BICL BASED COMMUNICATION MECHANISM IN VEHICULAR ACTIVE NETWORKS

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Abstract

In this paper we proposed a novel mechanism (BICL)for communication, coordination and a protocol is designed for vehicular active networks . BICL permits each sensor node to autonomously determine its next-hop selection and channel access strategy using bio-inspired next-hop selection and channel access profitability measures. Based on these profitability measures, BICL provides optimal performance in energy-efficient and reliable sensor–actor communication. Furthermore, using task allocation profitability measure, BICL also guarantees stable allocation of available tasks in a way that each task is accomplished by an actor node within a bounded time delay. Performance evaluations reveal that BICL significantly prolongs the network lifetime while providing highly reliable sensor–actor communication and effective task allocation for actor nodes.

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1. INTRODUCTION

Wireless sensor and actor networks (WSANs) consist of a number of communicating sensor and vehicular actor nodes for performing distributed sensing and acting tasks [1]. Energy-efficient, timely, and reliable sensor–actor communication are the main challenges for the realization of WSANs. Furthermore, cooperative control of actor nodes is also essential in realizing an effective task allocation among the actor nodes. In the literature, there are many studies on energy-efficient communication protocols for wireless sensor networks (WSNs) and WSANs [2]–[6]. However, the major common drawback of these proposals is the lack of autonomy in the operations of the network nodes. To provide the autonomous network operations for WSANs, in this paper, inspired by the prey model in foraging theory, we introduce the B+ Integrated cross layer (BICL) communication and coordination protocol for WSANs. BICL provides three different nature-inspired profitability measures called *next-hop selection*, *channel access*, and *task allocation profitability* for the sensor and actor nodes. The aim of these measures is to control the rate of gain in energy efficiency, reliability, and stability of the network operations.

Using the next-hop selection profitability measure, each sensor node selects its next hop node in an energy-efficient way. Sensor nodes also schedule their transmissions by means of channel access profitability to provide a reliable sensor–actor communication. Based on the task allocation profitability, each actor node selects and accomplishes a set of tasks. BICL is a fully autonomous algorithm and produces an optimal performance in prolonging network lifetime and reliable sensor–actor communication. Moreover, it also provides stable allocation of available tasks in a way that each task is accomplished within a bounded time delay by the most appropriate actor node. The BICL protocol can be applicable to any data type observed in the sensed field. For example, if sensor nodes sense the humidity level of an agricultural field, these levels are first sampled, and data packets are formed using these samples to transmit to actor nodes. Here, we note that, aside from the prey model, the marginal value theorem in behavioral ecology and biological division of labor phenomenon can also be adopted to develop autonomous communication and coordination techniques for WSANs and WSNs, as proposed in [7]–[9]. These works are promising in showing how biological principles can be applied to WSANs and WSNs to develop efficient communication and coordination schemes.

1.1 Design Principles of BICL :

In this section, we first describe the network model and assumptions, and formulate the cross-layer optimization problem. Then, we review a *prey model in foraging theory*, based on which we develop a BICL communication model for WSANs.

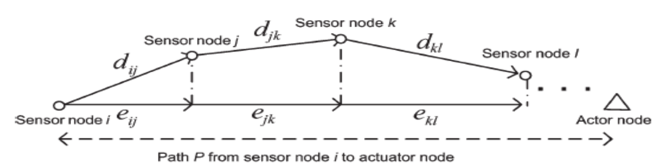


Fig. 1. Data path from sensor node i to the actor node. Hop distances (d_{ij} $\forall i, j$) and effective hop distances (e_{ij} $\forall i, j$) are shown in the path.

A. Network Model and Problem Formulation:

We consider a network architecture in which N sensor nodes are deployed in an environment. Sensor nodes separately detect and transmit event information to M vehicular actor nodes. Each source node samples the event signal and transmits the generated data frames with an average reporting frequency, i.e., f (in frames per second). Sensor nodes participating in data transmission and/or reception are called active sensor nodes.

The wireless channel is assumed to be shared in fixed duration time slots, which are, in turn, captured by sensor nodes in order not to interfere with each other. Using a time slot, a sensor node either transmits or receives a data frame. The duration of a time slot consists of two intervals named frame transmission and acknowledgment (ACK) interval. In the frame transmission interval, sensor nodes transmit the frame header and payload. The frame header includes the identity (ID) number of the source node that initially generates the current packet. This enables each sensor node to infer how many source nodes it serves to route toward the actor node.

B. Prey Model in Foraging Theory

Foraging theory is a field in behavioral ecology to mathematically describe models based on which the foraging animals search for nutrients and choose which ones to consume [12]– [14]. The fundamental claim in foraging theory is that animals search for and obtain nutrients by maximizing their energy intake E per unit time T. This strategy is mathematically characterized by the maximization of an objective function of (E/T) [14]. One of the classical foraging models is the prey model. The prey model describes a forager searching for different prey types in a particular environment. Each prey holds a certain energy intake. The forager must search for and recognize a prey for the energy intake. Once it encounters and recognizes a prey, it decides whether to handle it [12]. Assume that there are k different types of prey in the environment. T_i is the expected time required to handle prey type i, and ν_i is the expected amount of energy intake obtained from handling prey i. The average rate of encounter with prey i is λ_i. p_i is the probability that prey type i is handled once it is found and recognized. Hence, the average rate of gain of a forager, i.e., J, can be defined as a ratio of the total expected energy intake to expected amount of time spent for searching and handling the prey types

$$J = \frac{\sum_{i=1}^{k} p_i \lambda_i \nu_i}{1 + \sum_{i=1}^{k} p_i \lambda_i t_i}.$$

The prey model allows a forager to maximize J by finding the optimal values of $p_i\ \forall i$. In particular, the prey model uses a zero-one rule to maximize J such a way that each forager separately decides which prey should be consumed by settin p_i either $p_i = 0$ or $p_i = 1$. In this paper, this mechanism is mainly adopted and used for an autonomous communication and coordination protocol for WSAN.

C. Inspiration from Prey Model

Here, to establish a bio-inspired communication and coordination model for WSAN, we consider sensor and actor nodes as forager. Similar to a forager searching for prey, each sensor node searches for the possible next hop node and available time slots to forward its packets toward an actor node. Each actor also searches for and performs available tasks associated with the event. Hence, for a sensor node, its possible next hop nodes and available time slots are considered as prey in the prey model. Available tasks are also considered as prey types that are searched and performed by the actor nodes. Based on these analogies, we define three profitability measures named as *the next-hop selection*, *channel access*, and *task allocation profitability*. Using the next-hop selection profitability, each sensor node selects its next hop node. Based on the channel access profitability, each sensor node determines its transmission strategy. Actor nodes use the task allocation profitability to share and perform the available tasks

2. BICL TASK ALLOCATION FOR ACTOR NODES

In this section, we introduce an actor task allocation scheme based on a *task allocation profitability* measure.

Then, we investigate the stability of the given task allocation mechanism.

A. Task Allocation Profitability :

We assume that, initially, M vehicular actor nodes randomly roam in the environment. When an event occurs in the WSAN environment, an actor node called the master actor node is selected to collect the event data generated by source nodes. The master actor node is also selected as the closest actor node to all source nodes. Based on the event information received from the source nodes, the master actor node is assumed to estimate a four-tuple for each of available tasks,1 i.e., $F_i = \{b_i, m_i, x_i, y_i\}$ to characterize the properties of task i. b_i denotes the prioritized time2 for task i and is given as $b_i = o_i G_i(t)$, where o_i is the constant priority of task i, and $G_i(t)$ is the elapsed time at time t since task i first appears in the environment. As soon as task i is performed at time t, $G_i(t)$ is set to zero. m_i is the encounter rate of the master actor node with the task i. x_i and y_i are the coordinates of the estimated location of task i.

The master actor node periodically estimates or updates the four-tuples for each task appearing in the environment, i.e., F_i $\forall i$, and broadcasts them to other actor nodes. Using the received four-tuples, each actor node decides which task to perform first and sends a request to the master to allocate the decided task. Once the request message is acknowledged by the master, the task is performed by the actor node. To perform a task, the vehicular actor node must also come to the close proximity of the task location. Hence, based on the task location, the task allocation time, and its capability in task performance, each actor node estimates its task completion time, i.e., ρ_i. Briefly, ρ_i is a time duration in which the actor node allocates task i and goes to its close proximity and performs it.

B. *Stability of BICL Task Allocation*

Here, the boundedness of time delay, i.e., $G_i(t)$ $\forall i$, is deduced to prove the stability of the given task allocation mechanism by the following theorem:

Lemma 1: Task allocation algorithm in BICL guarantees that any task i is definitely allocated and performed within a delay bound given as

$$\lim_{t\to\infty} G_i(t) < \frac{\rho_{\min} o_{\max} \rho_i}{o_{\max}\rho_i - o_i \rho_{\min}} + \rho_{\max}$$

where O_{max} is the maximum of the priority values, i.e., $O_i <$ O_{max} $\forall i$, and P_{min} and P_{max} are the minimum and maximum of the task completion time values, i.e., $P_{min} < P_i < P_{max}$ $\forall i$.
Proof: Assume that, at time t, task i has not been performed during τ units of time, and all of other tasks are performed at least once in this duration. Hence, at time t, task selection profitability of task i can be given as

$$\psi_i = \frac{G_i(t) o_i}{\rho_i} = \frac{\tau o_i}{\rho_i}.$$

BIO-INSPIRED CROSS-LAYER PROTOCOL OPERATION

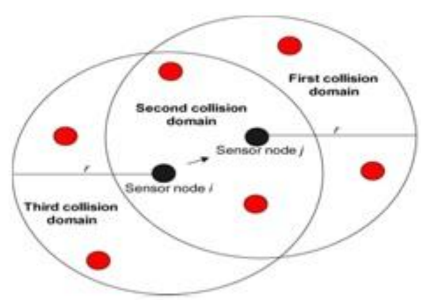
In this section, we introduce the next-hop selection and channel access operation of BICL.

A. Next-Hop Selection

BICL enables each sensor node to select its next hop node by means of the next-hop selection profitability, i.e., θ_{ij}, given in (10). For the computation of θ_{ij} $\forall j$, sensor node i needs to find $H(d_{ij})$, e_{ij}, and E_j $\forall j$ for all of its neighbors toward the master actor node. Here, we assume that each sensor node foreknows its own location, as well as the location of its neighbors by means of an existing localization technique3 [10]. Hence, it can compute all Euclidean distance to its neighbors and corresponding effective distances, i.e., d_{ij}, e_{ij} $\forall j$, and also computes $H(d_{ij})$ $\forall j$. Each sensor node periodically measures and broadcasts its residual energy to all of its neighbors. Therefore, each sensor node i also knows the residual energy level of its neighbors, i.e., E_j $\forall j$. Substituting $H(d_{ij})$, e_{ij}, and E_j into (10), each sensor node I determines θ_{ij} $\forall j$ and establishes its next-hop selection set U_i including all IDs of its possible next hops. Then, using U_i, sensor node i selects its next hop node as a sensor node providing the maximum next-hop selection profitability, i.e., the next hop of sensor node i is sensor node j such that $\{j / \forall k \in U_i : \theta_{ik} < \theta_{ij}\}$.

B. Channel Access and Rate Control

After the selection of its next hop, each sensor node computes its channel access profitability, i.e., ϑ_i in (16), to select its transmission probability p_i. For the computation of ϑ_i, sensor node i periodically estimates the arrival rate of its successful



Collision domains for the link between sensor nodes *i* and *j*. transmissions using the maximum likelihood estimation mechanism given in (15). In one second, sensor node *i* records time intervals between successful packet transmissions, i.e., T_k $\forall k$. At the end of each second, it computes the estimation of the arrival rate of the successful transmissions, i.e., λ, using (15). Based on the cumulative distribution function of the normal distribution $N(\lambda,\lambda)$, i.e., $\Phi(.)$, sensor node *i* computes its channel access profitability as $\vartheta i = 1 - \Phi(fsi)$.

Each sensor node i regulates its transmission probability in an interval given as $p_{min} < p_i < p_{max}$, where p_{min} and p_{max} are the minimum and maximum of the transmission probability, respectively. Initially, each sensor node sets its transmission probability as p_{min} and starts to transmit to its next hop. For a successful transmission of sensor node i, there must be no other transmission in the first, second, and third collision domains, as shown in Fig. 2. Assume that there are g active sensor nodes that transmit with transmission probability p in the first, second, and third collision domains. Therefore, the probability of a successful transmission of sensor node i, i.e., R_i, can be given as

$$R_i = p(1-p)^{g-1}.$$

To find the optimal p that makes R_i maximum

$$\frac{\partial R_i}{\partial p} = (1-p)^{g-1} - (g-1)p(1-p)^{g-2} = 0.$$

This yields the optimal p, i.e., p, as $p = 1/g$. To compute p, each sensor node i first discovers the number of active sensor nodes in its collision domain, i.e., g. To this end, each active sensor node sends a message to all of its neighbors to notice that it is an active sensor node. This enables each sensor node to discover the number of active sensor nodes g in its collision domains. Then, it sets p_{max} as $p_{max} = p = 1/g$. Furthermore, p_{min} is set to a sufficiently low value within the interval [0, 1]. In the simulation experiments, p_{min} is selected as $p_{min} = 0.05$. BICL enables each sensor node to periodically update its transmission probability starting with p_{min}. The aim of this update is to keep the channel access profitability ϑ_i above a predefined threshold value,[4] i.e., $\underline{\vartheta}$. The transmission probability update strategy of BICL is given here.

1) If sensor node i finds ϑ_i as $\vartheta_i < \underline{\vartheta}$ and $p_i < p_{max}$, it updates p_i as $p_i = p_i + \zeta$, where ζ is a small positive constant.

2) If sensor node i finds ϑ_i as $\vartheta_i \geq \underline{\vartheta}$, it does not change the current value of p_i.

Based on the updated transmission probability, for the access to the channel, each sensor node generates a uniformly distributed random number h from the interval [0, 1] at the beginning of each time slot. If $p_i > h$, sensor node i transmits to its next hop at the beginning of current slot. Otherwise, sensor node I does not make any transmission during current time slot. For a successful delivery from sensor node i to sensor node j, there must be no other transmission in the first, second, and third collision domains, as shown in Fig. 2. After a successful delivery, the ACK frame that sensor node j transmits to sensor node i can still collide with the possible ACK frames that are transmitted by the sensor nodes in the first collision domain. For example, assume that, in the first, second, and third collision domains, there is no other transmission, except sensor node i.

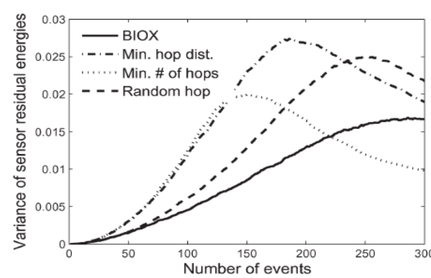
Assume also that, in the first collision domain, at least one sensor node receives a frame from the outside of the collision domains. In this case, sensor node i successfully delivers a frame to sensor node j. However, if the sensor node in the first collision domain also succeeds to receive a data frame from outside of the collision domains, the ACK frame of sensor node j and this sensor node can collide, and current transmission attempts become unsuccessful.

To mitigate the probability of ACK collision, BICL allows each sensor node j to send multiple ACKs in the ACK transmission interval for each of the successfully received frames as follows.

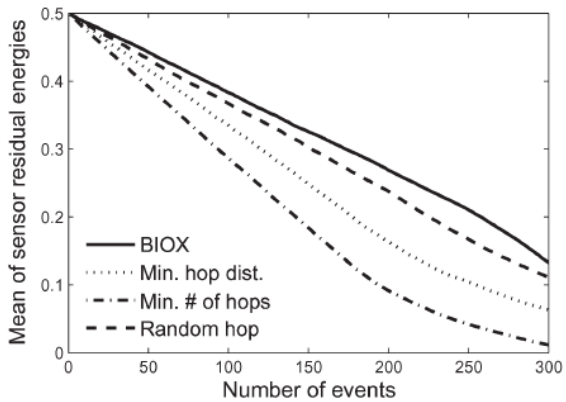
1) During the frame transmission interval, sensor node I transmits a data frame to sensor node j with probability p_i. Sensor node i also listens to the channel on whether or not the transmitted data frame has collided.

2) If the transmitted frame has collided, it is retransmitted with probability p_i.

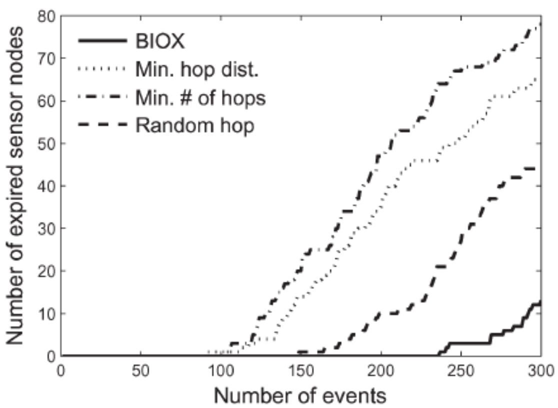
3) If sensor node i successfully delivers a packet to sensor j within the frame transmission interval of a slot, sensor node j immediately sends an ACK frame for this frame in the ACK transmission interval of the slot. ACK frame



(a)



(b)



(c)

(a) Variance of sensor residual energies with increasing number of events. (b) Mean of sensor residual energies with increasing number of events. (c) Number of expired nodes with increasing number of events.includes the IDs of all frames previously received within a fixed time interval.

4) This mitigates the probability of ACK collision in a way that sensor node i can eventually receive an ACK frame including ID number of successfully delivered data frames even if sensor node i did not previously receive an ACK frame belonging to the data frame that is successfully delivered.

Eventually, using next-hop selection and channel access profitability, BICL allows sensor nodes to estimate and adapt their communication parameters to provide energy-efficient and reliable sensor–actor communication in WSAN.

CONCLUSION

In this paper, inspired by a prey model in foraging theory, we have introduced the BICL Communication and Coordination Protocol for WSANs. BICL is a unified algorithm that incorporates medium-access-control, routing, and transport layer functionalities to enable each sensor node to separately select and access its next hop node using the bio-inspired next-hop selection and channel access profitability measures. BICL also uses the bio-inspired task allocation profitability measure for efficient allocation of the available tasks associated with the event. BICL provides an optimal performance for the energy-efficient and reliable sensor–actor communication, and task allocation. Due to its fully autonomous operations, BICL can steadily keep the network in a highly reliable and energy-efficient state. This renders BICL a robust and energy-efficient protocol for the realization of future WSAN applications.

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