Message-initiated Constraint-Based Routing for Wireless Ad-hoc Sensor Networks

Ying Zhang
Palo Alto Research Center
3333 Coyote Hill Road
Palo Alto, California 94304
Email: yzhang@parc.com

Markus Fromherz
Palo Alto Research Center
3333 Coyote Hill Road
Palo Alto, California 94304
Email: fromherz@parc.com

***Abstract*— Most existing routing mechanisms today differ in routing objectives and routing strategies, however all the existing routing protocols have in common that the routing objective and destination specification are fixed, and that the routing objective is incorporated only implicitly. In this paper, we propose a general message specification mechanism to explicitly encode the routing destinations, constraints and objectives in messages, so that general-purpose instead of objective or destination specific routing strategies can be applied. Using general-purpose routing strategies while specifying quality-of-service (QoS) properties at the application layer explicitly in messages, QoS-aware strategies for individual messages are obtained. We also propose two frameworks of general-purpose routing strategies for this type of message specification.**

I. Introduction

One may divide ad-hoc routing strategies into two categories: *structure-based* or *connectionless*. A structure-based routing strategy builds and maintains a routing structure, such as a spanning tree or a set of forward links, while a connectionless routing strategy makes the decision of routing at every hop.

There are three elements for a routing protocol: destination specification, routing objectives and routing strategies. Most existing protocols, however, use a *fixed* destination specification, routing objective and routing strategy. Most early protocols are address-based, while GPSR [1] and GEAR [2] are geographical location-based. Directed Diffusion [3] first proposed a general attribute-based publish/subscribe scheme in ad-hoc sensor networks. In most cases, routing objectives are implicitly embedded in strategies. For example, AODV [4], DSR [5] and TORA [6] use shortest path, i.e., minimum number of hops, as the routing objective, while ABR [7] uses the degree of association stability, and SSR [8] uses signal stability or strength as one of the routing objectives in addition to the shortest path. GEAR uses energy level as a routing objective, in addition to the shortest path, while information-driven routing such as CADR [9] uses information gain to guide the routing process.

All the existing routing protocols are implicitly associated with their routing strategies. Most early source-initiated protocols (AODV, DSR, TORA, ABS, SSR) are structure-based, as is Directed Diffusion. Structure-based strategies are more suitable for relatively stable networks, since maintaining and repairing structures can be costly for dynamic networks. Connectionless routing strategies, e.g. search-based or constrained flooding, do not maintain the network structure explicitly. *Search-based methods* normally discover routes by selecting the next “best” hop at every node on the route. Routes may differ from message to message, even to the same destination node, and there is no structure maintenance. For example, GPSR uses a simple location-based greedy type of search, CADR deploys a greedy strategy using the information gain metric, and GEAR applies a modified version of real-time search. Recent work on randomized routing [10] chooses the next hop according to some distribution. Reinforcement learning routings have also been studied, e.g. Q-routing [11] and ant-based routing [12]. *Constrained-flooding strategies* [13], on the other hand, allow each node to independently make the decision of rebroadcast, while making trade-offs between robust message delivery and total energy cost.

We propose here Message-initiated Constraint-Based Routing (MCBR), a general message specification mechanism to explicitly encode the routing destinations, constraints and objectives in messages, so that *generic-purpose* instead of *objective-specific* or *destination-specific* routing strategies can be applied. The separation of routing specifications and routing strategies makes it possible for exploring *meta* routing strategies, allowing quality-of-service (QoS) requirements at the application layer for individual messages. We also propose two types of meta routing strategies for MCBR: one is search-based and another is constrained-flooding. Properties of the two meta strategies are discussed. Unlike other QoS routing approaches [14] where an optimal route has to be found before sending actual messages, messages *discover* and *learn* their routes on their way to the destinations in our frameworks. Due to page limitations, this paper focuses on MCBR *specification* and frameworks of *meta-strategies*, rather than *performances* of particular strategies.

II. MCBR Specification

We use the term *Message-initiated Constraint-Based Routing* (MCBR) to indicate routing mechanisms with constraint-based destinations and objectives specified in messages. In MCBR, each node in the network has a list of *attributes*, whose types are predefined. Attributes can be anything from geographical locations to network bandwidths, from sensor values to internal clocks. The values of attributes can be constant, such as a node identifier or a unit cost, or can change from time to time. For example, a mobile node changes its locations, a stationary node can still obtain different sensor readings if its environment changes. A *routing destination* is explicitly represented by a set of constraints on attributes. Furthermore, in addition to destinations, *local route constraints*, if any, are explicitly specified. Examples of local route constraints are: avoiding a noisy area, avoiding congestion, and avoiding low-energy nodes, etc. Finally, a *routing objective* is explicitly stated, such as a shortest path, maximizing energy levels over the route, maximizing connectivity over the route, or minimizing congestion, etc.

An MCBR *protocol specification* for a message m is a tuple $\langle v_m^0, \mathcal{C}_m^d, \mathcal{C}_m^r, o_m \rangle$ where v_m^0 is the source of the message, $\mathcal{C}_m^d$ is the set of destination constraints, $\mathcal{C}_m^r$ is the set of route constraints and o_m is the objective. The *goal* of routing is to deliver the message from v_m^0 to one (unicast) or all of the destination nodes (multicast) satisfying $\mathcal{C}_m^d$ via intermediate nodes $p : v_m^1, \ldots, v_m^{n-1}$ such that $\mathcal{C}_m^r$ is satisfied at v_m^i and $\min_p \sum_i o_m(v_m^i)$.

MCBR separates routing objectives and destination specifications from routing strategies, which enables the coexistence of various generic meta strategies.

III. Meta-Strategies

Both structure-based and connectionless strategies can be applied to MCBR. Connectionless strategies are studied here due to the suitability to dynamic and ad-hoc networks.

A. Search-based strategies

We developed a framework of search-based routing strategies for MCBR, with objective estimation based on routing specification via MCBR. We explored the broadcast channel of wireless networking, so that value iterations in reinforcement learning is realized in a cost effective way. Furthermore, implicit acknowledgement for forward messages is implemented, such that the neighborhood management and the symmetric network assumption, which are problematic to most search-based methods, can be lifted in a certain degree.

The learning-based routing consists of two phases: *forward message* phase and *update estimate* phase. The forward message phase is a policy improvement phase, i.e., deciding which neighbor to pass the message to according to its current estimation. The update estimate phase is a penalty learning phase, the estimates shall be improved when more nodes are visited by this type of message. The update estimate phase is also used for implicit message *confirmation*, so that if the confirmation is not arrived from the forwarded node within certain time period, the forward phase will be activated again for sending the message to one of the other neighbors. This guarantees that the message arrives to its next hop, if there is one. The pseudo code is illustrated in Figure 1, where $o_m(w)$ is the value of the local objective function of o_m at node w, and $Q_m(v,w)$ is an estimate of $\min_p \sum_i o_m(v_m^i)$ from node w, at node v, and $Q_m^0(v,w)$ is its initial estimate. The algorithm does not assume a static network. Even with a static network, the routes may vary from time to time as a result of learning. One can combine the broadcast of the new estimate and the forwarding of the message in one packet to reduce the total number of messages by half; in which case, only the node with the forwarding address will continue the forward message phase, all the other neighbors will only do the update estimate phase.

Forward message phase:

> **received_message** (m) at node v from node u **do**
>   **if** new(m) **then**
>   **for all** w with $(v,w) \in E_m$ **do**
> $Q_m(v,w) \leftarrow Q_m^0(v,w)$; **end**
>   **end**
> $Q_m(v) \leftarrow o_m(v) + \min_w Q_m(v,w)$;
>   **broadcast_Q**$(Q_m(v))$ to all neighbors
>   **if** satisfied$(\mathcal{C}_m^d)$ **then return**; **end**
> $w \leftarrow$ argmin$_w Q_m(v,w)$; (random tie break)
>   **send_message**(m) to w;
> **end**

Estimate update phase:

> **received_Q** (Q_m) at node u from node v **do**
> $Q_m(u,v) \leftarrow Q_m(u,v) + \alpha(Q_m - Q_m(u,v))$;
> **end**

Fig. 1. Search-based strategy for MCBR

The theoretical bounds on this type of strategy can be established for static networks. Both the message complexity and time complexity of the reinforcement routing are $\mathcal{O}(nd)$, where n is the number of nodes and d is the diameter of the network. Furthermore, it approaches the optimal route after delivering at most n messages, and the message complexity of converging to an optimal route is bounded by $\mathcal{O}(nd)$.

B. Initial objective estimation for MCBR

For reinforcement learning type of routing strategy, if the initial estimates are close to optimal, the actual time of delivery a single message and the actual time of convergence to optimal routes are close to minimum. One advantage of a declarative routing requirement via MCBR is to give accurate initial objective estimate based on its specification. The objective estimation shall be based on both the properties of destination constraints and objective functions. Destination constraints are used to estimate the minimum number of hops to the destination, while objective functions are used to estimate the minimum cost along the path. Let C be a constraint and $s(C)$ be the degree of satisfaction of C; $s(C)$ is zero iff C is satisfied. Let ΔC be the maximum change possible for $s(C)$ in one hop. The minimum number of hops based on constraint C is $h(C) = s(C)/\Delta C$. Given the estimate of the number of hops h to the destination, an additive objective O can be estimated as $o_{min}h$, where o_{min} is the

received_message $(m,\, Q_m(u))$ at node v from node u **do**
  if new(m) **then**
    for all w with $(v,w) \in E_m$ **do**
      $Q_m(v,w) \leftarrow Q_m^0(v,w)$; **end**
  end
  $Q_m(v,u) \leftarrow Q_m(u)$;
  $Q_m^{new}(v) \leftarrow o_m(v) + \min_w Q_m(v,w)$;
  $Q_m(v) \leftarrow Q_m(v) + \alpha(Q_m^{new} - Q_m)$;
  if satisfied$(\mathcal{C}_m^d)$ **then return**; **end**
  if $(m,\, Q_m(v))$ is in transmit queue and $Q_m(v) > Q_m(u)$,
  then remove m; **return**; **end**
  if $((Q_m(v) - Q_m(u)) < T)$
    broadcast_message$(m,\, Q_m(v))$ to all neighbors
      after $k(Q_m(v) - Q_m(u)) + \delta$ time units;
  end
end

Fig. 2. Constrained-flooding strategy for MCBR

minimum value of o over the network.

Variations in this framework include probabilistic node selection, adaptive learning rates, and forward update estimates.

C. Constrained-flooding strategies

In contrast to the search-based methods, where each node decides which of the neighboring nodes to forward the message to, flooding-based strategies decide whether or not to broadcast at each node. Comparing to search-based strategies, flooding-based strategies are more robust to the dynamic changes of the network, do not require neighborhood management and work well without the symmetric network assumption. The drawbacks of the flooding-based strategies are the message collision in dense networks and the potential large energy consumption if the flooding is not controlled.

A couple of gradient-flooding type of strategies are developed [13]; all requiring a cost field be established beforehand. We propose a constrained-flooding framework, where the cost, i.e., the objective, can be learned if not known at a priori. Figure 2 illustrates the basic idea. Like other gradient-flooding routing protocols [13], the cost is transmitted together with the message. In addition, the cost at each node is updated every time a message is arrived. The update rule is the same as the search-based strategies. Two techniques are used here to control the flood, (1) cost difference: if the receiving node estimates a lot more cost than the transmitting node, no action is taken, except updating its cost field, (2) time difference: add transmit time difference to the broadcast, so that nodes with better estimates transmit first, while duplicate messages are suppressed.

Variations in this framework include adaptive threshold, adaptive learning rates, adaptive time delay constants, and probabilistic decision making.

IV. Conclusion

We have presented in this paper a framework of message-initiated constraint-based routing, MCBR, for ad-hoc wireless networks, which makes routing strategies independent from routing objectives and destination specifications. We have also proposed two frameworks of meta routing strategies. Such connectionless and QoS-aware strategies guarantee delivery when there is a path and convergence to the optimum when a network is stable, and automatically adapts to different routes when a network has been changed.

An MCBR protocol, together with both search-based and constrained-flooding meta strategies, has been implemented in NesC on TinyOS-1.x and demonstrated with 50 motes in hardware and 100 motes in the TOSSIM/TinyViz simulation environment. Future work along this line includes developing network and application models as well as performance evaluations for variations of these two meta-strategies.

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