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A Method for Developing a Knowledge-Based System for Use in Simulating Behaviours in Mobile Ad Hoc Network Agents

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Abstract
This paper considers a mobile ad hoc network (MANET) as a socio-technical system with human-machine- characteristics. From this perspective, it is argued that a cognitive MANET will need certain human behaviours if it is to acquire intelligence reminiscence of a human social system. To achieve this, the spatial relationships among the MANET nodes require algorithms to process the node actions in order to create robust system-level behaviours from those relationships. We develop a technique known as KANA (a Knowledge Action Network for Agents) for use in developing such intelligence behaviours. KANA has two primary knowledge elements: a network- and a fuzzy matrix- representation of the nodes and edges in a MANET. The KANA algorithms have been used to model and simulate MANET behaviors in order to discover its sociometric properties

Keywords
Agents, Fuzzy matrix, KANA, Knowledge-based, MANET, Sociometrics

I. Introduction

Younis, et al. [1, 2] observed that a MANET is a rich commodity with so much rich information that it of interest to adversaries. With a MANET capability to have access to so much military related operational information, Younis and his colleagues [2] advocated the design of cognitive MANETs. Many researchers have approached the problem of designing cognitive MANETs from the stand point of multi-agent systems [3, 4] and artificial intelligence and self-organized network models [5].

The uses of agents in simulations to analyze a MANET performance are based on the idea that the entity behaviors in the MANET are active in their worlds and can be represented by computer algorithms. These include behavioral singularity, collectively, or an emergent behaviors resulting from the agent interactions [6]. While good results have been achieved, it is noted in [6] that this idea is too simplified by assuming that all agents have cognition similar to humans who can independently perceive their world and react to it. In this paper, we consider a MANET as a socio-cognitive system which is able to perform intelligent actions, make rational decisions, and consider interrelated activities around its domain of influence.

In a MANET, the spatial connections or relationships of the actions from its nodes require some algorithms to process and update it behaviors and actions in relationship to other nodes. In this respect, we develop a technique known as KANA (a Knowledge Action Network for Agents). KANA has two primary knowledge elements: a network representation and a fuzzy matrix representation of the nodes and edges in the network. A fuzzy representation is chosen because we assume that each node in a MANET has some perceptionor a degree of belief assignment between zero to one [0, 1] that represents how a MANET node views other nodes with respect to extrinsic behavioral characteristics, such as trust, cooperation, and information sharing. We also consider how each node in a MANET views itself in terms of intrinsic behavioral attributes such as adaptation, decision-making, and risk taking. KANA algorithms contain the fuzzy mathematical models to represent these behaviors which can be used to discover sociometric properties of a MANET.

II. A Simplified Description of A Manet As A Network Topology

In MANET, nodes communicate via wireless *links*. Each node has a limited transmission range. We assume that two nodes are connected with each other if the distance between them is smaller than the maximum of their transmission range. That is if tr_A and tr_B are transmission ranges of agent A and B respectively where A and B are connected if and only if $d(A,B) \leq max(tr_A, tr_B)$. All the links in the network are bi-directional, however, connections between nodes is asymmetric. The level to which an agent A is connected to another agent B is different from the level of B to A (Fig. 1).

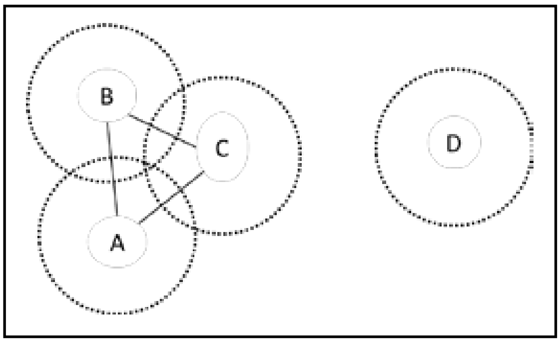

Fig. 1: MANET node connections with illustrative spheres of influence through transmission range interactions.

A MANET topology is dynamic because the connectivity among the nodes changes as they are moving. While moving, the nodes can stay connected to other nodes but they can also be completely without neighbors. They can move everywhere within their areas of influence but they are not allowed to go out of the areas. In addition, no new nodes can enter the network unless such nodes satisfy the necessary conditions of cooperation. A node in a MANET will always know who its neighbors are. Therefore, while moving, a node will immediately know its new neighbors. In this paper, a MANET node is referred as an agent.

III. A Knowledge Action Network for Network Agents (KANA)

The collection of algorithms to represent perception, cognition, and actions in a MANET is referred to here as a Knowledge Action Network for Agents (KANA). KANA is designed to capture how knowledge is used by agents to achieve intended system-level actions. Capturing the knowledge entails the formalization of mathematical algorithms to represent social-behaviors, interactions, collaborations and information sharing among entities in a system.

The first part of KANA is understanding node connectivity in a MANET. Traditionally, researchers look at graph or network connectivity in two ways—as either vertex connectivity or edge connectivity. As an illustration, consider a five-node MANET layout with its regions of connectivity (Fig. 2). The connectivity weights are converted to an equivalent fuzzy matrix. To do this, an algorithm based on disk geometry representation is developed. The disk geometry representation is like a Venn diagram of regions of access (RoA). That is, for two disks; a distance metric of information transmission using RoA is calculated. The algorithm is given in equation 1.

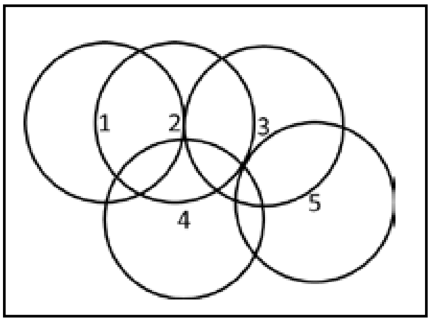

Fig 2. An example of five-node MANET.

$$a_{ij} = \begin{cases} r_i^2 \cos^{-1}\left(\frac{d_{ij}^2+r_i^2-r_j^2}{2d_{ij}r_i}\right) + r_j^2 \cos^{-1}\left(\frac{d_{ij}^2+r_j^2-r_i^2}{2d_{ij}r_j}\right) - \frac{1}{2}\sqrt{(-d_{ij}+r_i+r_j)(d_{ij}-r_i+r_j)(d_{ij}+r_i-r_j)(d_{ij}+r_i+r_j)} & if\ d_{ij} \neq \\ \pi r_i^2 & if\ d_{ij} = 0\ and\ r_i \le r_j \\ \pi r_j^2 & if\ d_{ij} = 0\ and\ r_j \le r_i \\ 0 & \end{cases}$$

(1)

In Equation 1, r_i is the radius of node i, d_{ij} is the Euclidean distance between node i and node j; and the algorithm uses the "Circle-Circle Intersection" of Weisstein [7]. As an example, consider a two-node MANET below in Fig. 3. As example, $d_{12} = 1, r_1 = 0.5$, $r_2 = 0.75$, then

$$a_{12} = (0.5)^2 \cos^{-1}\left(\frac{1^2+0.5^2-0.75^2}{2\times 0.5}\right) + (0.75)^2 \cos^{-1}\left(\frac{1^2-0.5^2+0.75^2}{2\times 0.75}\right) - \frac{1}{2}\sqrt{(-1+0.5+0.75)(1-0.5+0.75)(1+0.5-0.75)(1+0.5+0.75)}$$

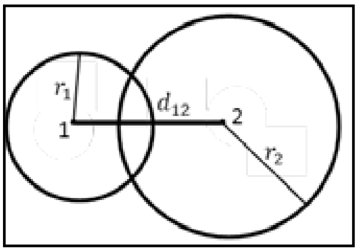

Fig 3. An example of a two-node network

$$= 0.25 \times \cos^{-1}(0.6875) + 0.5675 \times \cos^{-1}(0.875) - \frac{1}{2}\sqrt{(0.25)(1.25)(0.75)(2.25)}$$

$$= 0.25 \times (0.8127) + 0.5675 \times (0.5054) - 0.3631$$

$$a_{12} = 0.1269$$

Definition 1: Let x_1 be a node with center 1 and radius r_1 and x_2 the node with center 2 and radius r_2, then we define the fuzzy connectivity from x_1 to x_2 (denoted $x_1 \longrightarrow x_2$) to be $\frac{a_{12}}{\pi r_1^2}$. Similarly, $x_2 \longrightarrow x_1 = \frac{a_{12}}{\pi r_2^2}$.

For the sample network, $x_1 \longrightarrow x_2 = \frac{0.1269}{3.14\times 0.25} = 0.1616$

$$x_2 \longrightarrow x_1 = \frac{0.1269}{3.14 \times 0.25} = 0.0718$$

As another illustration, consider four agents x_1, x_2, x_3 and x_4 respectively located at the geometric points, $(5,3)$, $(5,3)$, $(5,6)$ and $(4,7)$ with radius 4, 5, 6 and 3. The fuzzy connectivity matrix Z is calculated as

$$Z = \begin{bmatrix} 1 & 1 & 0.8936 & 0.2223 \\ 0.6400 & 1 & 0.7807 & 0.2226 \\ 0.3971 & 0.5421 & 1 & 0.2500 \\ 0.3952 & 0.6185 & 1 & 1 \end{bmatrix}$$

Proposition 1: If a MANET is fully connected, , and the nodes are involved in a communication action without movement, it will end up after a certain time behaving as a single node. In other words if a MANET is represented by its fuzzy connectivity matrix A; there exists an $n \in \mathbb{N}$, such that $A^n = ones(n)$.

Proof

Let $A = (a_{ij})_{1 \le i,j \le n}$ a full MANET connectivity matrix; let $A^k = (a_{ij}^k)$ be the k- power of A [8]. We will prove that:

$(a_{ij}^k)_{k\in\mathbb{N}}$ is an increasing and bounded sequence; hence converging.

$a_{ij}^k = \oplus_{l=1}^{n} (a_{il}^{k-1} \otimes a_{lj}^{k-1})$; in this "sun" the term when $l = j$ is $a_{ij}^{k-1} \otimes a_{jj}^{k-1} = a_{ij}^{k-1}$ because $a_{jj}^{k-1} = 1$. We thus have. $a_{ij}^k \le 1$

$a_{ij}^k \le 1$ for all $1 \le i,j,k \le n$.

Definition 2: (Addition of fuzzy matrices). Giving two fuzzy matrices $A = (a_{ij})_{\substack{1\le i\le m \\ 1\le j\le n}}$ and $B = (b_{ij})_{\substack{1\le i\le r \\ 1\le j\le s}}$ representing two configurations of MANET nodes, if $dimension(A) = dimension(B)$ i.e., $m = r$ and $n = s$, then a fuzzy addition $A \oplus B$ is defined as $A \oplus B = (c_{ij})_{\substack{1\le i\le m \\ 1\le j\le n}}$ where $c_{ij} = max(a_{ij} + b_{ij}, 1)$ is the Lukasiewicz t-conorm [9,10].

Definition 3: (multiplication of fuzzy matrices) Giving two fuzzy matrices $A = (a_{ij})_{\substack{1\le i\le m \\ 1\le j\le n}}$ and $B = (b_{ij})_{\substack{1\le i\le s \\ 1\le j\le s}}$, if

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$dimension(A,2) = dimension(B,1)$ i.e.,$n = r$ then a fuzzy multiplication $A \otimes B$ is defined as $A \otimes B = (c_{ij})_{\substack{1 \le i \le m \\ 1 \le j \le n}}$; where $c_{ij} = \oplus_k (a_{ik} \otimes b_{kj})$ and $a \otimes b = max(a + b - 1, 0)$ is the Lukasiewicz t-norm and the associated Lukasiewicz t-conorm is defined by $a \oplus b = min(1, a + b)$.

Proposition 2: Fuzzy square matrices have the special property that for every fuzzy square matrix A, there exist $n \in \mathbb{N}$ such that $A^{n+1} = A^n$. That is, the relational matrix $A_{n \times n}$ induced by n –node MANETs, after a period of sharing information, will likely have a converging behavior. That is matrix A is stationary. This can be shown from assumptions in Vasantha, et al. [11].

Proof: Proof: Let $A = (a_{ij})_{\substack{1 \le i \le n \\ 1 \le j \le n}}$ be a fuzzy square matrix of size n.

Case 1. $(\forall 1 \le i, j \le n), a_{ij} < \frac{n}{(2n-1)}$, then letting $A^2 = (c_{ij})_{\substack{1 \le i \le n \\ 1 \le j \le n}}$,

$$c_{ij} = (a_{i1} \otimes a_{1j}) \oplus (a_{i2} \otimes a_{2j}) \oplus \ldots \oplus (a_{in} \otimes a_{nj})$$

$$a_{ik} \otimes a_{kj} = max(0, a_{ik} + a_{kj} - 1) < max\left(0, \frac{2n}{(2n-1)} - 1\right) = \frac{1}{(2n-1)}$$

$$\Rightarrow c_{ij} = (a_{i1} \otimes a_{1j}) \oplus (a_{i2} \otimes a_{2j}) \oplus \ldots \oplus (a_{in} \otimes a_{nj}) < \frac{n}{(2n-1)} = a_{ij}$$

Let $A^3 = (d_{ij})_{\substack{1 \le i \le n \\ 1 \le j \le n}}$,

$$d_{ij} = (c_{i1} \otimes a_{1j}) \oplus (c_{i2} \otimes a_{2j}) \oplus \ldots \oplus (c_{in} \otimes a_{nj})$$

since $c_{ik} \otimes a_{kj} < a_{ik} \otimes a_{kj}$, we deduce that $d_{ij} = (c_{i1} \otimes a_{1j}) \oplus (c_{i2} \otimes a_{2j}) \oplus \ldots \oplus (c_{in} \otimes a_{nj}) < c_{ij}$

We prove that with $A^n = (a_{ij}^{(n)})_{ij}$, $(a_{ij}^{(n)})_{n \in N}$ is a decreasing sequence lower bounded by 0 thus converging.

Case 2: $(\forall 1 \le i, j \le n)$, $a_{ij} \ge \frac{n}{(2n-1)}$; the same reasoning as in case 1 applies only by switching strictly lower than in case 1 with greater than.

Case 3: General case: With $A = (a_{ij})_{\substack{1 \le i \le n \\ 1 \le j \le n}}$, $A^2 = (a_{ij}^{(2)})_{\substack{1 \le i \le n \\ 1 \le j \le n}}$;

if $a_{ij} < a_{ij}^{(2)}$, then $\forall n \ge 1$, $a_{ij}^{(n)} < a_{ij}^{(n+1)}$.

Prove by induction

$a_{ij}^{(1)} < a_{ij}^{(2)}$ by assumption

Let's suppose that $\forall m < n$, $a_{ij}^{(m)} < a_{ij}^{(m+1)}$; prove that $a_{ij}^{(n+1)} < a_{ij}^{(n+2)}$

$$a_{ij}^{(n+1)} = (a_{i1}^{(n)} \otimes a_{1j}) \oplus (a_{i2}^{(n)} \otimes a_{2j}) \oplus \ldots \oplus (a_{in}^{(n)} \otimes a_{nj})$$

$$a_{ik}^{(n)} \otimes a_{kj} = max(0, a_{ik}^{(n)} + a_{kj} - 1) < max(0, a_{ik}^{(n)} + a_{kj}^{(2)} - 1) = a_{ik}^{(n)} \otimes a_{kj}^{(2)}$$

As this is true for $k = 1, 2, \ldots, n$,

$$a_{ij}^{(n+1)} = (a_{i1}^{(n)} \otimes a_{1j}) \oplus (a_{i2}^{(n)} \otimes a_{2j}) \oplus \ldots \oplus (a_{in}^{(n)} \otimes a_{nj}) < (a_{i1}^{(n)} \otimes a_{1j}^{(2)}) \oplus (a_{i2}^{(n)} \otimes a_{2j}^{(2)}) \oplus \ldots \oplus (a_{in}^{(n)} \otimes a_{nj}^{(2)}) = a_{ij}^{(n+2)}$$

Example: $A = \begin{bmatrix} 0.8 & 0.4 & 0.5 \\ 0.5 & 0.9 & 0.1 \\ 0.6 & 0.6 & 0.3 \end{bmatrix}$; $A^7 = A^6 = \begin{bmatrix} 1 & 1 & 0. \\ 1 & 1 & 0. \\ 1 & 1 & 0. \end{bmatrix}$

The fuzzy algorithm to implement the procedure in Mathlab software is shown in Exhibit 1 below.

Exhibit 1: A Mathlab algorithm for fuzzy product

```
function [C] = fuzzyproduct(B,A)
function [c] = probasum(a,b)
c = a + b - (a * b);
end
if size(A,2)~ = size(B,1)
  fprintf('\n The product is not possible \n')
  close()
else
  C = zeros(size(A,1),size(B,2));
  D = zeros(size(A,1),size(B,2),size(B,1));
  for i = 1:size(A,1)
    for j = 1:size(B,2)
      for k = 1:size(B,1)
        D(i,j,k) = A(i,k) * B(k,j);
        C(i,j) = probasum(D(i,j,k),C(i,j));
      end
    end
  end
end
end
```

As an example, consider the matrix A derived from a five-node MANET:

$$A = \begin{bmatrix} 1.0000 & 0.3910 & 0 & 0.1114 & 0 \\ 0.3910 & 1.0000 & 0.3910 & 0.5594 & 0.1114 \\ 0 & 0.3910 & 1.0000 & 0.5594 & 0.5594 \\ 0.1114 & 0.5594 & 0.5594 & 1.0000 & 0.3910 \\ 0 & 0.1114 & 0.5594 & 0.3910 & 1.0000 \end{bmatrix}$$

The matrix elements, a_{ij} represent a fuzzy view of the node j from node i. Each entry of the principal diagonal of the connectivity matrix is equal 1 with the assumption that any node is fully viewed from its location. The fuzzy product computation is shown below and it converges to **ones(A)** according to Proposition 1.

$$A^2 = fuzzyproduct(A, A) = \begin{bmatrix} 1.0000 & 0.3910 & 0 & 0.1114 & 0 \\ 0.3910 & 1.0000 & 0.3910 & 0.5594 & 0.1114 \\ 0 & 0.3910 & 1.0000 & 0.5594 & 0.5594 \\ 0.1114 & 0.5594 & 0.5594 & 1.0000 & 0.3910 \\ 0 & 0.1114 & 0.5594 & 0.3910 & 1.0000 \end{bmatrix}^2$$

$$= \begin{bmatrix} 1.0000 & 0.6522 & 0.2057 & 0.3831 & 0.0852 \\ 0.6522 & 1.0000 & 0.7611 & 0.8613 & 0.5180 \\ 0.2057 & 0.7611 & 1.0000 & 0.8815 & 0.8549 \\ 0.3831 & 0.8613 & 0.8815 & 1.0000 & 0.7611 \\ 0.0852 & 0.5180 & 0.8549 & 0.7611 & 1.0000 \end{bmatrix}$$

$$A^3 = fuzzyproduct(A, ans) = \begin{bmatrix} 1.0000 & 0.8484 & 0.5572 & 0.7021 & 0.3617 \\ 0.8484 & 1.0000 & 0.9464 & 0.9740 & 0.8369 \\ 0.5572 & 0.9464 & 1.0000 & 0.9805 & 0.9617 \\ 0.7021 & 0.9740 & 0.9805 & 1.0000 & 0.9333 \\ 0.3617 & 0.8369 & 0.9617 & 0.9333 & 1.0000 \end{bmatrix}$$

$$A^{18} = \begin{bmatrix} 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 0.9999 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 0.9999 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \end{bmatrix}$$

And

$$A^{19} = \begin{bmatrix} 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \\ 1.0000 & 1.0000 & 1.0000 & 1.0000 & 1.0000 \end{bmatrix}$$

This node connectivity tells an agent when to initiate a movement to increase its connectivity. This definition has two extreme cases:

The full-connected connectivity matrix $ones(n)$ where the node connectivity of all nodes is equal 1; and the totally disconnected network $eye(n)$ where all nodes have connectivity 0.

Learning, Predicting, And Adaptation By Manets

MANET agents should be able to acquire five important macro-level traits of intelligence. They should be able to Predict, Envision, Anticipate, Reason, and Learn. Thus, a MANET node is considered an agent with the ability to acquire and exhibit the PEARL characteristics.

With the assumption that a MANET node can control its behavior when exposed to different stimuli, we reason from the classical control theory governing dynamic systems. This is shown in equation (3). The rate of change of the MANET system is a fuzzy matrix governing the process dynamic of the network, and its initial system state fully described.

$$\dot{X} = AX + BU \qquad (3)$$

The matrix $A_{(nxn)}$ represents a process that describes how an agent i influences agent j through some interactions, U is an influence vector that describes the intrinsic node characteristic, U has pxn dimension, with n = number of MANET nodes, and p = number of intrinsic factors considered. Assuming that each node in the network evaluates each node with respect to each object, we can define a pairwise, non-symmetric, preference $n \times n$ matrix, which defines X.

We can discretize equation 3 to obtain time-dependent values as follows:

$\dot{x} = Ax + b$ is $\frac{x_{t+1}-x_t}{\Delta t} = Ax_t + b$

$$\frac{x_{t+1}-x_t}{\Delta t} = Ax_t + b \Rightarrow x_{t+1} - x_t = \Delta t(Ax_t + b) \qquad (4)$$

$$\Rightarrow x_{t+1} = x_t + \Delta t(Ax_t + b)$$

$$\Rightarrow x_{t+1} = (I + \Delta tA)x_t + \Delta tb$$

Let $B_t = I + \Delta tA$ and $b_t = \Delta tb$, $x_{t+1} = B_t x_t + b_t$; x_t is the network configuration at time t, and x_{t+1} is the network configuration at time $t+1$.

The discrete form is now defined in equation 5.

$$X_{t+1} = A_t X_t + BU \qquad (5)$$

The general MANET state evolution equation of the network in term of fuzzy matrices is given by equation 6.

$$X_{t+1} = (A_t \otimes X_t) \oplus B_t \qquad (6)$$

Where $\otimes$ is the fuzzy multiplication of fuzzy matrices and $\oplus$ is the fuzzy addition; A_t, and B_t are matrices representing the behavior evolution process at t iteration, and, X_t is a matrix of the network configuration represented by the adjacency matrix at time t.

4. Conclusion

We discussed KANA, a fuzzy-based analytics for use in modeling MANET behaviors. A fuzzy connectivity matrix is used to represent the relationships of the MANET nodes. The KANA algorithms represent these fuzzy node relationships with other nodes. The fuzzy matrix is derived using a region of access (ROA) model suggested [7]. A ROA represents a MANET sphere of influence. A MANET with n nodes has a fuzzy matrix in which each row of the matrix is associated to a node in the MANET and the element a_{ij} of the matrix is a fuzzy number representing how a node i “views” node j within the same MANET architecture. An example of a node viewpoint may be in terms of how information is shared with other nodes. It is shown that after a “sufficiently large number of iteration interactions between nodes”, the fuzzy matrix converges to a “zero-one” matrix. This finding is similar to a Markov ergodic property. In our case, it is assumed that MANET nodes are likely to learn and behave alike when all its behavioral primitives are averaged over time within the space of all the system's states. Thus, the values of “0” and “1” simply means that two edges of the network with “1” are fully connected, while “0” means no connectivity between the node with its comparators.

This observation has been applied a MANET agent simulation experiments [12].

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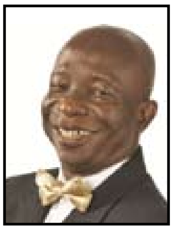
Authors' Profile



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