A biomimetic ranking system for energy constrained mobile wireless sensor networks

Andrew C. Markham, Andrew J. Wilkinson

***Abstract*—Routing in highly mobile, energy constrained wireless networks remains an open research area. The majority of energy aware protocols are designed for stationary networks, and conversely, mobile ad hoc protocols rarely incorporate information about node energy. Obtaining global information about energy distribution across the network is wasteful of scarce resources, so we introduce a ranking system based on social dominance hierarchies found in nature. The Adaptive Social Hierarchy (ASH) is a simple means of assessing node rank, utilizing only local information. Both single-copy and multi-copy routing protocols using our ranking system are presented. As an application, we consider equipping a wide variety of wild animals with wireless collars. We also show how a simple cross-layer protocol can be constructed which further conserves energy of low level nodes.**

Keywords-Social Hierarchy; Adaptive Routing; Cross layer

I. Introduction

A major problem in mobile wireless sensor networks (i.e. designed for data-gathering rather than for peer-to-peer sharing) is assessing the 'best' path that a message should take for eventual delivery to a base-station or exit point from the network. In sparse networks, this problem becomes even more apparent, when there may never be an end-to-end network route rendering 'traditional' protocols such as AODV [1] and DSR [2] useless. Thus delivery is undertaken in a store-and-forward manner, with nodes exchanging packets on contact with one another, to form a Delay-Tolerant-Network (DTN) [3]. If the mobility patterns of nodes are highly dynamic and essentially unpredictable, determining the optimal path is impossible. Flooding strategies (such as Epidemic Routing [4]) can achieve the optimal solution by sending the message down *all* possible paths, but at an unacceptably high overhead in terms of network resources (memory and energy usage). Scalability is poor, as network usage rises as the square of the number of nodes, leading to a critical limit on the number of network nodes. Refinements to the Epidemic protocol control the flooding by limiting message replication. However, few protocols take into account the heterogeneity across nodes in terms of intrinsic node parameters (such as energy) and extrinsic parameters (such as connectivity), simply treating all nodes as being identical in all respects and controlling the flood in a stateless fashion [5], [6]. Protocols which do take these differences into account assume global knowledge of node parameters, which scales poorly and involves a large network overhead in sharing these parameters [7]. We present here an elaboration of our previous work based on a biologically inspired self-ranking system [8].

As an application of our cross-layer routing protocol we consider a wireless sensor network designed for wildlife monitoring. Animals are equipped with collars which collect data (such as GPS positions or activity profiles) and relay it in a multi-hop fashion using low power wireless links. Energy is severely constrained and the collars must operate for as long as possible. Furthermore, the memory and computation power of the microcontroller in the collars is limited, precluding the use of intensive algorithms. However, the size of the batteries in each collar can be made to vary according to the weight of the host animal, leading to a widely diverse network.

This paper is organized as follows. First, a background review is presented of similar routing protocols, followed by an examination of social dominance hierarchies which occur in Nature. We then formulate a similar social hierarchy, and show how this ranking system can be used for the purposes of both routing and medium access. Simulation results are presented for the application of wildlife tracking. Finally, we discuss future directions for this research and draw conclusions.

II. Related Work

Epidemic routing is based on mimicking the spread of a disease through a population and is essentially a flooding mechanism for disconnected networks, but leads to high network resource usage [4]. To control network usage, variants have been presented in the literature, such as Spray and Wait [6] and Oracle based schemes [3]. However, none have considered the problem of heterogeneity with respect to energy and assume nodes are equal in all respects.

ZebraNet provided the first comprehensive examination of the use of wireless sensor networks for animal tracking [9], [10]. GPS equipped collars were fitted on zebras and exchange information in an epidemic fashion. Their routing algorithm is very simple and leads to buffer overflow as every node in the network stores information from every other node. They only considered fitting the collars on a single type of animal. The

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Shared Wireless Infostation Model (SWIM) is a routing protocol that addresses some of the issues faced by the Epidemic routing protocol [5]. Their main contribution is in the form of 'anti-packets' – messages that prevent nodes from buffering data that has already been delivered to the base-station. However, like ZebraNet, they concern themselves with instrumenting a single species – whales. Sikka *et al.* present a wireless sensor network designed to monitor a typical farm environment [11]. They also do not consider using the capabilities of different animals to lead to a better performing network.

III. The Need for a Ranking System

A. Naturally Occurring Social Hierarchies

Social hierarchies naturally occur in a number of species and are typically motivated by differences in physical attributes such as size or weight. Some individuals can be regarded as being 'fitter' than others based upon a set of measurable characteristics. Anemones for example, form a hierarchy based upon size, in which larger anemones are more aggressive towards smaller anemones [12]. Crayfish form a social dominance structure based on length, in which the shorter crayfish defer to the largest, super-dominant individual [13]. Social hierarchies can also be found in fish (Malawi Cichlids [14] and salmon [15]); insects (ants [16], bees [17] and wasps [18]) and mammals (baboons [19] and coyotes [20]). Thus it can be seen that social hierarchies are a common organizational structure in a wide variety of organisms.

A linear social dominance hierarchy is characterized by a group that is led by the largest or fittest member – the super-dominant or alpha individual. All other members of the group submit to this animal. The next in the hierarchy, the beta member is superior to all other members barring the alpha and so on. Thus, the weakest (omega) member in the pack will be subordinate to all other members. However, it must be noted that this is not a static structure, and the hierarchy adapts rapidly to changes. Animals alter their role in the hierarchy through a series of encounters or tournaments with other animals. When a new animal is inserted into a group, the social hierarchy will undergo a rapid flux until it reorganizes into a stable structure.

Social dominance hierarchies are used in the Animal Kingdom to control access to scarce resources. For example, in the whiptail wallaby (macropodus parryi), the individual animal's rank within the social hierarchy determines their access to estrous females [21].

Using these biological lessons, it can be seen how diversity in terms of fitness leads to a unified, self-organizing structure. By applying these principles to the structure of a wireless network that is diverse over some attributes, a similar self-organizing hierarchy can be formed. Tournaments are enacted upon pairwise encounters of nodes, the outcome of which determine the rank of nodes. The rank of each node controls its access to scarce network resources, with highly ranked nodes assuming a more active role in the network.

B. The Adaptive Social Hierarchy

Based on the commonly occurring social hierarchies found in nature, an analogous structure is constructed in a group of nodes based on a measurable attribute. Essentially, this maps an arbitrary set of node parameters into an ordered list, where the rank of a node corresponds to its position in the list. From this, nodes can determine how 'fit' they are with respect to their peers, without requiring global knowledge of the ordering of the network wide nodal parameters.

Each node is able to measure certain metrics on an absolute scale, such as battery energy or percentage connectivity. It forms a belief about its ranking within the network. Thus associated with each measured parameter α^i is a perceived rank R^i. A node with a ranking of 1 is at the top of the social hierarchy (corresponding to an alpha individual), whereas the lowest rank node will have a rank of 0 (corresponding to an omega individual).

When two nodes meet, they can assess whether these rankings are in concordance or disagreement with the relative ordering of the measured parameters. If the ordering of the parameters agrees with the ordering of the rankings, then they are reinforced. This is equivalent to an animal reinforcing its position in the social hierarchy. However, if the ordering of the parameters contradicts the rankings, then the nodes switch ranks. This is roughly analogous to an animal rapidly falling in ranking as the result of a failed aggressive encounter. Through these two actions, a form of local feedback is effected ensuring that the rankings will over time agree with the ordering of the measured parameters.

The tournament rules are shown in Fig. 1. Four simple rules are used in total. If the relative ranking of a node j agrees with the relative ordering of the parameter i, then this is reinforced either in a positive direction

$$R_j^i = (1-\delta) R_j^i + \delta \tag{1}$$

or a negative direction

$$R_j^i = (1-\delta) R_j^i \tag{2}$$

The innovation parameter, $0 < \delta < 1$, controls the speed at which the rankings adjust to new information. A large value of δ results rankings rapidly changing, leading to an unstable hierarchy. A very small value of δ leads to a long convergence time to the equilibrium position.

However, if the relative order of the parameter i is opposite to the relative order of the rankings, then nodes j and k simultaneously exchange their ranks:

$$R_j^i \leftarrow R_k^i \tag{3}$$

This 'switching' action has the effect of rapidly correcting a node's rank. This mechanism results in much faster

	$E_i > E_j$	$E_i < E_j$
$R_i > R_j$	$R_i = R_i(1-\delta) + \delta$	$R_i = R_j$
$R_i < R_j$	$R_i = R_j$	$R_i = R_i(1-\delta)$

Figure 1: Tournament outcomes based on node energy (E) and perceived rankings (R). Arrows indicate how the ranking of each node changes. If a node's perception of rank is correct, then its rank is reinforced either in a positive or negative direction. If a node's energy relative to its competitor contradicts its perception of rank, then it switches its rank with that of the competitor.

convergence times than if the learning procedure was only used.

To demonstrate the performance of the ranking system, four nodes are initialized with random rankings between 0 and 1. The measured parameter, α, is such that node 4 is superior to node 3 is superior to node 2 and so forth. At each point in the simulation, two nodes are picked at random and the tournament rules run. After 50 iterations, the node parameters are altered such that the order is opposite to the initial order of the parameters. The rankings of the nodes are shown in Fig. 2. This demonstrates that the nodes rapidly switch their ranks in the beginning, followed by a slow convergence towards the equilibrium point. When the order of the parameters alters, the nodes change their rankings within 5 iterations to regain the correct ordering. Thus it can be seen that the combination of the switching and reinforcement leads to nodes assuming their correct rank and adapting to changes in the measured parameter.

The overhead of the ranking algorithm is small and scales to any number of nodes without an increase in memory usage or computation time. This is because each node estimates its own rank, rather than attempting to track every other node's parameters in the network. Furthermore, without exchanging explicit global parameter information, nodes are able to achieve correct ranking using only local information.

IV. Routing protocols

The process of routing in a sparse mobile network devolves to deciding whether to transfer a message when two nodes are within radio contact of one another. If the message is transferred, then the originating node can either keep the message for future possible transmission or discard it to make room for new messages. The decision to transfer can be made at random or can be based upon some metric of how much better the other node will be at delivering the message to a base-station. By suitable choice of α parameters, a node's ranking can represent its suitability in transferring messages. For example, if the measured parameter is the energy of a node, then transferring messages to a higher ranked node is equivalent to sending messages up an energy gradient. The

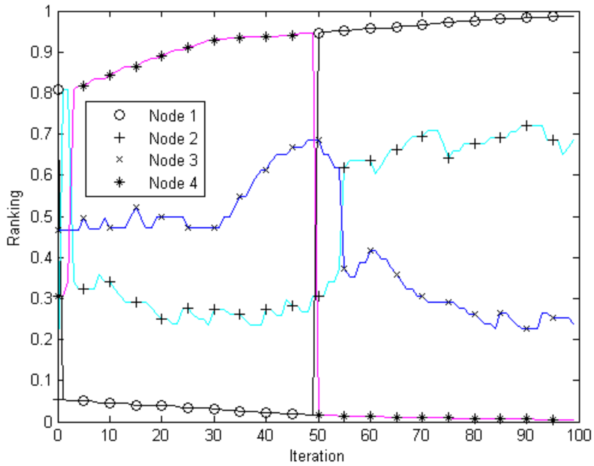

Figure 2: Rank trajectories with meeting in a four-node four-level network (δ = 0.1). At 50 iterations, the rank orders of the nodes are reversed.

ranking of a base-station is fixed to 1, such that it will be a top ranked node in the network and thus the end point. Hence, nodes can find base-stations without knowing their addresses.

A node's overall rank within the network can be calculated as a function of the individual ranks. This function could be a weighted sum, or a weighted product, depending on the application. More complex functions can also be used, for example that prevent nodes being active in the task of routing if their energy has a very low rank, even if their network connectivity is very good.

A naïve routing protocol would be to send messages to any node with a greater rank. However, this is equivalent to sending messages to any node with greater energy. Thus, it would appear as though calculating the rank is unnecessary. However, if the rank is discretized to L levels (where L is much smaller than the number of nodes in the network, N), then the power of the ranking system becomes apparent if nodes only send messages to nodes with a greater level. This is because the traffic density per node is independent of N, and only depends on the number of levels in the hierarchy [8]. The traffic density of a level k node is given by

$$D_k = \frac{\lambda L}{L-k+1} \qquad (4)$$

where λ is the average node traffic density in messages per unit time. This equation shows that if L = N as in the case of a network without a ranking system, the traffic density grows with N, leading to rapid node exhaustion. Thus using a social hierarchy leads to a highly scalable network as buffer usage does not increase with increasing number of nodes.

A. Adaptive Social Hierarchy Routing (ASH)

In this strategy, if a node encounters another node with higher level, it transfers its message to the new host and then deletes the message from its buffer. This is a simple routing

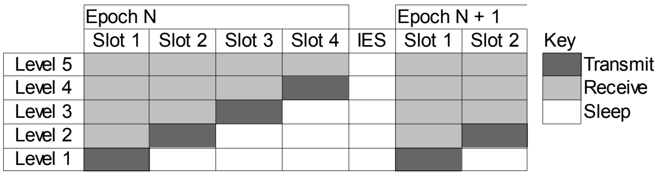

Figure 3: Cross layer slotted access scheme. Slots are assigned based on node level. Low level nodes spend the majority of their time sleeping which conserves their energy.

method, and leads to low network overhead as each message will be routed a maximum of L times (if the rankings are stable). However, if a node fails for any reason, the messages it is carrying will be removed from the network. In addition, the latency of this protocol is high.

B. Redundant Adaptive Social Hierarchy (rASH)

To reduce the probability of a message being lost through host failure and also to reduce the latency, messages can be replicated. Thus, when a message is delivered, a node can keep its copy for possible future delivery to another node. This strategy increases traffic density and buffer requirements. Thus there is a trade-off between redundancy and resource use. The ranking of nodes lends itself well to a natural choice of the degree of redundancy required. Clearly, duplicating a message across low level nodes does not achieve any useful redundancy, as these nodes are not active in disseminating information and are likely to be severely resource constrained compared to their higher ranked peers. Thus, messages are replicated with a probability that increases with increasing level. Hence, delivery amongst low level nodes will resemble direct routing (with low traffic overhead, but high latency) and delivery between high level nodes will resemble epidemic routing (with high traffic overhead and low latency). The probability of a level k node sending a message to a level j node is given by

$$P(Transmission_{k\to j}) = \begin{cases} 1\,(j>k) \\ \rho_T\,(j=k) \\ 0\,(j<k) \end{cases} \tag{5}$$

where ρ_T is the horizontal (i.e. across the same levels in the hierarchy) transmission probability. Once the message has been sent to a higher level node, the node can either keep the message or delete it. The probability of a level k node keeping a sent message for future replication is given by

$$P(Replication) = \rho_R^{\,N-k+1} \tag{6}$$

where ρ_R is the replication constant. The probability of replication increases with k, resulting in epidemic delivery between high level nodes.

C. Cross Layer Medium Access

As the routing protocols only transfer information to nodes with a greater level, information does not flow down the hierarchy. Hence, a level 1 node will never receive messages

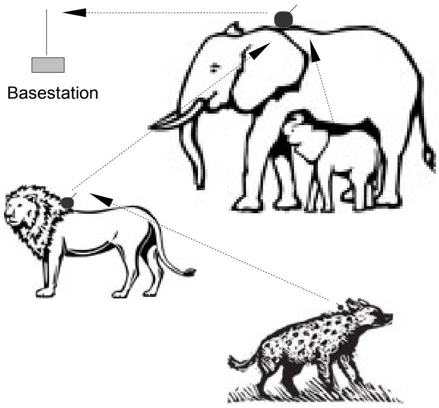

Figure 4: Application scenario: Animal borne collars route network data in a store-and-forward fashion. Collars carry different sized batteries according to the weight of the host. An adaptive hierarchy is formed from these differences, leading to a longer lived network.

from a higher level node. Thus, access to the communication medium can also be controlled preferentially based on node rank. An example of a MAC schedule is shown in Fig. 3 for a five level network. It can be seen that the lowest level node spends the majority of its time in a low power sleep mode, only waking if necessary to transmit a message. During its transmission slot, all the higher level nodes will be listening for transmissions. Thus, a low level node does not need to contend with a high level node for access to the medium, and spends the majority of its time asleep, conserving energy. The Inter Epoch Sleep (IES) gap is a period when all nodes enter the low power sleep mode. As levels in the hierarchy are not statically assigned, if a node assumes a role that depletes its energy rapidly relative to its peers, its relative fitness will decrease and it will descend the hierarchy, resulting in lower energy usage.

V. Application: Wildlife Animal Telemetry

Wildlife tracking collars are used to acquire GPS fixes, accelerometer data indicating activity and host temperature. This data is typically stored on-board for eventual retrieval, though some versions incorporate a low power UHF radio for download to a hand-held logger. One problem with the existing radio collars is that substantial disturbance needs to be made to the animal's environment to download the data, biasing the results.

As an application of a highly mobile, energy constrained, sparse wireless sensor network, we consider the example of animals fitted with collars which comprise two-way wireless units and a microcontroller. Data is transferred in a multihop fashion when nodes are within range of each other. In this way, collars collect data from other collars (typically with a lower rank) to send to a base-station. This way, the motion of the animals is used to automatically collect the data, as opposed to a researcher having to enter the field and locate the animals for manual data download.

Animals vary widely in terms of their bodyweight. A standard 'rule' in the wildlife tracking community is that the weight of a device placed on an animal may not exceed 5% of

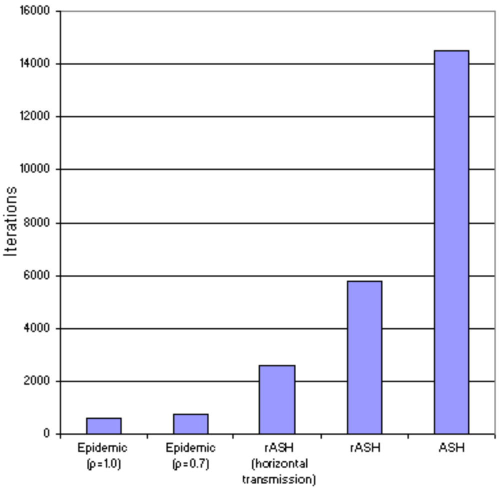

Figure 5: Mean time to first node expiry for the various protocols

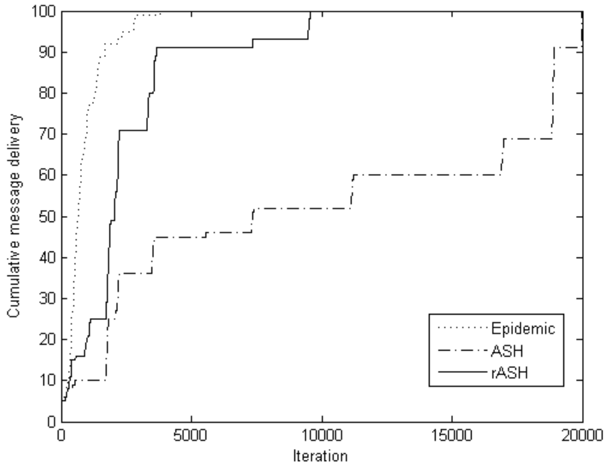

Figure 6: Latency for delivery of 100 messages to base-station for Epidemic ($\rho_e = 0.7$), ASH and rASH ($\rho_T = 0.9$; $\rho_R = 0.9$)

the animal bodyweight [22]. Take for example the weight of a bull African Elephant which, when fully grown, can weigh 6 000 kg. In comparison, a small animal such as a Vervet monkey only weighs a few kilograms. Thus, for this rather restrictive example, there is a three order of magnitude difference in weight and correspondingly for the tag weight that each animal can carry. We argue that this difference should be exploited to the benefit of the operation of the network. In this way, the lightweight animals can use the capabilities of the heavyweight animals to result in a more efficient and longer lived network. This enforced diversity differs from existing research which treats all animal collars as being equal, leading to unfair loading on low energy collars. This is shown in Fig. 4.

VI. Results

The performance of this scheme is assessed with respect to epidemic routing, with handover probability ρ_e [4]. The simulation environment is a square of side 10 km, radio range is circular of 900 m and 100 nodes move according to the random waypoint mobility model with a non-zero minimum speed (after [23]) and maximum speed of 6 m/s. Nodes randomly generate information with a Poisson rate of 1 packet every 100 seconds. We assume that transmission of a single packet consumes 1 unit of energy, and the overhead of communicating rank and energy for our protocol uses 0.05 units of energy. Nodes are assigned energies in proportion to the traffic densities calculated using Eq. (4) - the lowest level nodes have an energy of 200 units and the highest level nodes have an energy of 2 000 units. We use a 10 level network in this simulation, and the rank is a measure of the energy of a node.

The results from the simulation are shown in Fig. 5 demonstrating the mean time to first node expiry. As expected, epidemic routing performs the worst, exhausting nodes rapidly through excessive traffic usage. Even when the flooding is limited, using a smaller value of ρ_e, traffic is still high. Furthermore, as epidemic routing does not take into account the relative energies of nodes, all nodes participate equally in the task of routing. Two results are shown for rASH, one with horizontal transmission ($\rho_T = 0.9$ $\rho_R = 0.9$) and one without ($\rho_T = 0.9$ $\rho_R = 0.0$). When horizontal transmission is enabled, nodes share messages with other nodes of the same rank, leading to good traffic delivery, but also to higher loading than the case without horizontal transmission. For the latter case, messages are not duplicated across the same level, but multiple copies can be sent to higher level nodes (as they will not be deleted). The time to first failure of nodes using the rASH protocol is substantially greater than those using the epidemic protocol, as nodes with small amounts of energy essentially act as leaf nodes, routing no traffic. The ASH protocol preserves the lifetime of low energy nodes, but it should be noted that this is a single copy-routing strategy, thus there only is ever one instance of a message in the network, with the implication that redundancy is poor.

A second simulation was conducted to compare the time that a message takes to reach the base-station using the various routing algorithms. Node energy was unlimited in this case, and 100 messages were generated at random nodes at the start of the simulation. The results are shown in Fig. 6, showing that the epidemic routing algorithm with a handover probability of 0.7 routes 90% of the packets to the base-station within 1700 iterations. The redundant ASH (rASH) routing protocol delivers 90% of packets to the base-station within 2 600 iterations. The single copy routing ASH routing strategy suffers from excessive delays, taking over 18 000 iterations to route 90% of the packets to the base-station.

Thus, it can be seen that the rASH routing protocol can conserve the lifetime of low ranked nodes, whilst still achieving latencies comparable to epidemic routing. This is due to the combination of direct delivery for low rank nodes and a flooding protocol for high ranked nodes.

VII. Future Directions

The concept of forming a social hierarchy shows a great deal of promise for effectively routing information in an energy constrained wireless network. The simulation results presented here only considered ranking nodes by energy. However, nodes attached to wild animals will show manifestly different connectivity patterns and clustering. For example, many animals travel in herds - these are regions of good connectivity. Similarly, most wild animals need to visit certain resources, such as watering holes, relatively frequently. By exploiting these connectivity patterns, well connected nodes can assume a high rank with regards to being useful for delivering information timeously.

An area for future research is the formulation of a realistic mobility model that encapsulates salient parameters of animal behaviour, such as herding and fleeing from predation. This will then be used to investigate multiple hierarchies, such as connectivity, energy and delivery probability. A decision algorithm will be used to choose at each point in time the path that a message should take, that is likely to bring it closer to its destination.

VIII. Conclusion

This research takes a very common (and hence successful) structure in the Animal Kingdom, the social hierarchy, and adapts it to a wireless sensor network designed for diverse animal monitoring and tracking. The social hierarchy is thought to reduce conflict in animal groups, and here it is used to reduce energy use for low ranked nodes. Based on a simple routing rule, and a means of dynamically assessing global energy distribution through locally acquired information, nodes adaptively choose an activity level that dictates their role within the hierarchy. Each node chooses its role itself, with no centralized control, resulting in a system that scales well to large numbers of nodes.

A controllable degree of redundancy is incorporated, that floods messages amongst high level nodes to improve delivery time, whilst conserving the energy of low level nodes. This work is a novel application of a common ethological structure that results in a powerful routing algorithm which is simple to implement on low power microcontrollers.

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