Exploiting Multi-Spatial Correlations of Motion Data in a Body Sensor Network

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***Abstract*—Human body motions usually exhibit a high degree of coherence and correlation in patterns. This allows exploiting spatial correlations of motion data being captured by a body sensor network. Since human bodies are relatively small, earlier work has shown how to compress motion data by allowing a node to overhear at most $\kappa = 1$ node's transmission and exploit the correlation with its own data for data compression. In this work, we consider *multi-spatial correlations* by extending $\kappa = 1$ to $\kappa > 1$ and constructing a partial-ordering *directed acyclic graph (DAG)* to represent the compression dependencies among sensor nodes. While a minimum-cost tree for $\kappa = 1$ can be found in polynomial time, we show that finding a minimum-cost DAG is NP-hard even for $\kappa = 2$. We then propose an efficient heuristic and verify its performance by real sensing data.**

***Index Terms*—Body sensor network, data compression, inertial sensor, pervasive computing, wireless sensor network.**

I. Introduction

A *BODY SENSOR NETWORK (BSN)* consists of a set of sensor nodes deployed on a human body to monitor physiological signs, such as motions. Nodes periodically report sensing data to a sink via wireless links. This work is motivated by two observations. First, since a BSN is likely fully connected, overhearing among nodes is possible. This opens a space to relieve collision and contention among transmissions. Second, since human body motions have inherent rhymes, it typically results in strong spatial correlations among measurements of different nodes. This opens another space to compress sensing data when overhearing is possible.

How to exploit spatial correlations has been extensively considered in *wireless sensor networks (WSNs)*. In multi-hop WSNs, data compression may be performed by relay nodes via data aggregation [1]–[4]. For slow-changing environments, model-driven data acquisition models are proposed in [5]–[7]. Recently, overhearing-based data compression has been considered in [8], [9]. In [8], how to exploit *single-spatial correlations* of motion data is studied. Reference [9] adopts a simplified model for single-spatial correlations and considers data collection in multi-hop WSNs.

In this letter, we extend [8] by considering *multi-spatial correlations* of motion data in a BSN. By overhearing multiple nodes, the spatial correlations of motion data can be better exploited, resulting in better compression ratios. However, such an extension is nontrivial. To solve the overhearing dependencies among nodes, we formulate the problem as one of finding an optimal DAG that minimizes the total amount of transmissions in a BSN. We show this problem to be NP-hard and propose a heuristic. Experimental results with real BSN motion data are presented, which show more than 50% improvement over [8].

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II. Multi-Spatial Data Compression

A. Problem Definition

We consider a BSN with n sensor nodes $v_1, v_2, \ldots, v_n$ deployed on a human body. Each node has an inertial sensor. Via wireless links, nodes periodically report their readings to a sink in a round-by-round fashion. Since a human body is relatively small, nodes are assumed to be mostly fully connected and thus overhearing is possible.

In order to reduce transmission, a node may conduct data compression. Let us consider three models. In Fig. 1(a), each node simply compresses its own data individually. In Fig. 1(b), a node may compress its data based on its spatial correlation with another node. In Fig. 1(c), the compression may be based on correlations with multiple nodes. Reference [8] adopts the model in Fig. 1(b) and uses an offline phase to learn the spatial correlations among sensors. A case study in Pilates exercises shows significant compression effect using the model in Fig. 1(b).

In this work, we extend [8] by considering the *multi-spatial data compression (κ-MDC) problem*. A node v_i may compress its data based on overhearing the data of a set S_i of nodes. The average size of the compressed data sent by v_i is denoted by $c(v_i \,|\, S_i)$. Note that when no spatial correlation is applied, $S_i = \emptyset$. Our goal is to find a proper set S_i for each v_i such that $\sum_{i=1}^{n} c(v_i \,|\, S_i)$ is minimized. To be more practical, we enforce $|S_i| \leq \kappa$ for a constant κ.

The problem can be formulated as follows. We model the links of the BSN by a complete directed graph $G = (V, E)$, where $V = \{v_1, v_2, \ldots, v_n\}$. The operation of letting v_i overhear $S_i \subseteq V \setminus \{v_i\}$ is formulated as finding a subset $E_i \subset E$ such that $\langle v_j, v_i \rangle \in E_i$ iff $v_j \in S_i$. So there are $\binom{n-1}{0} + \binom{n-1}{1} + \cdots + \binom{n-1}{\kappa}$ combinations for the selection of S_i. The corresponding transmission cost is $c(v_i \,|\, S_i)$. It follows that any DAG $G' = (V, E' \subset E)$ found from G represents an acyclic overhearing relation among nodes and has a total cost of $\sum_{i=1}^{n} c(v_i \,|\, S_i)$. The concept is shown in Fig. 2. Our goal is to find the minimum-cost DAG. From G', the transmission sequence can be determined by a topological sort on G' [10].

Note that $c(v_i \,|\, S_i)$ may be represented by conditional entropies and should be learned in advance from offline training. Also note that in practice v_i may fail to overhear some nodes in S_i. In this case, v_i may either transmit only $c(v_i)$ or

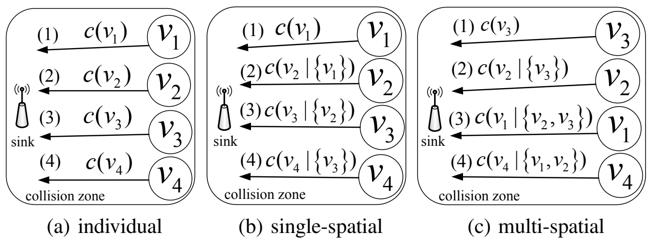
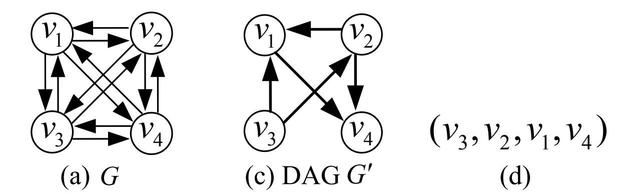


Fig. 1. Data compression models. $c(v_i \mid S_i)$ means the compressed size of v_i's data after v_i overhears S_i.



$\lvert S_i \rvert = 0$	$\lvert S_i \rvert = 1$	$\lvert S_i \rvert = 2$
$c(v_1)$	$c(v_1 \mid \{v_j\}), j = 2,3,4$	$c(v_1 \mid \{v_j, v_k\}), j,k = 2,3,4$
$c(v_2)$	$c(v_2 \mid \{v_j\}), j = 1,3,4$	$c(v_2 \mid \{v_j, v_k\}), j,k = 1,3,4$
$c(v_3)$	$c(v_3 \mid \{v_j\}), j = 1,2,4$	$c(v_3 \mid \{v_j, v_k\}), j,k = 1,2,4$
$c(v_4)$	$c(v_4 \mid \{v_j\}), j = 1,2,3$	$c(v_4 \mid \{v_j, v_k\}), j,k = 1,2,3$

(b)

Fig. 2. An example of 2-MDC: (a) G, (b) all dependency relations, (c) a possible DAG G', and (d) a topological sort of G'.

suboptimal $c(v_i \mid S'_i)$ such that the transmissions of nodes in S'_i have been overheard by v_i. That is, the DAG G' represents the best strategy, but each node can dynamically change its compression strategy at a higher cost when needed.

B. Complexity Analysis

In [8], it is shown that finding a minimum-cost DAG for $\kappa = 1$ can be solved efficiently in polynomial time. Below, we show that even for the simplest generalization of $\kappa = 2$, finding an optimal DAG is NP-hard. The proof is based on a variant of the *feedback arc set (FAS)* problem, a well-known NP-hard problem [11].

Definition 1. Given a digraph $G_f = (V_f, E_f)$, the FAS problem is to find a feedback arc set $E'_f \subseteq E_f$ with the minimal size $|E'_f|$ such that $G'_f = (V_f, E_f \setminus E'_f)$ is a DAG.

Lemma 2. *The FAS problem remains NP-hard for in-degree-2 digraphs, where each node has at most two incoming arcs.*

Proof: It is known that the FAS problem remains NP-hard for digraphs in which the total in-degree and out-degree of each node is no more than three [12]. By noting that in such digraphs, no node with three incoming arcs can be in a cycle, the lemma follows directly. ■

Theorem 3. *The κ-MDC problem is NP-hard for $\kappa \geq 2$.*

Proof: We will show the case of $\kappa = 2$, and other cases can be shown similarly. The proof is based on reduction from Lemma 2. Given an in-degree-2 digraph $G = (V, E)$ of the FAS problem, we construct an instance of the κ-MDC problem $G' = (V, E' \supseteq E)$, a complete digraph whose cost $c(\cdot \mid \cdot)$ is described later. Note that both problems ask for finding DAGs, the former by removing arcs from G and the latter by selecting arcs from G'. Hence, the cost of removing an arc from G is translated to the additional cost when this arc is not selected from G'.

Below, we show how to assign $c(v_i \mid S)$ for any v_i and S. For each v_i that has no incoming arc in G, we let $c(v_i) = 0$ and all other $c(v_i \mid S) = \infty$ (or a value large enough). For each v_i that has only one incoming arc $\langle v_j, v_i \rangle$ in G, we let $c(v_i) = 1$, $c(v_i \mid \{v_j\}) = 0$, and all other $c(v_i \mid S) = \infty$. Note that an additional cost is incurred when $\langle v_j, v_i \rangle$ is not selected from G'. Similarly, for each v_i that has two incoming arcs $\langle v_j, v_i \rangle$ and $\langle v_k, v_i \rangle$ in G, we let $c(v_i) = 2$, $c(v_i \mid \{v_j\}) = c(v_i \mid \{v_k\}) = 1$, $c(v_i \mid \{v_j, v_k\}) = 0$, and all other $c(v_i \mid S) = \infty$. The additional cost depends on how many of $\langle v_j, v_i \rangle$ and $\langle v_k, v_i \rangle$ are not selected from G'.

By this construction, the total cost of a DAG found from G' is the number of arcs to be removed from G. Hence, once the minimum-cost DAG is found from G', the optimum FAS of G is found. ■

C. A Greedy Cycle Breaker Heuristic

To the best of our knowledge, there is no known approximation for the κ-MDC problem. We thus propose a heuristic called *greedy cycle breaker (GCB)*, which is inspired by the FAS problem. Given a complete digraph $G = (V, E)$, it works by selecting an optimal subgraph and then breaking cycles greedily.

1) For each v_i, find the set $S^*_i \subseteq V \setminus \{v_i\}$ such that $|S^*_i| \leq \kappa$ and $c(v_i \mid S^*_i)$ is minimized. Then, for each $v_j \in S^*_i$, add arc $\langle v_j, v_i \rangle$ to set E'. This forms an optimal subgraph $G' = (V, E')$.
2) If the above G' contains no cycle, then G' is the minimum-cost DAG and the algorithm terminates. (There are many polynomial time algorithms to identify cycles in a graph.) Otherwise, continue to step 3.
3) Find a set $U \subseteq V$ such that for each $v_i \in U$, $S^*_i \subseteq U$ and the overhearing relations among U is a DAG. Note that U may be empty. Below, we will add nodes to U iteratively.
4) For each $v_i \in V \setminus U$, compute a suboptimal set $U^*_i \subseteq U$ such that the additional cost $c(v_i \mid U^*_i) - c(v_i \mid S^*_i)$ is minimal. Among all these nodes, choose the one, say v_i, such that the additional cost is minimal. Then, we add v_i to U and set its overhearing set to be U^*_i.
5) Repeat step 4 until $U = V$.

In our experience, such a greedy method is quite effective for motion data. Experimental results in Section III show that GCB is quite close to the optimum in most cases.

III. Experimental Results

We conduct experiments on real BSN motion data to verify the performance of GCB as well as the effects brought by multi-spatial correlations.

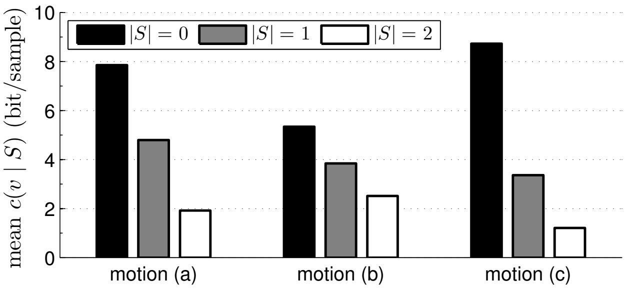


Fig. 3. The distributions of $c(v \mid S)$ by $|S|$.

A. Environment

We place $n = 10$ nodes on a human body to capture motions. Two nodes are placed on each limb, and the rest two are placed around the waist. Each node is a Jennic JN5139 microprocessor [13] with a ZigBee-compliant module and an ADXL345 triaxial accelerometer [14]. Each piece of raw data in each axis is 16 bits, and the sampling rate is set to 20 Hz. For ease of presentation, we use only one axis. The results can be straightforwardly extended to multiple axes.

We collect three sets of motion data: (a) walking, (b) walking upstairs, and (c) running. For each motion, we compare three data compression methods.

- **1-MDC:** This is the single-spatial compression method in [8].
- **2-GCB:** This is our GCB method with $\kappa = 2$.
- **2-OPT:** This is an exhaustive search for the optimum results of 2-MDC.

B. Compression under Ideal Channels

First, we consider ideal wireless channels as follows. We assume that nodes can overhear all intended packets without loss. Toward this end, we collect all nodes' raw data first and use two-third of them for learning inter-node correlations and the rest for testing. From the learning data set, we obtain the cost functions $c(v_i \mid S_i)$ through Huffman compression for all possible S_is. Its distribution is shown in Fig. 3. The results verify that multi-spatial correlations are worth exploiting.

Based on these $c(v_i \mid S_i)$s, we then develop different compression schemes. Then, we use the testing data set and run a simulation program to make comparison. The results are shown in Fig. 4. For motion (a), each piece of compressed data without overhearing is about 8 bits (refer to Fig. 3). The 1-MDC and 2-GCB methods reduce the data sizes to 4.3 bits and 2.1 bits, respectively. The optimum size by 2-OPT is 1.7 bits. The trends for other motions are similar. This verifies the effectiveness of GCB.

C. Compression under Lossy Channels

From the same learning and testing data sets, we further simulate environments with lossy channels as follows. Let $p_{ij}(t)$ be the probability that a packet sent by v_i at time t may be lost at v_j. We consider both static and dynamic channels. For the former, we consider a fixed value p_s for all $p_{ij}(t)$s. For the latter, we let each $p_{ij}(t)$ be randomly drawn from $[0, p_d]$, where p_d is a constant. When a node v_i loses any intended packet, it simply compresses by itself (thus the cost is $c(v_i)$ bits). The results are shown in Fig. 5. When $p_s = 0$ or $p_d = 0$, it represents the ideal channels. Evidently, a higher p_s or p_d would impair our schemes since there is a less chance for overhearing. One possible solution deserving investigation is to adaptively fall back to 1-MDC when the channels are found lossy.

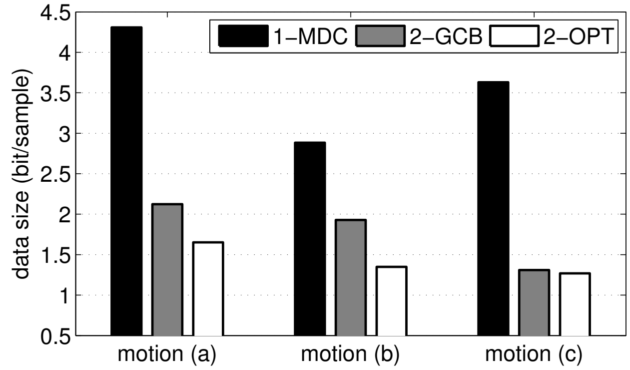
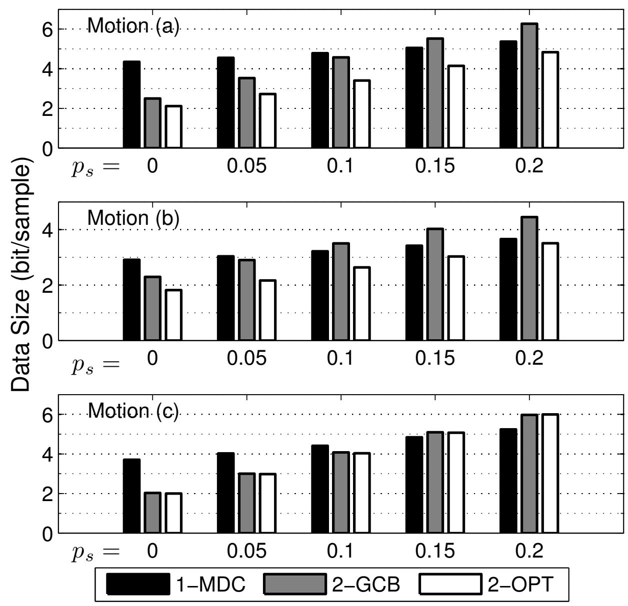
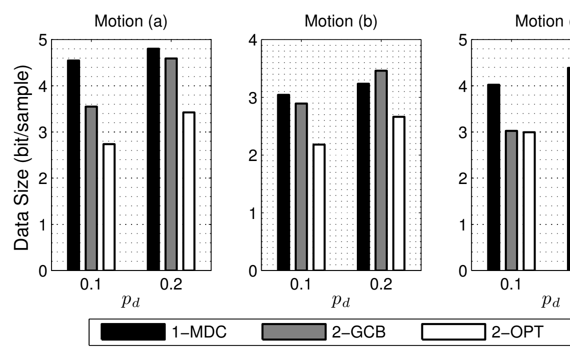


Fig. 4. Comparison of compressed data sizes under ideal channels.



(a) static channels



(b) dynamic channels

Fig. 5. Comparison of compressed sizes under lossy channels.

IV. Conclusions and Future Work

We have demonstrated how to exploit multi-spatial correlations in sensor data compression. We model the problem in a BSN and prove its relation with NP-hardness. We then propose a heuristic and verify its effectiveness through real experimental data under different channel models. For future work, it is desirable to consider more body motions and non-fully-connected networks.

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