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Efficiency Analysis of Blind Tree Based Search Algorithms Performance Based on Time, Number of nodes and Memory.

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Abstract - Blind algorithm is a type of algorithm that uses no information about the likely direction leading to the goal state. There exist some factors affecting the performance of blind algorithms which includes high execution time, low memory usage and number of nodes. This paper critically evaluated and prioritized these factors based on their influence on the performance of blind algorithms. Five blind algorithms (Breadth first, Depth-first, Iterative deepening, Bidirectional and Uniform cost) were selected for this research. These algorithms were implemented in C# programming language. Experiments were conducted on these algorithms by varying the input route lines of Arik airlines as case study to generate data. Factor analysis by principal component was used for the evaluation and validation of the most critical factor. The result proved that number of nodes was the main factor affecting blind algorithms.

Index term: Blind algorithms, Factor analysis, Principal component.

1 INTRODUCTION

Searching is a key computational mechanism in many artificial intelligence agents and the basic principle of searching is simply a deterministic goal. The efficiency with which searching is carried out often has significant impact on the overall efficiency of a program. Blind search algorithm is a class of algorithm that use no information about the likely direction of the goal state. The search algorithms are implemented as special cases of normal tree traversal [1]. The search problem is based on path cost and optimal solution [2]. Most of these techniques include breadth first, depth-first, iterative deepening, bidirectional and uniform cost. These techniques make use of evaluation function in determining the next best possible state.

The blind algorithms have been found to be applicable in areas such as artificial intelligence, route planning, manufacturing scheduling, protein design formation and land resolution. This paper aim at prioritizing the most critical factor affecting the efficiency of breadth first, depth-first, iterative deepening, bidirectional and uniform cost.

2 Background to Blind Search Algorithms

The blind algorithms that include breadth first, depth first, iterative deepening, bidirectional and uniform cost have their strengths and limitations as to execution time, memory usage and number of nodes visited. These factors were considered in the evaluation of the five blind or uninformed tree based search algorithms. Breadth first search algorithm is an algorithm that begins at the root node and explores all the neighboring nodes. Then, for each of those nearest nodes, it explores their unexplored neighbor –nodes and so on, until it finds the goal [2]. Breadth first search is a First In First Out (FIFO) approach. Depth first search is a search that progresses by expanding the first child node of the search tree that appears and thus going deeper and deeper until a goal node is found or until it hits a node that has no children [3]. Depth first uses Last In First Out (LIFO).

Iterative deepening search combines the advantage of both the breadth first and depth first algorithms [4]. It is complete and optimal. It has a memory requirement similar to that of depth-first search. IDS may seem wasteful because states are generated multiple times but it turns out not expensive [5]. Bidirectional algorithm searches simultaneously from the start state and backward from goal state until it meets at the middle. Bidirectional search is implemented by replacing the goal test with a check to see whether the frontiers of the two searches intersect. If they do, a solution has been found [5]. Uniform Cost Search

always expands the node on the fringe with minimum cost

g(n). it should be noted that if costs are equal or almost equal, it will behave similarly to BFS [4]. This paper prioritized the three factors considered based on their influence and factor analysis by principal component was used for the validation of the most critical factor.

2.1 Materials and Methods

The decision variables of the impact of execution time, memory usage and number of nodes visited are interrelated to one another. The performance of algorithms in one factor could affect its performance in another. The factor analysis by principal component was used in the evaluation and validation of the most critical factor. The following are the steps involved in the validation of the most critical factor using factor analysis by principal component;

1. To compute the mean and standard deviations of the variables;
2. Normalize the variables to zero mean and unit standard deviation;
3. Compute the correlation among the variables;
4. Prepare the correlation matrix;
5. Compute the eigenvalues of the correlation matrix;
6. Obtain principal factors by multiplying the eigenvectors by the normalized vectors;
7. Compute the values of the principal factors;
8. Compute the sum and sum of the principal factors in percentage; and
9. Plot the values of principal factors.

According to [6] in 2013, mathematical model for the evaluation of the decision variables is as follows:

$$y_i = \sum_{k}^{n} a_{i,k} X_k \ldots \ldots \ldots \ldots \ldots . \mathrm{I} = 1,2,3 \ldots \ldots \ldots \ldots \ldots \ldots ., m \qquad (1)$$

Where yi represents the ith assessor's observation of decision variable Xk; ai,k represents the assessment of kth decision variable by ith assessor.
For a sample population of blind search algorithms, system of linear equations is obtained expresses as:

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \cdot \\ \cdot \\ Y_m \end{pmatrix} = \begin{pmatrix} a_{1.1} X_1 + \cdots + a_{1,3} X_3 \\ \cdot \\ \cdot \\ a_{m,n} X_1 + \cdots + a_{m,3} X_3 \end{pmatrix}$$
)

The following statistics were generated and used for the purpose of achieving the stated goal of determining and validating the most critical factor using factor analysis

- Descriptive statistics
- Kaiser Mayer-olkin and Bartlett's test of sphericity
- Communalities
- Correlation
- Total variance explained

2.2 Data collection, Analysis and Interpretation of Results

Five (5) blind search algorithms (breadth first, depth first, bidirectional, uniform cost, iterative deepening search) were studied. Each of the five algorithms were implemented in C# language. Experiments were conducted on these algorithms by varying the input route lines of Arik airlines to generate data that were used for the analysis. The performance of the algorithms was tested for each of the experiment by varying the input routes to produce different results for the time taken, memory usage and number of nodes. The numbers of data generated were and each informed search algorithm has 28 records for the time taken, number of nodes and memory usage.

Data collection

The descriptive statistics for bidirectional search presented the mean, standard deviation and the sample size of the three variables considered. The mean and standard deviation of number of nodes visited, time taken (nanosecond) and memory usage (bits) has the results to be 13.93 and 10.684 (number of nodes), 5552.29 and 2437.282 (time taken), 5827 and 2836.084 (memory usage) respectively. The analysis was performed for twenty eighty time (28) on each of the algorithms.

The value of KMO should be greater than or equal to 0.5 for a satisfactory factor analysis. Hence the KMO value of 0.516 is satisfactory for bidirectional search. The p-value of Bartlett's Test of Sphericity which is 0.001 indicates that it is

significant since the p-value is less than the 5% significant i.e. 0.05. Any value less than 0.5 for KMO is not suitable for proper factor analysis, likewise, value greater than 0.005 for bartlett's test of sphericity does show show adequate representation of sample data.

According to the computed analysis, the analyzed results show that each factors show high correlation in terms of their loading on the five blind search techniques. A* search for instance, the correlation between time taken and number of nodes is 0.989, time taken and memory is 0.992 and number of nodes and memory is 0.994. The implication is that time taken is not likely to share the same factor with the number of nodes visited. On the other hand, number of nodes visited is likely to share the same factor with the memory.

The communalities of the performance indices generated for the blind tree based algorithms with principal component analysis as the extraction method are presented in Table (a) through Table (e) for all the five blind tree based search algorithms.

TABLE (a)
Communalities Statistics for Bidirectional Search

	Initial	Extraction
Number of nodes visited	1.000	1.000
Time taken (nanosec.)	1.000	1.000
Memory usage (bits)	1.000	1.000

TABLE (d)
Communalities Statistics for Iterative Deepening Search

	Initial	Extraction
Number of nodes visited	1.000	1.000
Time taken (nanosec.)	1.000	1.000
Memory usage (bits)	1.000	1.000

TABLE (b)
Communalities Statistics for Breadth First Search

	Initial	Extraction
Number of nodes visited	1.000	1.000
Time taken (nanosec.)	1.000	1.000
Memory usage (bits)	1.000	1.000

TABLE (c)
Communalities Statistics for Depth First Search

	Initial	Extraction
Number of nodes visited	1.000	1.000
Time taken (nanosec.)	1.000	1.000
Memory usage (bits)	1.000	1.000

TABLE (e)

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Communalities Statistics for Uniform Search

	Initial	Extraction
Number of nodes visited	1.000	1.000
Time taken (nanosec.)	1.000	1.000
Memory usage (bits)	1.000	1.000

In an attempt to evaluate the percentage contribution of each factor to the efficiency of the blind tree based search algorithms, the eigenvalue of each factor is generated. This is presented in Table 6 through Table 10. The eigenvalue of jth factor denoted by 'Ej' is calculated by:

$$E_j = \sum_{k=1}^{3} X_{i,j}^2 \qquad i = 1,2,3; \quad j = 1 \qquad (3)$$

Where Xi,j represents the number of decision variables considered in this study. Tables 6 to 10 present the eigenvalues, percentage contribution and cumulative percentage contribution of the three considered factors for each of the five blind search algorithms.

TABLE (f)

Eigen values for Bidirectional Search

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[b]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	1.858	61.921	61.921	1.858	61.921	61.921	1.343
2	.814	27.132	89.052	.814	27.132	89.052	1.299
3	.328	10.948	100.000	.328	10.948	100.000	1.572

TABLE (g)

Eigen values for Breadth First Search

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[b]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	1.744	58.117	58.117	1.744	58.117	58.117	1.424
2	1.060	35.325	93.442	1.060	35.325	93.442	1.175
3	.197	6.558	100.000	.197	6.558	100.000	1.589

TABLE (h)
Eigenvalues for Depth First Search

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[b]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	1.789	59.630	59.630	1.789	59.630	59.630	1.297
2	.808	26.922	86.551	.808	26.922	86.551	1.246
3	.403	13.449	100.000	.403	13.449	100.000	1.468

TABLE (i)

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Eigenvalues for Iterative Deepening Search

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[b]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	1.802	60.078	60.078	1.802	60.078	60.078	1.427
2	.854	28.456	88.534	.854	28.456	88.534	1.148
3	.344	11.466	100.000	.344	11.466	100.000	1.511

TABLE (j)
Eigenvalues for Uniform Search

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings[b]
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total
1	1.708	56.935	56.935	1.708	56.935	56.935	1.339
2	1.052	35.063	91.998	1.052	35.063	91.998	1.201
3	.240	8.002	100.000	.240	8.002	100.000	1.534

The three factors contributed a total of 100% to the efficiency of the five blind search algorithms. From the results obtained, number of nodes contributed 56.935%, time taken contributed 35.063% and memory usage contributed 8.002% impact on the efficiency of uniform cost. This can be presented in Figure 1 using Scree test to further establish our assertion

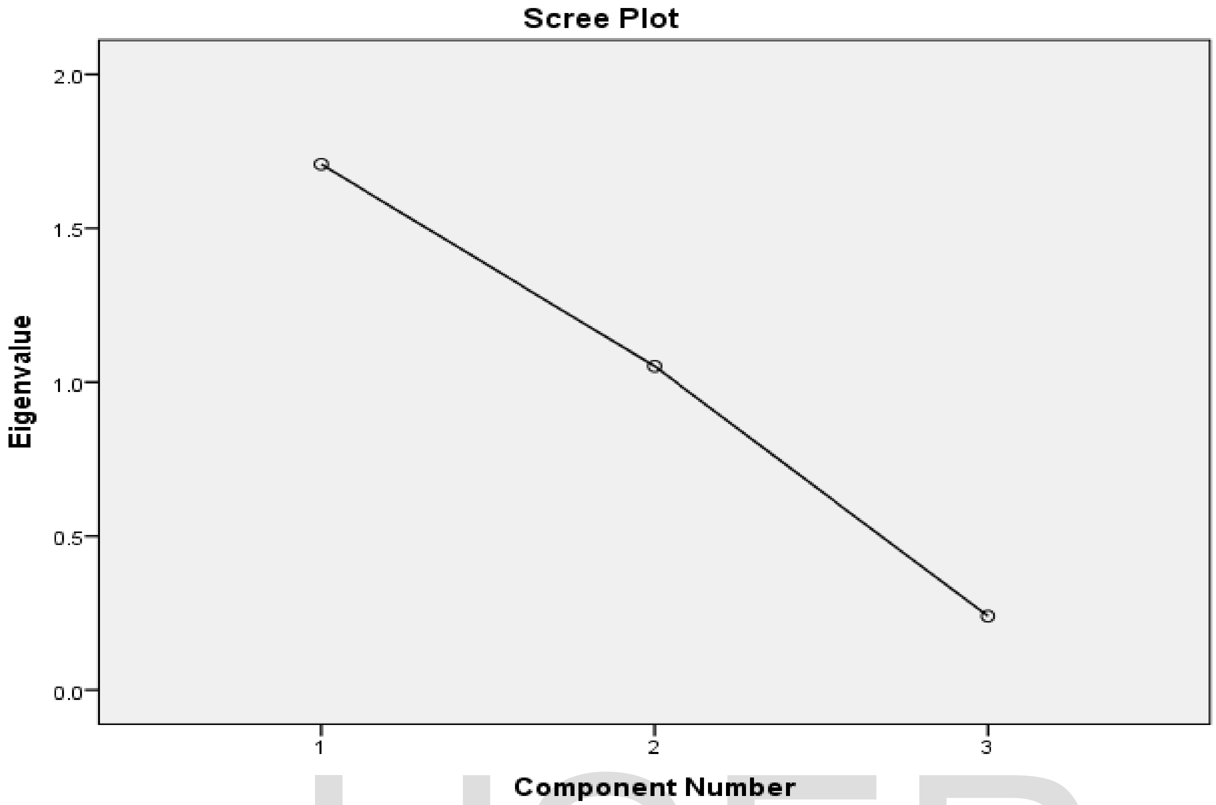

Fig.1 Scree Test showing Uniform Cost Search

3 Conclusion and Future Works

Eigenvalue was used to indicate how well each of the extracted factors fit data from the experimental result. From the analysis, the result showed that number of nodes visited contributed most by 61.921, 58.117, 59.630, 60.078 and 56.935% for bidirectional, breadth-first, depth-first, iterative deepening and uniform cost searching techniques respectively. The time taken came second, contributing 27.132, 35.325, 26.92, 28.456 and 35.063% while memory used was the least contributing 10.948, 6.558, 13.449, 11.466 and 8.002% for bidirectional, breadth-first, depth-first, iterative deepening and uniform cost search techniques respectively.

In summary it can be concluded that the number of nodes visited is the most critical factor affecting the five blind tree based search techniques and uniform cost is the most efficient blind tree based search techniques. It is highly recommended to explored the system environment and other types of factor analysis using different programming language.

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References

[1] Russell, S. and Norvig, P.: "Artificial Intelligence: A Modern Approach" AuthorStuart, 2012.
[2] Padharai ICS271,UC Irvine Pinar Yolum:"Principles of Artificial Intelligence", Department of Mathematical and Computer Science, University of Southern Denmark, 2007.
[3] Thomas H., Charles E., Ronald L., and Clifford S.:" Introduction to Algorithms" Second Edition, The MIT Press Cambridge, Massachusetts London, England McGraw-Hill,2012.
[4] Sean Thomas : Artificial Intelligence Programming In Prolog, USA, 2007
[5] Rusell, S. and Norvig, P.: "Artificial Intelligence, Pearson Education, International Upper Saddle, vol. 63, River, NJ, 2010.
[6] Olabiyisi S.O., Aladesae T.S., Oyeyinka F.I., and Oladipo Oluwasegun: "Evaluation of Critical Factors Affecting the Efficiency of Searching Techniques", *International Journal of Advanced Research in Computer Science and Software Engineering*, vol.3(7), pp.34-40, 2013.

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