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Adoption of Combinatorial Graph for Inhibitory Process in Optimization Problems

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Abstract

This work is the follow up of the 'Process of Inhibition' supporting neural network models constructed based on biological theories in the earlier works to perform successfully in solving the optimization type problems. The algorithmic implementation of process of inhibition is replaced using the proposed Combinatorial Inhibition Graph (CIG) in this work. This adopted graph produces better performance than the algorithmic implementation done in the earlier works and is found to be suitable for further neural implementation for the process of inhibition. The combinatorial graph which is also suggested suitable for achieving improved performance in a concurrent processing environment is appropriately adopted in this work. The implemented CIG was not only combinatorics in nature but also act as a multi relational graph in solving complex problem like sum-of-subset.

Keywords: Combinatorics, Multi relational graph, Inhibition, Sum-of-subset, Combinatorial Inhibition Graph (CIG).

INTRODUCTION

The exhaustive search and elimination of probable combinations that are bound to fail in producing desired results from the list of all combinations implemented through the previous work. It is improved through the proposed graph representation of the combinations and their interdependent patterns. This work suggests a Combinatorial Inhibition Graph (CIG) which is combinatorial in its properties in its primary form. This also happens to be a multi relational graph for the contemplation sequence of combinations to be tried. In spite of being complex multi-type inter connected graph, the work proposes a possibility of hierarchical concurrency possibilities for implementation of graphs in producing superior results. This work also reasonably eliminates combinatorial graph pruning from an option for further improvement as it will not suit for neurological implementation of the same. The reasoning behind the selection of such a data structure will be justified at once the characteristics of each basic model utilized positively correlating to the application chosen is elaborated.

RELATED REVIEW

In between using the process of inhibition to coordinate with a neural network in our previous work [1] and the provision of neural representation to the process of inhibition set as the objective for our future work, the extensive study of research literature introduced the area of combinatorics. Before exploring the relevance of combinatorics, this work can be explained as the byproduct of the knowledge of the subject intuitively utilizing the concepts of graphs, hyper graphs, multi-graphs in combinatorics coined into a data structure suitable to be adopted by a respective neural representation.

Combinatorics

Combinatorics is deeper than it is simply described in short as being the basic principle of counting. The works [2][3][4] describes how the combinatorics was used in solving optimization type problems. It is real that counting is a major part of combinatorics but as the name goes, it is about combining things. It is in how many ways these elements are related, but it is important to answer whether a certain combination is possible, or which combination is the optimum in some way.

In combinatorics, combinatorial optimization [5-10] which is composed of optimization problems dealt with graphs includes determining the optimum allocation of the resources in finding solutions to mathematical problems. The mathematical problems such as minimal spanning tree problems, travelling sales man problem etc., which are solved using exhaustive search normally. When the situation comes were exhaustive search is not possible or feasible due to the quantitative complexity of the problem, then finding the optimal solution out of feasible solutions is found to be better solvable using combinatorial optimization. It is a part of mathematical optimization which is related to algorithmic theory and computational complexity theory.

Multi relational and bipartite graph

The multi relational graphs have heterogeneous edges [11][12], where each edge is labeled to denote the type of relationship that exists between the vertices that they connect. This graph has the varieties of adoptions in the areas of academic researchers and industries. The bipartite graph is one, whose vertices can be divided into two disjoint and independent sets U and V be the two sets of vertices which are called parts of the graph in practice.

The two types of graphs namely multi relational and bipartite graph has become basis for the proposed and implemented data structure in this work. The proposed CIG have heterogeneous edges which represents different relationship between the vertices they connect. The vertices can be bipartite into two disjoint and independent sets which may use to perform matching between the different vertices.

OBJECTIVES

- The main objective of this work is to construct new combinatorial graph model (CIG), which should be multi relational bipartite graph.
- CIG should be suitable to optimize the process of inhibition.
- To provide the improved performance over exhaustive search elimination method through CIG data structure for sum-of-subset problem.

IMPROVED ALGORITHM FOR "INHIBITION AS PROCESS" USING PROPOSED DATA STRUCTURE

The exhaustive search and input elimination used in previous work [1] provided a clue about the approximation process followed by the brain. This didn't provide any possibility to the process of inhibition to get a network representation. It became necessary to identify the inter relationship of combinations of the items giving desired and undesired sums.

$$\sum_{r=0}^{n} {}_{n}C_{r} = 2^{n} \qquad (1)$$

The mathematical theorem (1) threw open the hidden regularity of interdependence between combinations where the subsets can be grouped according the number of items chosen at a time. The work [13] under the topic combinatorics not only theoretically ascertained the grouping of combination proposed in this paper but also upholds the sequence of our works before this. In the paper [13], first three sections arranged are partitioning relations, selection hypotheses for the partition and groupability of representatives. This order is interestingly supportive, because this can be correlated with the contents of our previous works [1][14][15]. A physically static portion [14] partitioning the 2^n possibilities of inputs, the dynamic portion of selection under biological theory of neural Darwinism (Selection) and in this paper grouping of possible inputs according to number of items for the given sum of subset problem is the order of our work that can be correlated to the order prescribed in [13].

Combinatorial Inhibition Graph (CIG)

This work suggests a graph model called Combinatorial Inhibition Graph (CIG) which will be a multi-relational bipartite directed graph which will be suitable to optimize the process of inhibition. The CIG is mathematically defined as a five-tuple (i.e),

CIG = {U, V, E_1, E_2, E_3}

Where,

U → A set of 2^n vertices pointing 2^n possible input combinations

V → A set of 2^n vertices holding the enumerated values of each possible input combination.

E_1→ A set of 2^n-1 edges connecting ordered pair of vertices (U_i,U_j) for all i = j-1.

E_2→ A set of 2^n edges connecting ordered pair of vertices (U_i,V_i) where i=0 to 2^n-1.

E_3→ A set of $\sum_{i=0}^{n} {}_{n}C_{i} * 2^{n-i} - 1$ edges connecting ordered pair of vertices (V_i,U_j) where i, j=0 to 2^n-1.

It is evident that the worst case situation for the sum-of-subset problem is to test all the 2^n possible combinations of inputs. By combinatorial optimization principle, if a basic combination exceed the boundary or satisfies the limit then the further related combinations are eliminated for testing. So no further inclusion is possible (i.e. according to biological theory set into an inhibited state) to produce the optimal result for each set of inputs accordingly. This principle suggested the proposed data structure to have 2^n vertices (U) which in the initial stage of the processing pointing to 2^n vertices (V), holding the enumerated value of all the possible input combinations. The edges between U and V are labeled as type E_2. If testing of any combination ends in a state, then no further addition is possible. The respective vertices pointing to all further related combinations of set U will be nullified so that those combinations are not tested.

The identification of inter relationship between combinations is enabled by the edges of type E_3. The edges of type E_1 are the connections in the graph which are used as a linked list to follow from one combination to other. The proposed multi relational graph is also an ordered graph according to type E_1 edges. It will be interesting to note that the graph pruning in combinatorics is not used in this implementation. It was possible to prune a vertex U_x from the graph instead of nullifying the content will reduce the processing complexity more. This was not found accommodative to the biological model because practically the brain does not eliminate a combination from contemplation but only eliminates the process for a combination after contemplating it to be in an inhibited state.

Implementation

This implementation sustains the optimization to the level of biological adoptability instead of maximizing it according to mathematical possibilities. The proposed CIG algorithm was implemented in C++ with the data structure shown in Fig.2. The algorithm illustrates that the graph iterates through all vertices in U. If U_i is not null, then it can reach all of its respective V_i to decode the enumerated value and set as input to network part. If there is an inhibition signal from any of the edge E_3, then the key value of corresponding vertex U is made to be null.

CIG Algorithm

```
Begin
  for all vertices U do
     If U_i is not NULL
        Reach the respective V_i
        Decode the enumerated value and set as input to Network part
        Check for Inhibition Signal
        If Inhibition Signal is True
           for all the edges of type E_3
              Reach Corresponding vertex U and make the key value as NULL
           end for
        end if
     end if
  end for
End
```

The data structure illustrated in fig.1 was conceived and was tested successfully to provide the improvement in performance over the exhaustive search elimination method which is tabulated as table1 and table2. It is also to be noted that the arrangement of items before the functioning of the network starts need not be included with the time complexity of the process.

Table 1. Performance Analysis for Exhaustive Search Elimination method

M (Desired sum) (A)	Execution time in nanoseconds (B)	Number of conditional verifications (C)	Number of Summation Performed (D)
7	1223	43	4
10	1406	43	4
20	1581	55	10
30	1754	66	14
40	2029	76	15

Table 2. Improved Performance of implemented Data Structure over Exhaustive Search Elimination method

M (Desired sum) (A)	Execution time in nanoseconds (B)	Number of conditional verifications (C)	Number of Summation performed (D)
7	920	20	4
10	960	20	4
20	1461	26	10
30	1509	30	14
40	1535	31	15

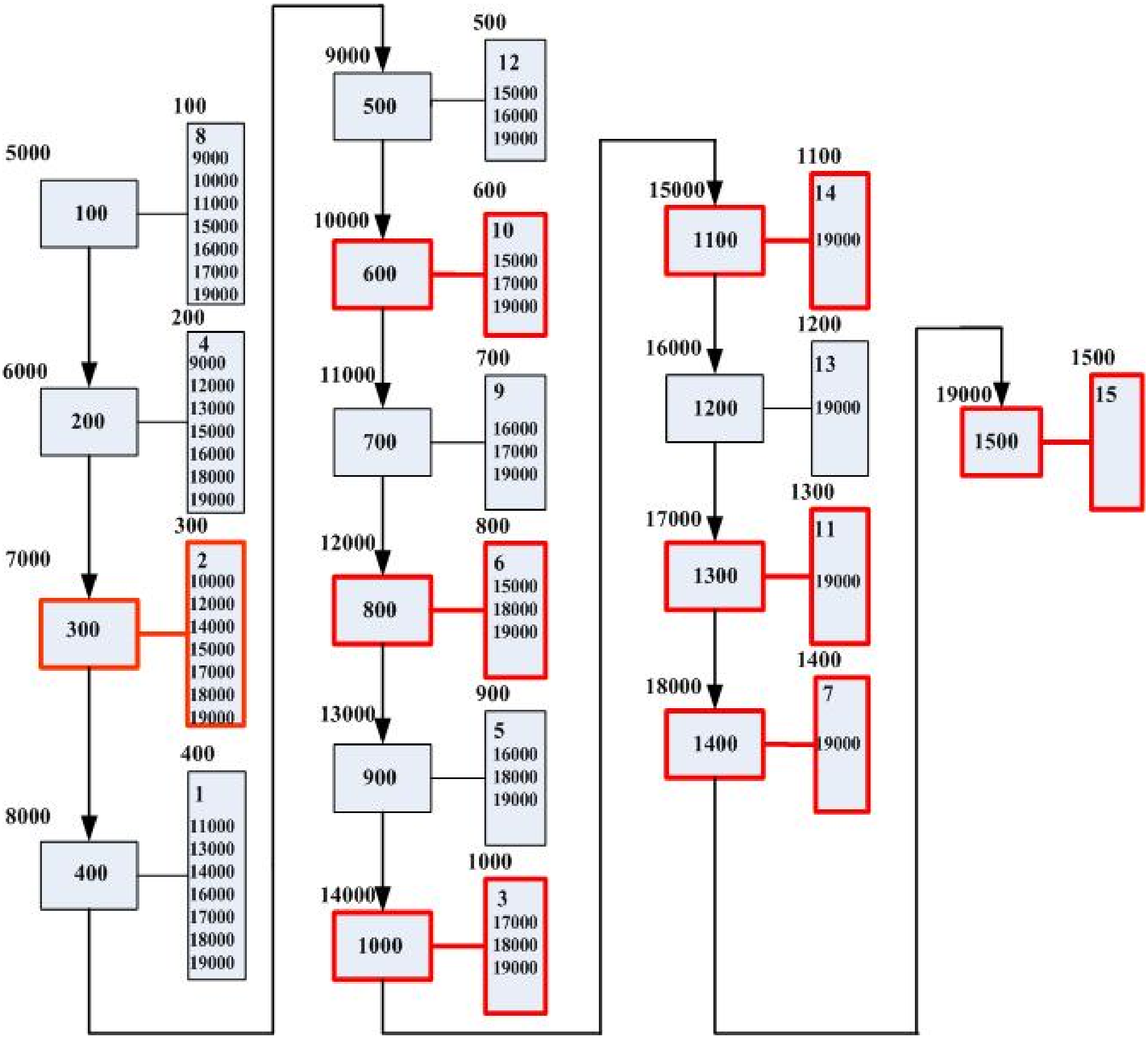

Figure 1. Maximum 2^n summations if and only if no addressing square boxes nullified after Inhibition

The fig.1 includes two shapes namely square and rectangle corresponding to two sets of inter-related data containers used in the data structure shown in C++ format in fig.2. Every numeric value of the combination is stored with the address of the pointers of the higher order patterns which includes its pattern shown in rectangular boxes. Fig.1. has $(2^n - 1)$ such rectangular boxes. The fig.1 also includes $(2^n - 1)$ square boxes, which are the pointers to the address of the numeric values of all possible combinations to be tested at the maximum during the process of finding the sum-of-subsets. If any combination produces an excess sum or the sum expected, then the address held by the pointers stored with the numeric value of such combinations are made null so that the summation of the respective numeric valued combination need not be performed.

```
struct block
{
    int no;
    int **blist[10];
    int count;
} ds[nc];

struct block *pt[nc];

[nc – number of combinations]
```

Figure 2. Data Structure using C++

RESULTS AND DISCUSSIONS

The successful implementation of CIG was tested with various n values with different desired sum. The table 1 and table 2 illustrate the results with the size 5 of n, which iterates for different desired sum. Table 1 elucidates the performance analysis for exhaustive search elimination method. Table 2 elucidates the improved performance of implemented data structure over exhaustive search elimination method. The column B shows the execution time of the respective algorithms in nanoseconds.

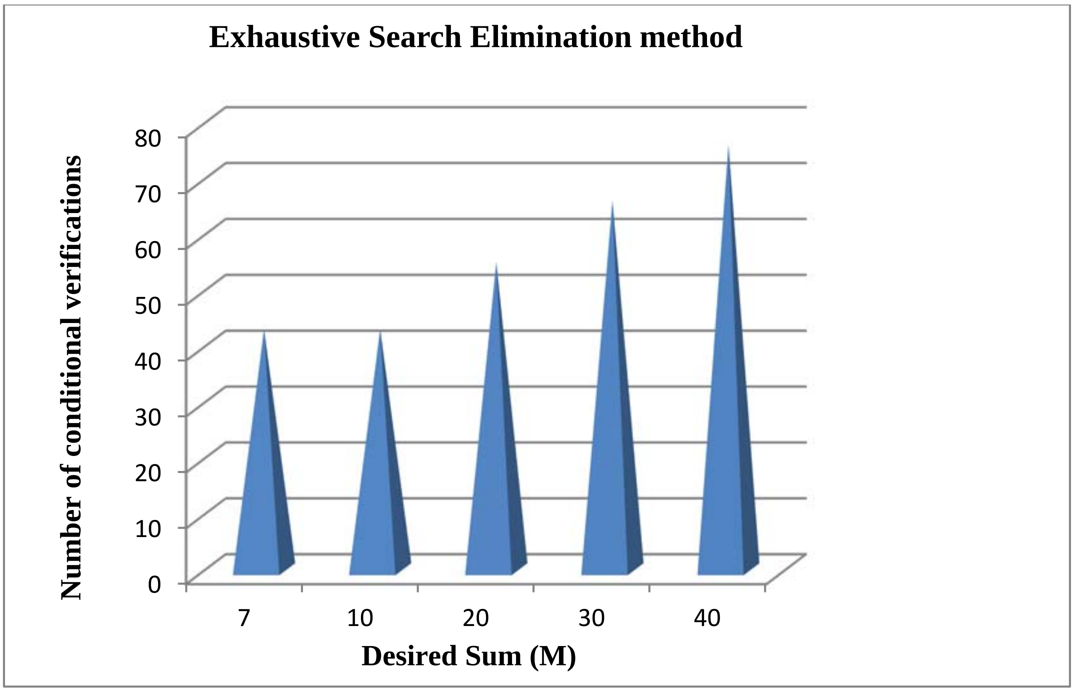

Figure 3. Characteristic diagram of implementation without proposed data structure

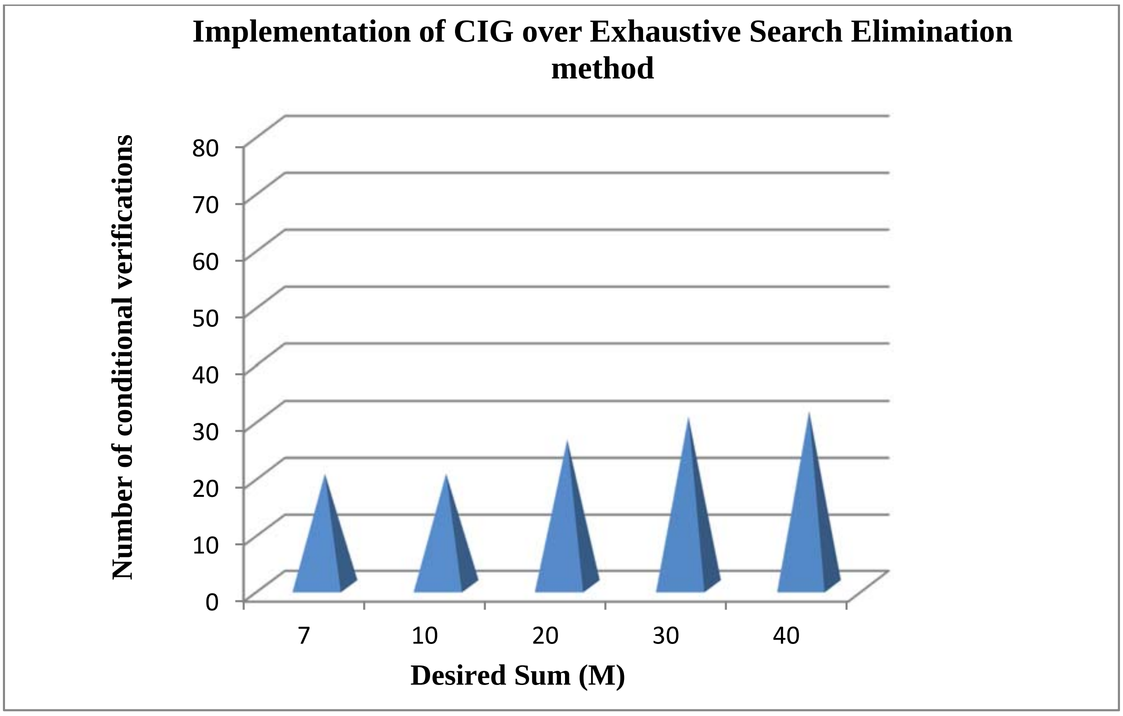

Figure 4. Characteristic diagram of implementation with proposed data structure

The improvements in performance shown through the columns B & C of the tables are charted through fig.3 and fig.4 depicting the number of conditional verifications done by the respective algorithms. This illustrates the characteristic benefit gained through the data structure representing the interdependencies between possible combinations. The similarity of column D of the tables illustrates the similarity between the methods in producing optimum results. The successful verification of the data structure opined the possibility of finding a neural model representation for the process of inhibition.

CONCLUSION

This work has proved that proposed combinatorial Inhibition Graph (CIG) is suitable to optimize the process of inhibition. This successful implementation depicts the improved performance in sum-of-subset problem over exhaustive search elimination method. The CIG was achieved through the multi relational bipartite graph which was found suitable for complex problem solving scenarios. The characteristic behavior matching between the CIG and a biological neural probability has formulated the possibilities of providing a neural model for the process of inhibition. This has created possibilities of a non-modular neural representation for optimization problems. In future, it is proposed to include a neural model section for the process of inhibition and to solve the problem of sequencing between different sections of a module.

REFERENCES

[1] Shyamala K, Chanthini P, "*Sum-of-Subset Implementation Using Neural Selection Principle and Cognitive Process of Inhibition*," has been "Accepted" in 1st International Conference on Communication, Networks & Computing (CNC – 2018), ITM University Gwalior, 22nd – 24th March 2018, Springer CCIS ("in-press").

[2] Guichard, David. "An Introduction to Combinatorics and Graph Theory." *San Francisco. The Creative Commons Attribution-Non Comercial-ShareAlike* 3 (2017).

[3] Van Lint, Jacobus Hendricus, and Richard Michael Wilson. *A course in combinatorics*. Cambridge university press, 2001.

[4] Combinatorial search, Online: https://www.cs.princeton.edu/~rs/AlgsDS07/24CombinatorialSearch.pdf

[5] Papadimitriou, Christos H., and Kenneth Steiglitz. *Combinatorial optimization: algorithms and complexity*. Courier Corporation, 1998.

[6] Ulungu, Ekunda Lukata, and Jacques Teghem. "Multi-objective combinatorial optimization problems: A survey." *Journal of Multi-Criteria Decision Analysis* 3.2 (1994): 83-104.

[7] Sait, Sadiq M., and Habib Youssef. *Iterative computer algorithms with applications in engineering: solving combinatorial optimization problems*. IEEE Computer Society Press, 1999.

[8] Kloks, Ton, and Rob Tijdeman. "The combinatorics of NG de Bruijn." *Indagationes Mathematicae* 24.4 (2013): 939-970.

[9] Harris, John Michael, Jeffry L. Hirst, and Michael J. Mossinghoff. *Combinatorics and graph theory*. Vol. 2. New York: Springer, 2008.

[10] Gross, Jonathan L., Jay Yellen, and Ping Zhang. *Handbook of graph theory*. Chapman and Hall/CRC, 2013.

[11] Multi-Relational Graph Structures from algebra to application Online: https://www.slideshare.net/slidarko/multirelational-graph-structures-from-algebra-to-application-3879972

[12] Rodriguez, Marko A., and Peter Neubauer. "A path algebra for multi-relational graphs." *Data Engineering Workshops (ICDEW), 2011 IEEE 27th International Conference on*. IEEE, 2011.

[13] Groupability: Kočinac, Ljubiša DR, and Marion Scheepers. "Combinatorics of open covers (VII): Groupability." *Fundamenta Mathematicae* 179.2 (2003): 131-155.

[14] Chanthini P, Shyamala K, "*Neural Darwinism Inspired Implementation of an Artificial Neural Network Model*," International Journal of Control Theory and Applications. Vol 10 (23), pp 7-16, 2017.

[15] Shyamala, K., Chanthini, P.: A Novel Approach in Solving 0/1 Knapsack Problem Using Neural Selection Principle. IEEE International Conference on Power, Control, Signals and Instrumentation Engineering. Issue-III., pp. 305--309 (2017)