# System Factorial Technology applied to Artificial Neural Network Information Processing

Christophe Tremblay, Bradley Harding, Sylvain Chartier, Denis Cousineau

University of Ottawa, School of Psychology, Ottawa, Canada
{ctrem040, bhard024, sylvain.chartier, denis.cousineau}@uottawa.ca

**Abstract.** System Factorial Technology is a recent methodology for the analysis of information processing architectures. SFT can discriminate between three processing architectures, namely serial, parallel and coactive processing. In addition, it can discriminate between two stopping rules, self-terminating and exhaustive. Although the previously stated architectures fit to many psychological skills as performed by human beings (i.e. recognition task, categorization, visual search, etc.), the analysis of processing architectures that lie outside of the five original choices remain unclear. An example of such architecture is the recall process as performed by iterative systems. Results indicate that an iterative recall neural network is mistakenly detected by SFT as being a serial exhaustive architecture. This research shows a limit of SFT as an analytic tool but could lead to advancements in cognitive modeling by improving the strategies used for the analysis of underlying information processing architectures.

**Keywords:** Neurodynamic Modeling, Artificial Neural Network, Bidirectional Associative Memory, System Factorial Technology

## 1 Introduction

Recent advancements in mathematical psychology have brought forth System Factorial Technology, or SFT [1, 2], a tool that can diagnose the type of information processing architecture behind a mental process [1]: serial processing, parallel processing, and coactive processing and possible stopping rules: self-terminating and exhaustive. This allows for a total of 5 possible architectures that can be identified by SFT (coactive architectures only have one possible stopping rule, namely self-terminating) [3-4]. The method works solely with the response times (RT) distributions of four conditions, obtained from the manipulation of the inputs that should independently affect two distinct sub-processes (in a 2 x 2 factorial design). The four conditions include the High-High (HH) condition, in which both sub-processes are working at a normal or artificially enhanced fashion. The High-Low and Low-High conditions (HL and LH) is where one sub-process is working in an artificially impaired fashion and the other operates normally or in an artificially enhanced fashion. Finally, the Low-Low condition is achieved

adfa, p. 1, 2014.

when both sub-processes are performing in an artificially impaired fashion. By measuring the Survivor Interaction Contrast (SIC) for each moment in time between the 4 condition distributions, we can create a curve [5]:

$$\mathrm{SIC}(t) = S_{LL}(t) - S_{LH}(t) - S_{HL}(t) + S_{HH}(t) \tag{1}$$

In which $S(t)$ is the survivor function of the RT distributions for the four conditions. Figure 1 presents the SIC curves associated with the different processing architectures.

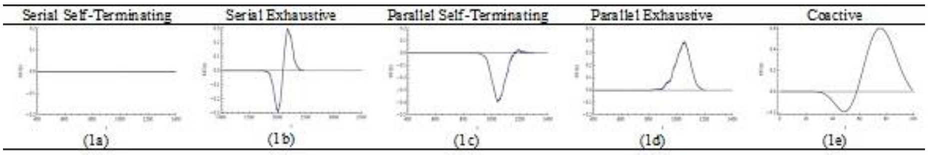


**Fig. 1.** Survival Interaction Contrast curves and their associated processing architecture.

Although SFT has been applied to a wide variety of mental processes, its applicability to architectures lying outside the five original categories has not yet been studied. One such architecture is an artificial neural networks in which signals are processed iteratively until the network settles in a stable configuration. Bidirectional Associative Memory (BAM) [6-7] models are neural networks in which output units are found through the iteration of the activation between two layers of parallel units. This process is expressed in Figure 2, where **W** and **V** are the weight connections, $\mathbf{x}_{(1)}, \mathbf{x}_{(2)}, \ldots, \mathbf{x}_{(N)}$ and $\mathbf{y}_{(1)}, \mathbf{y}_{(2)}, \ldots, \mathbf{y}_{(M)}$ are the input units. During the recall phase, the output units would be found by iterating through the network until a stable solution is found.

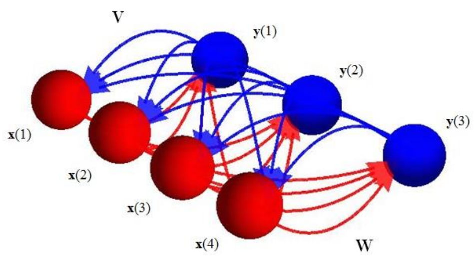


**Fig. 2.** Iteration process used in BAM recall.

Since the information processing architecture behind a BAM does not correspond to any of the five diagnosable architectures, the nature of the process detected by SFT remains to be established. This article therefore seeks to examine what SFT detects when the information processing architecture falls outside classical categories.

## 2 Simulation

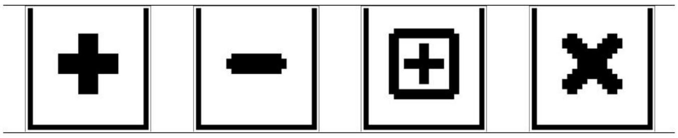

**Fig. 3.** Input patterns used in the first set of simulations.

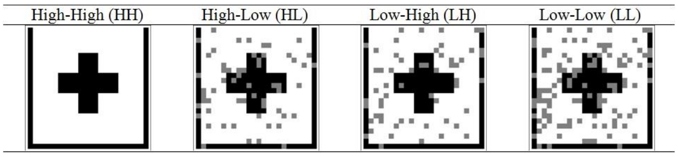


**Fig. 4.** Four stimuli used in the four recall conditions during the recall phase.

In this simulation, the input patterns consisted of 60 visual patterns of 576 pixels (a surface of 24 x 24 pixels). Examples of the stimuli used are presented in Figure 3. The network had to perform recall tasks with randomly distributed noise for a 2 x 2 design, as required for SFT analysis (HH, HL, LH, LL) as shown in Figure 4. In every Low condition, the input pattern was "masked" by setting 10% of the pixels to 0, therefore limiting the processing capability of the network. Masked pixels in the HL condition could not be masked in the LH condition. Consequently, the LL condition has 20% of the input patterns being masked, which were a combination of the masks used in HL and LH. The network was tested 2000 times in every condition and the mean numbers of iterations (*k*) to perform recall for the totality of input patterns were gathered. From the distributions, the SIC curve was found using Eq. 1 for every moment (*t*) of the survivor function.

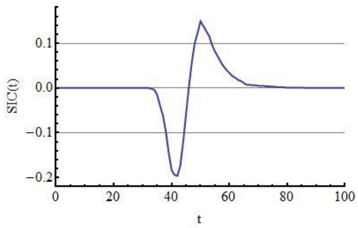


**Fig. 5.** SIC curve for recall task with bipolar images.

Results show that the number of iterations needed to perform the task in the four conditions was only slightly affected by the impaired conditions (an L sub-process). However, the recall was affected enough to distinguish an interaction pattern. All distributions followed an overall normal shape. The SIC curve shows clear evidence of a serial exhaustive processing architecture where the SIC curve is almost identical to what was presented in Figure 1b.

## 3 Discussion and Conclusion

The results presented here show evidence that the information processing present in a BHM produces response times (as represented by the number of iterations) that mimics a serial exhaustive architecture. However the BHM is built in a parallel fashion using units within layers that work in parallel. Therefore, facing new types of processing architectures, SFT can wrongly diagnose a processing architecture. These results are of concern as they show that SFT is capable of misclassifications. These results also weaken evidence for any particular architecture responsible for a mental process when the sub-process in question is not clearly understood. A possible explanation for the obtained results is that SFT detects the most important determinant of RT, hereby not detecting underlying subtleties in the architecture. These results also suggest that the SFT methodology could detect the overall information process rather than the underlying architecture used for that process.

In conclusion, this article presented a case study of the architecture detection using the SFT methodology on architectures that do not fall into classical categories. Results showed that the methodology incorrectly detects and assigns a category to the architecture. This research shows the necessity to improve the detection of architecture behind a process and presents an attempt for the understanding of artificial neural networks through the use of the System Factorial Technology. This research could lead to improved tools for modeling of human behavior using intelligent systems.

**Acknowledgement.**
This research was partly supported by the Natural Sciences and Engineering Research Council of Canada.

**References.**

1. Townsend, J. T., Nozawa, G.: Spatio-temporal properties of elementary perception: An investigation of parallel, serial, and coactive theories. Journal of Mathematical Psychology, 39(4), 321-359 (1995)
2. Fific, M., Nosofsky, R. M., Townsend, J. T.: Information-processing architectures in multidimensional classification: A validation test of the systems factorial technology. Journal of Experimental Psychology, 34(2), 356-375 (2008)
3. Schweickert, R., Giorgini, M., Dzhafarov, E.: Selective influence and response time cumulative distribution function in serial-parallel task networks. Journal of Mathematical Psychology, 44, 504-535 (2000)
4. Townsend, J. T., Wenger, M. J.: The serial-parallel dilemma: A case study in a linkage of theory and method. Psychonomic Bulletin & Review, 11(3), 391-418 (2004)
5. Fific, M., Townsend, J. T., Eidels, A.: Studying visual search using systems factorial methodology with target-distractor similarity as the factor. Perception & Psychophysics, 70(4), 583-603 (2008)
6. Chartier, S., Boukadoum, M.: A bidirectional heteroassociative memory for binary and grey-level patterns. IEEE Transactions on Neural Networks, 17(2), 385-396 (2006)
7. Chartier, S., Boukadoum, M.: Encoding static and temporal patterns with a bidirectional heteroassociative memory. Journal of Applied Mathematics, 2011, 1-34 (2011)