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# Data Aggregation in Body Sensor Networks: A Power Optimization Technique for Collaborative Signal Processing

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***Abstract*—Body sensor networks (BSNs) have proved their viability to greatly improve quality of medical care by providing continuous and in-home monitoring solutions. Highly constrained nature of the platform demands a design that efficiently utilizes limited resources of the system. Energy optimization techniques are especially desirable as the system lifetime is constrained by small batteries that power sensor nodes in a BSN. In this paper, we introduce a novel data-centering routing model to minimize communication energy, taking collaborative nature of signal processing for healthcare applications into consideration. Transmission energy for a path is determined as a compromise between the path length and the amount of data being transmitted along the path. Data produced by different nodes are aggregated to form packets of large size that consume smaller energy per bit. We formulate the problem as a minimum concave cost multicommodity flow problem and propose two approaches to find both optimal and approximate solutions. We evaluate performance of our energy minimization techniques on a variety of synthesized signal processing task graphs, as well as a real application for evaluating human postural control system. The results show an average of $35\%$ energy saving with the proposed routing against a simple shortest path approach.**

***Index Terms*—Body Sensor Networks; Signal Processing; Power Optimization; Routing; Data Aggregation.**

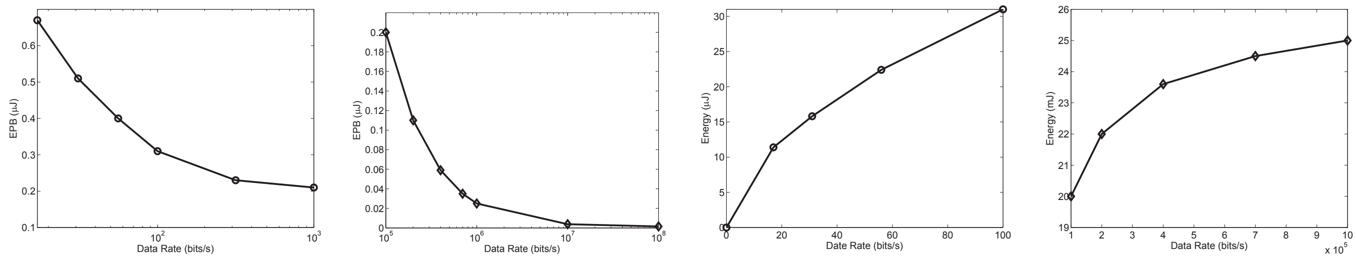
## I. Introduction

Light-weight mobile embedded platforms have caught considerable attention from researchers recently due to their effectiveness in a multitude of applications. A particular class of these systems, known as Body Sensor Networks (BSNs), uses a network of wearable sensors to monitor physiological signals collected from human body. Primary application domain of BSNs is continuous and remote healthcare monitoring. BSNs promise to foster the quality and broaden the scope of medical services in areas such as gait analysis [1], sports medicine [2], fall detection [3] and geriatric care [3].

The lifetime of the BSN platforms is constrained by small batteries that comply with user's comfort. A common approach for maximizing system lifetime is minimizing power consumption of the system. Power consuming components include sensing, processing, and communication modules. Because communication is much more expensive than computation [4], most of the energy is dissipated through data transmissions [5]. Consequently, special attention must be given to enhancing communication system for the purpose of energy minimization.

In BSNs, data transmissions are introduced according to a signal processing model. Data processing must conform to inter-node dependencies defined by the application. A node may not be able to process data locally unless it receives information from other nodes. Such inter-node dependencies introduce specific constraints for data processing. Two models used for data processing include *centralized* and *collaborative*. In a centralized approach, each node transmits raw sensor readings to a base station. The base station is responsible for processing the data and producing output. Although this method reduces computing stress at sensor nodes, it is inefficient in terms of energy consumption because the large amount of data sent to the base station requires significantly higher power usage and communication bandwidth. In a collaborative model, however, in-node processing is enabled by inter-node data transmissions. A node may receive input from other nodes for local processing. Primary role of in-node signal processing is data reduction. As a result, the collaborative approach is more desirable from power consumption perspective because transmitting processed data consumes less energy than transmitting raw data.

In this study, we propose a novel power optimization technique that minimizes communication energy by aggregating transmission data required for in-network processing. The key idea is to form larger packets for communication. It has been shown that larger packets have a lower energy per bit consumption [6]. In order to take advantage of this property, we buffer data before transmission and combine data of different sources when routing the data. While the aggregated data may be sent though longer paths, it can result in a smaller total energy consumption than that of a shortest path communication. The network is constructed by a number of body-worn sensor devices that function in a collaborative manner with respect to the specific goal of the application. The functionality of each sensor node is structured by several embedded signal processing modules that process sensor readings. The processing modules are interoperable in the sense that each task might be dependent on the output of other modules. We represent a network model that incorporates data dependencies and show that




(a) EPB - ZigBee (b) EPB - Bluetooth (c) Communication cost - ZigBee (d) Communication cost - Bluetooth

Fig. 1. Energy per bit (EPB) and total energy cost versus data rate for ZigBee and Bluetooth (based on energy models in [6] and [7]).

the problem of energy minimization is transformed into a minimum cost multicommodity flow problem on a complete graph. Furthermore, we demonstrate the effectiveness of the introduced optimization problem using experimental setting for physical movement monitoring applications.

## II. Related Work

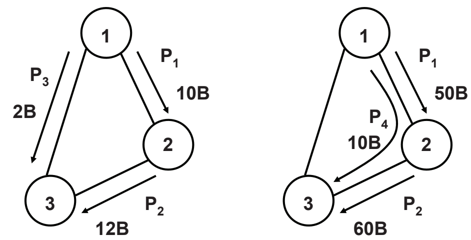
With the growing interest in designing wearable devices for healthcare applications, much research has been done on reducing power consumption on BSN platforms. Energy optimization mechanisms involve a wide range of researchers from hardware designer to communication and signal processing experts. The power saving approach in [8] uses thermoelectric MEMS generator for energy scavenging from surrounding environment. Human body heat can be also used to power wearable sensor nodes [9]. In communication domain, modifying standard protocols according to specific needs of a BSN application can lead to achievement of considerable power savings [10]. Furthermore, power-aware sensor nodes [11] can estimate the amount of transmission power they require to maintain the connectivity of the network. Using this concept, each node in the network can gracefully trade off performance for energy efficiency [12]. In [13], authors show that, compared to a star topology, a multihop architecture can reduce energy consumption in BSNs due to reduction in the packet delivery rates. Furthermore, energy limitations of BSNs have been addressed with respect to signal processing requirements. Authors in [14] pose an optimization problem for minimizing the number of active nodes and for maximizing system lifetimes while maintaining high classification accuracy for human movement recognition. Similarly, a task graph can be constructed using timing constraints and data dependencies [15] to determine the critical paths, which can be used in development of a scheduling mechanism to distribute the unused time (slacks) among tasks such that the overall energy cost is minimized. The heuristic node selection technique presented in [16] detects active nodes dynamically for distributed action recognition in BSNs.

Efficient routing of the data is one of the most important power saving techniques in traditional wireless sensor networks domain. There are two major routing models: address-centric and data-centric models. In address-centric approach, each source node sends data through the shortest path to the destination node without regard to the path taken by other nodes. In contrast, data-centric techniques take advantage of combining the data coming from multiple nodes to reduce the overall energy consumption. The process of joining multiple packets and forming a single transmission unit is called data aggregation [17]. Data aggregation can reduce the amount of data that is transmitted across the network. Most data aggregation models such as [18–20] use a data-centric approach for energy saving where each node in the network combines the data received from multiple source nodes and forwards the result to a sink node. In this model, different sources make observations of the same event and transmit the acquired data along predefined paths. Also, intermediate nodes aggregate similar packets according to an aggregation function and form a single forwarding packet. Such aggregation models cannot be used for BSN platforms because: 1) Sensor nodes in a BSN need to collaborate in order to make an observation about the event occurring in the system [21]. Thus, data processing is enabled by a set of inter-node dependencies that define communication for these systems. 2) The primary goal of data aggregation in wireless sensor networks is to reduce the number of transmissions by eliminating redundancy in the data [22]. However, our objective is to combine the data coming from different sources to form packets of large sizes; hence reducing communication energy.

Compared to traditional wireless sensor networks, BSNs encompass a different communication model. Body-worn sensor nodes are quite proximate with the possibility of direct transmissions. However, due to the collaborative nature of signal processing, a node may require intermediate results produced by other nodes in order to perform local processing. We present a data-centric communication model that maximizes the amount of path sharing in BSNs resulting in power reduction. This energy optimization technique is different from the traditional routing approaches investigated in wireless sensor networking field because it takes into consideration a collaborative signal processing model that is enforced by healthcare application. To the best of our knowledge, such study has not been done previously.

## III. Motivation

Due to the short distance between the nodes, transmission over the direct links has been the natural routing mechanism for BSNs. In this study, however, we reconsider this choice by introducing a new data aggregation technique. Compared




(a) Shortest path (b) Path sharing

Fig. 2. Transmission using shortest path, and path sharing.

to the single-hop routing, a multi-hop approach that combines data items from several nodes and forms large packets may require less energy for communication. In fact, as the packet size grows, the amount of energy per bit (EPB) decreases (Fig. 1(a) and Fig. 1(b)), turning the total energy cost into a concave function (Fig. 1(c) and Fig. 1(d)). In Fig. 1, EPB value and overall communication energy for ZigBee and Blutooth technologies are shown [6, 7]. To highlight concavity of the enery cost as a function of data rate, the graphs in Fig. 1(c) and Fig. 1(d) are shown only for data rates 0-100 bps and $10^5$-$10^6$ bps for ZigBee and Bluetooth respectively.

To better illustrate operation of our power optimization approach, we use a motional example shown in Fig. 2. The figure shows a BSN with three sensor nodes labeled as 1, 2 and 3. Assume that because of inter-node dependencies, node 2 needs to receive data items of size 10 bytes from node 1. Example of such requirement is dependency of feature extraction at one node (e.g. node 2) on features (e.g. 10 statistical features each of size 1 byte) calculated at another node (e.g. node 1). Also, local processing at node 3 is dependent of 12 bytes data items produced by node 2. A situation that implies such dependencies arises when node 3 needs to receive results of both segmentation (2 bytes showing start and end of a particular signal segment) and feature extraction (10 bytes) from node 2. Finally, node 1 assists node 3 by providing data items of size 2 bytes (e.g. providing segmentation information). In general, the type of assistance and production rate of the nodes are defined by signal processing requirements of the application.

Furthermore, suppose that system results can be reported every $T$=5 cycles. Fig. 2 shows two different scenarios for data transmission between pairs of nodes. In the first case shown in Fig. 2(a), each node uses the direct link (shortest path) in every cycle to convey data to the destination node. The paths are denoted by $P_1$, $P_2$, and $P_3$. This approach consumes 340 $\mu$J energy using a ZigBee radio because transmitting 10, 12 and 2 bytes consumes 27.10, 30.22 and 10.72 $\mu$J respectively and a total of 5 transmissions is required, one per each cycle. In another case shown in Fig. 2(b), node 1 uses a longer path, $P_4$, to transmit data to node 3. Only two transmissions, with larger packets, are required in this case because of data aggregations prior to transmissions at nodes 1 and 2. Each node buffers data for 5 cycles, forming packets of size 50, 60 and 10 bytes corresponding to node pairs (1,2), (2,3) and (1,3). Furthermore, by data aggregation, the 10 byte data generated by node 1 is added to the 50 and 60 bytes data generated by nodes 1 and 2 forming two packets of size 60 and 70. These packets are sent along (1,2) and (2,3) and consume 104 and 120 $\mu$J respectively. By storing data locally and using the path sharing scenario, energy consumption reduces to 223 $\mu$J giving a 34% energy saving.

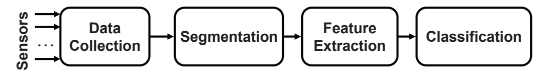



Fig. 3. Per-node signal processing for action recognition.

## IV. Preliminaries

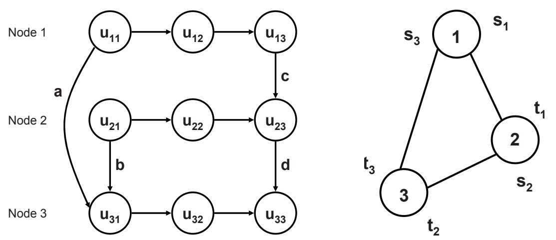
The focus of our study is human movement analysis by means of wearable motion sensors such as accelerometers and gyroscopes. The process of extracting information about human movements is complex because movements are usually introduced by simultaneous displacement and rotation of multiple body segments. Therefore, a network of motion sensors must be organized in order to effectively experience movements of different limbs. In the following subsections, we introduce a collaborative model of signal processing for BSN applications. This model is the basis for our power optimization problem that will be discussed in Section V.

### A. Per-node Signal Processing

Data collected by each sensor node in the network is required to undergo certain signal processing defined by the application. The purpose of signal processing is to reduce complexity of raw data and extract useful information that are specified by the application. An example of per-node signal processing for action recognition is shown in Fig. 3. The goal of this application is to detect basic transitional movements such as “sit-to-stand”, “lie-to-sit” and “kneel”. During *Sensor Reading*, each node samples all motion sensors integrated with that node. The raw data is then fed into the *Segmentation* block that determines where on the signal an action starts and where it ends. Statistical attributes that are calculated during *Feature Extraction* are used to build a classifier that recognizes an unknown movement as one of prespecified actions according to some *Classification* scheme.

### B. Inter-node Data Dependencies

In most cases, a single node cannot complete signal processing tasks without receiving assistance from other nodes. It is mainly due to data dependencies among sensor nodes. One application with such property can be detection of upper body sway during walking which can be used for fall monitoring. In this case, a node placed on the “leg” can segment walking data into gait cycles while a node placed on the “neck” cannot recognize the start and stop times of the gait cycle. The “neck” node is capable of measuring lateral sway. Therefore, the “leg” node produces segmentation data that can be used by the “neck” node for sway analysis.




(a) Task graph (b) Dependency graph

Fig. 4. A task graph and corresponding dependency graph for a network of three nodes. Dependencies shown by inter-node edges $a$, $b$, $c$, and $d$ in the task graph are traslated into the set of node pairs ($s_k$,$t_k$) = (1,2), (2,3), (1,3).

Another compelling application is Parkinson's Disease (PD) patient monitoring. Currently, clinical diagnosis of PD is done by physicians by observing a subset of cardinal symptoms of the disorder. Cardinal symptoms include "resting" tremor, muscular rigidity, bradykinesia or delayed initiation of movements, and a postural instability [23]. These symptoms are not equally pronounced during all of the human actions. For example, bradykinesia cannot be identified when a subject is perfectly still. In order to properly recognize PD symptoms, action recognition needs to be performed first. Based on the result of the action recognition a subset of symptoms can be targeted. Each symptom can be detected through collaboration of the nodes. For example, a high level description of muscular rigidity detection is as follows. A set of three sensor nodes positioned on "foot", "waist", and "wrist" collaborate for action recognition [24]. If the current movement is "walking", the "foot" node transmits its local results to a "shank" node for calculation of gait "stride time" (dependency between "shank" and "foot" nodes) [25]. The stride length information is then used by a "shoulder" node to verify the level of rigidity of the upper body. This is done by finding the relative phase of rotation of pelvis and thorax (dependency of "shoulder" node on "waist" and "shank") [26].

### C. Collaborative Processing Model

Our model for representing data dependencies among processing units is a direct acyclic graph (DAG) which we call a *task graph*. A task graph $G_T$=($V_T$,$E_T$) is constructed by a set of vertices $V_T$=$\{u_{ij}\}$ that denotes all processing tasks across the network, and a set of edges $E_T$ that specify *intra-node* and *inter-node* dependencies. Fig. 4(a) shows a simple network of three sensor nodes each running three processing tasks ($u_{i1}$ to $u_{i3}$) with four inter-node dependencies indicated by edges $\{a$, $b$, $c$, $d\}$.

### D. Network Model

In BSNs, communication is limited to a human body; hence, every two nodes are within the range of one another. A complete graph can be used to specify potentially available communication links. We introduce a *dependency graph* which considers both availability of single-hop transmissions and data dependencies introduced by signal processing.

***Definition*** *1:* Let $S$=$\{1,\ 2,\ \ldots,\ n\}$ be a set of $n$ sensor nodes with a given task graph $G_T$. A dependency graph $G_D$=($V_D$,$E_D$,$M$) is a complete graph represent by a set of vertices $V_D$=$S$, a set of edges $E_D$, and a set of source-destination pairs $M$=$\{(s_k$,$t_k)\}$ which specifies dependencies introduced by $G_T$.

Fig. 4(b) shows dependency graph for the task graph in Fig. 4(a). The four dependency links $a$, $b$, $c$, and $d$ in the task graph are transformed into the three source-destination pairs $M$ = $\{(s_1$,$t_1)$,$(s_2$,$t_2)$,$(s_3$,$t_3)\}$ in the dependency graph (both $b$ and $d$ refer to dependency between nodes 2 and 3).

We note that a data dependency in a task graph manifests itself in the form of a node pair ($s_k$,$t_k$) in the dependency graph. This implies that a dependency graph still represents a DAG. It is easy to show that any cycles in a dependency graph can be eliminated by decomposing some node of the cycle into two processing tasks and making incoming and outgoing edges adjacent to the tasks. Let path $\pi_{i,i}$ from node $i$ to $i$ is a cycle on a dependency graph $G_D$. Let ($i$,$j$)$\in \pi_{i,i}$ and ($k$,$i$)$\in \pi_{i,i}$ be outgoing and incoming edges at node $i$ respectively. One can decompose vertex $i$ into two vertices $u_{i1}$ and $u_{i2}$ and add a new directed link from $u_{i1}$ to $u_{i2}$. The cycle is eliminated by making edge ($i$,$j$) adjacent to vertex $u_{i1}$, and ($k$,$i$) adjacent to $u_{i2}$. The original cycle $\pi_{i,i}$ is now represented by the path $\pi_{u_{i1},u_{i2}}$ which has the same length as $\pi_{i,i}$ but different source/destination. The same process can be repeated to eliminate all existing loops on any given dependency graph and construct a DAG.

## V. Maximum Path Sharing

The purpose of our power optimization problem is to minimize the amount of energy due to inter-node communication. Our approach is motivated by the fact that larger packets consume less transmission energy per bit [27]. Therefore, combining transmission data from multiple nodes can lead to lowering the total communication energy. Our technique has two steps: 1) we buffer data on individual nodes until a given deadline $T$. 2) at time $T$, each node transmits its data along a path such that the total energy is minimized. The path is chosen as a compromise between path length and packet size. Therefore, a longer path might yield less energy consumption because of larger packets formed by aggregating data from different sources.

***Problem*** *1:* Given a dependency graph $G_D$ with $K$ pairs of source-destination ($s_k$,$t_k$), a set $\{d_1,\ d_2,\ \ldots,\ d_K\}$ of $K$ demands associated with pairs ($s_k$,$t_k$), and a cost function f($x_{ij}$) which denotes the energy cost of sending $x_{ij}$ units of data from node $i$ to node $j$, the maximum path sharing (MPS) problem is to find routes for all demands $d_k$ at minimum total cost.

### A. Problem Formulation

The problem described in Problem 1 can be formulated as a minimum cost multicommodity flow problem as follows.

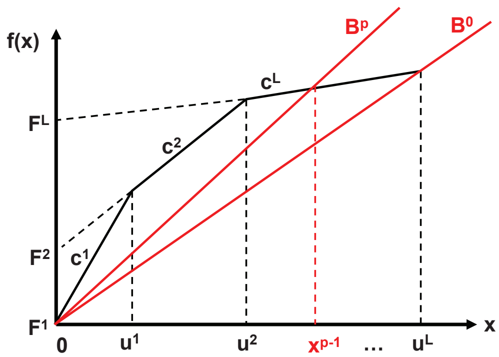



Fig. 5. Piecewise cost function

$$\text{Minimize} \quad \sum_{k=1}^{K} \sum_{(i,j)\in E_D} f(x_{ij}^k) \tag{1}$$

Subject to:

$$\sum_{k=1}^{K} x_{ij}^k \leq u_{ij} \quad \forall (i,j) \in E_D \tag{2}$$

$$\sum_{k=1}^{K} \sum_{j\in V_D} x_{ij}^k = \sum_{k=1}^{K} \sum_{j\in V_D} x_{ji}^k \quad \forall i \neq s_k, t_k \tag{3}$$

$$\sum_{i=s_k, j\in V_D} x_{ij}^k = - \sum_{i=t_k, j\in V_D} x_{ji}^k = d_k \quad \forall k \in \{1, \ldots, K\} \tag{4}$$

$$x_{ij}^k \geq 0 \quad \forall (i,j) \in E_D \;\; \forall k \in \{1, \ldots, K\} \tag{5}$$

where $x_{ij}^k$ represents the amount of commodity $k$ sent from node $i$ to node $j$. Equation (2) is the capacity constraint that ensures the total amount of flow on communication link between nodes $i$ and $j$ does not exceed the total bandwidth $u_{ij}$. Constraints (3) and (4) refer to flow conservation and demand satisfaction conditions respectively.

### *B. Problem Complexity*

The minimum concave cost multicommodity flow problem has been shown to be NP-hard even with a signal commodity [28]. Polynomial time algorithms exist only for problems with certain assumption on the network structure [29] or problem constraints [30]. In order to estimate solution to the maximum path sharing problem, we adopt the two approaches proposed in [31, 32].

### *C. Piecewise Linear Cost Approach*

In this section, we show that the maximum path sharing problem can be estimated when a piecewise linear cost function is used. In fact, our cost function is a nondecreasing concave function in the amount of flow $x_{ij}$, and can be represented as a piecewise linear function. The available capacity on each link can be divided into bins each with a constant slope corresponding to a linear cost. Fig. 5 shows

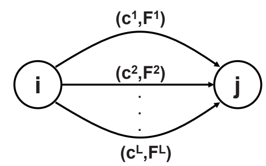



Fig. 6. Link expansion based on piecewise linear cost function

such a function with $L$ bins each being specified by lower and upper limits $u^{l-1}$ and $u^l$, a slope $c^l$, and a fixed cost $F^l$. Therefore, if $u^{l-1} < x_{ij} \leq u^l$, the cost associated with that link is given by:

$$f(x_{ij}) = F^l + c^l x_{ij} \tag{6}$$

*1) Integer Relaxation:* In the first approach, we expand the dependency graph $G_D$ and construct a new graph $G'_D$ in which each link $e_{ij}$ is replaced with $L$ parallel links $e_{ij}^1, e_{ij}^2, \ldots, e_{ij}^L$ corresponding to the $L$ bins in the piecewise linear function. This allows us to split the flow $x_{ij}^k$ of the $k$th commodity into $L$ pieces $x_{ij}^{k1}, x_{ij}^{k2}, \ldots, x_{ij}^{kL}$ that are sent through the parallel links. The cost associated with each link $e_{ij}^l$ in the transformed graph is directly suggested by the piecewise function and is a function of $F^l$, $c^l$, and the total amount of flow $\sum_{k=1}^{K} x_{ij}^{kl}$. Fig. 6 shows the graph expansion procedure. We further define a binary variable $y_{ij}^l$ associated with each link $e_{ij}^l$ in $G'_D$, which determines if the total amount of flow on that link is within the bounds ($u^{l-1}$ and $u^l$) defined by the piecewise function.

$$y_{ij}^l \;=\; \begin{cases} 1, & \text{if} \;\; u^{l-1} < \sum_{k=1}^{K} x_{ij}^{kl} \leq u^l \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Then the problem can be formulated as a mixed integer programming (MIP) problem as follows.

$$\text{Minimize} \quad \sum_{e_{ij}} \sum_{l=1}^{L} \left[ F^l y_{ij}^l + c^l \sum_{k=1}^{K} x_{ij}^{kl} \right] \tag{8}$$

Subject to:

$$\sum_{k=1}^{K} x_{ij}^{kl} \leq y_{ij}^l u_{ij} \quad \forall e_{ij} \;\; \forall l \tag{9}$$

$$y_{ij}^l u^{l-1} \leq \sum_{k=1}^{K} x_{ij}^{kl} \leq y_{ij}^l u^l \quad \forall e_{ij} \;\; \forall l \tag{10}$$

$$\sum_{l=1}^{L} \sum_{k=1}^{K} \sum_{j\in V_D} x_{ij}^{kl} = \sum_{l=1}^{L} \sum_{k=1}^{K} \sum_{j\in V_D} x_{ji}^{kl} \quad \forall i \neq s_k, t_k \tag{11}$$

$$\sum_{l=1}^{L} \sum_{i=s_k, j\in V_D} x_{ij}^{kl} = - \sum_{l=1}^{L} \sum_{i=t_k, j\in V_D} x_{ji}^{kl} = d_k \quad \forall k \tag{12}$$

$$x_{ij}^{kl} \geq 0 \quad \forall e_{ij} \;\; \forall k, l \tag{13}$$

**Algorithm 1** Dynamic slope scaling algorithm

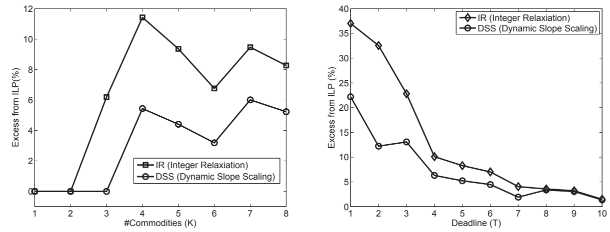
**Require:** Dependency graph $G_D$, commodities ($s_k$,$t_k$), demands $d_k$, piecewise cost function defined by $c^l$, $F^l$, $u^l$
**Ensure:** Minimize objective function in (1)
  $p \leftarrow 0$ {iteration zero}
  $B_{ij}^0 \leftarrow C^L + \frac{F^L}{u_{ij}}$ $\forall e_{ij}$ {initial cost}
  Minimize $Z^p = \sum_{k=1}^{K} \sum_{e_{ij}} B_p x_{ij}^{k,p}$
  **repeat**
    $p \leftarrow p + 1$ {next iteration}
    **for all** ($l \in \{1, \ldots, L\}$) **do**
      **if** ($u^{l-1} < \sum_{k=1}^{K} x_{ij}^{k,p-1} \leq u^l$) **then**
        $B_{ij}^p \leftarrow C^l + \frac{F^l}{\sum_{k=1}^{K} x_{ij}^{k,p-1}}$
      **end if**
    **end for**
    Minimize $Z^p = \sum_{k=1}^{K} \sum_{e_{ij}} B_p x_{ij}^{k,p}$
  **until** $Z^{p-1} - Z^p < \epsilon$

$$\sum_{l=1}^{L} y_{ij}^l \leq 1 \quad \forall e_{ij} \tag{14}$$

$$y_{ij}^l \in \{0, 1\} \quad \forall e_{ij} \ \ \forall l \tag{15}$$

Equation (9) is the capacity constraint. Note that for each link $e_{ij} \in E_D$ all corresponding edges $e_{ij}^l$ in the transformed graph have the same capacity $u_{ij}$. This constraint together with (14) and (15) ensure that only one link among the $L$ links $e_{ij}^l$ is chosen to send the flow assigned to an edge $e_{ij}$. Constraint (10) ensures that the total flow on a link $e_{ij}$ is sent through the link $e_{ij}^l$ with appropriate bounds ($u^{l-1}$ and $u^l$). The above formulation allows us to use a branch and bound approach [33] to find a lower bound on the solution. Furthermore, we solve the MPS problem by relaxing the integer condition in (15) and using common linear programming solvers. Although the above formulation allows to estimate the solution based on integer relaxation (IR) and calculate a lower bound solution, it runs on a relatively large network. Therefore, we introduce a heuristic, called Dynamic Slope Scaling (DSS), which runs on the original graph rather than the expanded one and estimates the solution by iteratively executing the integer formulation in (1)-(5).

*2) Dynamic Slope Scaling:* Major difficulty in solving the maximum path sharing problem is the concavity of the cost function in (1). Dynamic slope scaling (DSS) is a heuristic approach that minimizes the objective function by adaptively selecting a linear estimation of the concave cost. Although this approach uses the piecewise cost function to find a linear cost, the algorithm runs on the original dependency graph rather than the expanded network. We adopt the technique in [32] for specific structure of our multicommodity network. The approach in [32] solves minimum concave cost flow on networks with a single commodity. We update the algorithm as shown in Algorithm 1 to solve the problem for multicommodity case. The procedure starts with an initial linear cost which is fixed for all edges across the network, and is an underestimation of the concave function. This cost, labeled as $B^0$, is measured as the slope of the line connecting the origin to the point defined by the value of the piecewise cost at $u^L$ as shown in Fig. 5. We use the solution obtained by solving the problem with $B^0$ to recalculate a second linear cost (e.g. $B^1$). In each following iteration, we update the cost associated with a link based on the total flow assigned to that link in the previous step. The procedure is iterative and increases the value of the objective function in each iteration. It stops when the total cost does not increase anymore (difference between two consecutive iterations is less than $\epsilon$). Algorithm 1 shows the process of minimizing objective function using DSS method.




(a) Excess vs. K (b) Excess vs. T

Fig. 7. Percentage excess over optimal (ILP) for integer relaxation (IR) and dynamic slope scaling (DSS) with: (a) varying number of commodities and fixed deadline $T$=5, and (b) different deadlines and fixed number of commodities $K$=8.

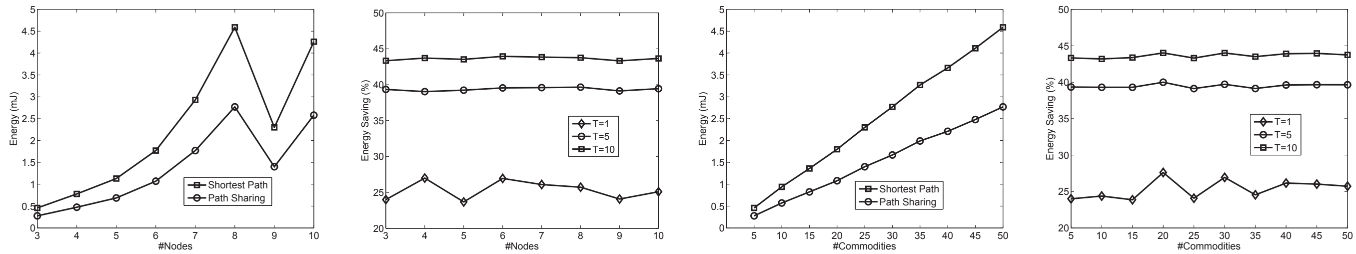
## VI. Experimental Results

To verify the effectiveness of the proposed power optimization techniques, we construct a body sensor network using multiple inertial sensor nodes. Each node consists of a TelosB [34] mote and two motion sensors including an accelerometer and a gyroscope. The motes are equipped with a Chipcon CC2420 radio (IEEE 802.15.4 standard) for communication. The system is used primarily for movement classification, which requires *segmentation*, *feature extraction* and *classification* as major processing tasks involved in per-node signal processing and inter-node communications. We assume that segmentation, feature extraction and classification produce data items of size 2, 10, and 1 bytes respectively. In Section VI-C, we expand this application for evaluating quality of postural control system during walking.

In Section VI-A, we compare performance of IR and DSS techniques with the optimal solution obtained from the ILP formulation. We then present the amount of energy savings obtained by the MPS approach and compare the results with that of a single-hop routing in Section VI-B. Since BSNs span a wide range of applications, we construct networks of varying sizes and configurations in terms of inter-node dependencies and data rates. We finally present our results on a specific example of physical movement monitoring in Section VI-C.

### A. Comparing Different Solutions

In this section, we compare the results obtained by integer relaxation (IR) and dynamic slope scaling (DSS) with those




(a) Energy vs. $n$ (b) Saving vs. $n$ (c) Energy vs. K (d) Saving vs. K

Fig. 8. Energy consumption and saving for networks of different sizes and architectures: (a) Energy versus number of nodes, with $T$=5 and $K$ as shown in Table I. (b) Saving versus number of nodes for different values of deadline, T. (c) Energy versus number of commodities for 8-node network, with $T$=5. (d) Saving versus number of commodities for 8-node network and different deadlines.

of the optimal solution. The optimal solution is obtained by solving the ILP formulation in Section V-C1 without relaxing the integer constraints in (15). For this comparison, we use a network of four sensor nodes with different configurations. First, we randomly add a sequence of 8 source-destination pairs to the network while transmission deadline is fixed at $T$=5. Fig. 7(a) shows the percentage by which the results obtained by the IR and DSS techniques exceed the optimal solution. The results are given for networks with varying number of commodities. The percentage of excess from the optimal values ranges from 0% to 11.43% for the IR approach with an average of 6.43%. It ranges from 0% to 6.01% for the DSS algorithm with an average of 3.03%. In the second test, we use the 8 commodity network and change the deadline from 1 to 10 cycles. The percentage of excess for the IR and DSS solutions is shown in Fig. 7(b). The results reported by the IR and DSS techniques exceed the optimal solutions on average 13% and 7.31% respectively.

The above analysis on approximation quality of IR and DSS shows that DSS algorithm outperforms the IR solution. We also note that DSS algorithm runs on a significantly smaller network compared to the network used for IR solution. Recall from Section V-C, the integer relaxation approach uses an expanded network with each network in the original graph being transformed to $L$ parallel links representing slope segments of the concave cost function as illustrated in Fig. 5. Therefore, due to more accurate approximation results and and lower complexity, we use the DSS algorithm to compute communication cost for the networks described in the rest of this paper.

### *B. Enery Saving on Random Networks*

To evaluate performance of the path sharing problem without restricting to a particular application, we run our algorithms on a variety of synthesized signal processing task graphs. The number of sensor nodes in the BSN varies from 3 to 10. For each network, a subset of all possible source-destination pairs is chosen at random to form a set of $K$ commodities. The second column in Table I shows the number of commodities for each network. The amount of demand associated with each commodity is determined randomly and based on possible data units generated by signal processing blocks (i.e. 2, 10, and 1 byte for segmentation, feature extraction, and classification). For example, a 3-node network has a set of 5 commodities (3,2), (2,3), (1,3), (2,1) and (1,2), and corresponding demands 10, 12, 1, 2 and 10 bytes.

TABLE I
AVERAGE ENERGY SAVING FOR NETWORKS OF DIFFERENT SIZES

| #Nodes | #Commodities | Saving |
|---|---|---|
| 3 | 5 | 35.56% |
| 4 | 8 | 36.58% |
| 5 | 12 | 35.48% |
| 6 | 19 | 36.81% |
| 7 | 32 | 36.51% |
| 8 | 50 | 36.38% |
| 9 | 25 | 35.51% |
| 10 | 46 | 36.06% |

Fig. 8(a) shows the amount of energy consumed by each network using the two routing approaches: shortest path and maximum path sharing. For this particular test, transmission deadline is 5 cycles. The path sharing outperforms the shortest path routing. As expected, energy consumption increases as the network becomes larger and number of communication pairs increases. The decrease in communication energy of the 9-node setting is a result of this network having a smaller number of commodities (25 as stated in Table I) than the 8-node and 7-node networks (50 and 32 respectively). Fig. 8(b) shows percentage of energy saving obtained by the path sharing for each network for three values of $T$. On average, we achieve 25.33%, 39.37% and 43.63% savings using an MPS routing for $T$=1, $T$=5 and $T$=10 respectively. Since longer deadlines allow for storing data over an extended period of time, larger packets can be produced, leading to higher energy savings. Yet, energy consumption can be reduced by 25.33% in the case of immediate transmission ($T$=1).

Fig. 8(c) shows the amount of energy consumed by the 8-node network while number of commodities ranges from 5 to 50. For this particular graph, transmission deadline is assumed to be $T$=5. Fig. 8(d) shows percentage of reduction in energy cost when the path sharing technique is utilized. Again, savings are measured for different transmission deadlines ranging from 1 to 10 cycles. This evaluation exhibits 25.33%, 39.49% and 43.64% energy reduction on average for 1, 5 and 10 cycles of transmission deadlines respectively.

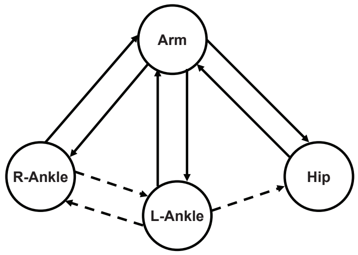



Fig. 9. Dependencies for action recognition and sway analysis.

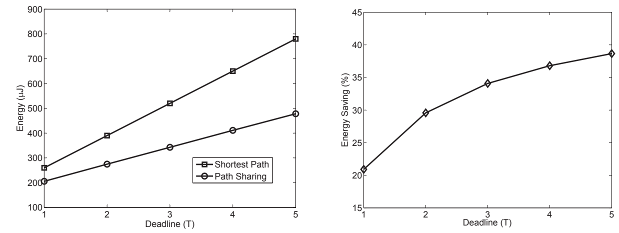
### C. Sway Analysis

Evaluating quality of balance stability during walking is important in elderly population. Detecting certain patterns in body movements can help in predicting balance abnormalities which may lead to falls in older patients. One important parameter being used for balance analysis is the sway of upper body, which can be detected by observing movements of the hips or neck. In this section, we show how the path sharing problem can reduce communication cost of a BSN platform for sway analysis during gait. The system is composed of four sensor nodes placed on “hip”, “arm”, “right-ankle” and “left-ankle”. The “hip” node is responsible for measuring sway, the angular rotation of upper body in lateral and sagittal planes. The nodes on the two ankles are used in collaboration to extract gait cycle parameters. Examples of such parameters include stride length, stride time, step width, gait speed, gait phases, etc. When the walking movement is detected, one of lower body nodes (e.g. “right-ankle”) sends information regarding gait parameters to the “hip” node where a final analysis on quality of stability is performed. The purpose of this analysis is to measure stability of postural control system during each phase of the gait and provide appropriate feedback to the patient. Since the system is aimed to assess balance control during walking, it must be able to detect walking first. Therefore, we use a node on the “arm” to make observations on upper body movements. All the four nodes need to collaborate for the purpose of action recognition prior to calculating gait parameters and measuring body sway. The “arm” node is assumed to be master for “segmentation” and “classification”. That is, every node segments signal readings locally and transmits the results to the “arm” node where beginning and end of each action are detected. The “arm” node will then send segmentation results to the other three nodes. The same process is repeated for classification. Fig. 9 illustrates all dependencies required for balance evaluation as described above. The three dashed lines account for dependency links that can be potentially folded into other paths by the path sharing approach.

We first perform an analysis on classification accuracy of this BSN model. The system is able to recognize actions with an accuracy of 93.87% with real data collected from three healthy subjects performing 25 transitional movements such as ’sit to stand’, ’sit to lie’, ’jump’, ’kneel’ and ’walk’. Table II shows the amount of data produced, per action, by each source node to be sent to a destination node. Human movements can occur at different speeds. We assume a normal walking speed of 110 steps/min. (55 actions/min. or 0.92 Hz) for our gait analysis study.

TABLE II
DATA UNITS GENERATED BY INDIVIDUAL NODES FOR SWAY ANALYSIS

| Dependency | Source Data | Data Rate (bytes/action) |
|---|---|---|
| R-Ankle $\rightarrow$ Arm | segmentation, classification | 3 |
| L-Ankle $\rightarrow$ Arm | segmentation, classification | 3 |
| Hip $\rightarrow$ Arm | segmentation, classification | 3 |
| Arm $\rightarrow$ R-Ankle | segmentation, classification | 3 |
| Arm $\rightarrow$ L-Ankle | segmentation, classification | 3 |
| Arm $\rightarrow$ L-Ankle | segmentation, classification | 3 |
| R-Ankle $\rightarrow$ L-Ankle | gait parameters | 5 |
| L-Ankle $\rightarrow$ R-Ankle | gait parameters | 5 |
| R-Ankle $\rightarrow$ Hip | gait parameters | 5 |




(a) Energy vs. deadline (b) Saving vs. deadline

Fig. 10. Energy consumption (a) and percentage of energy saving (b) for postural control evaluation network.

With the aforementioned experimental setup, we run the two routing algorithms on the network shown in Fig. 9. The shortest path approach consumes 779 $\mu$J energy while path sharing technique requires 478 $\mu$J to meet transmission needs of the network and a deadline of $T$=5 actions. We note that with the path sharing the total energy is reduced by 39.15%. Fig. 10 shows energy consumption and percentage of energy saving for different values of transmission deadline, with 32% energy saving on average.

## VII. Conclusion

In this paper, we presented a new energy minimization routing model based on the concept of data aggregation in body sensor networks. Since the overall energy per bit deceases as the packet grows in size, our approach considers routing data along the paths that minimize total communication energy by maximizing the amount of data sharing among routing paths. We showed that the maximum path sharing problem can be transformed into a minimum cost network flow problem. Our results on a variety of random networks and a real BSN architecture for evaluation of postural control system clearly demonstrate the effectiveness of the path sharing approach in reducing communication cost.

Currently, we solve the maximum path sharing problem based on integer programming formulation. As part of our ongoing research, we are working on developing combinatorial algorithms that find minimum cost routing paths on our dependency graphs. Furthermore, we plan on analyzing impact of retransmissions on overall communication cost.

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