Semantics-driven Sensor Configuration for Energy Reduction in Medical Sensor Networks

James B. Wendt, Saro Meguerdichian, Hyduke Noshadi, and Miodrag Potkonjak
Computer Science Department, University of California, Los Angeles
Los Angeles, CA 90095, USA
{jwendt, saro, hyduke, miodrag}@cs.ucla.edu

ABSTRACT

Traditional optimization methods for large multisensory networks often use sensor array reduction and sampling techniques that attempt to reduce energy while retaining full predictability of the raw sensed data. For systems such as medical sensor networks, raw data prediction is unnecessary; rather, only relevant semantics derived from the raw data are essential. We present a new method for sensor fusion, array reduction, and subsampling that reduces both energy and cost through semantics-driven system configuration. Using our method, we reduce the energy requirements of a medical shoe by a factor of 17.9 over the original system configuration while maintaining semantic relevance.

Categories and Subject Descriptors

C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and Embedded Systems; B.8.2 [**Performance and reliability**]: Performance Analysis and Design Aids; J.3 [**Life and Medical Sciences**]: Medical Information Systems

General Terms

Design, Algorithms, Performance

Keywords

Energy optimization, sensor networks, wireless health

1. INTRODUCTION

The evolution of the wireless sensor network has enabled its practical application for remote monitoring and analysis of a wide variety of environments (e.g. oceanic, urban, wildlife). More recently, these wireless sensor networks have also enabled remote sensing and remote monitoring of the human body. There is great potential for the medical community to benefit from such wearable sensing systems by utilizing their capacities for remote surveillance to observe and diagnose patient ailments and disease. These wireless health systems allow doctors to remove the constraint that they rely solely on in-person patient checkups and interviews in order to diagnose patient illness. By utilizing non-invasive wireless health monitoring, doctors are able to incorporate information gathered from the patient's day to day activities and routine into their professional medical diagnoses.

However, such multisensory systems are often expensive and have rigid energy and power requirements due to their wireless framework and remote deployment. Due to the often complex design, expensive cost, and energy demands that can accompany such wireless sensor networks, wireless medical sensing systems have not yet made headway into widespread use. Medical sensing systems can contain very large sensor arrays; for example, a commercial medical shoe might contain as many as ninety-nine sensors [1]. Not only are these sensors expensive and make up a shoe that costs thousands of dollars, but they also draw power and consume energy. However, a medical shoe is inherently a mobile device, attaching a large battery pack or requiring frequent recharges are a strong deterrent to the adoption of such a medical shoe by the common patient.

In order to minimize the cost and energy demands of these sensor networks, techniques for sensor coverage, selection, and sampling have been proposed. These techniques often focus on maintaining full predictability of the original array while reducing the sensor count and coordinating sensor subsampling.

In a great majority of sensor network applications, readings from a single sensor are not sufficient for extraction of information, knowledge, or decision processes. Furthermore, we are rarely interested in the raw sensed data, but rather more interested in the semantic information it provides. For example, in a sensor network distributed among the trees of a wildlife preserve, we are rarely interested in the temperature of many or even all points in a given area but rather more concerned with the early detection of fire.

Traditional approaches to sensor selection for energy reduction in multisensory systems remove redundant sensors from the array while maintaining full sensor predictability [2]. However sensor predictability (i.e. raw data prediction) is not necessary when the essential information is the semantic information itself (e.g. fire detection). Thus, our key conceptual contribution is the reduction of energy using semantics-driven sensor configuration; we reduce the energy requirements of the sensor network while maintaining system relevance, in particular, for medical diagnosis.

This is achieved through a two step process, using coarse

ISLPED'12, July 30–August 1, 2012, Redondo Beach, CA, USA.

grained energy reduction techniques followed by fine grained techniques. We explain these steps in detail in Section 4.

In coarse grained energy reduction we introduce sensor fusion and bottom-up selection techniques that maintain semantic relevance. In Section 4.1 we describe our sensor placement algorithms, including: sensor selection, which iteratively chooses sensors that most improve semantic prediction accuracy; adjacent sensor fusion, in which sensors are physically or electronically combined; search space pruning for runtime reduction; and a generic method for comparison of orthogonal semantics.

Our fine grained energy reduction technique employs a very similar approach to the coarse grained technique, but applies to sampling instead of sensors. Ultimately, we find a minimal subsampling configuration that reduces energy while maintaining semantic relevance.

Our technical contributions are algorithms and methods for (i) sensor selection with an accompanying method for ranking and sorting of arbitrary semantics, (ii) sensor fusion, and (iii) sampling configuration, all of which employ the key conceptual idea that energy reduction is semantics-driven.

We use as our driving example, a medical shoe fitted with ninety-nine pressure sensors on the sole. The semantics this system is designed to compute are gait characteristics, shown by VanSwearingen et al. to be highly correlated with disease and the risk of falling [3].

2. RELATED WORK

The emergence of embedded sensor networking has introduced new scientific and engineering challenges. Much attention is now focused on energy and power reduction in wireless sensor networks due to the often large networks and their constant power demands [4]. Current energy optimization methods focus on hardware design, signal processing, and sensor selection [5] [6] [7].

Recent attention in wearable sensing systems has fostered a growing interest in medical-based sensing devices [8] [9]. Like research in other wireless sensing systems, current attention in the wireless health domain focuses on the utility and convenience of such systems as well as their cost and energy demands [8] [10] [11] [12] [13].

Investigations have been made into the application of gait analysis in wearable sensing systems such as sensor-equipped shoes [11] [12] [13]. These provide solutions for semantic computation from raw sensor data, but do not leverage gait analysis for energy optimization. Efforts employing gait analysis for energy optimization are preliminary and limited to analysis of same size sensors and prediction of only single semantic measurements [14] [15] [16].

3. PRELIMINARIES

3.1 Semantics-driven Energy Reduction

In general, sensor selection is best applied on large multisensory arrays for maximal energy savings. Traditional approaches remove redundant sensors from the original array while maintaining full sensor predictability [2]. However, in semantics-driven devices, such as medical sensors for diagnosis, sensor predictability (i.e. raw data prediction) is not necessary. The essential information that the system is intended to measure are the diagnostic semantics (e.g. gait characteristics in a medical shoe).

Our semantics-based sensor configuration technique for energy reduction benefits sensor networks that are ultimately designed for measuring semantics from the raw data. For example, if a sensor network is required to measure temperature in a forest using thermometer sensors, traditional techniques for sensor selection are sufficient to reduce energy and cost of the system. If, however, the purpose of the forest sensor network is to detect fire through the analysis of temperature measurements, we claim that using a semantics-driven approach to sensor selection—rather than raw data predictability—yields stronger semantic prediction and energy reduction over traditional approaches.

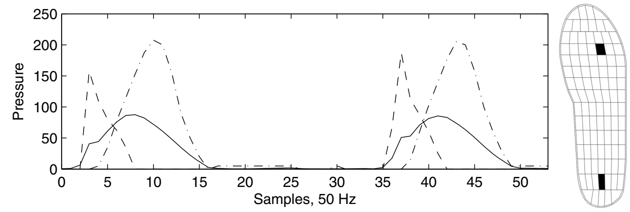


Figure 1: Pressure measurements of two steps of a single foot measured by sensors on the heel (dash), toe (dash-dot), and averaged over all ninety-nine sensors (solid). The heel and toe sensors are shaded on the Pedar mapping [1].

3.2 Medical Shoe

Medical sensor networks are inherently semantics-driven systems. A doctor is very often not concerned with the raw measurements of the sensors (e.g. accelerometers, pressure sensors, electrochemical biosensors); but rather, more concerned with the semantic information derived from those sensors (e.g. distance/speed of an impact, gait characteristics, glucose levels).

We perform our semantics-driven energy reduction methodology on a wireless medical wearable sensing system containing a large multisensory array, known as the Hermes shoe [17]. This platform is designed with the purpose of assessing balance and instability in patients through the measurements of ninety-nine passive resistive pressure sensors distributed on the sole of the foot using the Pedar plantar mapping [1].

The processing unit samples data from these pressure sensors at 50 Hz using a 16-bit analog-to-digital converter. An example of the sensor mapping and typical step profile is depicted in Figure 1. The data consists of hundreds of steps from five subjects.

3.3 Gait Characteristics

Medical shoes similar to the Hermes platform have been used in a variety of applications, from sports science to elderly care. In this paper, we choose gait characteristics, such as step stride, change in step stride, maximum pressure, lateral pressure difference, and guardedness (time between heel and toe landing) as the semantics for our study. VanSwearingen et al. have concluded that these gait characteristics correlate to a number of ailments and diseases in the elderly and directly contribute to the prediction of risk of falling in this population [3]. This strong correlation between gait and risk is a powerful means to help medical professionals diagnose these ailments with the availability of such gait data.

We normalize and extract these gait characteristics measured collectively by all ninety-nine sensors as well as measured by the individual sensors independently. Our sensor selection procedure conducts metric prediction using the metric measurements at each sensor, while our sampling solution determines the best sampling of raw data for a given set of sensors and their metric prediction model. We separate our data into training (80%) and testing (20%) subsets.

4. ENERGY REDUCTION

Energy reduction is achieved by applying two sequential steps to the design space: coarse grained optimization, which includes sensor fusion and selection, followed by fine grained optimization, which includes subsampling configuration.

In describing the coarse grained technique, we introduce our semantics-driven sensor selection algorithm that reduces the original multisensory array to a minimal subset of sensors that accurately predicts the semantics introduced in Sections 3.1 and 3.3. This approach is a bottom-up selection process which begins with an empty set, then iteratively adds sensors until a sufficient minimal set is found that accurately predicts the semantics to a specified threshold.

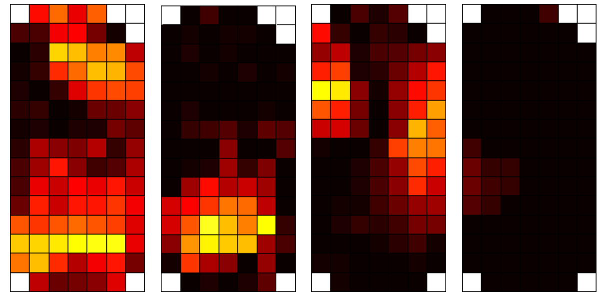
Our fine grained energy reduction technique applies a similar approach, however is performed on sensor-samples instead of sensors. A sensor-sample is a single measurement of a unique sensor at a discrete time step. In this approach, sensor-samples are iteratively removed from the minimal sensor set (found via coarse grained optimization) while maintaining semantic prediction accuracy.

Theoretically, it is possible to bypass the coarse grained sensor selection process and only apply fine grained subsampling to the original design. However, the exponential search space of this problem, along with the huge number of sensor-samples that accompanies a large multisensory array, renders this problem near impossible to solve in a reasonable amount of time. Given s samples and n sensors there are 2^{sn} possible solutions. By applying coarse grained sensor selection first, we reduce n to a small constant and reduce the problem size.

Additionally, while our primary concern is the reduction of energy usage in these medical devices, another equally important concern is the reduction of their cost, which is proportional to the number of sensors. Even if in a reasonable amount of time we could find an optimal solution using only sensor-sample selection, it is not immediately evident that this solution would ultimately reduce the number of required sensors. For example, a hypothetical solution could be that only a single sample measurement is taken at each of the ninety-nine sensors per step. While this drastically reduces energy usage, the cost of the shoe remains exorbitantly high since no sensors are removed. Coarse grained sensor selection ensures cost reduction in addition to energy reduction.

4.1 Coarse Grained Optimization

Our coarse grained optimization technique reduces both energy consumption and cost of the sensor network by combining and removing sensors from the original array while maintaining prediction accuracy of the aforementioned gait characteristics. A key observation in Figure 2 is that while clear correlations might exist between the measurements of a few individual sensors and the individual semantics, between the four semantics it is not immediately apparent which small subset of sensors can predict all semantics simultaneously well.



(a) (b) (c) (d)

Figure 2: Individual sensor coefficients of determination for (a) average maximum step amplitude, (b) change in step stride, (c) lateral pressure difference, and (d) guardedness. The lighter the sensor, the more correlated it is to the metric; darker shadings denote weaker correlations.

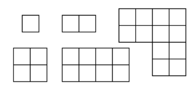


Figure 3: Shapes used in sensor fusion, pre-computed prior to sensor selection.

We explore two degrees of freedom in searching for a minimal set of optimal predictors: sensor *fusion* and sensor *selection*. Combining sensors electronically or physically reduces the total energy spent in sensing since the fused sensor acts as a single sensor and is sampled as one. We find that these fused sensors are often better semantic predictors than individual sensors.

We employ three steps to achieve coarse grained energy and cost reduction. The first step is sensor fusion. The second step is pruning, in which we eliminate combinations of sensors and fused sensors whose semantic measurements are highly correlated with one another. This ensures that pairs of sensors that yield no significant advantage in prediction over each other are not considered for combination, thus reducing the problem size. The final step is sensor selection.

4.1.1 Sensor Fusion

A fused sensor is a set of adjacent sensors physically or electronically combined with one another to create a single, larger sensor whose measurements are averaged over its new area. Including sensor fusion as an additional dimension in sensor selection provides benefits in semantic prediction. A fused sensor effectively becomes a new sensor to consider, it helps reduce noise between its constituent sensors, and simultaneously reduces system energy requirements.

However, for the purposes of sensor selection, coupling the fused sensor solution space (2^n) with that of sensor selection (2^n) yields a hugely exponential search space. In order to reduce this effect we pre-select a number of fused sensor shapes. By choosing a static set of these combinations and treating them as unique sensors, we restrict the search space.

We use application specific knowledge to pre-construct a number of fused sensor shapes. For example, the correlations of determination for the semantics in Figure 2 reveal that potentially good sensor combinations might be squares, rectangles, or L-shapes. Thus, from the existing ninety-nine sensors, we construct five new fused sensors, as depicted in Figure 3, and apply them and their rotations across the

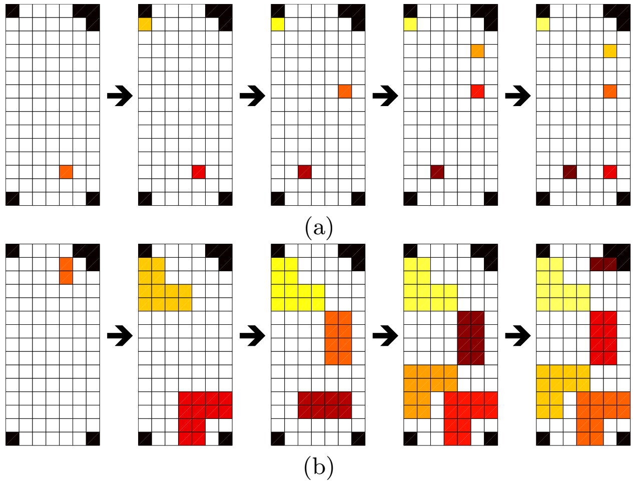


Figure 4: Top sensor configurations at iterations $1 \le i \le 5$. Solution (a) limits sensor selection to individual sensors, (b) includes sensor fusion.

sensor mapping, effectively adding 544 fused sensors to the selection pool.

4.1.2 Pruning

With 643 total sensors to consider, the exponential search space remains large. Even with our approach to sensor selection that reduces the number of potential sensor groupings considered at each iteration to the constant k (described in Section 4.1.3), sensor selection is still a very time consuming task. By pruning the search space and reducing the number of sensors considered at each iteration, we instead use that computation time to increase the value of k and thereby drive our algorithm to find a more optimal solution. The key observation is that if two sensors give similar predictions for each metric, then there is likely no benefit in having them both in the same predictive set. In experimentation, pruning had minimal, if any, impact on sensor selection while still reducing overall computation time.

We use this observation to formulate the pruning problem as a complete weighted graph, where each sensor is a node and each edge has weight equal to the maximum difference between the predicted values for each metric by the two corresponding sensors. We then prune all edges with weight greater than ω, where ω is a specified similarity threshold. Now, adding a sensor s to a predictive set eliminates all sensors with edges to s as future candidates for that set, since those sensors will not add any additional information about the gait metrics.

4.1.3 Sensor Selection

Our semantics-driven sensor selection procedure, described in detail in Algorithm 1, is a bottom-up selection process. It systematically selects the best combinations of sensors until a minimal subset that accurately predicts the required semantics is found.

Figure 2 represents significantly strong linear correlations between a sizeable portion of sensors and three of the semantics. Thus, we use linear regression for semantic prediction; however, our method can easily be implemented using almost any prediction model. For example, it could be postulated that a linear regression model is not best for guardedness prediction given the low correlation values per sensor

Algorithm 1 Sensor Selection

Input: S_1 = set of sensor configurations of size 1
Input: k = # of configurations retained between iterations
Input: G = pruned graph of sensor-semantic correlations as described in Section 4.1.2, $N_G(s)$ is the of set neighboring sensors to s in G

```
1:  i = 1
2:  while ε > threshold_error do
3:      i = i + 1
4:      T = GetGreedyRep(S_{i-1}, k)
5:      for 1 ≤ j ≤ k do
6:          for all sensors s, s ∉ T[j], s ∉ N_G(T[j]) do
7:              Append T[j] ∪ s to S_i
8:          end for
9:      end for
10:     S_i = SortByPredictionError(S_i)
11:     ε = GetPredictionError(S_i[0])
12: end while
```

Output: Top sensor configuration, $S_i[0]$

in Figure 2d. Interestingly, while no single sensor is an adequate predictor for guardedness using a linear model, after a couple iterations of sensor selection, guardedness prediction error drops drastically. This intuitive result derives from the fact that the guardedness metric is inherently derived from the measurements of at least two sensors.

The prediction error of sensors varies from metric to metric. Due to the very application-specific nature of these semantics, some are inherently harder to predict (change in step stride) while others are very well suited to the sensor and system design (amplitude). Because of these discrepancies, it can be very difficult to determine the relative prediction accuracy of a single sensor against two different metrics. We overcome this barrier by mapping the prediction error of a given sensor for a given metric to the cumulative distribution function of the prediction errors of all the sensors for that same metric. This binds the error to a normalized value that is relative to the rest of the system's prediction capabilities. Now, we are able to compare metric predictions and correctly rank our sensors by how well they predict each metric relative to one another. Our ranking function weights each metric equally, since ultimately we are most interested in designing a medical device that can provide the doctor with the most information. This functionality is embodied in the *SortByPredictionError* and *GetPredictionError* functions in lines 10 and 11 of Algorithm 1.

While sensor fusion and pruning help to reduce the search space, they still only do so nominally. The process of combining all previously considered sensor combinations with the set of remaining sensors at each iteration still grows exponentially. Thus, at each iteration, instead of looking at all possible sensor combinations, we only investigate combinations with the best k size subset of the previous iteration's results; for every set in the best k solutions from the previous iteration, we create $O(n)$ new sensor configurations. This reduces the original exponential problem formulation complexity to $O(kn^2)$.

It is important that the k-size best subset retained between two iterations contains both top predicting sensor sets as well as a representative distribution of the current solution space. This ensures that our selection process drives to

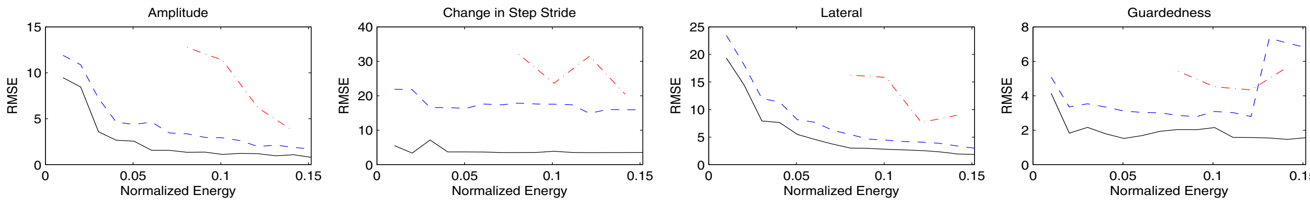


Figure 5: Coarse grained optimization. Root mean squared testing error in prediction using best selected sensors using only single sensors (dash), using sensor fusion (solid), and results from [2] (dash-dot). Units are *pressure* for amplitude and lateral, and *samples* for step stride and guardedness.

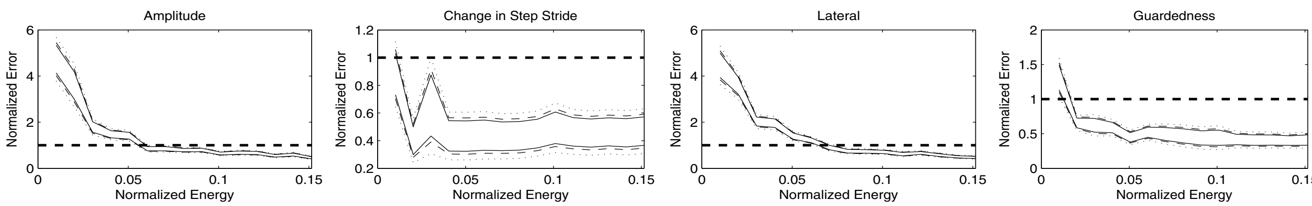


Figure 6: Coarse grained optimization using sensor fusion. Semantic prediction error as a percentage of desired error threshold (thick dashed); 90% confidence interval (solid), 95% (dashed), 99% (dotted). When the prediction error reduces to the threshold for all semantics, sensor selection is complete.

an optimal solution quickly while providing neighboring solutions that could potentially find other local minima. This is done through a greedy selection of the top $k/2$ configurations and an evenly distributed selection of $k/2$ configurations from those remaining. This functionality is embodied in the *GetGreedyRep* function in line 4 of Algorithm 1.

4.2 Fine Grained Optimization

While sensor selection is a crucial step for reducing the cost and complexity of wearable medical sensing systems, energy is ultimately spent mainly in sampling. Therefore, the sampling strategy is of utmost importance to energy optimization of any sensor network. We conduct subsampling post-selection, based on the following key observations: (i) during ambulation, the foot spends a majority of the time in the air and therefore applying no pressure to any sensors; (ii) a single sensor is sufficient to detect the start and end times of a step; and (iii) during a step, applied pressure follows multimodal behavior predictable from semantic information, as described in [2] and [18].

Based on the first two observations, we add a sensor that covers the entire sole and sample it at the full rate (50 Hz) solely to detect the start and end times of steps. Note that this sensor is large and therefore subject to a high signal-to-noise ratio, rendering it ineffective for predicting gait metrics. Without loss of accuracy, we can begin sampling all other selected sensors only when the foot lands, and stop sampling as soon as the foot leaves the ground.

We formulate the sampling reduction problem as a simple variation of our sensor selection algorithm presented in Algorithm 1. Again, this is an iterative process, but now, at iteration i, the k strongest predicting and representative sets of $n-i$ sensor-samples are returned, where a sensor-sample is a single sampling point of a single sensor, and n is the number of coarse grained selected sensors times the number of samples in the step. Therefore, we make the following modifications: S_i now represents a set of sensor-sample configurations at iteration i, s is a sensor-sample in question to be removed, and line 7 now reads, Append $T[j]-\{s\}$ to S_i. Note that by using this approach, each sensor can have a different sampling rate, as only one sample of one sensor is removed at each iteration. Furthermore, the same strategy for pruning can be applied as in sensor selection, with sensor nodes replaced by sensor-sample nodes.

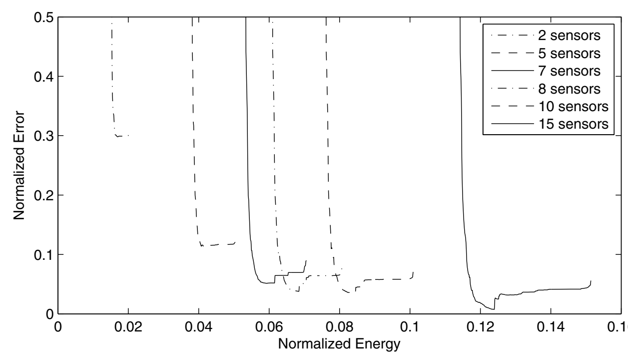


Figure 7: Fine grained optimization applied to the best configurations found in coarse optimization. Curves are constructed from right to left as sensor-samples are removed iteratively. The four semantic errors are normalized for equal comparison between semantics. Normalized energy is the fraction of energy expended on the new configuration over the original array of ninety-nine sensors sampled at 50 Hz.

5. RESULTS

5.1 Coarse Grained Optimization Results

We perform the semantics-driven sensor selection algorithm with pruning on individual sensors only, then incorporating sensor fusion, and compare both results to a traditional sensor selection technique that retains raw data predictability. In both Figures 4a and 4b the selected sensors are well distributed over the inside and outside of the foot, cover both the heel and the toe, and generally attempt to cover the highest correlated areas depicted in Figure 2.

Semantics-driven sensor selection clearly performs better than traditional selection (see Figure 5). For the same level of energy reduction, semantics-driven selection predicts a factor of 5.8 times and 1.6 times better than the traditional approach for the change in step stride and guardedness metrics, respectively. Analysis of the amplitude and lateral semantics shows that semantics-driven sensor selection provides a factor of about 4 times better energy reduction over traditional methods for a constant prediction error rate. Between semantics-driven selection using individual sensors and fused sensors, the latter provides much better prediction capabilities, and thus, greater energy gains.

Figure 6 shows that semantics-driven sensor selection reaches the desired error threshold by the seventh iteration, returning a factor of 14.1 in energy reduction over the original ninety-nine sensor system design. Recall that while the correlations between individual sensors and the guardedness metric are nearly non-existent (Figure 2d) the semantics-driven sensor selection process reduces the prediction error of this metric immediately in the second iteration, a testament to the semantics-driven procedure.

5.2 Fine Grained Optimization Results

We apply fine grained optimization to the best sensor configurations of size 2, 5, 7, 8, 10, and 15 sensors found in the coarse grained step. In all cases, fine grained optimization further reduces energy from the coarse grained solution by the equivalent of one to three sensors sampled at 50 Hz. For example, applying fine grained optimization to the 10 sensor solution reduces the energy consumed by the configuration to the equivalent of employing 8 sensors at 50 Hz (see intersection of 8 and 10 sensors in Figure 7).

As we reduce energy in Figure 7, prediction error dips slightly, but for the most part, remains relatively flat until those sensor-samples that are most crucial for semantic prediction are removed. This result is expected due to the predictable nature of the pressure signals, gait metrics, and physiological events, in general, as observed by [2] and [18].

As we reduce sensor-samples the prediction error initially decreases slightly. This is because in the initial iterations, the sensor-samples that are removed are those that actually impair the prediction model. Though as expected, eventually the iterative removal of sensor-samples begins to have a negative effect on prediction and the error rises sharply. At this point we stop the fine grained optimization process and present the final configuration.

While coarse grained optimization reduces the original array to seven best predicting sensors, applying fine grained optimization further reduces energy to 5.6% of the original sensor array, a factor of 17.9 overall improvement.

6. CONCLUSION

We have presented a novel approach for energy reduction in medical sensor networks using a semantics-driven approaches to sensor selection and subsampling. We leverage the key observations that the raw sensed data is unimportant, that only the metrics relevant to diagnosis are needed, and that the important metrics can be easily derived from the raw data. Consequently, our key contributions are as follows: (i) a bottom-up iterative approach to selection of a minimal set of best predicting sensors; (ii) a novel procedure for physically or electronically combining adjacent sensors to reduce sampling cost while improving prediction strength; and (iii) an extension of our sensor selection algorithm to minimize the sampling rate of individual sensors while maintaining accuracy. Our approach yields a cost reduction of 93%, and furthermore reduces energy by a factor of 17.9 over the original system configuration of ninety-nine sensors sampled at 50 Hz.

7. REFERENCES

[1] Novel.de, Pedar, 2007, http://www.novel.de/

[2] H. Noshadi et al., "Energy optimization in wireless medical systems using physiological behavior," *Wireless Health*, pp. 128-136, 2010.

[3] J. M. VanSwearingen et al., "The modified gait abnormality rating scale for recognizing the risk of recurrent falls in community-dwelling elderly adults," *Physical Therapy*, 1996.

[4] G. Anastasi et al., "Energy conservation in wireless sensor networks: A survey," *Ad Hoc Networks*, vol. 7, no. 3, pp. 537-568, 2009.

[5] V. Leonov, P. Fiorini, S. Sedky, T. Torfs, and C. Van Hoof, "Thermoelectric mems generators as a power supply for a body area network," *Solid-State Sensors, Actuators and Microsystems*, vol. 1, pp. 291-294, 2005.

[6] Y. Liu et al., "Critical-path based low-energy scheduling algorithms for body area network systems," *RTCSA*, pp. 301-308, 2007.

[7] S. Xiao et al., "Transmission power control in body area sensor networks for healthcare monitoring," *IEEE Communications Journal*, pp. 37-48, 2009.

[8] K. Lorincz et al., "Mercury: a wearable sensor network platform for high-fidelity motion analysis," *SenSys*, pp. 183-196, 2009.

[9] A. Krause et al., "Unsupervised, dynamic identification of physiological and activity context in wearable computing," *ISWC*, pp. 88-97, 2003.

[10] M. Rofouei, M. A. Ghodrat, M. Potkonjak, and A. Martinez-Nova, "Optimization Intensive Energy Harvesting," pp. 272-275, *DATE*, March 2012.

[11] S. Popovic et al., "A reliable gyroscope-based gait-phase detection sensor embedded in a shoe insole," *IEEE Sensors Journal*, vol. 4, no. 2, 2004.

[12] K. Oshima et al., "A human probe for measuring walkability," *SenSys*, pp. 353-354, 2009.

[13] V. Erickson, A. U. Kamthe, and A. E. Cerpa, "Measuring foot pronation using RFID sensor networks," *SenSys*, pp. 325-326, 2009.

[14] J. B. Wendt and M. Potkonjak, "Medical diagnostic-based sensor selection," *IEEE Sensors*, pp. 1507-1510, 2011.

[15] J. B. Wendt, S. Meguerdichian, H. Noshadi, and M. Potkonjak, "Energy and Cost Reduction in Localized Multisensory Systems through Application-Driven Compression," *DCC*, pp. 411, 2012.

[16] J. B. Wendt, S. Meguerdichian, and M. Potkonjak, "Small is Beautiful and Smart," to appear in *Tele-Healthcare Computing and Engineering: Principles and Design*, ed. by Fei Hu, Science Publishers, 2012.

[17] H. Noshadi et. al, "HERMES: Mobile balance and instability assessment system," *BioSignals*, 2010.

[18] S. Meguerdichian et al., "Semantic multimodal compression for wearable sensing systems," *IEEE Sensors*, pp. 1449-1453, 2010.