DTN Routing based on Search Theory – An Overview

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Summary
This paper explores the theoretical approach to improve existing Delay and Disruption Tolerant Networking routing algorithms using Search Theory. Search Theory is a discipline within the field of operations research, whose applications range from deep-ocean search for submerged objects to deep space surveillance for artificial satellites. DTN deals with networks in challenged environment. DTN focuses on deep space to a broader class of heterogeneous networks that may suffer disruptions, affected by design decisions such as naming and addressing, message formats, data encoding methods, routing, congestion management and security. DTN is part of the Inter Planetary Internet with primary application being deep space networks. The hypothesis behind modeling DTN routing as a search game is based on the understanding that when the DTN agents are in the mode of Search game, routing decision based on Search theory becomes a prudent choice.

Key words:
DTN - Delay and Disruption Tolerant Networking, IPN – Inter Planetary Internet, AUDTHMN- Alagappa University Delay Tolerant Habitat Monitoring Network, Alunivdtnsim – Alagappa University Delay Tolerant Network Simulator, LTP – Lick Lider Transmission Protocol, PRoPHET – Probabilistic Routing Protocol using History of Encounters and Transitivity, Lebesgue Measure, Ky Fan's minimax theorem, Neyman-Pearson lemma.

1. Introduction

Delay and Disruption Tolerant Networking (DTN) [7] [18] refers to broad class of Wireless Ad-hoc networks that operate in challenged environments plagued by delays and disruptions [12]. DTN is part of the Inter Planetary Internet, an initiative started at the Jet Propulsion Laboratory (JPL) by Vint Cerf et.al a few decades ago. DTN has evolved over the years with major research contributions from academicians and Industry. DTN is a network of regional networks. It acts as a overlay on regional networks. DTN supports interoperability by accommodating mobility and low Radio Frequency (RF) power capabilities of the nodes involved. DTN includes RF, Ultra Wide Band (UWB) networks, Optical and Acoustic networks. Though simultaneous connectivity may be absent, a combination of store & forward, along with node mobility makes message delivery possible. The bundle protocol [8] is a DTN protocol based on overlay technique. It can be used on any convergence layer such as TCP, UDP and LTP. The Lick-Lider Transmission protocol [11] is another DTN specific protocol operating at convergence layer. While the bundle protocol moves data packets (bundles) end to end, the LTP is more of a point to point type. While the space applications which are the primary beneficiaries of the DTN [10] have provided ample scope for its research, many terrestrial applications has been conceived that use and contribute to DTN research. Few of such terrestrial applications [11] include:

(i) Reindeer herd tracking by the Saami tribesmen in Arctic Circle.
(ii) Zebra tracking to monitor the movement of zebra and manage their habitat effectively in Africa.
(iii) Early detection of the invasion of Australian cane toads, a pest and invasive species in non-native regions.
(iv) Seismic monitoring in Mexico for early warning system against earth quakes, volcano and land slides.
(v) SenDT – an initiative by the Trinity College Dublin Ireland to monitor lakes in Ireland.
(vi) DTN - Simple Text Message application over android OS introduced in Nexus One Cellular phones by Google Inc.
(vii) AUDTWMN[4] – A proposed water monitoring application Test bed for DTN research [1][2][3].

Based on DTN's applicability for a multitude of terrestrial applications [9], the authors devised upon a DTN based Habitat monitoring network that will serve the dual purposes of Wildlife conservation and research. It can be used to monitor habitat parameters of Blackbuck (Antelope cervicapra) in wildlife context and as a test bed for DTN in research context. Monitoring habitat of Blackbuck in Vallanadu Sanctuary in district of Tuticorin [24] seemed to be an important wildlife conservation need due to the following reasons:

(i) Blackbuck population has been hugely decimated in India due to indiscriminate hunting prior to Independence, developmental pressure and agricultural needs.
(ii) The Vallanadu sanctuary is small with area of 16.41 square kilometers with small population of Blackbuck restricted to the hillock comprising the sanctuary.

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(iii) The vegetation is mainly scrub forest with thick acacia growth that prevents assessment of the Blackbuck number.
(iv) The sanctuary receives scant rainfall and is characterized by hot, dry summers and cold, wet winters.
(v) The Blackbucks have regular habit of coming out of the scrubs and graze on the fallow lands on the eastern side of the sanctuary.

With all the above factors, combined with absence of sophisticated surveillance methods, constant monitoring of habitat parameters and knowledge of their territorial behavior helps to better manage them for conservation and preservation. The rest of the paper describes the design considerations for the proposed AUDTHMN and its routing based on Search Theory.

2. Design Considerations

The application intends to monitor the movement of the Blackbucks [22] in the Vallanadu Sanctuary. The application is also scalable so as to accommodate other habitat parameters such the water holes, the salt pits and noise levels in the sanctuary. The application must lend itself to be a research tool by enabling simple interface and reconfigurable components. With all these pre-requisites the following design has been conceived by the authors.

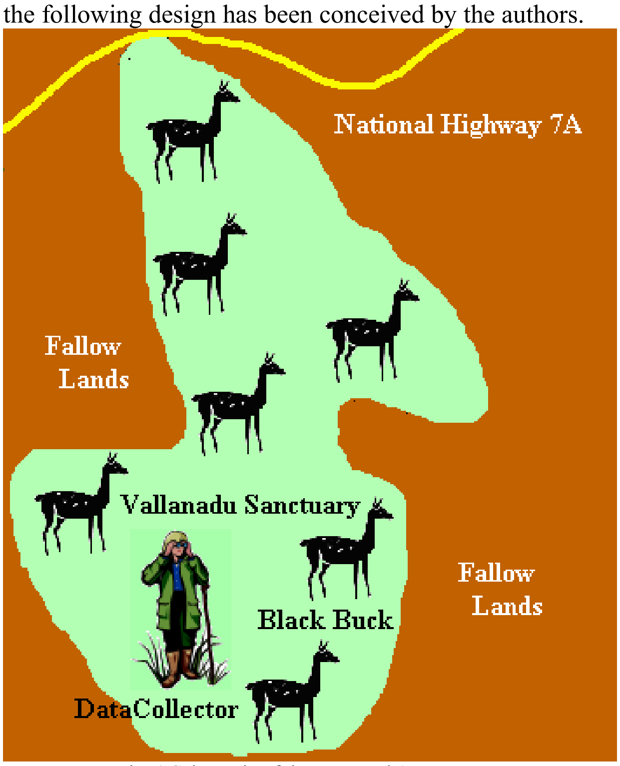

Fig. 1 Schematic of the proposed AUDTHMN.

As discussed, Vallanadu is one of the few places in Tamil Nadu, where natural population of Blackbucks still exists. The Vallanadu Blackbuck sanctuary is an isolated hillock with scrub forest in Tuticorin district. The forest type is thron scrub composed of thorny hardwood and xerophytes. The thick acacia growth makes it difficult to assess the exact numbers. The Blackbucks have regular habit of coming out of the scrub and grazing in fallow lands on the eastern side of the sanctuary. The proposed application involves fitting a percentage of the Blackbuck population with radio collared DTN nodes. The DTN nodes comprise of GPS data logger that keeps recording the location of the Blackbuck at regular intervals of time. The collected data is then transferred to the Data collector who may be a wild life staff in-charge of maintaining the statistics of the Blackbucks. No permanent or semi permanent infrastructure is used as data mule between the Blackbuck nodes and data collector. Hence the Data collector goes in search of the Blackbucks on scheduled frequency such as monthly or quarterly basis. Hence the routing of data from Blackbucks to the Data collector is influenced by the search methods of the Data collector and the hiding behavior of the Blackbucks. The authors propose to use dtn2.5 on the nodes. The dtn2.5 running on Ubuntu Linux 9.10 platform serves as excellent DTN nodes [6]. In lab environment, DTN bundles were successfully sent across using the bundle protocol.

3. Search Theory

Search Theory [21] came into being during World War II with the work of B.O Koopman and his colleagues in the antisubmarine Warfare Operations Research Group (ASWORG). Search Theory is a major discipline within the field of operations research, whose application range from deep-ocean search for submerged objects to deep-space surveillance for artificial satellites. Since World War II, the principles of search theory have been applied successfully in numerous important operations including the 1966 search for the lost H-bomb in the Mediterranean near Palmoares, the 1968 search for the lost nuclear submarine Scorpion near the Azores and the 1974 underwater search for unexploded ordnance during clearing of Suez Canal. The US coast guard employs search theory in its open ocean search and rescue planning. Search theory is also used in astronomy and in radar search for satellites. Numerous additional applications include industry, medicine and mineral exploration. Work in Search theory can be classified according to the assumptions made about measures of effectiveness, target motion, and the way in which search effort is characterized

3.1 Measure of Effectiveness

Among the many measures of effectiveness that are used in search analysis, the most common are:
(i) Probability of detection.
(iii) Expected time to detection.

(iii) Probability of correctly estimating target "whereabouts".
(iv) Entropy of posterior target location probability distribution.

The Objective of an optimal search is to maximize the probability of detection with some constraints imposed on the amount of search effort available. For a stationary target, when the detection function is concave or the search space and search effort are continuous, a plan that maximizes the probability of detection in each of successive increments of search effort will also be optimal for the total effort contained in the increments. For stationary targets, it often theoretically possible to construct a "uniformly optimal" search plan. This is a plan for which probability of detection is maximized at each moment during its period of application. If a uniformly optimal search plan exists, it will:
(i) Maximize the probability of detection over any period of application.
(iv) Minimize the expected time to detection.
In a "whereabouts" search, the objective is to estimate correctly the target's location in a collection of cells given a constraint on search cost. The searcher may succeed either by finding the target during search or by correctly guessing the target's location after search. The optimal whereabouts search consists of an optimal detection search among all cells exclusive of the cell with the highest prior target location probability. If the search fails to find the target, one guesses that it is in the excluded highest-probability cell. Optimal whereabouts search plan for moving target may be found by solving finite number of optimal detection search problems, one for each cell in the grid. Consideration of entropy as a measure of effectiveness is useful in certain situations and can be used to draw a distinction between search and surveillance. For certain stationary target detection search problems with an exponential detection function, the search plan that maximizes the entropy of the posterior target location probability distribution conditioned upon search failure is the same as the search plan that maximizes the probability of detection. In surveillance search, the objectives are usually more complex than in a detection search.. For example, one may wish to estimate target location correctly at the end of a period of search in order to take some further action.

3.2 Target Motion

Assumptions about target motion have considerable influence on the characteristics of search plans and the difficulty of computation. Results were usually obtained by considering transformation that would convert the problem into an equivalent stationary target problem. The first computationally practical solution to the optimal search problem for stochastic target motion involving a large number of cells and time periods is based on exponential detection functions, finding whose necessary and sufficient conditions for search plans for discrete time and space, and provided an iterative method for optimizing search for targets whose motion is described by mixtures of discrete time and space Markov chains. General treatment of moving target search is based on allowing efficient numerical solution in a wide class of practical moving target problems which include non-pMarkovian and non exponential detection functions. The existence of optimal search plans for moving targets is not to be taken for granted as there are cases with no allocation function satisfying necessary conditions. There may appear to exist optimal plans, however they may concentrate on sets of measure zero and which may be outside the class of search allocation functions that are being considered. There are theoretical evidence that show the existence of optimal plans whenever the search density is constrained to be bounded.

3.3 Search Effort

Search effort may be either discrete (looks, scans, etc.) or continuous (time, track length, etc.). In problems involving discrete search effort, the target is usually considered to be located in one of the several cells or boxes. The search consists of specifying a sequence of looks in the cells. Each cell has a prior probability of containing the target. A detection function b is specified, where b(j,k) is the conditional probability of detecting the target on or before the kth look in cell j, given that the target is located in cell j. A cost function c is also specified, where c(j,k) is the cost of performing k looks in cell j. An early solution to this problem for independent glimpses and uniform cost has been given. In this case, for $0 \leq a_j \leq 1$, $b(j,k) - b(j,k-1) = a_j(1-a_j)^{k-1}$ for all j and for $k > 0$; $c(j,k) = k$ for all j and $k \geq 0$. A variant of the Neyman-Pearson lemma is used to obtain an optimal plan for the general case where b(j,k)-b(j,k-1) is a decreasing function of k for all j. In problems involving continuous effort, the target may be located in Euclidean n-space or in cells as in the case of discrete search. In the first case, it is assumed that the search effort is "infinitely divisible" in the sense that it may be allocated as finely as necessary over the entire search space. Similar to discrete search effort, there is a detection function b, where b(x,z) is the probability of detecting the target with z amount of effort applied to the point x, given that the target is located at x. If x is a cell index, then z represents the amount of time or track length allocated to the cell. If x is a point in Euclidean n-space, then z is a density. The original solution to the search problem made use of an exponential function for b of the form $b(x,z)=1-\exp(\kappa z)$, where κ is a positive constant that may depend on x.

3.4 Solution to an Optimal Search Problem

Optimal theory can be applied to an important class of stationary target search problems where the prior probability distribution function for target location is normal and the detection function b is exponential. Many search problems that occur in practice are of this form. Let X denote the plane, and let A be some arbitrary region of interest. Then the prior probability that the target's location $\tilde{x}$ is in A is given by $Pr[\tilde{x} \in A] = \int_A p(x)dx$, where $p(x)=1/2\pi\sigma 2 \exp(-|x|^2/2\sigma^2)$ is the circular normal density function with mean at the origin and variance σ^2 in both coordinate directions. The distance of x from the origin is denoted by |x|. Let F be the class of non negative function defined on X with finite integral. By definition, this is the class of search allocation functions, and for $f \in F$, $\int_A f(x)\,dx$ is the amount of search effort placed in region A. It is assumed that the unit of search effort is "time" and thus the "cost" C associated with the search is the total amount of time consumed. In this case $c(x,z) = z$, and the cost functional C is defined by $C[f] = \int_x c(x,f(x))dx=\int_x f(x)dx$. The measure of effectiveness will be probability of detection. Hence the "effectiveness functional" D is assumed to have the form $D[f] = \int_x b(x,f(x))p(x)dx$, where b is the detection function. As mentioned earlier, the detection function is assumed to be exponential, and hence for $R > 0$, $b(x,z) = 1 - \exp(-Rz)$. The coefficient of R is called the "sweep rate" and measures the rate at which search is carried. If suppose the search allocation function f is constant over A, zero outside of A, and corresponds to a finite amount of search time T, then for $x \in A$, $f(x)=T/area(A)$, since by definition $T = \int_x f(x)dx=f(x_0)\int_A dx=f(x_0)area(A)$ for any $x0 \in A$. The detection functional can be written $D[f]=\int_x b(x,f(x))p(x)dx = \int_A\{1-\exp[-RT/area(A)]\}p(x)dx = \{1-\exp[-RT/area(A)]\}\int_A p(x)dx = \{1-\exp[-RT/area(A)]\}Pr[\tilde{x} \in A]$, which is called the "random search formula".

Using Lagrange multipliers, one can find sufficient condition for optimal search plans for stationary targets that provide efficient methods for computing these plans. The point wise Lagrange l is defined as follows: $l(x,z,\lambda)=p(x)b(x,z)-\lambda c(x,z)$ for all $x \in X$, $z \geq 0$, and $\lambda \geq 0$. If we had an allocation f^*_λ that maximizes the point wise Lagrangian for some value of $\lambda \geq 0$, which is, $l(x,f^*_\lambda(c), \lambda) \geq l(x,z,\lambda)$ for all $x \in X$ and $z \geq 0$, then we can show that $D[f^*_\lambda]$ is optimal for its cost $C[f^*_\lambda]$, that is, $D[f^*_\lambda] \geq D[f]$ for any $f \in F$ such that $C[f] \leq C[f^*_\lambda]$. The plan f^*_λ maximizes the detection probability over all plans using effort $C[f^*_\lambda]$ or less. The proof is based on considering that $f \in F$ and $C[f] \leq C[f^*]$. As $f(x) \geq 0$, $p(x)b(x,f^*_\lambda(x))-\lambda c(x,f^*\lambda(x)) \geq p(x)b(x,f(x))-\lambda c(x,f(x))$ for $x \in X$. Integrating both sides over X, we obtain $D[f^*_\lambda]-\lambda C[f^*_\lambda] \geq D[f]-\lambda C[f]$ which along with $\lambda \geq 0$ and $C[f] \leq C[f^*_\lambda]$, implies that $D[f^*_\lambda]-D[f] \geq \lambda(C[f^*_\lambda]-C[f]) \geq 0$. This proves that f^*_λ is an optimal plan for its cost $C[f^*_\lambda]$. The way to calculate optimal search plan is to choose a$\lambda \geq 0$ and find f^*_λ to maximize the point wise Lagrangian for λ. For each $x \in X$, finding $f_\lambda(x)$ is one-dimensional optimization problem. If the detection function is well behaved (e.g. exponential), one can solve for f^*_λ analytically. Since $C[f^*_\lambda]$ is usually a decreasing function of λ, one can perform a binary search to find the value of λ that yields cost $C[f^*_\lambda]$ equal to the amount of search effort available. The resulting f^*_λ is the optimal search plan.

In the case of bi-variate normal target distribution and exponential detection function, $C[f^*_\lambda]$ and the optimal plan can be computed. The result is that for T amount of search time, the optimal allocation function f* (dropping the subscript, which depends on T) is given by

$$f^*(x) = \begin{cases} 1 \quad (r_0^2 - |x|^2) & \text{for } |x| \leq r \\ 0 & \text{otherwise} \end{cases}$$

Where all search is confined to a disk of radius r0 defined by $r^2_0=2\sigma\sqrt{(RT/\pi)}$. The probability of detection corresponding to f* is

$$D[f^*] = 1 - \left(1 + \frac{r_0^2}{2\sigma^2}\right) \exp\left(-\frac{r_0^2}{2\sigma^2}\right)$$

And the expected time to detection $\tilde{\tau} = 6\pi\sigma^2/R$.

For a given amount of search effort T, the optimal search plan concentrates search in the disk of radius r_0, which then expands as more effort becomes available. The optimal search plan can be approximated by a succession of expanding and overlapping coverage. Search is repeated in the high probability areas for optimal search in many situations. The probability of detection depends on the ratio r_0/σ and increases to 1 as search effort increases without bound. The expected time to detection is finite and varies directly with σ^2 and inversely with the sweep rate R [23].

However, the Blackbuck is not stationary and hence this cannot be taken as criteria for routing. Hence the Optimal search for moving target is analyzed.

4. Optimal Search for Moving Targets

Optimal search problems divide into 4 categories depending on target's behavior. The first division depends on whether the target is evading or not, that is, whether there is a 2 sided optimization of both the searcher's and target's strategy, and whether the target's behavior is independent of the searcher's action. Within each of these categories the target can be stationary or moving. For stationary target, its location is specified by probability distribution. However, the Blackbuck is a moving target for the searcher (data collector). The movement and location of the target (Blackbuck) is specified by stochastic process $X = \{X_t : t \geq 0\}$. The random variable X_t gives the target's location at time t. For moving target problems, the time horizon is specified. The search is to take place in the time interval [0,T], and we wish to maximize the probability of detecting the target by time T. Being considered as discrete time search problem, t = 0, 1, 2, 3, ..., T. The results stated for discrete can be appropriated for continuous time. The results are stated for continuous search space Y. A search plan ψ specifies the allocation of search effort in space and time. $\psi(y,t)$ = effort density placed at point y at time t for y Є Y, t = 0, …, T. Search effort is constrained by the rate at which effort can be applied. As per function m, m(t) = effort available for search at time t, for t = 0, …., T, and search plans, ψ, must satisfy $\int_y \psi(y,t)dy \leq m(t)$ for t = 0, …, T. Again $\psi(y,t) \geq 0$ is required for all y and t. Let ψ(m) be the set of search plans that satisfy the foregoing constraint. For each sample path ώ of the process X, the probability of detecting the target by time t, given that it follows that path, is a function of the weighted total effort density, $\zeta(\psi,ώ,t)={}^t\sum_{s=0} W(X_s(ώ), s)\ \psi(X_s(ώ),s)$, which accumulates by time t on the target over the course of the path. The weight W(y,s) represents the relative detectability or sweep width against the target if it is located at point y at time s. There is a detection function b: $[0,\infty] \rightarrow [0,1]$ such that $b(\zeta(\psi,ώ,t)$ is the probability of detecting the target by t given that it follows path ώ and that search plan ψ is executed. Letting E denote expectation over the sample paths of X, we define $P[\psi]=E[b(\zeta(\psi,.,T))]$ to be the probability of detecting the target by time T with plan ψ. The optimal detection problem is to find a plan ψ*Єψ(m) such that $P[\psi^*]\geq P[\psi]$ for all ψЄψ(m). Such a plan is called T-optimal. A Practical set of efficient algorithms for calculating optimal search plans.

The targets namely the Blackbucks are shy creatures and hence try to evade the searcher (Data collector). As the target is trying to avoid detection, this becomes a 2 sided search for moving target. In the case of stationary target's objective is to choose its location to make the search as difficult as possible. This problem is usually modeled as a 2 person game with target wishing to maximize the mean time to detection and the searcher wishing to minimize it. The solutions are typically mixed strategies for searcher and target. When the target moves, the 2 sided game becomes more complex.

5. Search Games

The Data Collector would like to detect the mobile hider namely the Blackbuck as soon as possible. It is basically a "hide and seek" game that can be formulated as mathematical problem. Search games [20] can be considered in graphs, bounded regions and unbounded domains. While some problems have complete solutions, some only have upper and lower limits. The search game is formulated with the following considerations. The search takes place in a set Q to be called the "search space". The search space Q is usually either a graph (a connected set of arcs of arbitrary type) or a compact region in R (Sanctuary), but it can also be an unbounded domain. The searcher (data collector) usually starts moving from a specified point O, called the origin, and is free to choose any continuous trajectory inside Q, subject to a maximal velocity constraint (on foot and in scrub forest) which is normalized to 1. As to the hider (Blackbuck), in some of the problems it will be assumed that the hider is immobile (resting, grazing, nursing) and can only choose his (its) hiding point, but we shall also consider games with a mobile hider who can choose any continuous trajectory inside Q. It will always be assumed that neither the searcher (data collector) nor the hider (Blackbuck) has any knowledge about the movement of the other player until their distance apart is less than or equal to the discovery radius r (this is the radio range of the Wi-Fi in the DTN nodes), and that very moment capture (detection and hence data transfer) happens. The Lebesgue measure of Q is denoted by u. If Q is a graph, u is the total arc length, while if Q is a region in R, then u is the area, volume, and so on. The discovery rate, denoted by g, is the maximal Lebesgue measure of a set that can be swept by the searcher is 1, it follows that g=1 for a graph. In the case that Q is a two-dimensional region, the sweep in one unit of time is 2r. By similar reasoning, g is equal to πr2 for the three-dimensional regions, and so on. The expression u/g is closely related to the value of several search games. Actually, u/g is equal to the length of a closed trajectory, denoted by a "tour," that sweeps all the points of Q without overlap. Such a tour exists for Eulerian graphs. (A tour with a very little overlap exists for two-dimensional regions.)

Each search problem is presented as a two-person zero-sum game. A pure strategy of the searcher is a continuous trajectory, S, with velocity not exceeding 1. As to the hider, we have to distinguish between 2 cases: If the hider is immobile, he (it) can only choose his (its) hiding point H, whereas if he (it) is mobile, his (its) strategy H is a continuous trajectory. The next step in describing the search game is to present a cost function (the payoff) C(S,H) which has to represent the loss of the searcher (or the effort spent in searching) if the searcher uses strategy S and the hider uses strategy H. Since the game is assumed to be zero-sum, C(S,H) also represents the gain of the hider, so that players have opposite goals: The searcher wishes to make the cost as small as possible , while the hider wishes to make it large. The natural choice for the cost function is the time spent until the hider is captured. For the case of a bounded search space Q, this choice presents no problem, but if Q is unbounded and if no restrictions are imposed on the hider, he can make the capture time as large as desired by choosing points that are very far from the origin. We overcome that difficulty by imposing a restriction on the expected distance of the hider from the origin or by normalizing the cost function. Given the available pure strategies and the cost function C(S,H), the value v(S) guaranteed by a fixed trajectory S is defined as the maximal cost that could be paid by the searcher if he uses the trajectory S; thus $v(S)=\sup_H C(S,H)$. The value $VP=\inf_S v(S)$ represents the minimal capture time that can be guaranteed by the searcher if he uses a fixed trajectory, but in all the interesting search games the searcher can do better on the average if he uses random choices out of his pure strategies. These choices are called "mixed strategies." A mixed strategy of the searcher is denoted by s and a mixed strategy of the hider is denoted by h. If the players use mixed strategies, the capture time is a random variable, so that each player cannot guarantee a fixed cost but only an expected cost. The expected cost of using the mixed strategies s and h is denoted by c(s,h). The maximal expected cost v(s) of using a search strategy s, $v(s)=\sup_h c(s,h) = \sup_H c(s,H)$, is called the "value of strategy s," and the minimal expected cost v(h) of using a hiding strategy h, $v(h) = \inf_s c(s,h) = \inf_S c(S,h)$,is called the "value of strategy h." If there exists a real number v that satisfies $v = \inf_s v(s) = \sup_h v(h)$, we say that the game has a value v. In this case, for any $\varepsilon > 0$, there exists a search strategy s_ε and a hiding strategy h_ε which satisfy $v(s_\varepsilon)<(1+\varepsilon)v$ and $v(h_\varepsilon)>(1-\varepsilon)v$. Such strategies will be called "ε-optimal strategies." In the case that there exists s* (respectively, h*) such that v(s*)=v [respectively, v(h*)=v], then s* (respectively, h*) is called an "optimal strategy." In general, if the sets of pure strategies of both players are infinite, the game need not have value. However, using Ky Fan's minimax theorem, it has been proven that any search game of the discussed type has a value and an optimal search strategy. The existence theorem remains valid if one allows the searcher to use only trajectories that belong to a specific subset of all the trajectories on the condition that this sub-set is compact.

6. Search for Blackbuck in a Sanctuary

The search space Q is a multidimensional region and the detection radius r is small (40-250m) in comparison with Q (16 Sq Km) in magnitude. Searching for an immobile hider (A resting Blackbuck) in a two-dimensional region is relatively simple because in this case it is possible to find a tour L with length smaller than $(1+\varepsilon)u/2r$ which sweeps all the points of Q (in the sense that if the searcher goes along L, he will surely find the hider). u is the total arc length of Q. This property makes the problem very similar to the search on Eulerian graph. Thus, choosing each one of the directions, of encircling L, with probability ½ guarantees a value $(1+\varepsilon)u/4r$. On the other hand, it is true for an immobile hider in general that by choosing a completely randomized strategy (uniform hiding distribution in Q) he can make sure that the capture time is at least u/2g, which is equal to u/4r for a two dimensional region. Thus the value of the search game for an immobile hider in a two dimensional region is u/4r. The foregoing result is based on the fact that two dimensional regions can be covered by narrow strips with little overlap. The analogous construction for three dimensions would require covering the region with narrow cylinders, but in this case the overlap would not be negligible. The value of the search game exceeds u/2g (because the hider can use the completely randomized strategy) and is below u/g (which is the value for a mobile hider), but the exact value for three or more dimensions is still an open problem.

Also analyzed is a mobile hider like Blackbuck in a multidimensional region. The princess and monster game for two or more dimensions, which had remained an open problem since 1965 had been solved by Gal in 1979. The details of the proofs are rather complicated, but the results can be explained quite easily. The value v, of the princess and monster game in two or more dimensions satisfies v = (u/g), where u is the Lebesgue measure of the search space and g is the discovery rate. The search strategy, s*, which guarantees an expected capture time of less than $(1+\varepsilon)u/g$, can be constructed as follows:

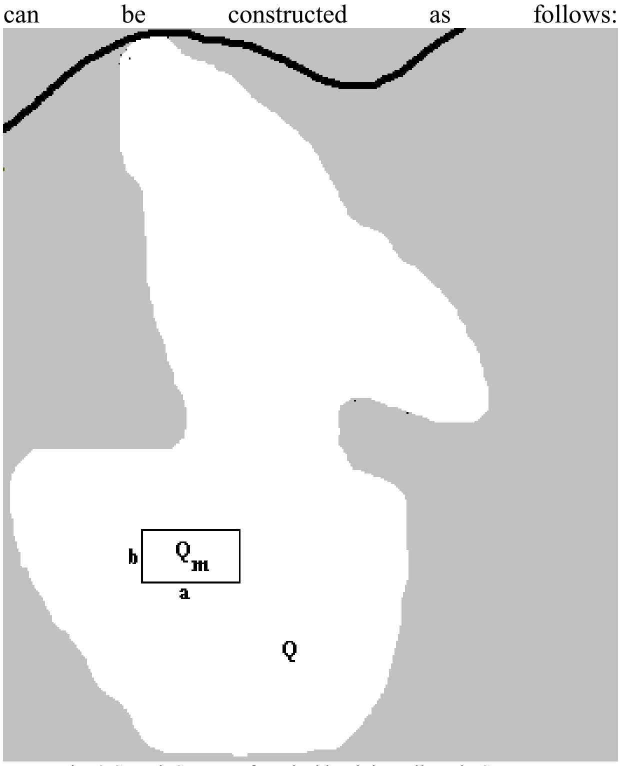

Fig. 2 Search Strategy for Blackbuck in Vallanadu Sanctuary

The search space Q is covered by a set of parallel and similar narrow rectangles $Q_1,\dots, Q_m,\dots, Q_M$; a rectangle Q_m is randomly chosen (Figure x) and examined by moving n times forward and backward along trajectories parallel to a, with height b chosen randomly each time; then another rectangle is randomly chosen, and so on. It turns out that for each rectangle, the search strategy is "efficient". Thus if n is chosen properly (large enough to "absorb" the effect of the time spent in going from one rectangle to another but not too large), the expected capture time guaranteed by s* is less than $(1+\varepsilon)u/g$. The strategy h* of the hider, which keeps the capture time above $(1-\varepsilon)u/g$ (on the condition that the hider's velocity is not too small), is described as follows. Choose a random (uniformly distributed) point Z_1 and stay there a time period D; then choose another random point Z_2 (independently of Z_1), move as fast as you can towards it, and stay there another time period D, and so on. The "resting time" should not be too long, so that the area swept by the searcher in a time interval of length D will be small relative to the volume of Q; but on the other hand, to keep the probability of capture during motion relatively small, the hider should not move too frequently and thus D should not be too short. An important property of multidimensional princess and monster game is the following. There exists a function P(t), which decreases exponentially in 1, such that for all t both the searcher and the hider can keep the possibility of capture after t around P(t). This property can be used to show that the optimal strategies described above are still optimal even if we replace the capture time by a more general cost function. It should also be noted that above a small threshold, the value is independent of the hider's velocity. The results were extended in several directions where-in the detection radius is not uniform in Q, with several searchers etc., which are beyond the scope of this paper.

7. Search based Routing

The proposed AUDTHMN is represented as graph in figure 3. The preliminary design consists of 4 layers. The first layer is the source layer that comprises of the Blackbucks carry radio collared DTN nodes. The radio collars carry the electronics payload that log their habitat data namely their movement in the sanctuary. This can be carried out by COTS SiRF star III GPS data loggers some of which are only 21 grams in weight and have the form factor of a matchbox. DTN2.5 can be run on a SBC, which can take the GPS data log from the flash memory of the logger and encapsulate them into DTN bundles and forward it appropriately. The intelligent forwarding part, which constitutes the routing scheme, is designed based on the search theory aspects that were discussed. Logically each modified DTN application shall maintain a table that has the capture time for each Blackbuck. The capture time is below $(1+\varepsilon)u/g$ based on search strategy s* and above $(1-\varepsilon)u/g$ based on hide strategy h*. The schematic shown in figure 3 depicts 7 Blackbucks under consideration. The hide strategy of each Blackbuck is different being dictated by its behavioral aspects. The hide strategies for Blackbucks B_1 to B_7 is denoted as h_1* to h_7*. In this simple scenario, only one data collector C_1 goes in search of the Blackbucks to establish radio contact and retrieve the habitat data. Hence the collector search strategy is s* being dictated by scientific methods that best suits the topography of the sanctuary and stamina of the searcher. All the DTN nodes carried by both the Blackbucks and the data collector maintains the individual capture time of all the Blackbucks. The hop layer in this case is dynamically created by identifying the Blackbucks with least capture times and making them as Hop Layer 1. Now, the other Blackbucks that carry their own habitat data forwards it to the Hop Layer 1 Blackbucks when they come in radio contact. The Hop layer 1 Blackbucks have least capture times and come in radio contact with the data collector more often than the pure source layer bucks. Thus a dynamic routing scheme based on the capture time comes into effect. Multiple layers of hop layer can be created based on preference, however it adds to the computational complexity in the nodes. This routing scheme can be scaled to multiple data collectors too who may have different search strategies.

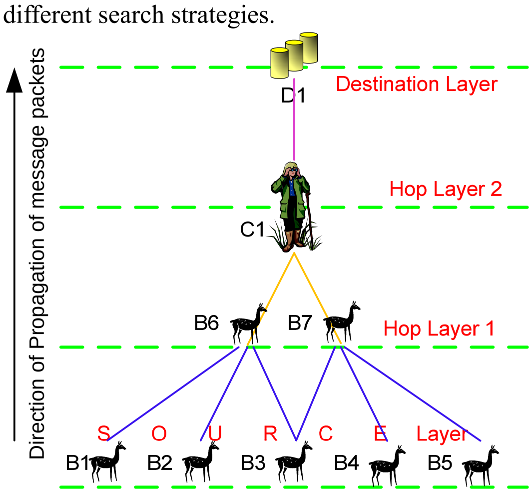

Fig. 3 AUDTHMN represented as Graph

In Ideal scenarios, the maximum capture time $(1+\varepsilon)u/g$ guaranteed by search strategy s* equals minimum capture time of $(1-\varepsilon)u/g$ guaranteed by hide strategy of h*, in which case $\varepsilon = 0$. However, the basic assumption is that $\varepsilon > 0$ and hence the ideal scenario does not theoretically work which is in-line with the practicality. The more the behavioral differences among Blackbucks, the more are the hiding strategies which make the search based routing even more effective.

6. Conclusion

This paper theoretically explores the use of Search Theory as routing policy [14] for DTN bundle routing. Being a theoretical overview, the paper does not discuss experimental treatment or results which may be beyond its scope. A glimpse of the proposed Alagappa University Delay Tolerant Habitat Monitoring Network, an environmentally significant application, has also been presented. This research is at the early concept stage for AUDTHMN. The future scope of work proposed by the authors includes:

(i) Detailed analysis of the Search Theory Routing with respect to different forms and sides.
(ii) Simulate the Game Theory based routing using Alunivdtnsim [5] and analyze its performance in comparison to other existing DTN routing protocols [16][17] such as (a) Spray and Wait [15], (c) PRoPHET [19] and (d) MaxProp [13] and proposed [18] DTN routing schemes.
(iii) Experimentation and subsequent implementation of the same in DTN bundles.
(iv) The results of Search Theory Routing schemes applied in AUDTHMN to be theoretically extrapolated to the Inter-planetary counterparts.
(vi) Field testing of AUDTHMN and its delivery performance
(vii) Physical realization of AUDTHMN, deployment and operation.
(viii) Search Theory routing for other applications such as smart sensors in Battle field, ZebraNet, etc.,

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References

[1] Laveen Sundararaj, Palanisamy Vellaiyan, "Throughput Enhancement in AUDTWMN using Throwboxes – An Overview", ICIWE 2010 : International Conference on Internet and Web Engineering, Singapore August 25-27, 2010. ISSN: 2070-3740 & ISSN: 2070-3724.
[2] Laveen Sundararaj, Palanisamy Vellaiyan, "Delay Tolerant Networking routing as a Game Theory problem – An Overview", International Journal of Computer Networks, Kuala Lumpur, Volume (2): Issue (3). ISSN 1985-4129.
[3] Laveen Sundararaj, Palanisamy Vellaiyan, "Delay Tolerant Network Routing based on Rendezvous value (R) – A Theoretical Overview", European Journal of Scientific Research, London, Vol 43 Issue 2 June 2010, ISSN: 1450-216X / 1450-202X.
[4] Laveen Sundararaj, Palanisamy Vellaiyan. "An Overview of Alagappa University Delay Tolerant Water Monitoring Network". International Journal of Computer Science and Network Security, Korea, Volume 10, Number 5, May 2010. ISSN: 1738-7906.
[5] Laveen Sundararaj, Palanisamy Vellaiyan. "Alunivdtnsim – An Overview of a simple Delay Tolerant Network simulator". In Proceedings of the National Conference on Information, Communication & Networking, SRM EEC Chennai, April 2010.
[6] Laveen Sundararaj, Palanisamy Vellaiyan, "DTN Work Update", DTNRG meeting March 2009, a NASA event, Google HQ, CA.(http://down.dsg.cs.tcd.ie/dtnrg-at-google/)
[7] Kevin Fall, Senior Member, IEEE, and Stephen Farrell, "DTN: An Architectural Retrospective", IEEE Journal on Selected Areas in Communications, Vol.26, No 5, June 2008.
[8] K. Scott and S. Burleigh, "Bundle Protocol Specification," Internet RFC 5050, Nov 2007.
[9] Laveen Sundararaj, Palanisamy Vellaiyan, "Planned DTN Work", DTNRG meeting May 2007, Trinity College Dublin, Ireland. (http://down.dsg.cs.tcd.ie/misc/DubDTN/)
[10] V. Cerf, S. Burleigh, A. Hooke, L. Torgerson, R. Durst, K. Scott, K. Fall, and H. Weiss, "Delay–Tolerant Networking Architecture," Internet RFC 4838, April 2007.
[11] S. Farrell and V. Cahill, Delay– and Disruption–Tolerant Networking. Artech House Publishers, 2006, ISBN: 1-59693-063-2.
[12] Stephen Farrell, Vinny Cahill, Dermot Geraghty, Ivor Humphreys and Paul McDonald, "When TCP Breaks, Delay- and Disruption-Tolerant Networking", IEEE Internet Computing July-August 2006.
[13] J. Burgess, B. Gallagher, D. Jensen, and B. N. Levine, "MaxProp: Routing for Vehicle-Based Disruption-Tolerant Networks", Proceedings of IEEE Infocom, April 2006.
[14] Zhensheng Zhang, "Routing in intermittently connected mobile ad hoc networks and delay tolerant networks: overview and challenges" Communications Surveys & Tutorials, IEEE, Volume 8, Issue 1, First Quarter 2006 Page(s):24 – 37.
[15] Thrasyvoulos Spyropoulos, Konstantinos Psounis, and Cauligi S. Raghavendra, "Spray and Wait: An Efficient Routing Scheme for Intermittently Connected Mobile Networks", Proceedings of ACM SIG-COMM Workshop on Delay-Tolerant Networking (WDTN), 2005.
[16] Thrasyvoulos Spyropoulos, Konstantinos Psounis, and Cauligi S. Raghavendra, "Single-copy routing in intermittently connected mobile networks", Proc. Sensor and Ad Hoc Communications and Networks SECON, pages 235-244, October 2004.
[17] Sushant Jain, Kevin Fall, and Rabin Patra, "Routing in a delay tolerant network", SIGCOMM '04: Proceedings of the 2004 conference on Applications, technologies, architectures, and protocols for computer communications, pages 145-158, New York, NY, USA, 2004. ACM.
[18] K. Fall, "A Delay-Tolerant Network Architecture for Challenged Internets," in Proc. ACM SIGCOMM '03. New York, NY, USA: ACM Press, 2003, pp. 27–34.
[19] A. Lindgren et al., "Probabilistic Routing in Intermittently Connected Networks", Mobile Comp. and Commun. Rev., vol. 7 no.3, July 2003.
[20] Andrey Garnaev, Search Games and Other Applications of Game Theory. Springer; 1 edition, June 15, 2000.ISBN-10: 3540671951.
[21] D. Chudnovsky and G. Chudnovsky, Search Theory. Marcel Dekker, Inc, 1989, ISBN: 0-8247-8000-0.
[22] Fritz R. Walther, Elizabeth C. Haber and Gerald A. Grau, Gazelles and Their Relatives: A Study in Territorial

Behavior. William Andrew (January 14, 1984).ISBN-10: 0815509286.
[23] B. O. Koopman, Search and Screening. General Principles with Historical Applications.Pergamon, 1st edition, June 1980.ISBN-10: 0080231357.
[24] Tamil Nadu Forest Department, Vallanadu Blackbuck Sanctuary. (http://www.forests.tn.nic.in/wildbiodiversity/ws_vbs.html)

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