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Nature-Inspired Optimization: Optimizing Distance of Emergency Response Wagons en Route to Railway Crossing Accident Location

Israel Edem AGBEHADJI[a,b], Richard C MILLHAM[c1], Simon James FONG[d] and Richard Koblah AGBEHADZI[e]

[a] *Durban University of Technology, South Africa*
[b] *Ghana Communication Technology University, Ghana*
[c] *ICT and Society Research Group, Durban University of Technology, South Africa.*
[d] *University of Macau, Macau, China*
[e] *University of Lome, Togo*

Abstract. The problem is that when an accident occurs at a railway crossing, emergency response wagons are unable to get to the accident location on time. In this study, we consider the location of emergency response wagons and railway accident location and apply a nature-inspired search strategy as a solution to compute the optimal distance for an emergency response wagon such that when an accident occurs the expected time to reach the accident location can be minimized. The outcome suggests the ideal objective function, haversine method, because it produced the optimal minimal distance of 994,691.90km with a computational time of 1.05s for KSA over comparative algorithms namely BAT and (Ant Colony Optimization) ACO.

Keywords: Nature-inspired optimization, railway crossing, emergency response

1. Introduction

Railway crossing or railway level crossing represents a place where a railroad track crosses a road. An obstacle may include but is not limited to cars, animals, and human, that need to be cleared to allow smooth movement of the train. However, many accidents occur when a train is placed in shunting mode while travelling below a speed of 45km/h [1]. Few technologies have been proposed to monitor faulty equipment at railway crossings [2], including the use of global positioning system (GPS) and general packet radio services (GPRS) equipment for railway crossings to ensure effective warning signals and safety on rail systems [3]. Though parameters for assessing the level of safety at the railway level crossing [4] have been identified, many challenges still affect the smooth movement of a train, and despite its locomotive whistle, railway accidents continue to happen thereby stretching the limited resources of an emergency response

[1] Corresponding author: richardmillham@hotmail.com

unit. Therefore, the study's objective is to optimize an emergency response wagon locations so that wherever an accident happens, the expected time to reach accident location can be minimized. The remainder section of the paper is organized as follows: related work (section 2), method (section 3), results (section 4), and conclusion (section 5).

2. Related work

Railway systems are complex with a time-varying nonlinear behavior [5]. Such systems are required to work at their optimum despite any constraints. Railway accidents can greatly cause damage to an infrastructure therefore selecting an ideal location for use as an emergency medical center is key [6]. Aside from this, maintaining an optimized schedule for emergency rescue wagons could maximize productivity and avoid major impact of train accidents [7]. Liu, Li [8] indicates that among the factors that influence the selection of a location to place an emergency medical facility is the new facility's capacity. For instance, it has been applied in siting emergency humanitarian facility [9] and also to group patients per county [10]. Thus, a collision free route ensures an effective delivery of services [11].

There are many railway accident prevention strategies including the use of reinforcement learning method proposed by [12], installation of real time mobile communication tools [13], use of sensors to detect movement on rails and to provide alert messages, classification of the cause of railway accident using the entropy weight method leading to railway accident evaluation standard [14]. Habib [15] suggested the use of artificial intelligence and machine learning techniques to identify risk of accidents from "Experience Feedback". Wang, Ma [16] combined K2 scoring algorithm and graph based convolutional neural network to predict railway freight accidents. Again, railway line tracking system that detects an animal and trigger an alarm around 5km away has been proposed [17]. There is an optical flow estimation that leveraged the modified Lucas-Kanade method to classify obstacles using K-means clustering algorithm [18]. Deep learning methods for object detection in railway systems require large number of datasets which is very costly to set up. However, a small data set leads to poor classification performance which was addressed by [19] where a few samples used produced good detection accuracy. Muduli and Ghosh [20] identified the jaywalker characteristics in non-lane-based environment in terms of speed of walking, location of a person in the road environment, frequency count and the direction of an approaching traffic, and the speed and type of closest approaching vehicle. This approach uses "MediaPipe" for detection of key characteristics in the pedestrian body while Yolov4 and "DeepSORT" was used to detect and track road users to get trajectory data. Ideally, society expects accident free railway crossings and since this is an expansive expectation, this research contributes to finding a solution to railway crossing accident problem using an optimization technique for an emergency response wagon. An optimization technique can be used to solve complex railway systems to achieve optimal performance. As mentioned earlier, nature-inspired optimization methods can minimize cost, time and resource in performing a task. Example of nature-inspired optimization methods, include but are not limited to genetic algorithm [21], ACO [22] and BAT[23]. KSA performed well over other nature-inspired algorithm [24], and this is the motivation to apply KSA as an optimization method.

3. Method

3.1 Problem description

The problem description is that people get hit or killed by trains at railway crossing which requires immediate medical attention. Initially, an emergency response office receives an information from any sensor-enabled device or emergency call, then they record and relay the emergency call to all stationed emergency response wagons within its coverage. Any emergency response wagon closer to the railway crossing accident scene is expected to move from its current station to the railway crossing accident scene and provide urgent medical care, afterwards it carries the accident victim to a medical facility and then returns to its station. All railway crossing accident locations are identified in terms of coordinates showing the longitude and latitude.

3.2 Kestrel algorithm formulation

Kestrels belong to falcon family of birds and they learn by hovering and perching on objects to find preys. Mathematical models underlying the kestrel-based search algorithm (KSA) are formulated in terms of basic rules such as improve, reduce and check rules [25]. Parameters for the KSA include but not limited to decay constant parameter φ that represents the length of time for the source of trail to decay. The idea of a decaying lifetime of a call is to ensure that ambulances respond only to recent, rather than historical calls. In planning, this bobbing represents the count on best locations that were identified en-route to accident location. Thus, KSA optimization algorithm for the problem description can be summarized into algorithmic stages as improve rule (algorithmic stage1), reduce rule (algorithmic stage 2), check rule (algorithmic stage 3), and fitness function (algorithmic stage 4), as expressed below:

>>***Initially***: *load location of wagon* x_i *and railway crossing accident location* x_j
>>***Start***: *Set model parameters*

Algorithmic stage 1	
Step 1: *initial* $\vec{x}(t)$ *value obtained from random encircling expression*	
Step 2: *initial coordinate of emergency response wagon* x_i	
Step 3: *initial coordinate of an originator* x_j	
Step 4: *Compute* $\beta_o e^{-\gamma r^2}$	(1)
Step 5: *Compute* γ at time *t* from the Reduce rule	(2)
Step 6: *Compute* f_{t+1}^k	(3)
Step7:*Compute* **position** $x_i^k(\mathrm{t}+1) = \vec{x}(t) + \beta_o e^{-\gamma r^2}(x_j - x_i) + f_{t+1}^k$	(4)
Step 8: *Display* **optimal position**	

Algorithmic stage 2	
Step 1: *Compute* $\gamma_t = \gamma_o e^{-\varphi t}$	(5)
Step 2: *Compute* $\varphi = \frac{ln\ 0.5}{-t_{\frac{1}{2}}}$	(6)
$if\ \varphi \rightarrow \begin{cases} \varphi > 1, trail\ is\ new \\ 0, otherwise \end{cases}$	

Algorithmic stage 3
For ***t*****=1 to Max_itr**
Step 1: *Compute* $fitness\ Obj\left(x_i^k(\mathrm{t}+1)\ \right)$ *//using results from algorithmic stage 1*
Step 2: $\boldsymbol{if}\ \ fitness\ Obj^{\ i+1} < fitness\ Obj^{\ i}$
$fitness\ Obj^i = fitness\ Obj^{i+1}$ (7)
$New_{position}(x_i^k) = Old_{position}(x_i^k)$
End if
Step 3: *Update position* $x_i^k(t+1)$ (8)
End for
Step 4: *Display emergency response wagon assigned to accident location*

Algorithmic stage 4**: Fitness objection:** $fitness\ Obj\left(x_{i+1}^k\right) = (\varphi, \lambda)$
// where: φ represents a change in latitude (that is: Δφ =φ$_2$-φ$_1$), λ: a change in longitude // (that is: Δλ =λ$_2$-λ$_1$), R represents the earth's radius (R = 6,371km)
For each position {
Evaluate fitness function as follows
Evaluate: *Fitness 1 // based on the "Equirectangular" approximation*
$u = \Delta\lambda\ * \cos\left(\frac{\Delta\varphi}{2}\right)$ (9)
$v = \Delta\varphi$ (10)
$d = R * \sqrt{u^2 + v^2}$ (11)
Evaluate: *Fitness 2 //based on the "Haversine" method*
$a\ =\ sin^2(\Delta\varphi/2)\ +\ cos\ \varphi 1\ \cdot\ cos\ \varphi 2\ \cdot\ sin^2(\Delta\lambda/2)$ (12)
$c\ =\ 2\ \cdot\ atan2(\ \sqrt{a}, \sqrt{(1-a)}\ )$ (13)
$d\ =\ R\ \cdot\ c$ (14)
End for

>>Output: Distances

3.3 Emergency response center notification hub

The center notification hub is responsible for receiving railway crossing accident information and sends alert to *k* number of emergency response wagons in the coverage area *N* in vector representation where $N_i = \{N_1, \ldots, N_k\}$. The mapping function responsible for notification push can be expressed as follows:

$$(P_i^k) \leftrightarrow \begin{pmatrix} N_1 \\ \cdot \\ \cdot \\ \cdot \\ N_k \end{pmatrix} \rightarrow (P^* \leftrightarrow N^*) \tag{15}$$

Where: P_i^k represent the originator or originating device located at the railway crossing, *N* is vector representation of all wagons in *i*= (1, …, *k*). The resultant P^* is mapped to the selected N^* using the mapping function defined as $f(x_i^k)$ which is the fitness objective function $fitness\ Obj\left(x_{i+1}^k,\right)$ based on equirectangular approximation formula and haversine formulas for distance computation. Figure 1 depicts the conceptual structure to provide an optimal distance for an emergency wagon.

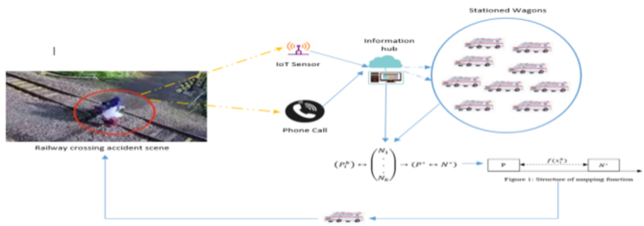

Figure 1: Conceptual structure

4. Results

The location data is fed into the algorithm as vector representation *N*= ({lat1, long1}, {lat2, long2}) and a single value distance is outputted. Where lat1, lat2 refers to latitudes (north/south) and long1, long2 refers to longitudes (east/west) in Degrees (D). Initially, the coordinates are presented as lat1 = 50.3222821D; long1 = -60.242588D. Table 1 shows the result of the experiment of KSA, and Table 2 shows the comparative analyses results of comparative algorithms (BAT and ACO). The computational time is in seconds (s) and wagon identifiers are numbered as Wag1,…, Wag9.

Table 1: Experimental results on optimal distance using KSA.

Wagon Identifier	Initial wagon coordinates (D) (lat2, long2)	Equirectangular approximation (km)	Haversine formula (km)	Computational **time (s)**
Wag1	(50.5830510,-60.512500)	2,002,765.00	1,121,567.98	1.44
Wag2	(51.212801,-60.732354)	2,272,909.30	1,890,516.01	1.40
Wag3	(50.4623411,-60.812375)	2,853,906.45	1,076,912.99	1.45
Wag4	(51.4521171,-60.721244)	1,123,119.09	1,032,876.11	1.30
Wag5	(51.5212801,-60.602388)	1,221,432.40	1,002,356.00	1.41
Wag6	(50.3232821,-60.231489)	1,091,324.91	994,691.90	1.05
Wag7	(51.4814312,-60.981354)	1,387,122.37	1,212,321.83	1.21
Wag8	(51.6643410,-60.772387)	1,190,612.56	1,078,281.92	1.46
Wag9	(52.3212801,-60.462375)	2,121,812.82	1,700,819.43	1.43

Table 2: Experimental results on optimal distance using BAT and ACO

Wagon Identifier	BAT			ACO		
	Equirectangular approximation (km)	Haversine formula (km)	Time (s)	Equirectangular approximation (km)	Haversine formula (km)	Time (s)
Wag1	30,112,411.57	9,108,062.87	1.76	80,321,632.56	2,325,986.32	1.90
Wag2	29,036,451.09	2,748,504.92	1.87	90,364,258.32	2,963,214.33	2.89

Wag3	25,316,985.36	4,840,176.09	1.75	85,378,993.12	3,987,556.14	2.87
Wag4	20,236,956.32	4,353,260.28	1.70	89,236,447.12	3,477,489.12	2.88
Wag5	36,361,238.39	5,596,137.45	1.80	79,325,114.36	4,889,236.12	2.70
Wag6	38,312,965.15	3,625,112.32	1.82	78,364,821.33	1,268,972.00	2.71
Wag7	37,399,112.33	4,663,195.32	1.78	77,378,154.33	6,312,658.00	2.72
Wag8	36,982,164.32	5,556,349.32	1.81	95,788,665.31	5,378,688.00	2.95
Wag9	28,394,112.30	6,356,114.32	1.83	90,558,645.22	6,978,663.00	1.91

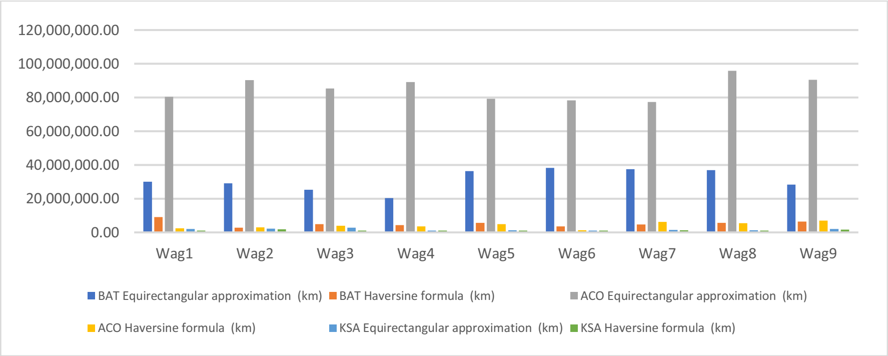

Figure 2: Display on results of comparative algorithms

The experimental results show the haversine formula generated 994,691.90km as the minimum optimal result in KSA. Again, the computational time for Wag6 was 1.05s which can be translated to suggest the time to arrive at the railway crossing accident location, which is the least between ACO and BAT. These results are illustrated in Figure 2. Thus, KSA continues to demonstrate impressive performance at providing near-optimal location information which can be confirmed in this study.

5. Conclusion

This study considered the problem of placing an emergency response wagon at a location that can minimize the distance and time to a railway crossing accident location. KSA was able to produce minimal distance and time required en-route to railway crossing accident location. This finding further demonstrates the capability of KSA towards addressing real-world problems. Again, future work would require comparison of KSA with other similar nature-inspired algorithms.

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