other respects. In particular, random graphs cannot explain the ubiquitous presence of clustering, modularity and hubs in real networks. Some of these problems were solved by the introduction of more sophisticated models at the end of the nineties in the last century.

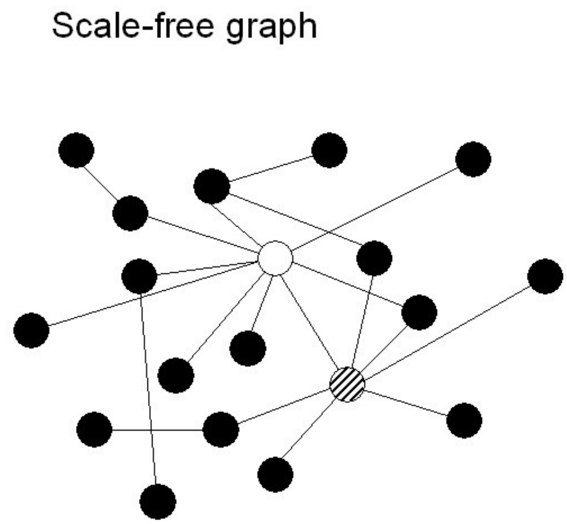
Small-world network (graph)

Small-world networks, according to Watts and Strogatz, are a class of networks that are “highly clustered, like regular lattices, yet have small characteristic path lengths, like random graphs.” These characteristics result in networks with unique properties of regional specialization with efficient information transfer. Watts and Strogatz (1998) considered a network on a ring, where each vertex is connected to k neighbors, k/2 in the clockwise direction, and k/2 counter clockwise. This is an ordered, lattice-like network. It has a high clustering coefficient, a long average shortest path length, no modularity or assortativity, a symmetric degree distribution, and no hubs. Next, with a probability p, edges are disconnected and attached to a randomly chosen other vertex. For p = 1 all edges are reconnected, and a random network is obtained, with all corresponding properties such as low clustering and short path lengths. The interesting region is for intermediate values of p. Even for small but non zero values of p, with only a small fraction of rewired edges, the path length already drops to very low values, while the clustering coefficient still maintains its original high values. This type of network, that combines high clustering with short path lengths, is called a small-world network. Despite its apparent simplicity it is in fact a very powerful model of many real networks that often display the same combination of high clustering and short path lengths. However, the Watts and Strogatz (WS) model fails to explain other important properties of natural networks such as modularity and broad degree distributions with hub like nodes. This last problem was solved in another model.



Scale-free networks

Barabasi and Albert proposed a model of a growing network. At each iteration, a new vertex is added, and it is connected to existing vertices with a probability that depends upon the degree of that node. As a consequence, nodes with a high degree are more likely to receive more connections, increasing their degree even further. This is an example of positive feedback or preferential attachment. The most interesting feature of the model is the shape of its degree distribution. After a sufficient number of iterations the degree distribution becomes a power law: P(k) = kgamma, where gamma = 3. This power law distribution reflects the presence of large number of highly connected nodes or hubs. Networks with a power law degree distribution are referred to as scale-free (SF). In contrast to WS networks, scale-free networks can explain the presence of hubs in networks, and suggest a growth scenario that gives rise to these hubs. For these reasons SF models have become very important in modern network research. However, even SF models have their limitations: they do not explain clustering very well, they are not assortative, and have no real modules.



Clustering coefficients

In undirected networks, the clustering coefficient Cn of a node n is defined as Cn = 2en/(kn(kn-1)), where k_n is the number of neighbors of $_n$ and e_n is the number of connected pairs between all neighbors of *n* [1, 2]. In directed networks, the definition is slightly different: Cn = en/(kn(kn-1)).

$C_n = \frac{2e_n}{k_n(k_n-1)}$ non-directed network

$C_n = \frac{e_n}{k_n(k_n-1)}$ directed network

In both cases, the clustering coefficient is a ratio N / M, where N is the number of edges between the neighbors of n, and M is the maximum number of edges that could possibly exist between the neighbors of n. The clustering coefficient of a node is always a number between 0 and 1.

The average clustering coefficient distribution gives the average of the clustering coefficients for all nodes n with k neighbors for k = 2,…. NetworkAnalyzer also computes the network clustering coefficient that is the average of the clustering coefficients for all nodes in the network.

The clustering coefficient of a node is the number of triangles (3-loops) that pass through this node, relative to the maximum number of 3-loops that could pass through the node.

[1] Watts D.J., Strogatz, S.H.: Collective dynamics of 'small-world' networks. Nature 393 (1998) 440-442

[2] Barabási, A.L., Oltvai, Z.N.: Network biology: understanding the cell's functional organization. Nat Rev Genet 5 (2004) 101-113

Graph Theory in MEG/EEG

The ER, WS and SF models each constitute major steps forward in this respect. However, as we have indicated, none of these models solves all problems. We need new models that explain how networks can emerge, and how high clustering, short paths, modules and hubs can arise with a minimum number of realistic assumptions. In addition, such models should explain the nature of dynamical processes taking place on the networks, as well as the circular causality between network topology and network dynamics. These are the challenges of modern network theory.

Coherence and VICS

The analysis of the correlations of two sources can be done in a single pair of source data or a group of source pair. The design of "VICS" was to perform coherence analyses for all possible source pairs in a volumetric source image with a set of time-slices. The coherence is a statistic that can be used to examine the relation between two signals or data sets. It can be used to estimate the causality between the input and output or the connectivity of two datasets. Although the computation of tw-source relationship is easy by a few clicks, the interpretation of the outcomes of those measures in terms of brain networks and activity remains challenging and should be exercised with caution.

Many measures of connectivity exist, and they can be broadly divided into measures of functional connectivity (denoting statistical dependencies between measured signals, without information about causality/directionality), and measures of effective connectivity, which describe directional interactions. The characterization of the correlation between channels can be done with 3D coherence images, it is possible to analyze and describe certain network features in more detail with external toolboxes.

Major Innovations in Source Coherence Analyses

The analysis of the relationship of two source-waveforms is not new. The major innovations are to: (1) systematically analyze source coherences in volumetric source images for all possible pairs; (2) analyze source coherence in both low- and high-frequency source data; and (3) volumetrically visualize source coherence in 3D coordinates.

Menu for Launching VICS Windows

The menu for launching VICS windows is in the Main Frame of the MEG Processor program, which is under the VICS menu (Figure 1). MEG/EEG data for source coherence analysis can be volumetric source data, sensor waveforms and spectrograms with or without pre-processing. This manual describes the various graphical elements that make up VICS computing, analyzing and visualizing modules throughout the software application.

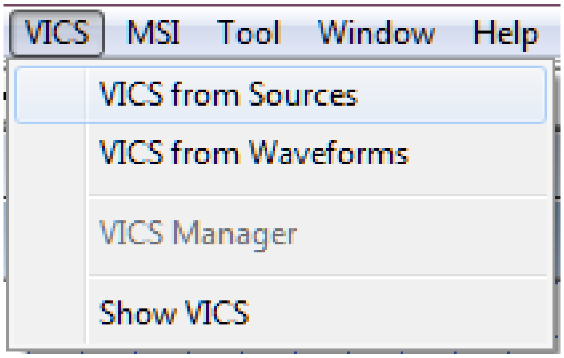


Figure 1. Menu for launching VICS (Volumetric image for Coherent Source) Windows.

Compute VICS with Source Images

Selection of “VICS from Sources” menu launches the main window for computing VICS with source images, which are volumetric source with multiple time slices. The Window GUI application allows you to configure parameters and processing options for computing volumetric coherence images as well as other kinds of analysis.

VICS computing is performed after volumetric source data have been acquired and reviewed. Here is the recommended procedure for standard computing using “VICS from Sources” program:

a) Check and verify that you have the correct source data using MSI Studio (see the MSI Studio Guide).
b) If the Settings for Computing VICS main window has not been launched. Select “VICS from Sources” in the Menu (see “Menu for Launching VICS Windows”)
c) Check and analyze the source data to determine the trial or trigger. Typically, current trial (“Current”) is selected for computing VICS.
d) Find and select the source image file
e) Decide the voxel item ID. This program supports multiple voxel values for one spatial point. To minimize the use of memory, one voxel item ID can be selected for computing coherence images.
f) During the launching of the window for Settings for Computing VICS, the program gets the available source data from the current trial. The program also checks the integrity and sanity of the source data and may report warning/error messages if necessary.

g) Use the window for “for Settings for Computing VICS” to inspect the source data as well as suitable parameters. If required or necessary, change the data selections.

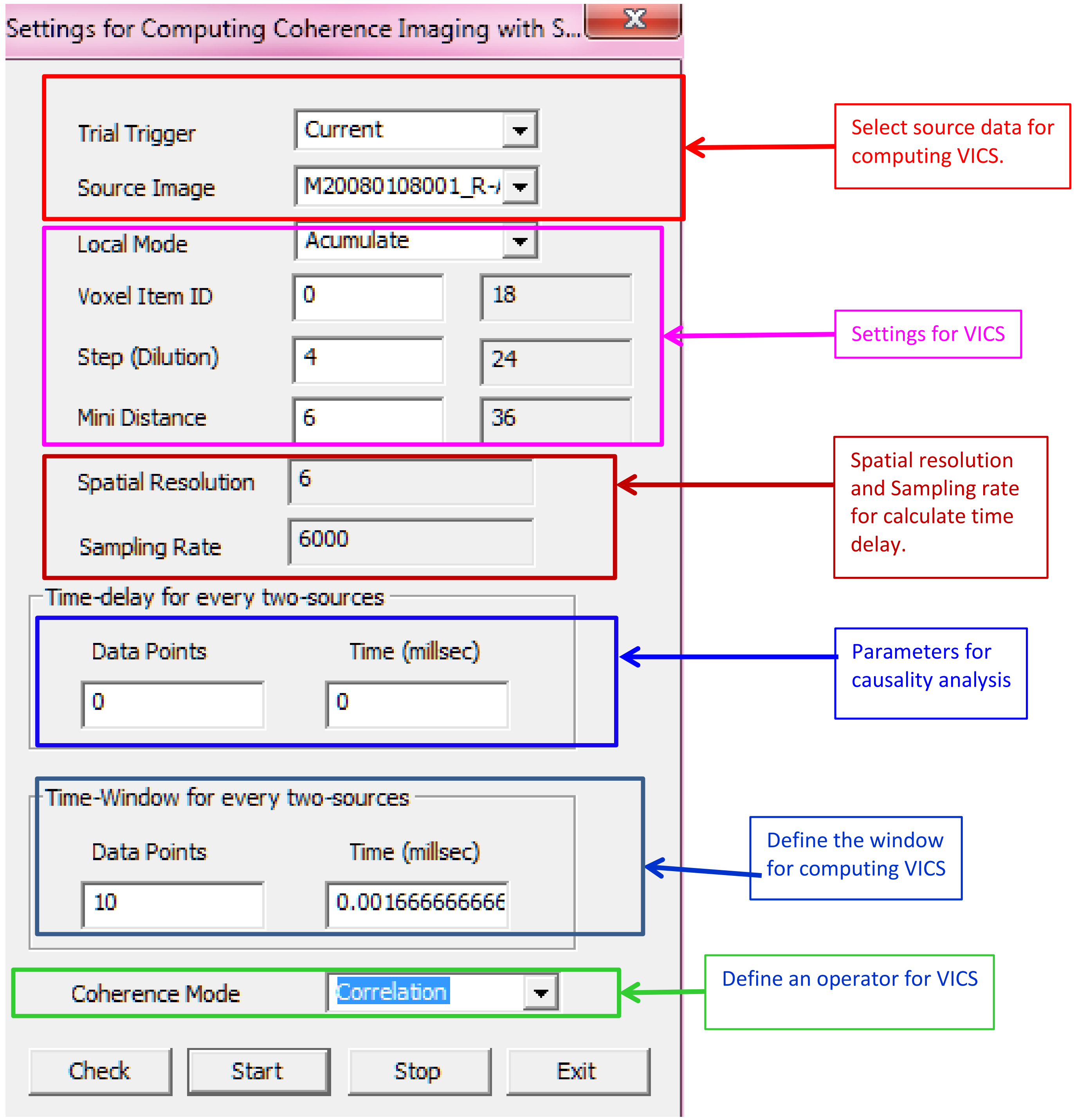


Figure 2. Settings for analyzing the correlations of every source pairs in volumetric source images.

Main Modules in VICS Computing

The full suite of VICS computing comprises the following components.

- Source Data Selection
- VICS parameters
- Time delay for Causality Analysis (Granger)
- Time window for correlation, coherence or association
- Start VICS computing

Target data (Source Data)

The data selection specifies the trial, or a type of triggers, which typically include a group of trials, to be used for VICS computing.

VICS parameter

The coherence value can be computed for computing VICS.

Local Mode: It has at least two options: accumulate and best. The correlation of two sources can be computed for each voxel (step = 1) or a local area (step > 1). If the correlation is computed from a local area, an averaged value (accumulate) or the best value can be stored in VICS.

Voxel Item ID: One voxel item ID is typically selected to be used for computing VICS. Since this program supports multiple voxel values for one spatial location, the selection of voxel item ID define which component is of interest. Appropriate use of this option can minimize the use of memory and avoid computing voxel components that are not useful.

Step (Dilution): The step or dilution defines the spatial resolution in VICS, which is of course relative to the volumetric source images. If the Step is 1, there is no dilution and the spatial resolution of VICS will be equal to that of the original source images. If the Step is larger than 1, the spatial resolution will be diluted, consequently, the Local Mode should be selected carefully.

Mini Distance (Minimum Distance): The step or dilution defines the spatial resolution in VICS, which is of course relative to the volumetric source images. If the Step is 1, there is no dilution and the spatial resolution of VICS will be equal to that of the original source images. If the Step is larger than 1, the spatial resolution will be diluted, consequently, the Local Mode should be selected carefully.

Spatial Resolution: The spatial resolution is the original spatial resolution in volumetric source image, which is provided for appropriately defining the Step and Minimum Distance for computing VICS. By using the spatial resolution, you may define Mini Distance and Step to analyze the functional correlations in various brain lobes (e.g. left and right temporal lobes).

Sampling Rate: Sampling rate indicate the sampling rate in the original source images, which is provided for appropriately calculating the time window and time delay for computing VICS.

Causality Analysis and Time-Delay

To analyze the causality relationship of two sources, the time-delay parameter is provided to define if a source always follows another source. If source A is always behind source B, then source A is probably the results of source B or the activation of B causes the activation of source A.

The causality analysis (Granger) is a statistical hypothesis test for determining whether one time series is useful in forecasting another or cause events in another. Specifically, a time series channel A is said to Granger-cause channel B if it can be shown, usually through a series of t-tests and F-tests on lagged values of A (and with lagged values of B also included), that those A values provide statistically significant information about future values of B.

A long held belief about neural function maintained that different areas of the brain were task specific; that the structural connectivity local to a certain area somehow dictated the function of that piece. Collecting work that has been performed over many years, there has been a move to a different, network-centric approach to describing information flow in the brain. Explanation of function is beginning to include the concept of networks existing at different levels and throughout different locations in the brain. The behavior of these networks can be described by non-deterministic processes that are evolving through time. That is to say that given the same input stimulus, you will not get the same output from the network. The dynamics of these networks are governed by probabilities so we treat them as stochastic (random) processes so that we can capture these kinds of dynamics between different areas of the brain.

Correlation/Covariance and Time-window

The time-window defines the time period that generates enough data points to quantitatively determine the relationships of a two-source pair. Theoretically, the time-window should be equal or close to the time-period of source activation.

The program provides the “Correlation” and “Covariance” operators for analyzing the relationships of source pairs.

Sliding Time Window

The step of sliding time window in source coherence analysis is 1.

Running Source Coherence Analysis

Click the “Start” button will start to run the VICS computing. Once it is started, the window title bar will show the progress of the computing.

The VICS computing calls several internal dynamically linked libraries to perform a variety of operations. Here are some steps:

1) Check and select the source data for VICS Computing.
2) Check and correct the parameters for VICS computing, if necessary.
3) Estimate the necessary memory, if necessary
4) Compute coherent source data for each source pair
5) Compute the summary of all source pairs, if necessary
6) As usual, the volumetric image for coherent sources are available to be viewed using source coherent Viewer.

Compute VICS with Waveforms

Selection of “VICS from Waveforms” menu launches the main window for computing VICS with waveforms. The Window GUI application allows you to configure parameters and processing options for computing volumetric coherence images as well as other kinds of analyses.

VICS computing is performed after waveform data have been acquired and reviewed. Here is the recommended procedure for standard computing using “VICS from Sources” program:

a) Check and verify that you have the correct dataset and trials in the Waveform Viewer (see the MEG Processor Main Frame Guide).
b) If data averaging is necessary or required, do the averaging first. Once multiple trials have been averaged successfully, there is at least one averaged trial (“virtual trial”) will be added to the MEG dataset, which is available in the main Frame for waveform viewer.
c) Filtering and/or removing DC-offset is typically required or necessary. If you do think so, apply the filtering/DC-offset to the targeted trial;
d) Check and analyze the MEG/EEG data to determine the interest of time-window. Though there is no standardized way, it is a good idea to use “Overlay” viewer to determine the interest of time-window with all “sensors”.
e) If the Settings for Computing VICS main window has not been launched. Select “VICS from Waveforms” in the Menu (see “Menu for Launching VICS Windows”)
f) During the launching of the window for Settings for Computing VICS, the program gets the available source data from the current trial. The program also checks the integrity and sanity of the source data and may report warning/error messages if necessary.
g) Decide the voxel item ID. This program supports multiple voxel values for one spatial point. To minimize the use of memory, one voxel item ID can be selected for computing coherence images.

h) Use the window for "for Settings for Computing VICS" to inspect the data as well as suitable parameters. If required or necessary, change the data selections.

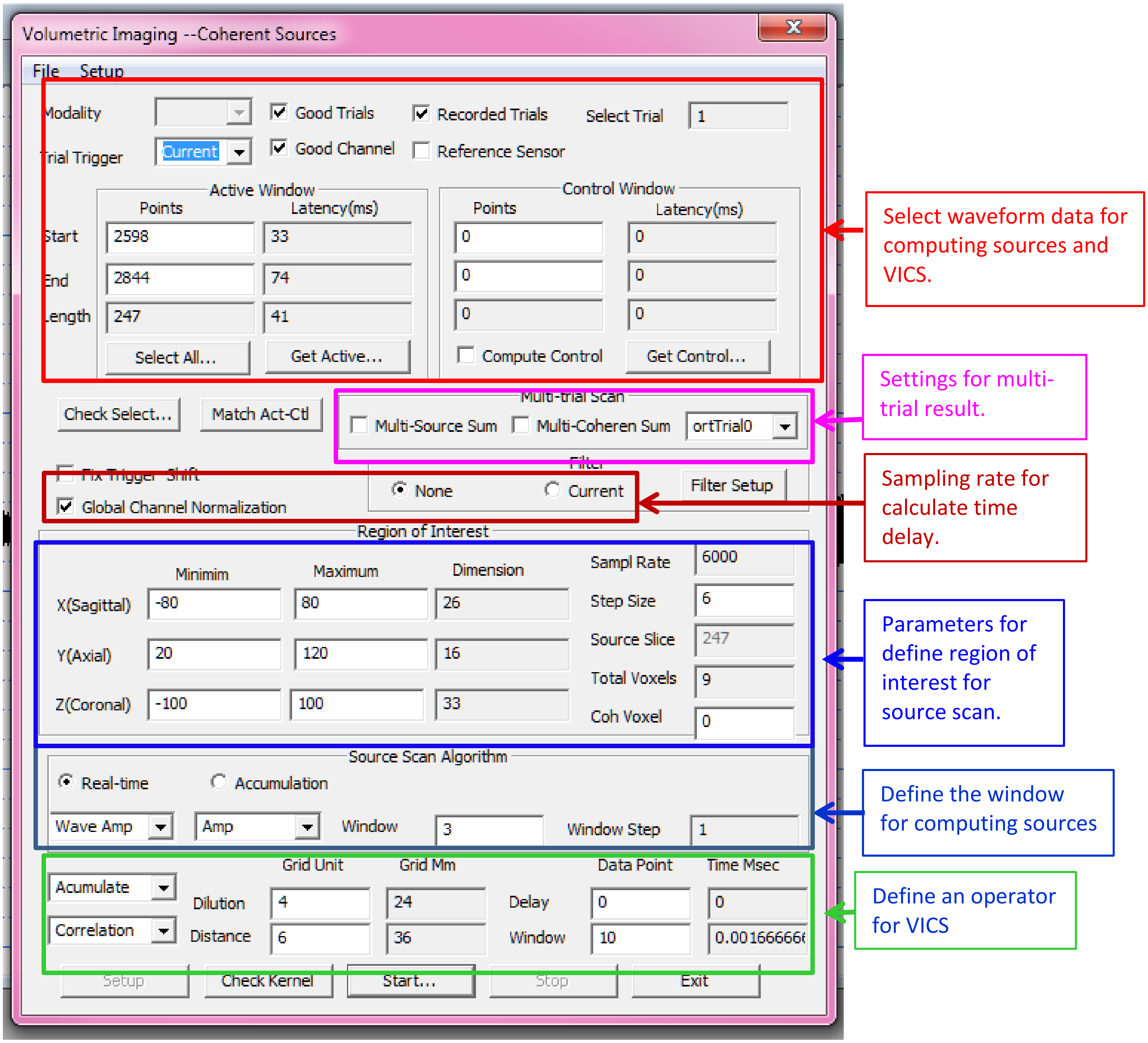


Figure 2. Settings for computing VICS with waveform data.

Main Modules in VICS Computing

The full suite of VICS computing comprises the following components.

- Wave Data Selection
- Pre-processing for source localization
- Source Data specification
- VICS parameters
- Time delay for Causality Analysis (Granger)
- Time window for correlation, coherence or association
- Start source-VICS computing

Target data (Time windows)

The data selection specifies the trial, channels to be used for wave CxC computing. The time window parameters specify active- and control-state time windows relative to named triggers or markers or the trial synchronization time point (typically zero). You may use the "Get…" button to get the selection for either active or control time window. You may also change or add the parameters by typing in the edit controls (fields) manually.

Time windows are defined relative to some event in the data — either the beginning of the trial (time zero) or a marker. Triggers (one group of Markers) are added automatically by the Data Acquisition application when the data is acquired. Typical markers are added by the adding Marker programs. They can also be added manually to mark an event of interest using the Selection Mark application.

If you are generating a single-state image, only active-state windows can be defined. If you are generating a dual-state image, both active- and dual-state windows can be defined.

To define a window:

1) Click the "Get Active" or "Get Control" button (Active States or Control States) to get the selection in the waveform viewer window.
2) You may click the "Select All…" to select all data points.
3) To use the control data, you must select "Compute Control" checkbox.
4) The Check Select will check the selection of the data.
5) The Match Act-Ctl (Active-Control) will match the size of the active and control selection so that they have the same length.

Pre-processing for source scan

Wave form data can be preprocessed by using DC-offset, Filter and more advanced settings. Raw sampling rate is shown to help define the parameters such as low and high pass filter as well as the time-window and steps.

Target region (ROI for Source Scan)

The Image Dimensions panel provides options for specifying which voxels to use when computing an image. The minimum and maximum volumes in the X, Y and Z directions specifies the bounding coordinates of the target volume cube, or region of interest (ROI) in millimeters. The dimension values define the grid size in voxel unit. This target volume contains a 3-D grid of points, separated on each axis by the specified Resolution, or step size. To generate volumetric source image, each voxel within the specified ROI will be evaluated. In other words, the region of Interest for source scan defines a volumetric grid or 3D grid with a list of coordinates for which a set of source coefficients are to be computed.

To define a ROI or target volume:

1) Enter the start (Minimum) and end (Maximum) values for each axis. (See “Head Coordinate System” in MSI Studio Guide for a description of X, Y, Z coordinates.).
2) Set the Step Size (resolution) to the desired value in millimeter. Note: Although it is possible that a strong signal that falls between grid points will be missed, a smaller resolution value will significantly increase computation time.

The meaning of the “coefficients” depends on the source localization algorithms.

Single-state or Dual-state Image

The single-state option generates a functional map based on the active state only (i.e., measurements taken when the brain is being stimulated). The dual-state option generates a functional map that results from the subtraction of control-state data (measurements taken when no stimulation is applied) from active state data. To generate a dual-state image, you must select both active and control data for source scan.

Storage of source data

For source data based on one trial, the results are typically stored with that trial. For source data based on multiple trials, the results, which are typically referred as “sum-source”, are stored in a selected trial. It is necessary to define the targeted trial for storing the results before source scanning.

VICS parameter

The coherence value can be computed for computing VICS.

Local Mode: It has at least two options: accumulate and best. The correlation of two sources can be computed for each voxel (step = 1) or a local area (step > 1). If the correlation is computed from a local area, an averaged value (accumulate) or the best value can be stored in VICS.

Coherent Voxel Item ID (Coh Vxl ID): One voxel item ID is typically selected to be used for computing VICS. Since this program supports multiple voxel values for one spatial location, the selection of voxel item ID define which component is of interest. Appropriate use of this option can minimize the use of memory and avoid computing voxel components that are not useful.

Dilution (Step): The step or dilution defines the spatial resolution in VICS, which is of course relative to the volumetric source images. If the Step is 1, there is no dilution and the spatial resolution of VICS will be equal to that of the original source images. If the Step is larger than 1, the spatial resolution will be diluted, consequently, the Local Mode should be selected carefully.

Distance (Minimum Distance): The step or dilution defines the spatial resolution in VICS, which is of course relative to the volumetric source images. If the Step is 1, there is no dilution and the spatial resolution of VICS will be equal to that of the original source images. If the Step is larger than 1, the spatial resolution will be diluted, consequently, the Local Mode should be selected carefully.

Step Size (Spatial Resolution): The spatial resolution is the original spatial resolution in volumetric source image, which is provided for appropriately defining the Step and Minimum Distance for computing VICS. By using the spatial resolution, you may define Mini Distance and Step to analyze the functional correlations in various brain lobes (e.g. left and right temporal lobes).

Sampling Rate: Sampling rate indicate the sampling rate in the original source images, which is provided for appropriately calculating the time window and time delay for computing VICS.

Causality Analysis and Time-Delay

To analyze the causality relationship of two sources, the time-delay parameter is provided to define if a source always follows another source. If source A is always behind source B, then source A is probably the results of source B or the activation of B causes the activation of source A.

The causality analysis (Granger) is a statistical hypothesis test for determining whether one time series is useful in forecasting another or cause events in another. Specifically, a time series channel A is said to Granger-cause channel B if it can be shown, usually through a series of t-tests and F-tests on lagged values of A (and with lagged values of B also included), that those A values provide statistically significant information about future values of B.

A long held belief about neural function maintained that different areas of the brain were task specific; that the structural connectivity local to a certain area somehow dictated the function of that piece. Collecting work that has been performed over many years, there has been a move to a different, network-centric approach to describing information flow in the brain. Explanation of function is beginning to include the concept of networks existing at different levels and throughout different locations in the brain. The behavior of these networks can be described by non-deterministic processes that are evolving through time. That is to say that given the same input stimulus, you will not get the same output from the network. The dynamics of these networks are governed by probabilities so we treat them as stochastic (random) processes so that we can capture these kinds of dynamics between different areas of the brain.

Correlation/Covariance and Time-window

The time-window defines the time period that generates enough data points to quantitatively determine the relationships of a two-source pair. Theoretically, the time-window should be equal or close to the time-period of source activation.

The program provides the “Correlation” and “Covariance” operators for analyzing the relationships of source pairs.

Sliding Time Window

The step of sliding time window in source coherence analysis is 1.

Sanity Checks

If both active and control data are used, the source localization program applies a “sanity check” to differential images to examine whether active and control MEG measurement conditions are well balanced. Differential imaging should cancel out the “common mode” brain activity. This implies that the source difference between active and control states over the entire head should be small compared to the common mode.

$$p = \sum_{i=1}^{v} (a_i - c_i)/(a_i + c_i)$$

Source scan applies an equation to all non-zero voxels (only within the head boundary), where a and c are the active and control source power of each voxel. In this simple test, if the ratio exceeds a 25% threshold, poor suppression of common mode brain activity is indicated. This, in turn, suggests either poor experimental design or corrupted MEG data.

Running Source Coherence Analysis

Click the “Start” button will start to run the VICS computing. Once it is started, the window title bar will show the progress of the computing.

The VICS computing calls several internal dynamically linked libraries to perform a variety of operations. Here are some steps:

1) Generates the multiple-sphere origin information needed for an accurate head model, if necessary.
2) Filters data and computes covariance of data if necessary
3) Computes sensor lead fields and/or weights on a grid of points throughout the head.
4) Computes the source power or kurtosis of the source time-series if necessary
5) Finds local maxima in the source image.
6) Computes covariance of data in full bandwidth
7) Computes two sets of source time-series for source peak (maxima) — one using full bandwidth and one using the high-pass filter.
8) Check and select the source data for VICS Computing.

9) Check and correct the parameters for VICS computing, if necessary.
10) Estimate the necessary memory, if necessary
11) Compute coherent source data for each source pair
12) Compute the summary of all source pairs, if necessary
13) As usual, the volumetric image for coherent sources are available to be viewed using source coherent Viewer.

VICS Manager

VICS data can be viewed, edited and analyzed quantitatively with VICS Manager. In the new version of this program, operation can be applied to VICS data.

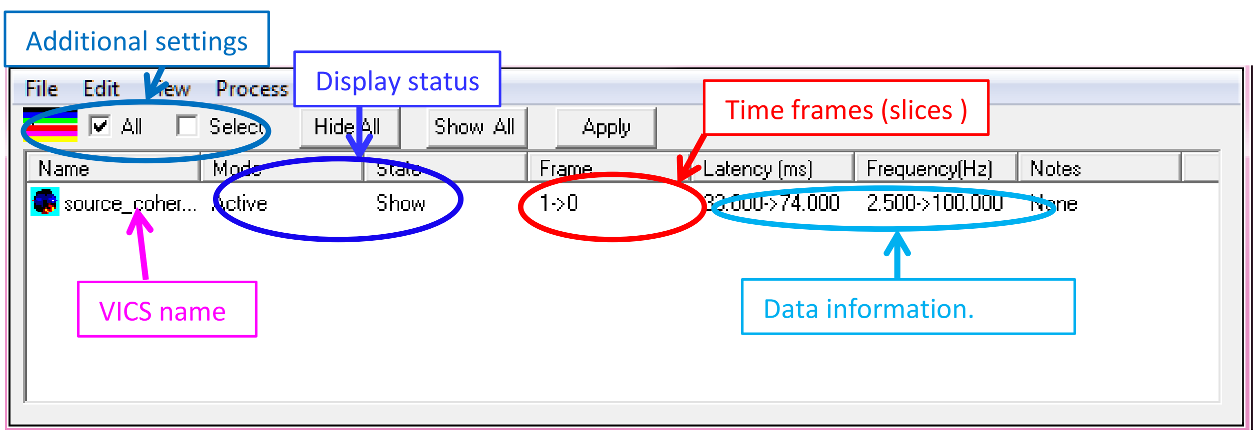


Figure. 3. VICS (volumetric image for coherent sources) manager.

Multi-Time Frames (Slices) to One Slice with Averaged Values.

VICS data can have many time-slices. Multi-time slice data may reveal dynamic changes of all source pairs. To quantify the characteristics of all source pairs during the entire period of time, a function (Multi-Time Frame to One with averaging) has been designed to accumulate multiple time slices to one slice by averaging the values for each pair across all time frames. The one slice may reveal the stationary correlations of all source pairs.

Multi-Time Frames (Slices) to One Slice with Picked Best Values

VICS data can have many time-slices. Multi-time slice data may reveal dynamic changes of all source pairs. To quantify the characteristics of all source pairs during the entire period of time, a function (Multi-Time Frame to One with Best Values) has been designed to accumulate multiple time slices to one slice for each pair across all time frame. The one slice may reveal the stationary correlations of all source pairs.

Zero Diagonal Values (self-correlation)

The diagonal values in source coherence data indicate very focal correlation or the correlation in the same spatial location. For example, in covariance matrix of very focal data, the diagonal values may reflect the diffusivity of source data. In correlation matrix, the diagonal values may be 1. This program has designed function to zero diagonal value. To zero diagonal values, launch the VICS Manager, then select the Edit Process-> Zero Diagonal.

Visualization of VICS Data (Neural Networks)

VICS data can be visualized in 3D to analyze the neural network in the brain. In 3D visualization, VICS data can be plotted as many "Links", those links reflect the correlation or interaction of two-source.

Launching Neural Network Viewers

Since this program computes the correlation or interaction of source pairs in several ways, the data visualization windows may be different from the conventional coherence viewers.

3D Neural Network Viewer

3D Neural Network Viewers for VICS are commonly used to analyze the spatial correlation of brain activity/activation in a specified time range. In this program, one link shows a link of one source pair. If there is no time-delay between the two sources, there is no information about possible causality. In other words, a link between sources A->B is similar to a link between sources B->A. One line indicate one link.

If color is used, red color is typically used to represent positive correlation or interaction (plus), while blue color is typically used to represent negative correlation or interaction (minus). One small ball (cube) is typically used to represent one source location. This is kind of "coherence" plots of all source pairs in 3D coordinate in a specified time interval.

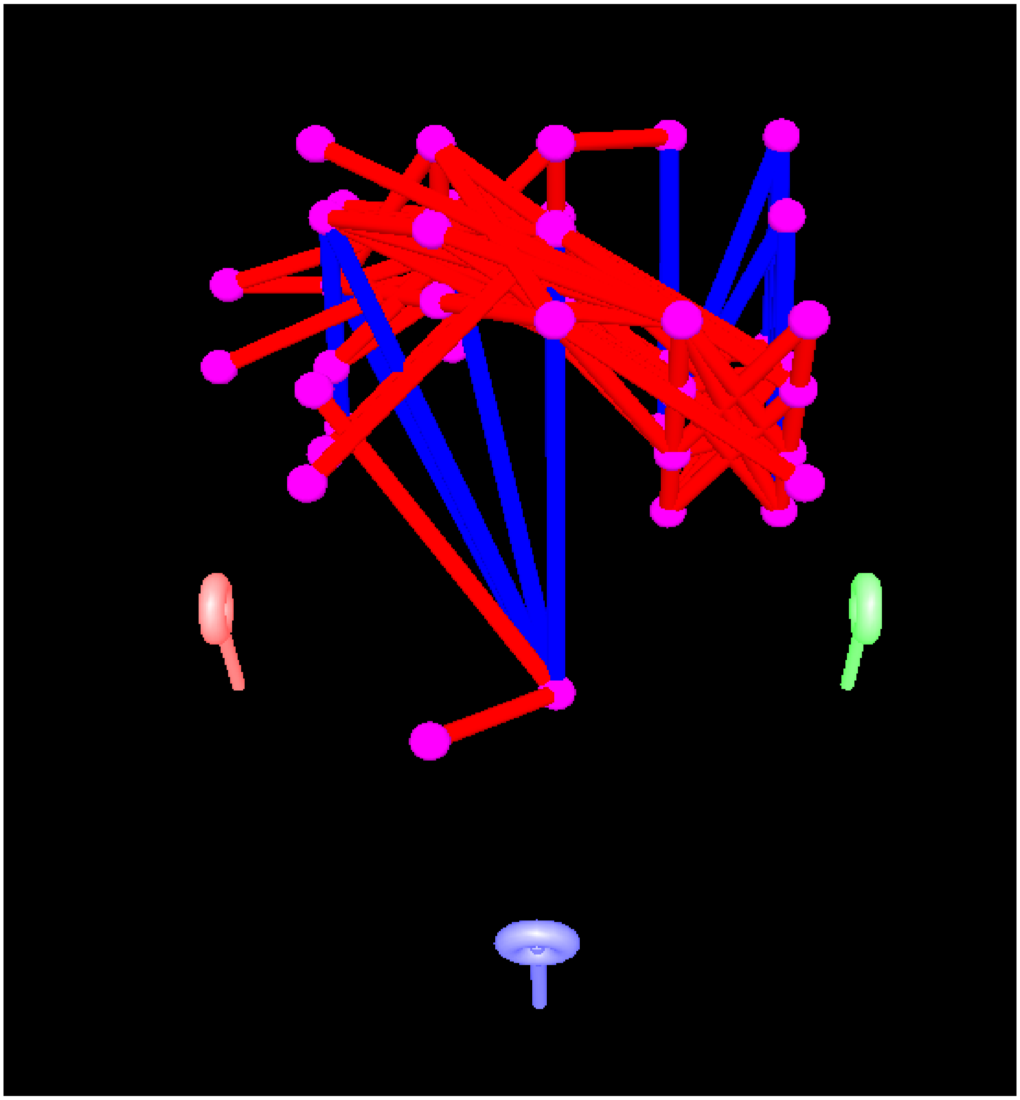


Figure 9. Visualization of neural networks by linking all source pairs in VICS data. The three tori are fiducial points.

Display Controls for 3D Neural Network Viewer

The 3D Viewer provides a set of options and controls for appropriately displaying the spectral data. All the options and the controls are on the top of the window (or Dialog). The Dialog provides a lot of flexibility and power for you to control the display. The following figure shows the details about the display items and their controls.

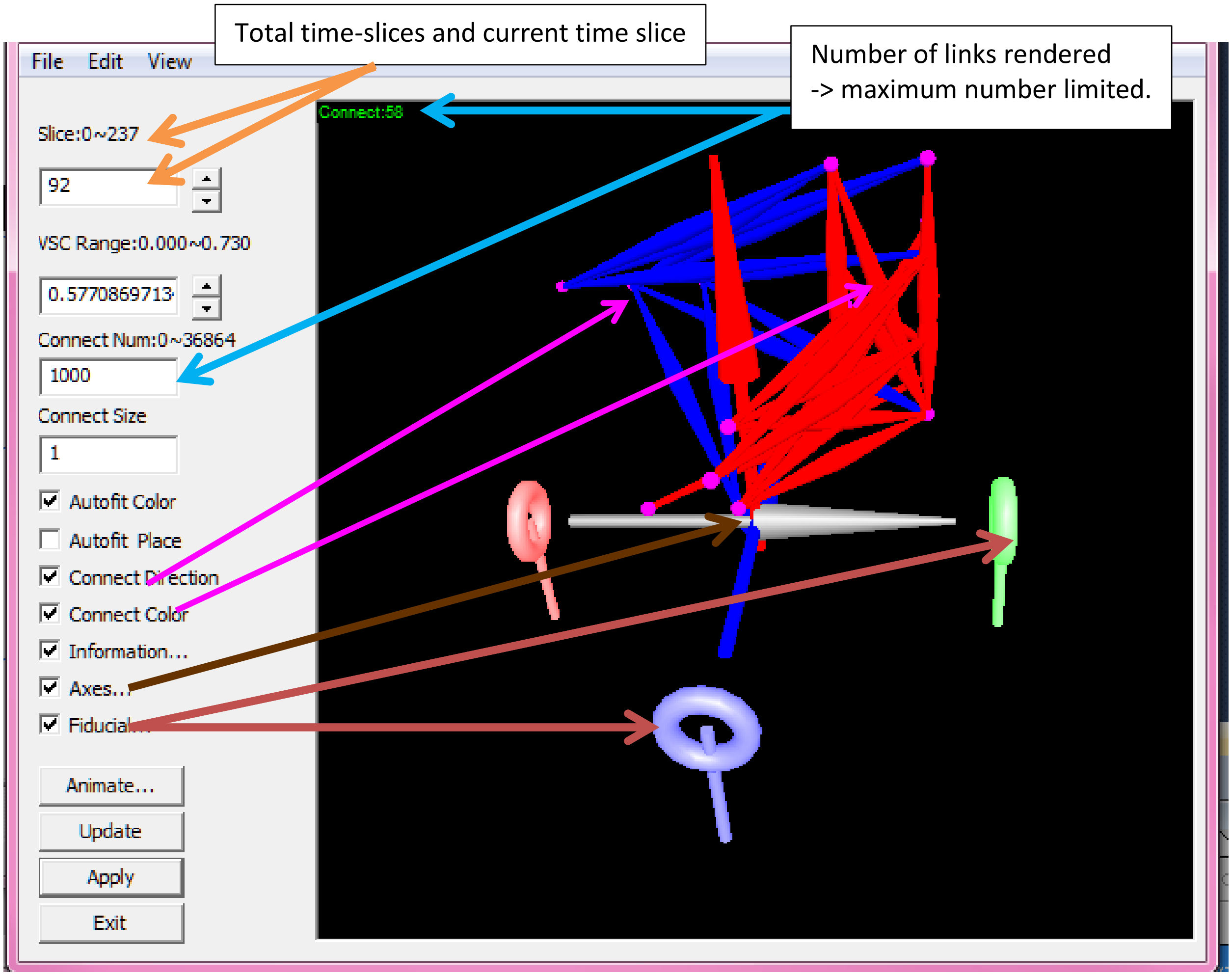


Figure 10. The options and controls of neural network viewer for all source pairs reached certain thresholds.

Operations in 3D Neural Network Viewer

The 3D neural netowrk viewer provides a set of tools to operate and analyze VICS data. If the 3D links is computed with multiple time slices, you may select to show the correlation or interaction of source pairs in certain latency range or time interval.

The number of links can be defined by use both top percentile and absolute threshold. To avoid time-delay, you may limit the maximum number of links or connections. If the number of links meeting the threshold is larger than that of the maximum number of links, the number of links rendered in the 3D viewer will change to red.

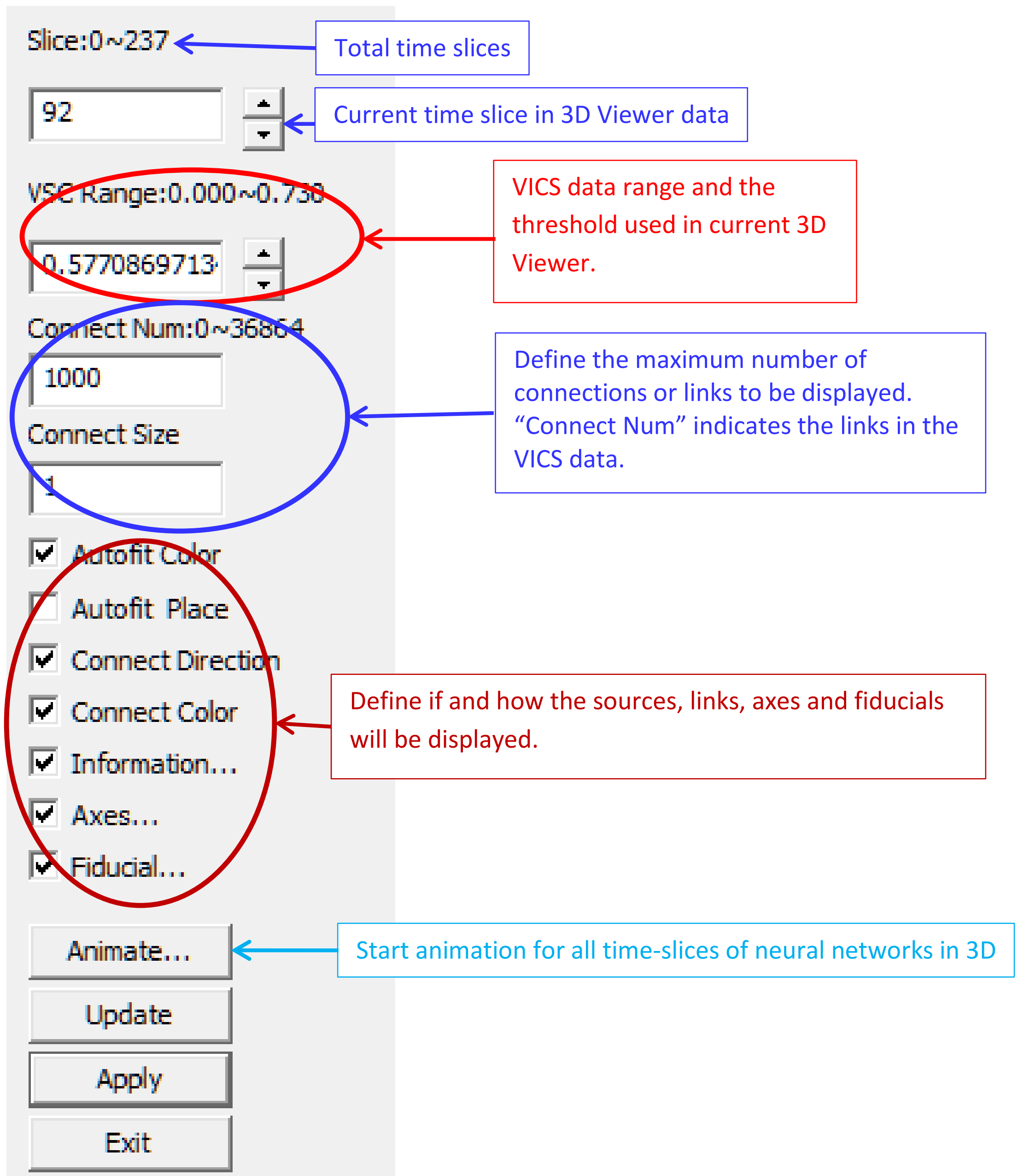


Figure 11. Controls and options in 3D neural network viewer.

Menu in 3D Neural Network Viewer

The 3D neural network viewer can be used to visualize and analyze the correlation and interaction of all source pairs or a group of source pairs.

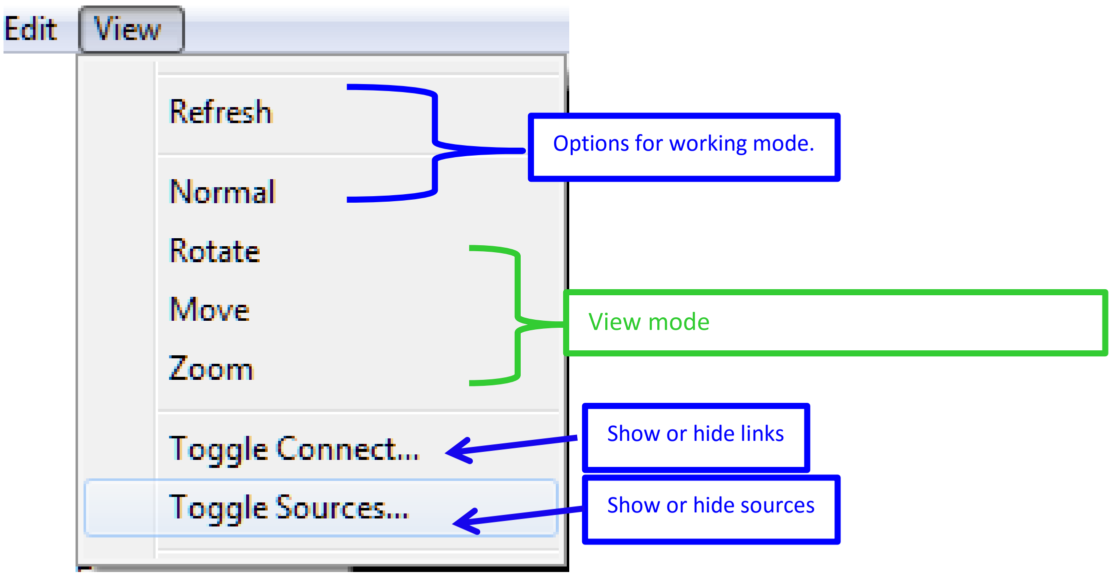


Figure 12. Menu in 3D neural network viewer.

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