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Bio-inspired Search Approach Cross-Domain Location Mapping for Smart Mobile Service System

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Abstract: The health care service sector is very critical in every country. Although governments have made significant efforts to improve health infrastructure and train more qualified health professionals, the majority of them cannot find jobs within public health facilities. Furthermore, patients queue at health care facilities for hours daily for basic health care services while job creation and reducing these long queues remains a challenge in most developing countries. By leveraging the ubiquitousness of mobile technology, patients can be assisted to request health care services, to be delivered at their locations by qualified healthcare professionals. Given the critical nature of health care services, it is imperative to deliver services on-time without delays. In this regard, finding an optimal path between the service originator and the location of health care professionals is important. In this study, location data was used to provide near-optimal location information by mapping location data between patient and health professional domains. Our mapping approach centers on the hunting behavior of the Kestrel bird and through this, an algorithm is proposed for cross-domain location mapping. The mathematical model that is proposed in this study's major contribution as well as the application of the Kestrel-based Search Algorithm (KSA) for location data generation to find the optimal distance from an initial location. The result is promising in terms of the optimal distance between two locations using the haversine and equirectangular approximation formulas. The KSA was juxtaposed with other renowned meta-heuristic algorithms such as the BAT, Wolf Search Algorithm with Minus Previous Step (WSA-MP), and Ant Colony Optimization (ACO). Results obtained indicate that the equirectangular approximation formula with the KSA has the minimal distance which in practice implies that nature-inspired algorithms can be adopted in location mapping where randomization is essential, especially in a mobile health application.

Keywords: Bio-Inspired Algorithm, Cross-Domain Location Mapping

Introduction

The health care (Issel, 2014) system of low-income countries is challenged with inadequate infrastructure, poor ambulance services, and inferior technology. Though employment is one of the major challenges, it presents an opportunity for innovation. As society evolves, the quest to use technological application that supports mobility becomes the fundamental component as it helps in providing timely information. In this context, mobility encompasses the use of mobile computation to facilitate work practices (Hameed, 2003). For instance, in countries such as Ghana, Kenya, and South Africa, there is a technological platform that enables mobile money transfer (Kendall *et al.*, 2011). The advantage of the mobile money platform is that it reduces the cost per transaction and also investment in physical infrastructure (Kendall *et al.*, 2011). In Ghana, such a platform also supports the payment of services including renewing national health insurance membership and many more. It has transformed the payment of premiums in the health insurance sector and reduced the long queues at their office premises, which are often witnessed during the renewal of premiums. The use of mobile technology in health care could transform and enhance service delivery in the healthcare sector while avoiding the stress of queuing for healthcare services in hospitals, especially among aged persons in developing nations. However, a peculiar challenge of mobile technology is the unreliable nature of the communication infrastructure, especially mobile networks (Carrasco-Escobar *et al*., 2019), which hinders prospective mobile interventions in developing countries. Thus, designing a mobile application for health care delivery to aged persons can be confronted with usability issues. Although exploring usability associated with an aged person's use of the mobile application is not within the scope of this research work, studies by Agbehadji *et al*. (2019a) suggested the assisted service request. This refers to the use of a trusted family member to request service on behalf of another person because of the critical nature of health information. Subsequently, a model for assisted service request and delivery was proposed in previous work by Agbehadji *et al*. (2019b). However, to deliver the service at a location, it is imperative to search for the optimal distance. In this study, the previous work by Agbehadji *et al*. (2019a) is enhanced to include the use of cross-domain location information between the user such as a patient/person who requests/may assist by requesting health care service on behalf of another, and the health professional/nurse, to find the optimal distance of a nurse who can offer the requested health care service. Such enhancement will support mobility by making use of location information. The proposed system is known as "smart mobile health care" connotes the ability to demonstrate intelligence in finding optimal distance. The gap this study seeks to fill is to determine the optimal distance between a generated location data and an initial reference location data by applying nature-inspired algorithms. Subsequently, the equirectangular approximation and haversine formulas are applied for the evaluation of the proposed model to determine the optimal distance.

Related Works

Health care systems are transitioning gradually toward an integration-based health care process between a patient and a caregiver (Nasi *et al*., 2015). The adoption of mobile technology in medicine and health care has transformed many aspects of clinical practice. Nowadays, it is commonplace to find mobile technology in health practice for patient management and monitoring, health record maintenance and access to patient referrals via emergency, using alerts and reminders for work planning, supervision, and disseminating information between health workers (Agarwal *et al*., 2015; Ventola, 2014). Additionally, patients can self-manage their health-related activities by using mobile technology. The idea of point-of-care serves as a means by which health care professionals access the required information resources of a patient and provides targeted care (Nasi *et al*., 2015).

However, mobile communication is among the fastest-growing sector worldwide Agbehadji *et al*. (2019) and nowadays, it is ordinary to see people with mobile devices which makes it possible for the majority of people to receive short message services and other real-time messages. Similarly, organizations now prefer to use short message services (text messaging) in their operations. Free *et al*. (2010) investigated the use of Interactive Voice Response (IVR) and Short Message Services (SMS) in health care services and suggested that it can improve sending and receiving information in areas that are difficult to reach. However, the full potential has not been realized because of an unreliable network, and cultural and socio-techno-economic and policy regulatory impediments (Agbehadji *et al*., 2019b; Kaplan, 2006). That notwithstanding, the design of mobile applications needs re-alignment with the realities of rural areas where access to a reliable network is problematic. Two approaches to address the unreliable nature and high latency of mobile networks are asynchronous data access and sending data in a relatively small amount. The asynchronous data access approach is the locking of the user interface thread of the mobile device resulting in the stalled user interface. Secondly, sending data to the mobile device of the user is a relatively small amount since mobile devices have low computational abilities. Other approaches to address these challenges include the use of asynchronous data access and automatic queries via a paging algorithm which has two operations - an insert and a select.

The design of mobile health systems requires a thorough understanding of the targeted health care system and also satisfy the demand constraints of several vested interests including patient, hospitals, administrators, and health professionals (Vélez *et al*., 2014). An interesting trend in mobile technology applications is the use of location-based services that supports either online or offline location maps. On the one hand, offline location mapping does not need using an internet connection, thus making it suitable in poor mobile coverage areas and it is also beneficial when traveling, especially abroad when Wi-Fi connection might be unreachable. Carrasco-Escobar *et al*. (2019) proposed the open mobility mapping tool Geo ODK, to help in tracing self-reported patient information where access to the internet is unreliable. The Geo ODK tool is a mobile application that provides "offline visualization and mapping of geo-referenced data" such as points, shapes, and traces on a person's mobile devices. On the other hand, the online location map only works in places where there is network coverage/internet. The dichotomy of location-based services has not been fully utilized to support health-related applications. The use of mobile device location identifiers (location code) and time identifiers provides timely location data on the movement of persons and their identity because of the Global Positioning System (GPS) chip embedded in smartphones. Examples of other location-based detection technologies include Wi-Fi and Radio-Frequency Identification (RFID). Moreover, the detection technologies require the consent of the phone user to track the coordinate axis of a location. The GPS tracker uses a geofencing method that inspects location data received from GPS chips embedded in smartphones to trigger an action. However, geofencing is susceptible to any kind of obstruction like in a closed area (room) and thus cannot provide an accurate location. On the contrary, the Bluetooth Low Energy (BLE) technology provides the absolute position of the device-user in an enclosed area to give location-aware notification services. When location codes in the form of latitudinal and longitudinal data are known, it is easy to find the distance between two locations using the haversine, spherical law of cosines, and the equirectangular approximation formulas.

In a cross-domain system, access to data control measures including user consent is vital to ensure the security of data and information. Gaining access to a person's location data and placing a request for health care service needs some form of authentication. Salehi *et al*. (2019) proposed a cross-domain system for a collaborative healthcare system that includes home and foreign healthcare domains, attribute authority, health care database, and data access structure. The domains include patients, nurses, and doctors whereas an inter-mediate domain considers the attributes in each domain and automatically controls access to information without the involvement of third-party control. Similarly, the idea of the roaming technique (Liu *et al*., 2014) and the group signature approach (Kuchta *et al*., 2017) have also been adopted to control access to health-related records. The declaration or definition of domain attributes organizes security controls and responds to authentication requests.

Nature-Inspired Search Methods

In recent years, nature-inspired search methods have demonstrated impressive potential as an approximation function in diverse problem domains due to their ability to avoid the non-promising search. Theoretically, the method is based on the behavior of animals in their natural environment (Agbehadji *et al*., 2020). Social hunting involves information sharing among search agents in their natural environment to enable convergence and capturing of prey (Siddique and Adeli, 2015). The search methods use objective function and iterative evaluation to estimate their current position and search direction. Some of the state-of-the-art nature-inspired algorithms within the group of particle swarm intelligence that have extensively been applied in different problem domains include BAT (Heraguemi *et al*., 2016), Particle Swarm Optimisation (PSO) (Kuo *et al*., 2011), Multiple Species Flocking (MSF) (Reynolds, 1987), Ant Colony Optimization (ACO) (Stutzle and Dorigo, 2002), Wolf Search Algorithm with Minus Previous step (WSA-MP) (Tang *et al*., 2012; Agbehadji *et al*., 2016), Social Spider Algorithm (SSA) (James and Li, 2015), Dung Beetle Algorithm (DBA) (Agbehadji *et al*., 2018a), Artificial Bee Colony (ABC) (Bui *et al*., 2020), Firefly (Yang, 2009), Elephant Herding Optimization (Li *et al*., 2020), Monarch Butterfly Optimisation (MBO) (Feng *et al*., 2021), Krill Herd Algorithm (KHA) (Wang *et al*., 2019a), Earthworm Optimisation Algorithm (EWA) (Wang *et al*., 2018), etc. Swarm Intelligence is a nature-inspired method that uses "swarm behavior" to adapt and make a decision depending on their position within a search space and neighboring particles (Agbehadji *et al*., 2018b). Some of the nature-inspired algorithms are hereby briefly discussed.

A. Bat Algorithm

BAT is based on microbats' echolocation behavior in which rates of ejaculation and loudness are of varying pulses (Heraguemi *et al*., 2016). In the BAT algorithm, all bat uses their echolocation to sense the distance; they move with velocity such that bats fly randomly in a way in which wavelength and loudness are varying in looking for prey. They can modify the frequency of their pulse rate and depend on the proximity of their target, they also adjust the rate of the pulse; and variation in loudness. The mathematical equation could be summarised as follows where the new positions x_i(t) and velocities v_i(t) can be calculated as follows:

$$\left.\begin{aligned} x_i(t+1) &= x_i(t) + v_i(t+1) \\ v_i(t+1) &= v_i(t) + \left(x_i(t) - p(t)\right)\cdot f_i \\ f_i &= f_{\min} + \left(f_{\max} - f_{\min}\right)\cdot \beta \end{aligned}\right\} \quad (1)$$

where, β is a random vector with uniform distribution, the range of which is [0, 1], p(t) is the current global optimal solution and $f_{\min} = 0$, $f_{\max} = 1$. It achieves global search by controlling loudness and pulse rate.

B. Particle Swarm Optimization

A member of the family of swarm intelligence is Particle Swarm Optimization (PSO) which allows particles to share information about their positions with each other particle. While flying over a place, a swarm of birds must find a specific point to land, and, in this instance, defining which point the whole swarm should land is a complex problem, as it is dependent on issues of maximizing the availability of food and minimizing the risk of the existence of predators (De Almeida and Leite, 2019). The benefit of swarm behavior includes as an individual particle decides, it yields an "emergent behavior" relying on the internal interaction among particles to determine a likely optimal result. Thus, swarm behavior leads to "collective intelligence" (Agbehadji *et al*., 2016). In the formulation, a particle i comprise a vector xi for location and vector vi for velocity. Every particle follows the direction of its previous best location (xBest) as well as the global best location (gBest) in the population at every iteration as follows:

$$\begin{aligned} v_i^{t+1} &= \omega v_i^t + c_1 r_1 \left(xBest_i^t - x_i^t \right) + \\ & c_2 r_2 \left(gBest_i^t - x_i^t \right) \\ x_i^{t+1} &= x_i^t + v_i^{t+1} \end{aligned} \quad (2)$$

where, c_1 represents the individual coefficient of acceleration, c_2 stands for the global coefficient of acceleration, r_1 and r_2 are weightings that represent the local and global bests ($r_1, r_2 \in [0,1]$) and ω is inertia value.

C. Multiple Species Flocking

Reynolds (1987) has proposed a model called Multiple Species Flocking (MSF), that mimics the flocking behavior of birds using rules namely collision avoidance, velocity matching, and flock centering using other flocks as a reference point (Siddique and Adeli, 2015; Cui *et al*., 2006). In another study, MacArthur and Wilson (1967) presented a model based on "biogeography" which depicts the migration of birds and how species of birds become extinct. Furthermore, honey bees are a swarm behavior of bees in search of food sources and they collect food by foraging in flower patches (Siddique and Adeli, 2015). The flocking behavior of multiple species is determined by weighting the actions of the four rules and summing them to derive the net velocity v for an active boid, as expressed by:

$$v = w_{ar} * \vec{v}_{ar} + w_{sp} * \vec{v}_{sp} + w_{cr} * \vec{v}_{cr} \quad (3)$$

where, v denotes the boid's velocity in the virtual space and w_{ar}, w_{sp}, w_{cr} are pre-defined weight values in respect of the alignment rule, separation rule, and cohesion rule respectively.

The alignment rule is expressed by:

$$d\left(F_i, A_c\right) \le r_1 \wedge d\left(F_i, A_c\right) \ge r_2 \Rightarrow \vec{v}_{ar} = \frac{1}{n}\sum_i^n \vec{v}_i \Big\} \quad (4)$$

where, r_1 and r_2, with $r_1 > r_2$, represent the radius r of the boid's visibility range and minimum distance among them respectively and $d(F_i, A_c)$ represents the distance between current boid A_c and its flockmate. Furthermore, F_i. $\vec{v}_i$ represents boid F_i velocity and n represents the number of neighbors.

The separation rule (or collision avoidance) avoids closeness between the boids, is expressed by:

$$d\left(F_i, A_c\right) \le 2r_2 \Rightarrow \vec{v}_{sp} = \sum_i^n \frac{\overrightarrow{\vec{v}_i + \vec{v}_c}}{d\left(F_i, A_c\right)} \quad (5)$$

where, $\vec{v}_{sp}$ represents the separation velocity and $\vec{v}_c$ $\vec{v}_i$ represent the current boid and i^{th} flockmate's velocities.
The cohesion rule (or flock centering) moves a boid towards the center of the flock or towards other nearby boids, which is expressed by:

$$d\left(F_i, A_c\right) \le r_1 \wedge d\left(F_i, A_c\right) \ge r_2 \Rightarrow \vec{v}_{cr} = \sum_i^n \left(P_i - P_c\right) \quad (6)$$

where, $\vec{v}_{cr}$ represents the cohesion velocity, P_i and P_c represent the position of current boid A_c and a neighbor boid F_i, and (P_i - P_c) calculates the directional vector point.

D. Ant Colony Optimisation

Ant colony optimization is based on the foraging behavior of natural ants in search of food sources After finding a source of food, natural ants will lay down a chemical pheromone trail to mark their path to enable other ants to traverse (Agbehadji *et al*., 2018a). Pheromone trail has an odor that is used as a means of indirect communication between ants. The pheromone laid will depend on the quantity, quality, and distance of the food source. Therefore, the pheromone trail decays or evaporates with time thus preventing real ants from converging prematurely; thereby real ants can traverse various terrains in their habitat. These natural or real ants can make probabilistic decisions to update their pheromone trail. Thence, the probability of ant *k* traveling from node *i* to *j* can be computed as follows:

$$P_{ij}^k(t) = \frac{\left[\tau_{ij}^{(t)}\right]^\alpha \cdot \left[\eta_{ij}^{(t)}\right]^\beta}{\sum_{l \in N_i^k}\left[\tau_{ij}^{(t)}\right]^\alpha \cdot \left[\eta_{ij}^{(t)}\right]^\beta} \quad (7)$$

where, τ_{ij} is the number of deposited pheromones on (*i*, *j*), η_{ij} is the visibility heuristic value which equals the inverse of the distance L_{ij}, α and β are weighting parameters and N_i^k represent the neighbor nodes that can be visited. The greater the solution, the more pheromone is laid.

The pheromone update process is formulated by:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ij}^k \quad (8)$$

where Δτk ij is the amount of added pheromones by ant k on (i,j) and ρ ∈ (0,1] represents the evaporation rate. $\Delta\tau_{ij}^k$ is expressed by:

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{f\left(S_k\right)} \text{if ant k is used} \left(i, j\right) \\ 0 \qquad \text{otherwise} \end{cases} \tag{9}$$

where, Q is a fixed value, sk is the solution constructed by ant k and $f(sk)$ is its cost function, which can be the path length (Lk).

E. Wolf Search Algorithm

Wolf Search Algorithm (WSA) mimics the hunting behavior of wolves (Agbehadji *et al*., 2018b). A variant of WSA is the Wolf Search Algorithm with Minus Step Previous (WSA-MP) (Stutzle and Dorigo, 2002; Tang *et al*., 2012) representing a wolf with memory that can know its previous position.

In the WSA, a passive prey represents a wolf without any food or better position (Agbehadji *et al*., 2018a). This mode can be represented by:

$$x_i^{t+1} = x_i^t + \alpha * r * rand() \tag{10}$$

where, a and r represent constants, rand is a random number drawn from a uniform distribution.

The escape rule is expressed by:

$$x_i^{t+1} = x_i^t + \alpha * s * rand() \tag{11}$$

where, x_i^t represents the wolf location, α represents the velocity, s is the step size within the visual range, *r and* is a random function generator for a position which is greater than the visual range and less than half of the solution boundary.

F. Social Spider Algorithm

Social Spider Algorithm (SSA) is a nature-inspired behavior that uses the social behavior of spiders in their natural environment (James and Li, 2015). Social spiders receive and analyze vibrations propagated on the social web to communicate and determine the potential food source (Frimpong *et al*., 2020). Thus, spiders become more aware of the presence of prey and inform neighboring spiders to cooperate in hunting. Vibration is generated when a spider goes from one location to another. At the time t, the vibration intensity I generated is estimated by:

$$I\left(P_a, P_b, t\right) = \log\left(\frac{1}{f\left(P_s\right) - c} + 1\right) \tag{12}$$

where, $f(P_s)$ is the fitness value of spider P, C is a confidently small value and, P_a and P_b represent the source and destination of vibration respectively.

The distance between a vibration source and P_a and its destination P_b is defined by 1-norm (Manhattan distance) as:

$$D\left(P_a, P_b\right) = \left\|P_a - P_b\right\|_1 \tag{13}$$

The vibration palliation obtained by a spider is estimated by:

$$D\left(P_a, P_b, t\right) = I\left\|P_a, P_b, t\right\| \cdot e^{-\left(\frac{D\left(P_a, P_b\right)}{\sigma, r_a}\right)} \tag{14}$$

where, r_a governs the palliation ratio and σ represents the standard deviation average including all spider locations.

G. Dung Beetle Algorithm

Dung beetle algorithm (DBA) uses the behavior of dung beetles namely ball rolling, dance, environment orientation, and path integration (Agbehadji *et al*., 2018b). Ball rolling is expressed as the distance d between two positions of the ball (x_i, x_{i+1}) on a plane is expressed using the straight-line equation as:

$$d\left(x_i, x_{i+1}\right) = \sqrt{\sum_{i=1}^{n}\left(x_{i+1} - x_i\right)^2} \tag{15}$$

where, x_i represents the initial position and x_{i+1} is the current position of the ball carried by a dung beetle on a straight line, n is the number of discrete positions.

Path integration is the change in position that is expressed by:

$$x_{t+1}^k = x_t^k + \beta_m \left(x_{i+1} - x_i\right)_t^k + \varepsilon \tag{16}$$

where, x_{t+1}^k represents the current position of a dung beetle, β_m represents motion cues.

Dance of beetle is the internal cue (I_q) of distance and direction is less than the external reference point (E_r) which is a random number. Thus orientation (δ) after the dance is expressed as:

$$\delta = \alpha * \left[E_r - I_a\left(d, M\right)\right] \tag{17}$$

where, α is a random parameter to control the dance, E_r is a specified point of reference, d represents the distance of internal cues, M represents the magnitude of direction expressed as a random number between 0 and 1.

H. Artificial Bee Colony Algorithm

Artificial Bee Colony (ABC) is based on the intelligent behavior of honeybees (Karaboga and Basturk, 2008). The colony of artificial bees consists of three groups of bees: Employed bees, onlookers, and scouts (Karaboga and

Basturk, 2008). The process of ABC algorithm is flexible because it obtains two control parameters such as maximum cycle number and colony size (Bui *et al*., 2020), to produce a candidate solution. The probability of the food source x_i being selected is as follows:

$$p_i = \frac{Fit(x_i)}{\sum_{i=1}^{N} Fit(x_j)} \tag{18}$$

where, $Fit(x_i)$ is a fitness value corresponding to the quantity of nectar and N is the number of bees employed. The neighbor's food source is expressed by:

$$v_{ij} = x_{ij} + \Phi_{ij}\left(x_{ij} - x_{ki}\right) \tag{19}$$

where, $\varphi ij \in [-1,1]$ represents a random value and k represents a random solution index selected from $N(k \neq i)$. A scout finds an alternate food source by:

$$x_i^j = x_{\min}^j + rand(0,1) \cdot \left(x_{\max}^j - x_{\min}^j\right) \tag{20}$$

where, $m_{\max}^j$ and $m_{\min}^j$ represent the low and high bound values respectively.

I. Firefly Algorithm

The Firefly Algorithm (FA) (Nguyen *et al*., 2018) is based on the flashing behavior of fireflies, especially at night (Tilahun and Ong, 2012). The rules steering the behavior are all fireflies are unisex; the brightness of a firefly; and attractiveness which is directly proportional to brightness but decreases with distance a firefly will move towards the brighter one and if there is no brighter one, it will move randomly. There are three procedures to update the distance between two fireflies, updating a step size and updating new solutions (Nguyen *et al*., 2018). The mathematical equation to depict the moves of brighter fireflies is summarised as follows:

$$x_i = x_i + \beta_o e^{-\gamma r_{ij}^2}\left(x_j - x_i\right) + \alpha\left(rand\left(0,1-\frac{1}{2}\right)\right) \tag{21}$$

where, x_i and x_j are locations of two fireflies, respectively. B_o and γ are attractiveness and light absorption parameters respectively.

J. Earthworms Optimization Algorithm

Earthworms aerate the soil and enrich the soil with their waste nutrients (Tuba *et al*., 2017). Naturally, the earthworm has two kinds of reproduction to generate its offspring. In the process of generating offspring, one aspect of the reproduction only generates one offspring by itself whiles the other generates one or more offspring at once, which is done by crossover operators. However, the high rate of crossover operators decreases the quality of fitness and produces worse offspring. Also, a low crossover rate leads to longer convergence to the optimal solution. Hence, the selection of crossover operator has more impact on the performance of algorithms that uses crossover operators such as the earthworm optimization algorithm (EWA) (Umbarkar and Sheth, 2015). The algorithm uses a weighted sum of the entire generated offspring to arrive at the final earthworm for the next generation. There are 2 types of reproduction which are Reproduction 1 and Reproduction 2 taking place in the earthworm.

Reproduction 1: This indicates that earthworms belong to the "hermaphrodites" group, where a single parent gives birth to the baby earthworm. This can be mathematically formulated in the equation:

$$T_{l1,m} = T_{\max,m} + T_{\min,m} - \eta T_{l,m} \tag{22}$$

Reproduction 2: When N = 1, 2, and 3, the determination of T_{l2} is carried out with the N offspring and it is mathematically derived in the equation:

$$T_{l2} = \sum_{m=1}^{N} \tau_m T_{N,m} \tag{23}$$

The weight factor is denoted by τ_m and $T_{N,m}$ are defined in (Kanna *et al*., 2021).

K. Monarch butterfly optimization

Monarch Butterfly Optimisation (MBO) imitates the behavior of migrating butterflies. In MBO algorithm, the population is grouped into two: One group updates the position using a "migration operator", while the other group modifies the position based on the butterfly "adjusting operator" (Wang *et al*., 2019b). The advantage of MBO is that it is easy to implement the search algorithm. The movement of individual i on the kth dimension in subpopulation1 can be mathematically expressed as follows (Feng *et al*., 2021):

$$x_{i,j}^k = \begin{cases} x_{r1,k}^t, if\ r \leq p \\ x_{r2,k}^t, otherwise \end{cases} \tag{24}$$

where, x_{t+1}^k indicates x^i the kth dimension of x_i at generation $t + 1$. The parameters r_1, r_2 is an integer indexes from subpopulation1 and subpopulation2 respectively. The new individual of subpopulation2 is expressed by the function:

$$x_{i,k}^{t+1} = \begin{cases} x_{best,k}^t, if\ rand \leq p \\ x_{r3,k}^t, if\ rand > p \wedge rand \leq BAR \\ x_{i,k}^t + \alpha * \left(d_{x_k} - 0.5\right) x_{i,k}^t + \alpha * \left(d_{x_k} - 0.5\right), if\ rand > p \wedge rand > BAR \end{cases} \tag{25}$$

The weighting factors α and *dx*

Table 1 shows an overview of the strengths and limitations of these nature-inspired algorithms.

Methods for the Proposed System

Model of Smart Mobile Health Care System

The current study extends previous work by (Agbehadji *et al*., 2019a) on m Health framework for service requests and delivery for aged persons. This framework consists of five domains explained as follows:

- *Health professional*: Renders health care service
- *Hospital*: represents a health care facility
- *Payment of service*: A platform for payment
- *Patient*: the aged person who requires the services
- *Health care services*: These are the services available on the smart mHealth platform for the Patient

The proposed mHealth framework integrates these five domains and therefore data access schema is imperative. The schema for data access defines the role of persons who interact with the information on the smart mobile health care system (Bacon *et al*., 2004). During data interchange, the following are used: Location and phone numbers. Given that health care information is critical, certain information is not accessed/shared with another domain. Moreover, it can be available based on the concept of "need-to-know". Based on self-reported mobility data shared by the patient, the location information is shared with the health professional through the push location notification hub. Therefore, it is referred to as cross-domain location information sharing for an optimal location search utilizing the proposed nature-inspired search method.

Push Location Hub

This hub sends an alert to *k* number of mobile nurses *N* to obtain their location data. The source of an alert is a patient who requests health care service at his/her location. The service request from the patient domain *P* pushes a request code to the nurse's domain in vector form $N = \{N_1, \ldots, N_k\}$ Additionally, each service request received on the database is sent to the location-based service feature to identify the coordinate of the mobile devices of both where the service originates from and location data of nurses. The push location notification mapping is expressed in Eq. (26) as:

$$(P) \leftrightarrow \begin{pmatrix} N_1 \\ N_2 \\ N_3 \\ N_4 \\ N_5 \end{pmatrix} \rightarrow \left(P \leftrightarrow N^*\right) \tag{26}$$

where, *P* represents an originator in the patient domain, *N* is a vector representing nurses in k = (1, …, 5). The result is *P* maps to the selected N^* using a mapping function $f\left(x_i^k\right)$ illustrated in Fig. 1.

Search Method for Cross-domain Location Mapping

The search method implements a kestrel-based algorithm (Agbehadji *et al*., 2016). The kestrel bird uses hovering (flight) and perch techniques to hunt. The hover mode displays an overall view of the location of preys while the perch mode captures a local view of a specific prey for hunt (Agbehadji *et al*., 2018a; Agbehadji *et al*., 2016; Agbehadji *et al*., 2020; Agbehadji *et al*., 2018b; Agbehadji *et al*., 2019b). The formula $\beta_o e^{-\gamma r^2}$ is used to compute the light reflection's attractiveness of trails and varies between 0 and 1, the variable β_o represents "initial attractiveness", *r* represents "Minkowski distance" and γ the decay rate. The decay constant φ shows the duration time (*t*) for a substance to decay to its half-life period $t_{\frac{1}{2}}$, γ_o represents the initial value of decay. The KSA demonstrated optimal search results when compared with the WSA-MP, BAT, and PSO (Agbehadji *et al*., 2018b) and also has the benefits of using a half-life of a radioactive substance as well as random encircling.

The other advantages of the KSA include its ability to adapt to changes to control the search for the global optimal solution. On the other hand, the WSA-MP is noted for its ability to remember its previous position in a search space to avoid unpromising positions. In addition, the WSA-MP is designed to solve complex problems and its efficiency strength is manifested when the search space dimension increases.

While applying the KSA, it simulates the random location of all nurses and consequently links the location between source and target. The optimal search position is selected by the objective function subject to the target location. The fitness objective function *fitness* $Obj\left(x_{i+1}^k\right)$ centers on "equirectangular approximation" and "haversine formulas" as performance is crucial for the proposed algorithm including choosing the (near) optimal solution.

The implementation of the KSA algorithm for the cross-domain location mapping is as follows:

Initially: *Load the Location Coordinates of all nurses* x_i *and a Patient* x_i

Start: *Set the parameters of the model*

Algorithm 1: Improve rule

Initialize $\vec{x}(t)$ *coordinate (0,0)*

Select location coordinate of a nurse x_i

Select location coordinate of an originator x_j

$$\text{Calculate}\ \beta_o e^{-\gamma r^2} \tag{27}$$

Find γ at time *t* from the reduce rule

$$\text{Compute } f_{t+1}^{k} \tag{28}$$

$$\text{Compute position } x_{i+1}^{k} = \vec{x}(t) + \beta_o e^{-\gamma r^2}\left(x_j - x_i\right) + f_{t+1}^{k} \tag{29}$$

Show results of the optimal position obtained

Algorithm 2: Reduce rule:

$$\text{Compute } \gamma_t = \gamma_o e^{-\varphi t} \tag{30}$$

$$\text{Compute } \varphi = \frac{\ln 0.5}{-t\frac{1}{2}} \tag{31}$$

$$f\ \varphi \rightarrow \begin{cases} \varphi > 1, \text{trail is new} \\ 0, \text{otherwise} \end{cases}$$

Algorithm 3: Check rule

For *t* = 1 to Max_itr

$\text{Calculate fitness } Obj\left(x_{i+1}^{k}\right)$ using Algorithm 4

$f\ \text{fitness } Obj^{i+1} > \text{fitness } Obj^{i}$

$\text{fitness } Obj^{i} = \text{fitness } Obj^{i+1}$

$New_{position}\left(x_{i+1}^{k}\right) - Old_{position}$

End if

Update the position x_{i+1}^{k}

End for

Output: Show ranked list of patient-to-nurse

Algorithm 4: Fitness objective function $\text{fitness } Obj\left(x_{i+1}^{k}\right) = (\varphi, \lambda)$

//Comments: φ denotes change in latitude which is ($\Delta\varphi = \varphi_2 - \varphi_1$), λ represents change in longitude which is ($\Delta\lambda = \lambda_2 - \lambda_1$), R is the earth's radius (with mean radius R = 6,371km)

For each position: Evaluate

Fitness Function-1 using Equirectangular approximation:

$$x = \Delta\lambda * \cos\left(\frac{\Delta\varphi}{2}\right) \tag{32}$$

$$y = \Delta\varphi \tag{33}$$

$$d = R * \sqrt{x^2 + y^2} \tag{34}$$

Fitness Function-2 using Haversine formula:

$$\alpha = \sin^2\left(\Delta\varphi / 2\right) + \cos\varphi 1 \cdot \cos\varphi 2 \cdot \sin^2\left(\Delta\lambda / 2\right) \tag{35}$$

$$c = 2 \cdot a\tan 2\left(\sqrt{a}, \sqrt{(1-a)}\right) \tag{36}$$

$$d = R \cdot c \tag{37}$$

End for

$$\text{Calculate bearing} \quad \theta = a\tan 2\left(\sin\Delta\lambda \cdot \cos\varphi 2, \cos\varphi 1 \cdot \sin\varphi 2 - \sin\varphi 1 \cdot \cos\varphi 2 \cdot \cos\Delta\lambda\right) \tag{38}$$

Output: Distances on Equirectangular approximation and bearing

The Smart Health Care System Processes

The search process starts after the service has been requested and the push location hub has dispatched an alert to the mobile nurse. The process is shown as:

Start: Use the smart mHealth app to request a service

Process 1: Service request

stage 1: Indicate the kind of service
stage 2: Indicate the service destination detail of a patient
stage 3: Dispatch a service request
stage 4: Select location data of originator using GPS, assign service ID
stage 5: Store service request ID
stage 6: Push notification information to a nurse

End

Start: Select service request ID

Process 2: Search for nurse

stage 1: Receives notification information
stage 2: Dispatch location data for mapping

End

Start: Load location data of all nurses and a patient

Process 3: Cross-domain location mapping

stage 1: Select the location coordinates of all nurses in the database
stage 2: Select the location coordinates of a patient
stage 3: Execute the KSA algorithm for cross-domain location mapping
stage 4: Show the ranked list of all optima distances of nurses to patient
stage 5: Dispatch feedback to the service initiator

End

Flowchart of the Proposed Model

The underlining flowchart for the proposed model is presented in Fig. 2 to include the initial data input, service request, mapping function, objective function, and the optimal results.

Evaluation of Results and Discussion

The Kestrel-based Search Algorithm (KSA) default parameters are z_{min} = 0.2, z_{max} = 0.8 representing the perched and flight modes parameter respectively (Agbehadji *et al*., 2019a); the frequency of bobbing pa is controlled by setting the default parameter to 0.9; and the half-life is 0.5 (Agbehadji *et al*., 2019b). The location data serve as input into the algorithm in vector form V= (long1, long2, lat1, lat2) and a single value distance is an output. The lat1, lat2 refer to latitudes while long1 and long2 represent longitudinal data respectively in Degrees (D). The haversine and equirectangular approximation formulas represent the objective functions to measure the distance between the random location of nurses and the initial location of the patient. Also, we computed the bearing of the patient for each nurse. In this current work, after obtaining the initial location data, the proposed algorithm was run on MATLAB R2020a environment and conducted all the experiments reported in this study on an Intel Core i5- 3210M CPU@ 2.50GHz speed with 6.00GB RAM running 64-bit Windows 10 Pro operating system. A total number of 100 iterations each was conducted such that the KSA and other renowned algorithms including the BAT, WSA-MP, and ACO produced random location data in longitude and latitude while the output is a single optimal distance which is linked to the distance of the patient. The fitness function expressed in "Algorithm 4" was also used as a fitness function in the comparative algorithms. This comparison is significant to enable performance evaluation of the proposed algorithm.

Initially, the patient's device was assumed at location: lat1 = 45.421527862548828D; long1 = -75.697189331054688D; lat2 = 53.64135D; long2 = -113.59273D. We computed the initial distance as 53,811,205.3525 km and 9,108,062.8679 km respectively for the equirectangular approximation and haversine formulas. The algorithms are evaluated and tested concerning the optimal distance between the locations of a health professional/nurse and the service destination (the location of the patient). The location data on latitudes (north/south) and longitudes (east/west) of the device of a health professional was randomly generated using Algorithm 1. Algorithm 2 reduces and links each position of nurses with the target location. The haversine formula and equirectangular approximation distance value as well as the respective bearing or direction are calculated using the various state-of-the-art nature-inspired algorithms considered. Initially, after the patient sent the service request, the results of the experiment using the KSA are shown in Table 2. In the experiment, there were all ten (10) different locations considered under the Equirectangular approximation and Haversine formula for the individual algorithms.

Table 2 and Fig. 3 displayed the experimental results obtained of the optimal distance of Equirectangular approximation and Haversine methods. The Equirectangular approximation distance for N#:34 was 101,590.6703km at 285 D while the Haversine distance at N#:04 was 7,975,532.5412 km at 272 D. The trend as shown in Table 2, indicates that, the equirectangular approximation formula when compared with the Haversine, has the minimum distances thus indicating an optimal concerning the initial location.

The experimental results of the BAT, WSA-MP, and ACO algorithms are presented in Table 3 and Fig. 4; Table 4 and Fig. 5; and Table 5 and Fig. 6 respectively.

Table 3 and Fig. 4 show the results of BAT, in which the distance for Equirectangular approximation at N#:03 was 26,351,473.6141 km at 259 D, while that of Haversine at N#:31 was 4,353,260.2792 km at 262 D.

Table 4 and Fig. 5 show the results of WSA-MP, in which the distance for Equirectangular approximation at N#:01 was 11,189,873.7696 km at 340 D, while that of Haversine at N#:02 was 5,759,899.8454 km at 335 D.

Table 5 and Fig. 6 show the results of ACO, in which the distance for Equirectangular approximation for N#:08 was 96,767,300.6730 km at 200 D, while that of Haversine at N#:02 was 2,095,940.6045 km at 335 D. Comparatively, in BAT, WSA-MP and ACO, it is observed that the Haversine resulted in minimal distance than the Equirectangular approximation. In other words, the Haversine distance was higher in some locations in KSA than in BAT, WSA-MP, and ACO. For instance, the Haversine distance in locations N#:04, N#:31; N#02 and N#02 are 7,975,532.5412 km; 4,353,260.2792 km; 5,759,899.8454 km; and 2,095,940.6045 km respectively for KSA, BAT, WSA-MP and ACO respectively at different bearings.

The experiment results also indicate that by using KSA, the minimal distance was obtained in Equirectangular approximation whereas BAT, WSA-MP, and ACO have higher distances.

The practical implication of these results for the deployment of the mobile app in cross-domain location applications is that KSA provides the optimal distance to a destination which can reduce time by using an Equirectangular approximation formula. For all the ten different locations considered under the Equirectangular approximation formula for each of the KSA, BAT, WSA-MP, and ACO algorithms respectively, the KSA gave the optimal and minimal distances among the algorithms. For instance, for N#:34, N#:02, N#:23, N#:62, N#:44, N#:10 and N#:76 the optimal and minimal distances given by the KSA are 101,590.6703km; 167,570.7533km; 276,530.3719km; 76,950.0097km; 62,709.1898km; 23,390.4274km and 47,638.8405 etc respectively. On the other hand, the minimal distances observed across the Equirectangular approximation and Haversine formulas by the ACO, WSA-MP, and BAT are N#:10 with 632,345.8832km at 165D; N#:15 with 1,361,258.0235km at 136D and N#:07 with 2,748,504.9171km at 262D respectively. These optimal distances are higher than those of KSA and this indicates the KSA algorithm has better performance than the comparative nature-inspired algorithms.

Table 1: Brief review of state-of-the-art metaheuristic/nature-inspired algorithms

Algorithm	Strength/Advantage	Limitation/Disadvantage
BAT	Uses parameter control, which can vary the parameter value during iterations.	speed of convergence is weak.
PSO	Only the most optimist particle can transmit information to the other particles. In other words, it is effective in global search	Suffers from partial optimism, which causes it to be less exact in the regulation of its speed and direction during the local search.
ACO	Adapts to changes such as new distances, thus it is flexible.	The time of convergence is uncertain. However, convergence is guaranteed.
WSA-MP	Can remember previously visited positions.	Performance depends on the manually chosen parameter.
ABC	Robust and highly flexible systems with two required parameters.	Weak local searchability.
MSF	When multiple species flock together it increases chances of detecting predator(s) (Ehrlich *et al*., 1988). Each individual generates complex global behavior that could represent the entire flock's behavior.	The boid only interacts with others in its environment (Cui and Potok, 2006).
DBA	Ability to integrate every path traversed.	Finding an external point of reference is user-dependent.
SSA	Ability to communicate with each other using web construction. The vibration information being shared is used for random walk (Baş and Ülker, 2020).	The larger the web structure, the time to converge is uncertain.
Firefly	Adaptive to change because of its strong signaling mechanism to communicate with other fireflies.	There is a weak local search due to the high probability of being trapped in local optima which influences the computational time (Shanmugapriya and Meera, 2017).
EWA	Ability to handle multi-objective optimization problems.	The selection of crossover operator has an impact on the performance of the algorithm.
MBO	Has a simple calculation process and requires less computational parameters, easy to implement by a program, proven as an effective tool to solve various kinds of optimization problems.	The search strategy easily falls into local optima, causing slow/premature convergence, and poor performance on many complex optimization problems.

Table 2: Results of optimal distance using KSA

Nurse location N#:	Equirectangular Approximation distance (km)	Bearing (D)	Nurse location N#:	Haversine distance (km)	Bearing (D)
N#:34	101,590.6703	285	N#:04	7,975,532.5412	272
N#:02	167,570.7533	270	N#:32	8,766,314.4604	269
N#:23	276,530.3719	281	N#:40	2,072,345.0094	279
N#:62	76,950.0097	271	N#:30	8,481,895.3924	271
N#:44	62,709.1898	262	N#:60	8,308,979.5954	275
N#:77	213,798.7444	270	N#:34	4,568,273.2623	181
N#:10	23,390.4274	271	N#:15	1,376,350.5873	185
N#:14	75,072.6673	271	N#:06	2,624,862.4164	189
N#:76	47,638.8405	268	N#:21	5,241,323.1972	181
N#:51	78,259.1125	262	N#:26	2,724,568.1165	188

Table 3: Results of optimal distance using BAT

Nurse location N#:	Equirectangular approximation distance (km)	Bearing (D)	Nurse location N#:	Haversine distance (km)	Bearing (D)
N#:03	26,351,473.6141	259	N#:31	4,353,260.2792	262
N#:04	24,777,455.4155	253	N#:55	8,247,325.2932	151
N#:06	24,769,092.6764	253	N#:16	5,596,137.4516	322
N#:19	16,042,994.9771	166	N#:06	4,840,176.0856	253
N#:36	23,790,157.5611	235	N#:04	4,841,555.7763	253
N#:66	64,865,320.4737	291	N#:100	9,108,062.8679	291
N#:100	28,043,264.3972	187	N#:07	2,748,504.9171	274
N#:58	28,496,774.4188	244	N#:06	3,960,740.9414	279
N#:08	32,022,504.5675	308	N#:69	9,108,062.8679	291
N#:99	39,118,968.7619	296	N#:08	5,880,790.3920	195

Table 4: Results of optimal distance using WSA-MP

Nurse location N#:	Equirectangular approximation distance (km)	Bearing (D)	Nurse location N#:	Haversine distance (km)	Bearing (D)
N#:01	11,189,873.7696	340	N#:02	5,759,899.8454	335
N#:04	16,971,746.194	165	N#:03	6,563,225.2881	331
N#:18	16,264,633.4097	166	N#:24	5,807,693.3807	250
N#:68	32,184,558.2946	250	N#:19	8,845,334.3308	206
N#:02	9,167,610.8346	110	N#:48	2,707,799.0566	356
N#:07	13,053,587.2289	340	N#:15	1,361,258.0235	136
N#:19	12,162,132.9255	340	N#:76	3,634,986.0536	214
N#:86	10,965,789.1542	158	N#:72	5,689,253.1532	256
N#:53	12,162,132.9255	340	N#:98	4,364,698.3652	314
N#:72	12,162,132.9255	340	N#:65	4,672,965.1244	304

Table 5: Results of optimal distance using ACO

Nurse location N#:	Equirectangular approximation distance (km)	Bearing (D)	Haversine Nurse location N#:	distance (km)	Bearing (D)
N#:08	96,767,300.6730	200	N#:02	2,095,940.6045	335
N#:07	97,378,124.1423	318	N#:04	1,159,069.7626	136
N#:09	11,195,762.1217	178	N#:08	8,514,490.0314	262
N#:04	22,417,713.2300	199	N#:09	1,843,212.7424	175
N#:10	64,551,232.1123	290	N#:10	632,345.8832	165
N#:63	15,133,342.3154	318	N#:75	5,948,314.0831	311
N#:75	17,639,631.2597	137	N#:21	9,031,995.2569	149
N#:79	35,067,731.5873	245	N#:18	5,597,687.6477	131
N#:88	48,356,575.6932	102	N#:52	8,962,802.3543	196
N#:58	88,403,693.2531	224	N#:66	6,897,040.8168	174

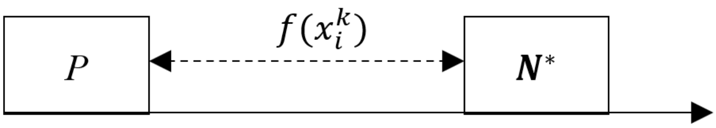

Fig. 1: Structure of mapping function

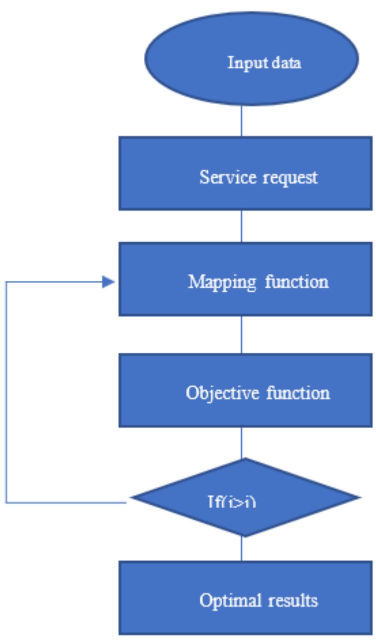

Fig. 2: Flowchart of the proposed model

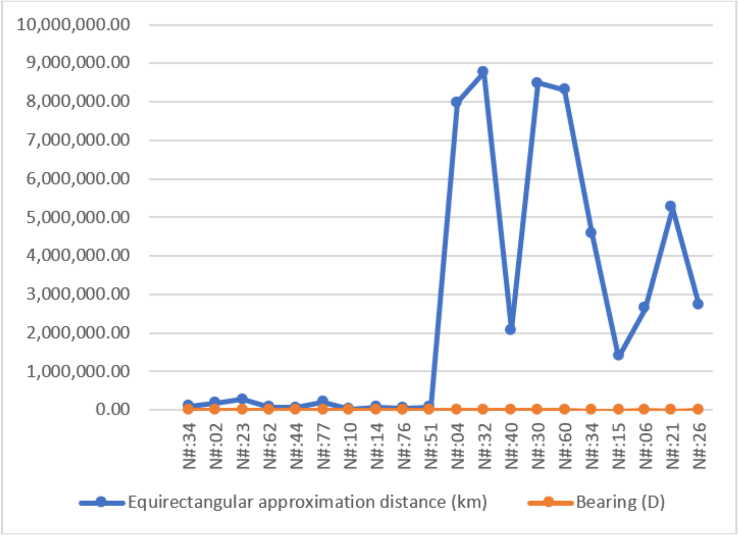

Fig. 3: Experimental results on optimal distance using KSA

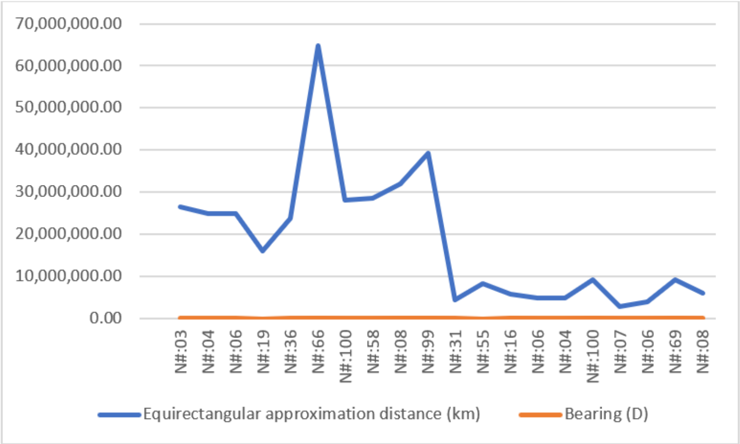

Fig. 4: Experimental results on optimal distance using BAT

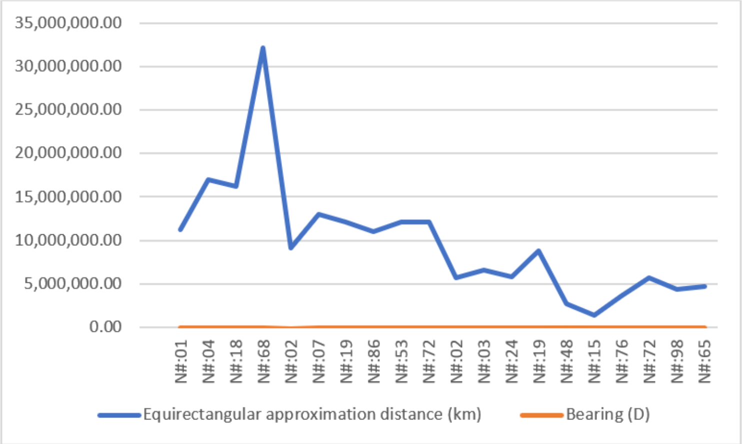

Fig. 5: Experimental results on optimal distance using WSA-MP

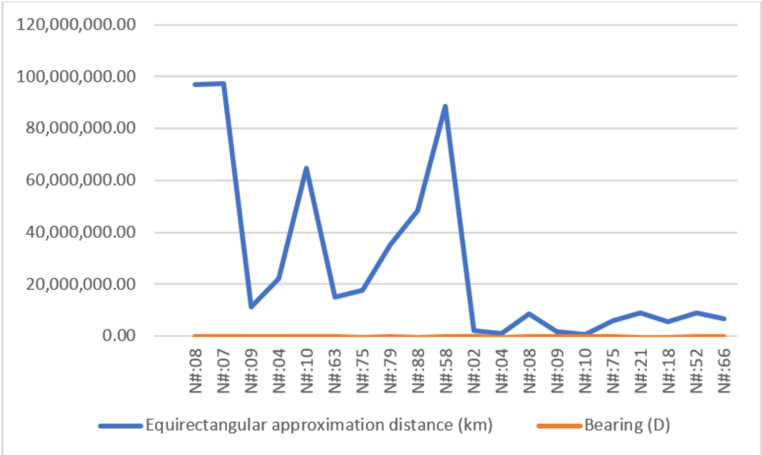

Fig. 6: Experimental results on optimal distance using ACO

Given that the location of nurses is dispersed and service requests can originate from different locations, the random search method applied in this study is imperative. However, the user requires internet connectivity to receive the push location notification services and this might be a limitation. Moreover, this could be overcome by considering offline push location notification services.

The time complexity of the models indicates the amount of time for the algorithm to run, as a function of the length of the input, where the length of input indicates the number of operations performed by an algorithm. Thus, input size (n), and order of growth (O) are parameters for the time complexity. Hence, for the models, the time complexity is linear O(n) concerning the input size. Additionally, the space complexity O(n) for the models is also linear even though every possible distance needs to be considered to find the optimal distance.

Conclusion

The current study has extended the earlier work on the m Health system framework for an assisted health care service request and delivery proposed by (Agbehadji *et al*., 2019a). By way of extension, the cross-domain mapping function is proposed based on a nature-inspired search method to find the minimum and optimal distances to another location. The experimental results show that the equirectangular approximation gives a near-optimal distance in the KSA than in BAT, WSA-MP, and ACO. However, apart from the KSA, BAT, WSA-MP, and ACO techniques utilized in the paper, other state-of-the-art computational intelligence algorithms including the Monarch Butterfly Optimization (MBO), Slime Mould Algorithm (SMA), Moth Search (MS) algorithm, Earthworm Optimisation Algorithm (EWA), Elephant Herding Optimisation (EHO) and Harris Hawks Optimisation (HHO), etc. can as well be applied to solve the problem of cross-domain location optimization. Thus, technically, this work can further be extended by using among others, these other nature-inspired search methods that were not considered in this current study. Future work will also consider the deployment of the model's smart health care mobile app and offline push location notification services.

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Author's Contributions

Israel E. Agbehadji: The paper background work, conceptualization, methodology, implementation, preparing, and editing of the draft manuscript.

Abdultaofeek Abayomi: The results analysis and comparison, editing of the mathematical equation, editing the final manuscript.

Murimo B. Mutanga: Review and editing of the manuscript.

Bankole O. Awuzie: Review and editing of manuscript, Supervision.

Alfred B. Ngowi: Review and editing of manuscript, Supervision.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues are involved.

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