AN ALGORITHMIC SOLUTION TO IMPROVE COMMAND CENTRE LAYOUT

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Abstract

A genetic algorithm was developed in this study to optimize the spatial layout of military command centres. The algorithm uses a textual string as the genetic encoding method, two genetic operations (i.e., selection and swap) for simulating an evolution process, a fitness function that reflects a human factors characterization of workplace layout requirements, and an elitist strategy for improving its search efficiency. To examine the effectiveness of the proposed algorithm, a simulation experiment was conducted using a hypothetical one dimensional layout problem. The results revealed that the algorithm identified the complete list of solutions that are theoretically optimal for the test problem. Compared to exhaustive search, the proposed algorithm increased search efficiency by more than 99%.

INTRODUCTION

Military command centres are a complex collaborative work environment where a team of operators work interdependently to support a common set of mission objectives. An important design consideration for such a work environment is its spatial layout, particularly the position and orientation of consoles and shared equipment in the workplace. Defence Research and Development Canada (DRDC) has been developing a modelling tool to support the design and evaluation of workplace layout. This paper describes an on-going research effort to create a layout optimization function for the tool based on the concept of genetic algorithm.

The layout of a workplace has been commonly characterized as a quadratic assignment problem where the goal is to establish a best mapping between a discrete set of m workstations to another discrete set of n workspaces (Gero & Kazakov, 1998). Because of inter-dependent work requirements that exist among operators, the layout quality can be assessed based on metrics that are sensitive to the relative proximity between workstations. For the layout of military command centres, such metrics often reflect a user-centred perspective with a focus on inter-operator interaction (e.g., communication) efficiency (Hendy, 1989).

The term genetic algorithm (GA) refers to a family of computational search methods that are inspired by the Darwinian evolution theory. Originally proposed by Holland (1975), the concept of genetic evolution has been introduced into the world of artificial systems and becomes a basis for developing algorithmic search and optimisation functions (Goldberg, 1989).

In a nutshell, the solution to a problem is treated in GA as an organism that can evolve over time. Each solution is represented by a unique sequence of genes, similar to the chromosome of an organism. Across generations, genetic operations are introduced to alter the chromosome, consequently changing the corresponding solution. Some operation (e.g., crossover) simulates the sexual reproduction process and requires two parent solutions. Others (e.g., mutate) only need a single parent solution for creating a new offspring. The quality of each solution is evaluated according to a fitness function. Based on the principle of evolution, diverse solutions are created by genetic operations and superior ones (i.e., those with a higher fitness score) are preserved in the population as evolution advances. With a sufficiently long evolution time frame, the superior chromosomes will converge, revealing solutions that are hopefully representing the theoretical optimum.

The development of a GA involves definition of the following key elements.

(1) An encoding scheme that establishes a mapping between design solutions and genetic expressions, i.e., chromosomes;

(2) A fitness function for evaluating the quality of genetic expressions;

(3) Genetic operations and the parameters that control their application in the evolution process;

(4) Algorithmic parameters such as the population size and a stop-rule for terminating the execution of the algorithm.

GA has been applied in a wide variety of domains. A large number of studies have been reported using GA for analyzing the layout problem of manufacturing systems (e.g., Balakrishnan & Cheng, 2000; Jang, Lee, & Choi, 2007; Wu, Chu, Wang, & Yan, 2007; Ficko & Palcic, 2013). It was the objective of this study to develop a genetic algorithm for improving command centre layout from a human factors perspective.

THE ALGORITHM

Genetic encoding scheme

The proposed algorithm uses a textual string for genetic representation of a layout solution. Assuming m operators (and their associated workstations) are to be positioned into n possible spaces ($m \leq n$), an n-digit string is created to indicate operator-to-space allocation. Each operator is represented in the string using a unique textual code. The length of the string corresponds to the number of spaces (i.e.,

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n) and each digit can be assigned with $m+1$ possible values (i.e., m operators plus the condition when the space is left unoccupied). In a valid solution, the codes for all operators should appear (i.e., a rule of completeness), and appear once only (i.e., a rule of non-redundancy), indicating each operator has been assigned to a single space.

Fitness function

An existing layout cost model was used in this study to construct a fitness function. A workplace layout is assessed in this model based on its impact on between-operator interaction effectiveness. A cost is computed to indicate the quality of interaction in four domains, i.e., auditory, visual, tactile, and distance (i.e., movement) (Hendy, 1989).

Between-operator interaction requirements are indicated in a priority weight matrix, as shown in Table 1 where a priority weight is assigned to each pair of operators and a distinction is made between a source and a receiver.

Table 1: A priority weight matrix for representing interaction requirements in a collaborative workplace.

		Receiver				
		Op1	Op2	Op3	…	Op(j)
Source	Op1		$p(1,2)$	$p(1,3)$		$p(1,j)$
	Op2	$p(2,1)$		$p(2,3)$		$p(2,j)$
	Op3	$p(3,1)$	$p(3,2)$			$p(3,j)$
	…					
	Op(i)	$p(i,1)$	$p(i,2)$	$p(i,3)$		$p(i,j)$

For each pair of operators, their interaction effectiveness is assessed by a quality measure that considers the distance displacement between the pair, the characteristics of the source and the receiver, as well as spatial obstructions, as shown in Eq(1).

$$q(i,j) = r(i,j)s(i,j)\prod_{h=1}^{n}\alpha(i,j,h) \times \prod_{k=1}^{m}\beta(i,j,k) \qquad (1)$$

where $q(i,j)$ is the quality of interaction between the ith *source* and jth *receiver*; $r(i,j)$ and $s(i,j)$ are a strength measure of receiver and source; $\alpha(i,j,h)$ and $\beta(i,j,k)$ are two types of transmission factors that represent an attenuation of interaction efficiency due to workspace obstructions.

The total layout cost (J) is then computed by aggregating the cost of all interacting operator pairs in the workplace, based on Eq(2). The importance of each pair of interacting operators is prioritized and a scaling factor is introduced to ensure the total layout cost score ranges between 0 and 1, with a smaller J score (i.e., lower cost) indicating a more effective layout.

$$J = \sum_{i=1}^{e}\sum_{j=1}^{e} k_0^{(v)}\left[1 - q^{(v)}(i,j)\right]p^{(v)}(i,j) + \qquad (2)$$

$$\sum_{i=1}^{e}\sum_{j=1}^{e} k_0^{(a)}\left[1 - q^{(a)}(i,j)\right]p^{(a)}(i,j) +$$
$$\sum_{i=1}^{e}\sum_{j=1}^{e} k_0^{(t)}\left[1 - q^{(t)}(i,j)\right]p^{(t)}(i,j) +$$
$$\sum_{i=1}^{e}\sum_{j=1}^{e} k_0^{(d)}\left[1 - q^{(d)}(i,j)\right]p^{(d)}(i,j)$$

where J is the measure of total layout cost; e is the number of operators; $q(i,j)$ and $p(i,j)$ are the quality and priority values for each pair of interacting operators i and j; $k_0^{(.)}$ are combined weighting and scaling factors for each domain of interaction; superscripts v, a, t, d indicate four interaction domains, i.e., visual, auditory, tactile, and distance.

To apply such a cost model in the proposed genetic algorithm, an inverse transformation was used to construct a fitness function F so that a larger score is better (i.e., fitter).

$$F = \frac{1}{J} \qquad (3)$$

Genetic operations

Two genetic operations, swap and selection, are specified in this algorithm. They ensure the introduction of new chromosomes (i.e., new layout solutions) in the population and the preservation of superior ones in the evolution process.

Swap. Swap is a customised genetic operation developed for the space layout problem. The operation involves value exchange between two random digit locations in a genetic string. It is applied to a single parent solution and creates a new offspring solution in the next generation.

An advantage of this operation is that it will not damage the validity of a genetic string, since the complete and unique occurrence of all operator codes are preserved in this operation.

Selection. The second genetic operation implemented in this algorithm is selection. It reproduces an identical copy of a parent solution in the next generation based on its fitness score. In this study, a roulette wheel method is used to control the selection operation and this method has been used in other studies in the past (e.g., Razali & Geraghty, 2011). It involves a two-step procedure. First the fitness of each solution in a parent generation is computed, and then the proportion of a solution's fitness of the total population fitness is calculated, and this value is used as the probability for selecting the specific solution for reproduction in the offspring generation.

This method reflects the "survival of the fittest" principle and ensures superior solutions (i.e., those with a higher fitness score) are more likely to be passed onto the next generation.

Elitist strategy

The use of genetic operations like swap is accompanied by a risk of destroying a good solution. To reduce such a risk, an elitist strategy was implemented in the proposed algorithm.

Such a strategy requires the tracking of the best solution (i.e., fittest) in each generation and compare the current best with the one from the immediate generation before. If the current best is worse, then an exchange is performed that replaces the worst solution in the current generation with the best solution from the generation before. Such a strategy ensures the best solution be passed onto the next generation and increases the algorithm's search efficiency.

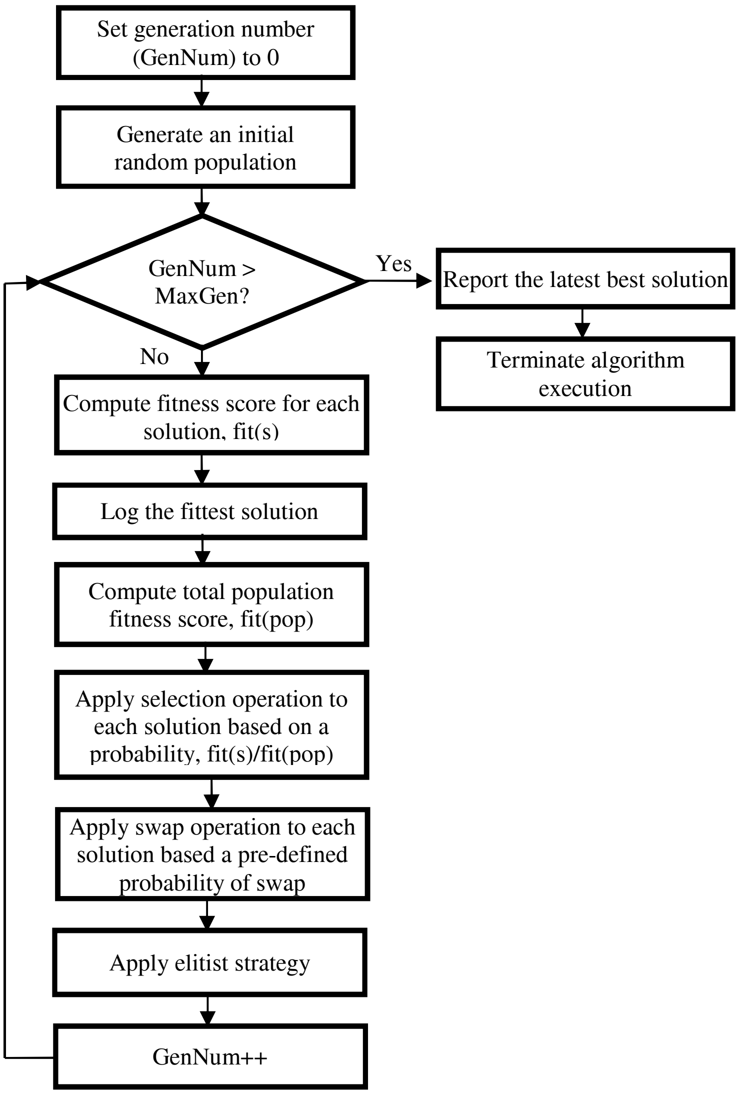

Figure 1: A flow chart of the proposed genetic algorithm.

Workflow

Figure **1**1 provides a flow chart to describe the computational procedure of the proposed algorithm. Firstly a set of random solutions is created to form the initial population. The fitness for each solution is assessed, and then compared to the total fitness score of the current population to compute the probability for selection. Two genetic operations are then applied: (1) each solution is copied into a mating pool (which is a construct in GA that holds selected solutions for application of genetic operations) based on its respective probability for selection; (2) swap is applied to each solution in the mating pool, based on the probability of swap. Upon completion of selection and swap, the elitist strategy is applied to ensure the best solution in the previous generation is not destroyed by genetic operations. Then all solutions in the mating pool are used to constitute the population of the next generation. This process advances iteratively with each new generation evolved from the previous one. The evolution process is stopped when the generation number reaches a pre-defined threshold (i.e., a maximal number of generation), at which point, the fittest individual identified in the last generation is reported as the best solution.

A SIMULATION EXPERIMENT

To investigate the effectiveness of the proposed algorithm, a simulation experiment was conducted, using a hypothetical one dimensional layout problem as a test case. This problem involved the assignment of a team of ten operators, and their workstations, to a workplace that is characterised as a single row of ten adjacent workspaces, as illustrated in Figure2. Each workspace is identical in size and shape, and can accommodate any one of the ten operators. The physical separation between any two adjacent spaces is a constant distance, denoted as d.

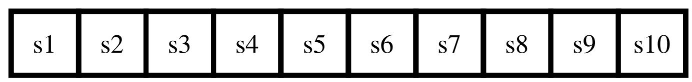

Figure 2: A single row of 10 workspaces used in the test problem.

To facilitate discussion, the operators were labeled from Op1 to Op10 and the following set of assumptions was introduced to define their organizational configuration.

1. Op1 is the lead (e.g., supervisor) of the team;
2. There exist three sub-teams based on their functional roles. Op2 and Op3 forms the first subteam; Op4, Op5, and Op6 the second subteam; Op7, Op8, and Op9 the third subteam;
3. Op2, Op4 and Op7 are the lead of each subteam; and
4. Op10 is a lone operator who does not belong to any subteam.

Such an organizational structure is typical for a military command centre, where a duty officer supervises a number of teams that are established for various functional purposes (e.g., plans and operations). Each functional team is comprised of a lead and a number of supporting technicians. The lone operator is a representation of such roles as liaison officers who are common in a command centre and often not included explicitly in any functional team.

Based on such an organizational structure, a set of between-operator interaction requirements was defined, as shown in Table 2. To simplify the discussion, interaction in this case was interpreted as physical access only, that is, a requirement for a source to move to a receiver's location. A single priority weight of 1 was adopted for all interacting pairs. In other words, if the value between a pair of operators is 1, it indicates work requirements for the corresponding source operator to walk to the receiver operator's location.

Table 2 was created based on the following set of physical access requirements. Note, a blank cell in this table indicates there is no interaction requirement between the corresponding pair.

1. The supervisor Op1 needs access to Op2-Op7, reflecting a common need for the supervisor to interact with most operators in the command centre.
2. For subteams 1 and 2, there are extensive within-team interactions, and mutual access requirements are specified between all members.
3. Subteam 3 is a slight variation from subteam 2, in which Op7 and Op8 require mutual access, and both of them require access to Op9, however Op9 only requires access to Op7 (i.e., not Op8).
4. There are substantial mutual access requirements among three subteam leads (Op2, Op4, and Op7).
5. Op2 has access requirements to members of other subteams (e.g., Op5, Op8).
6. No access requirement for Op10, either as a source or as a receiver.

Table 2: The priority weight matrix for indicating interaction requirements of the 10-operator team.

		Receiver									
		Op1	Op2	Op3	Op4	Op5	Op6	Op7	Op8	Op9	Op10
Source	Op1		1	1	1	1	1	1			
	Op2			1		1			1		
	Op3		1								
	Op4		1			1	1	1			
	Op5				1		1				
	Op6				1	1					
	Op7		1		1				1	1	
	Op8							1		1	
	Op9							1			
	Op10										

Such a simplistic model makes it easy to examine the layout solution analytically. With the consideration of only the distance (i.e., movement) domain, the fitness function can be simplified as follows.

$$F = \frac{1}{J} = \frac{1}{\sum_{i=1}^{e}\sum_{j=1}^{e} d^{(d)}(i,j) \times p^{(d)}(i,j)} \qquad (4)$$

where J is the measure of total layout cost; e is the number of operators; $d(i,j)$ is the distance between operators i,j; $p(i,j)$ is the interaction priority weight between operators i and j; the superscript (d) indicates the interaction domain.

RESULTS

The research objectives for the simulation experiment were to investigate whether the proposed algorithm could discover optimal layout arrangements and examine its search efficiency. Three key parameters for the algorithm were arbitrarily specified in this experiment, as shown in Table 3. The algorithm was run a total of 100 times with the initial population (for generation zero) randomly created in each run.

Table 3: The parameter setup of the algorithm in the experiment.

Parameter	Value
Population size	100
Probability of swap	0.1
Maximal generation	50

Figure 2 shows the fitness scores of both the best solution and the population average for each generation. Each data point is an average across 100 simulation runs.

It is apparent that both curves show a monotonic increase of value as the evolution process advances, indicating the algorithm's ability to continually improve the average quality of all solutions in the population, as well as the quality of the best one.

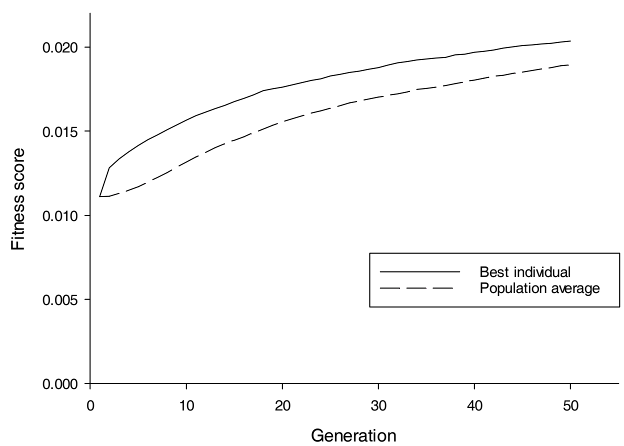

Figure 2: Fitness scores of the best solution and the population average.

Across 100 simulation runs, a total of eight unique optimal layouts were identified, as shown in Figure 3. All of them had a fitness score of $0.0213d^{-1}$ (which corresponds to a total separation of 47d for all interacting operator pairs). The solutions are color coded based on operators' organizational groupings. It is apparent that solutions 5-8 have the same sequences (i.e., layout arrangement), but in a reverse order, as solutions 1-4.

The following features are revealed in these solutions:

1. Op1 is positioned close to the centre of the workplace, supporting the supervisor's requirement to access many operators.

2. Operators from each of three subteams are grouped together, reflecting the strong within-team interaction requirements.

Solution#	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10
1	Op10	Op9	Op8	Op7	Op2	Op3	Op1	Op4	Op5	Op6
2	Op10	Op9	Op8	Op7	Op3	Op2	Op1	Op4	Op5	Op6
3	Op10	Op6	Op5	Op4	Op1	Op2	Op3	Op7	Op8	Op9
4	Op10	Op6	Op5	Op4	Op1	Op3	Op2	Op7	Op8	Op9
5	Op9	Op8	Op7	Op3	Op2	Op1	Op4	Op5	Op6	Op10
6	Op9	Op8	Op7	Op2	Op3	Op1	Op4	Op5	Op6	Op10
7	Op6	Op5	Op4	Op1	Op2	Op3	Op7	Op8	Op9	Op10
8	Op6	Op5	Op4	Op1	Op3	Op2	Op7	Op8	Op9	Op10

Figure 3: Eight optimal layout solutions for the 10-operator layout problem.

3. The leaders from two subteams (i.e., Op4, Op7) are positioned at the edge of their respective team groupings, towards the centre of the workplace, so that they are closer to each other reflecting an interaction requirement for subteam leads.

4. The placement of two members of subteam1 (i.e., Op1, Op2) are exchangeable in the solutions, which happens to produce identical fitness score. In contrast, subteams 2 and 3 have a unique within-team optimal arrangement due to Op2's requirements for accessing Op 5 and Op8.

5. The closer proximity between Op1 and subteam 2 (rather than subteam 3) is due to the lack of access requirement between Op1 and Op7, Op8 in subteam 3.

6. Op10 is positioned at the peripheral end of the workplace that is furthest from the supervisor Op1, due to the lack of interaction requirement with all others.

These solutions have been further confirmed by the analytical investigation as the theoretical optimum for the test problem. They are referred to as the true optimal solutions, in contrast to those obtained at the end of a simulation run but with a sub-optimal fitness score. In this experiment, a true optimal solution was discovered in 33% of the simulation runs.

The computational efficiency of the proposed algorithm was assessed based on the number of times that the fitness function was evaluated, which is an approximate measure of computational expense. In this experiment, for each simulation run, the fitness function was evaluated for a total of 5000 times (i.e., population size x maximal generation). In contrast, when an exhaustive search strategy is adopted (which involves the evaluation of the entire solution space), there exists a total of 3628800 possible solutions (i.e., P(10,10) = 10!) for the test problem, and a complete search through this space will therefore calculate the fitness function 3628800 times. Compared to exhaustive search, the proposed algorithm reflects an improvement in search efficiency by more than 99%.

CONCLUSIONS

The following two conclusions were reached from this study.

1. The proposed algorithm provides a viable way to search for optimal layout solutions. Based on independently repeated simulation, where the algorithm is run multiple times with a randomly generated initial population, it was able to identify the complete list of solutions that are theoretically optimal for the test problem.

2. The proposed algorithm is highly efficient. Using the exhaustive search as a benchmark and the number of times that the fitness function is evaluated as a measure, the algorithm increased the computational efficiency by more than 99%.

To sum up, a genetic algorithm was developed to search for optimal workplace layout solutions. This algorithm uses a textual string as the genetic encoding method, two genetic operations (i.e., selection and swap) for simulating an evolution process, a fitness function that reflects a human factors characterization of workplace layout requirements, and an elitist strategy for improving its search efficiency. The effectiveness of the proposed algorithm and its search efficiency has been confirmed to solve a hypothetical one dimensional command centre layout problem. This algorithmic solution will be integrated into a workplace modeling tool for layout optimization.

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