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MODELING COGNITIVE BRAIN PROCESSES WITH A GENERALIZED NET

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§1. Introduction

Studying the human brain is a great challenge to contemporary science. In the 1990s new techniques like fMRI have emerged and have complemented existing ones like EEG, PET, CT, SPECT, and MEG, which in turn have further developed [1]. All of them have been powerful aids to psychologists and physicians in the pursuit for better understanding of the brain structure and functioning. Applications of mathematical models in this area have, however, been limited. One successful route has utilized LISREL models [1] that have come from general psychology. It may be argued that since these results are confined in the framework of stepwise linear regression, they are insufficient for the task of brain modeling. Other paths of research have been concerned mostly with signal and image preprocessing rather than function modeling. Yet another way is to search for empirical evidence for some of the mechanistic models of neuronal ensembles developed by the Grossberg school in Boston University [2, 3]. This direction has not yet been tried, and if successful, may bridge the gap between currently accumulated brain imaging data, and known plausible mathematical models.

Finding statistically valid confirmations of elements of that theory is nontrivial task because it is by and large not clear what cognitive brain data can be matched onto which specific theoretical models. To this end a process of computational trial and error is inevitable. In this paper we propose to employ Generalized Nets (GN) to do the task of computational management of the described process. The definition, description, and relevant discussion of the concept 'Generalized Net" may be found in [4].

§2. Generalized net model

The goal of this paper is to outline the possibility of utilizing a GN for the statistical process of uncovering matches between empirical signal (image) fragments, and elements of theoretical models (pool prototypes). Below we shall construct a reduced GN (Fig. 1) with no temporal components, transitions, place and token priorities, place and arch capacities, and for which the tokens keep all their history. We shall describe the transition condition predicates and tokens without their full mathematical formalism for easier understanding.

Initially tokens α and β enter places l_1 and l_2 with the following initial characteristics:

α: x_0^{α} = "Measured brain signal (image) fragment, containing information about the studied cognitive processes";

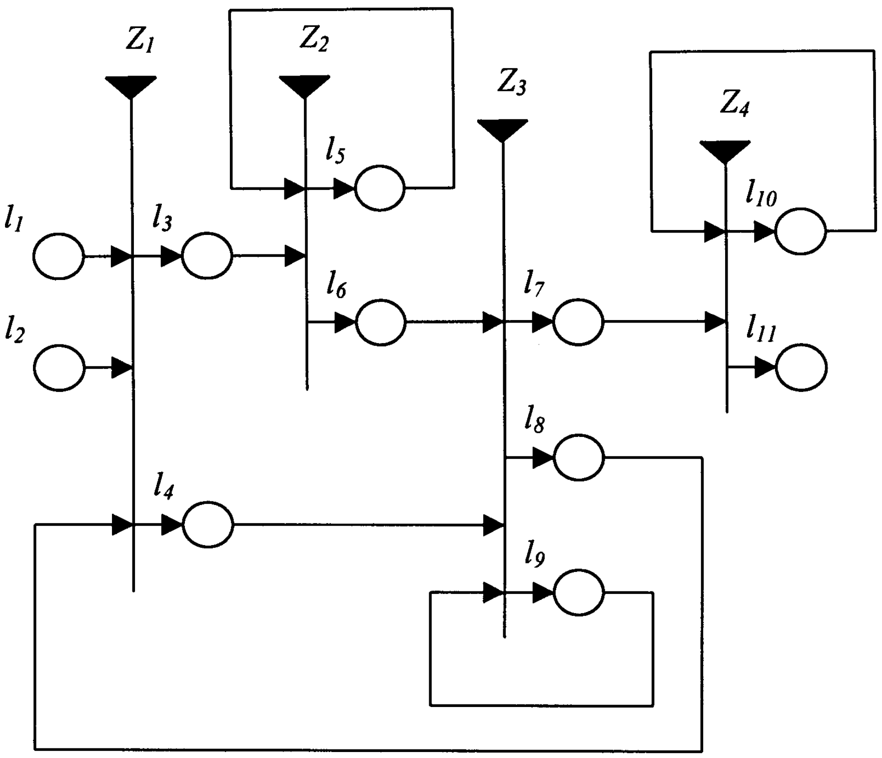

Figure 1. Structure of the GN.

β: x_0^{β} = "Pool of numerically generated prototypes of signals (images)."

The GN contains 4 transitions. The first one is Z_1, which may be described as follows:

Z_1 = < $\{l_1, l_2, l_8\}$,$\{l_3, l_4\}$,

	l_3	l_4
l_1	*true*	*false*
l_2	*false*	*true*
l_8	*false*	*true*

, $\wedge(l_1, \vee(l_2, l_8))$ >.

Token α enters l_3 and obtains characteristic x_1^{α} = "Total number of fragments", while in l_4 token β obtains characteristic x_1^{β} = "Sub-pool of cognitive process prototypes; Number N_β of elements in the current sub-pool". Let c be the current number of tokens to be generated in Z_2. Hence $1 \leq c \leq x_1^{\alpha}$.

Z_2 = < $\{l_3, l_5\}$,$\{l_5, l_6\}$,

	l_5	l_6
l_3	*true*	*true*
l_5	$W_{5,5}$	*true*

, $\vee(l_3, l_5)$ >.

Here predicate $W_{5,5}$ = "$c < x_1^{\alpha}$". This means that $W_{5,5}$ shall be *true* until the tokens in l_5 have numbers smaller than the total number of fragments, and *false* thereafter.
Then token α splits into two new tokens, – current and next, which are α_c and α_{c+1}, entering l_6 and l_5 respectively. Their new characteristics are, at l_6: "The c-th fragment" and at l_5: "Entire record without the first c fragments".

Transition Z_3 is described by:

Z_3 = < $\{l_4, l_6, l_9\}$,$\{l_7, l_8, l_9\}$,

	l_7	l_8	l_9
l_4	*false*	*false*	*true*
l_6	$W_{6,7}$	*false*	*false*
l_9	*false*	$W_{9,8}$	$W_{9,9}$

, $\wedge(l_6, \vee(l_4, l_9))$ >.

Here the predicates may be described as follows:
$W_{6,7}$ = "Token β has accomplished $N_β$ cycles for the current fragment at l_9."
$W_{9,8}$ = "Place l_5 is empty" & $W_{6,7}$.
$W_{9,9}$ = "Place l_5 is not empty."

The predicates may be described as follows. The $W_{6,7}$ means that token α shall leave l_6 and enter l_7 after all pool prototypes that have served as last characteristic of token β, have been compared with the last characteristic of token α. The $W_{9,9}$ and $W_{9,8}$ signify that token β shall do cycles at l_9 until there exist unanalyzed fragments from the original brain signal. When all comparisons between the characteristic of the last token α at l_6 and the sub-pools at l_9 are finished, token β goes from l_9 to l_8. Then β is ready for the next simulation with new brain signal.

Then at l_7 token α obtains characteristic "Best match between the current signal (image) segment and a pool prototype". The match should be understood in terms of a precision estimate. At l_8 token β does not obtain any characteristic. At l_9 token β obtains characteristic "Estimate of the match between the current sub-pool fragment and the current characteristic of α."

Finally, transition Z_4 may be described as follows.

$$Z_4 = < \{l_7, l_{10}\}, \{l_{10}, l_{11}\}, \begin{array}{c|cc} & l_{10} & l_{11} \\ \hline l_7 & true & false \\ l_{10} & W_{10,10} & W_{10,11} \end{array}, \vee(l_7, l_{10}) >,$$

where $W_{10,10}$ means "There exist more fragments to be processed", and $W_{10,11}$ is the opposite of $W_{10,10}$. The two divided tokens α unite at l_{10} and receive characteristic: "Concatenation of all brain signal fragments matched so far. Current precision estimate monitoring." The final α has characteristic: "Final matching. Total precision estimate." This happens at l_{11}.

Figure 1 with its description represents one run of the matching process. It is based on purely statistical estimates of precision and does not take into account possible contradictions to the theory. Those may be of the following type: a brain signal behaves most of the time like one of the pool processes, and intermittently switches to resemble another pool process. Possibly after several runs of the entire computational cycle a globally best match may be reached, which shall correct this type of errors. Ultimately a picture of "theoretic prototypes vs. empirical fragments" shall emerge, and its consistency shall be estimated by appropriate statistical measures.

References

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