Tele-Healthcare Computing and Engineering: Principles and Design

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Contents

Chapter 1

Small is Beautiful and Smart

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1.1 Abstract

A medical shoe consists of an insole equipped with sensors of single or multiple modalities that collect information that is beneficial for diagnosis, tracking, therapy, and many other health care tasks. Numerous important applications related to a variety of muscular and neural diseases may benefit from widespread use of medical shoes. However, they currently use too many sensors that use too much energy. For example, a shoe with 100 sensors easily costs several thousands of dollars. We introduce an approach for radical reduction and cost and energy requirements while essentially fully preserving the accuracy required for medical applications. In order to accomplish the reduction of required sensors we use three main concepts. The first is that the use of low spatial resolution often greatly facilitates creation of effective and low cost medical shoes. The second is that we identify which measurements and their derivatives are required for medical application. The third is that we apply a combination of statistical and combinatorial optimization techniques for the minimization tasks. The new approach reduces the required number of sensors to only eight with a very minimal signal distortion.

1.2 Introduction

Remote monitoring and remote control in military, wildlife, and urban environments are just some of the practical applications that have been made possible by the emergence of wireless embedded sensor networks. More recently, these wireless sensor networks have enabled remote sensing and remote monitoring of the environment of the human body. These devices have been realized in applications ranging from heavy duty military suits to single sensor wireless health systems.

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 will be able to incorporate information gathered from the patient's day to day activities and routine into their professional medical diagnoses.

Unfortunately, due to the often complex design, expensive cost, and energy demands that can accompany such wireless sensor networks, 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.

The three major desiderata for any medical sensor-based system are low cost, low energy, and relevance to medical diagnosis and treatment. Cost is often proportional to the number of sensors, while energy is proportional to the number of sensors and sampling rate. Relevance is determined by the ability of the sensing network to accurately measure or predict those properties which aid the professional medical diagnosis.

In order to satisfy the first two desiderata we can simply reduce the number of sensors required by the system in order to reduce cost and energy demands. However, it is crucial that such decisions be made with the third desideratum in mind, that the device remains relevant to the application. In Section 1.5.1, we describe our sensor placement algorithms, including: sensor selection, which iteratively adds sensors that most improve prediction accuracy of gait metrics; adjacent sensor combination, where sensors are physically or electronically combined and the average of their sensed pressures is sampled as one sensor; and search space pruning for runtime reduction and increased accuracy.

In addition to minimizing the size of the array while maintaining relevance, energy consumption can be lessened further by reducing the sampling rate of those remaining sensors. By separating the data into steps (distinct physiological events) and observing that most sensors need only be sampled within the context of a step, we extend our algorithms for sensor selection to sensor-sample removal. In this phase, described in Section 1.5.2, samples within a step are iteratively removed while maintaining accuracy of gait metric prediction for each step. The sampling intervals for each sensor, then, are defined from the time a step begins (the foot lands), triggered by a single sensor covering the entire foot and sensing at the full sampling rate.

It is important to note that our approach is orthogonal to traditional data compression methods, which can be applied to locally computed diagnostic metrics to further reduce total transmission energy.

1.3 Related Work

1.3.1 Wireless Sensing

The emergence of embedded sensor networking has introduced new scientific and engineering challenges [2] [3] [4] [5] [6] [7] [8]. 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 [9] [10]. Current energy optimization methods focus on hardware design, signal processing, and sensor selection [11] [12] [13] [14] [15].

An important problem addressed in literature is the sensor coverage problem [16] [17] [18] [19] [20] [21]. Sensors are placed and selected in such a way as to fully observe the physical space while minimizing the number of sensors, sensor usage, or energy expenditure. This is especially important in ad-hoc wireless networks in which the location of sensors may not be known *a priori* and local coverage may vary from node to node. This problem may also require ad-hoc sensor nodes to remain active in order maintain network connectivity. Energy-efficient solutions to the coverage and connectivity problem in wireless sensor networks are explored in [22] and [23]. Fan et al. present a simple and fast deterministic solution to the area coverage problem by determining whether all points in a region are covered by a given set of sensors [24]. This is accomplished by transforming the problem into an intersection points coverage problem which is simpler and more suitable for evaluation. Additionally, their solution handles sensors which may even have an arbitrary sensing shape.

Low power and low energy consumption are highly sought after characteristics in sensor nodes. In addition to choosing low power sensing and communicating devices, energy conservation techniques are also employed [25] [26]. Anastasi et al. present a survey on such energy conservation techniques, categorizing them into three main approaches: duty-cycling, data-driven conservation schemes, and mobility-based management [27].

Duty-cycling is achieved through two orthogonal approaches; location-based and connectivity-driven protocols. These approaches often attempt to exploit node redundancy to adaptively select a minimum subset of nodes to remain active, much like the sensor coverage problem. The location-based approach in duty-cycling defines which node to turn on based on the known location of the node. The connectivity-driven protocol will dynamically activate and deactivate sensor nodes while retaining network connectivity and/or coverage.

Span [28] and ASCENT [29] are connectivity-driven techniques that reduce energy consumption without significantly diminishing the capacity or connectivity of the network. Both are based on the principle that if a network has a sufficient clustering of nodes, only a subset of nodes need to be turned on at any one particular time. Each node makes a local decision on whether to sleep or join the network and does so through local prediction and estimation of how many neighbors will benefit from it being awake and consuming energy.

While duty-cycling schemes help to save energy through the physical turning on and off of sensor nodes, they are typically oblivious to the data being sampled at each node. Thus, data-driven approaches are employed to further improve the energy efficiency through data reduction (such as in-network processing, data compression, or data prediction) and energy-efficient data acquisition (such as subsampling) [27].

The Ken technique [30] uses replicated dynamic probabilistic models to minimize communication from sensor nodes to the network base station. This stochastic approach also takes advantage of spatial correlations across nodes. Building on spatio-temporal correlations between data, temporal analysis of sensed data is used to reduce energy in [31]. This approach dynamically estimates the optimal sampling rate at each node using change detection techniques. Purely spatial correlation is also used to sample nodes that are more densely packed in different sampling schemes [32].

Among the data-driven approaches for sensor networks, compression is one of the most researched techniques. Approximately 80% of power consumed by a sensor node is in data transmission, therefore, reducing the amount of data to be transmitted also reduces the total power consumption and energy expenditure. Kimura et al. present a comprehensive survey on data compression techniques in wireless sensor networks including in-network compression, ordering techniques, and low-complexity video and image compression [33].

Coding by ordering is a data compression scheme that moves data from sensor nodes in an interested region to an aggregating node which then funnels that data to the network backbone or central unit [34]. At the aggregation node, some data packets are dropped, however their information is not lost. The dropped data is retained within the ordering of packets and can later be inferred at the receiving node. Using this scheme with 128 nodes, 16 possible data values, and 100 nodes sending packets to an aggregation node, approximately 44% of data packets can be dropped without losing any information.

Other compression schemes involve aggregating data over long periods of time, thus capitalizing on the energy savings gained using low data rates [35]. Each individual node's data packet is combined with others of similar measured valued using a *shared prefix* header and a *suffix list*. The shared prefix holds the higher order bits of a set of nodes' measurements while the suffix list contains the lower order bits. If the measured values between nodes are expected to be close, the length of the prefix value can be set relatively long and gain more savings by reducing the total number of delivered packets. An advantage of this simple compression scheme is that the shared prefix technique can be used not only for measured values, but also for node IDs, timestamps, and geo-location data. However, the efficiency of this data compression technique depends directly on the length of the shared prefix, how close data measurements are between nodes.

A more rudimentary method of data and energy reduction as well as cost reduction is through sensor selection. The sensor selection problem has arisen in various applications including robotics, target tracking, and wireless networks. Techniques for sensor selection seek to remove sensors (or sensor-samples) from a set of potential sensors in order to physically decrease the number of sensors (or to decrease the duty rate of the existing sensors) in order to lessen energy usage and cost while maintaining high sensor array measurement accuracy and precision.

Joshi et al. perform sensor selection using a convex optimization technique [36]. They solve the problem of choosing a set of sensor measurements from a set of possible or potential sensor measurements that minimizes the error in estimating their parameters. Due to the exponential number of combinations of sensor measurements, they present a heuristic approach based on convex optimization for solving the sensor-sample selection problem approximately.

While Joshi et al. focus on sensor-sample selection, Noshadi et al. focus on pure sensor selection while maintaining full sensor array predictability [37]. In this technique, sets of sensors that are highly correlated are physically removed from the array, leaving behind a small subset that can accurately predict those removed. This scheme ultimately saves energy and cost by eliminating redundant sensors. However, this technique is limited to reducing the array while maintaining raw data prediction. In the context of medical sensing devices, raw data prediction is not necessary, but rather prediction of metrics relevant to medical diagnosis is what is most desired.

1.3.2 Medical Sensing

The recent attention in wireless sensing networks and wearable sensing systems has fostered a growing interest in medical-based sensing devices [38] [39] [40]. Tele-healthcare has significantly broadened its scope over the last few years due to the support it offers health professionals in the early detection, diagnosis, and prevention of diseases, as well as disease management, treatment, and at-home rehabilitation.

Tele-healthcare solutions expand the range of patient health data from in-office and hospital check-ups to non-invasive comprehensive patient monitoring during their day to day routines. Existing commercial systems including hearing aids, cochlear implants, heart pacemakers, and blood pressure sensors represented a total revenue of $5.2 billion in 2002 [41]. Today, tele-healthcare systems are becoming more complex [42] [43] [44]. Similar to research in other wireless sensing systems, current attention in the tele-healthcare domain focuses on the utility and convenience of such systems as well as their cost and energy demands [39] [45] [46] [47] [48]. The private nature of medical data also requires that these medical sensing solutions are secure. Current trusted remote sensing schemes are a solution for such embedded devices [49] [50].

1.4 Preliminaries

1.4.1 The Hermes Shoe Platform

We perform our sensor selection technique and subsampling procedure on the Hermes shoe platform [44], a wireless wearable sensing system comprised of a large multisensory array. This platform is designed with the purpose of assessing balance and instability in patients through the measurements of 99 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 60 Hz, and data is collected using a 16-bit analog-to-digital converter.

1.4.2 Gait Characteristics

VanSwearingen et al. conclude that gait characteristics such as step stride, change in step stride, maximum pressure, lateral pressure, and guardedness (time between heel and toe landing) correlate to a number of ailments and diseases in the elderly and directly contribute to the prediction of risk of falling in this population [51]. This strong correlation between gait and risk is a powerful means to help medical professionals diagnose these ailments with the availability of such gait metrics.

Investigations have been made into the application of gait analysis in wearable sensing systems such as sensor-equipped shoes [46] [47] [48]. Prior research has also leveraged gait analysis directly in design-time sensor selection for cost reduction and energy optimization [52]; however, this research is limited to analysis of same size sensors.

1.4.3 Data

The data consists of time-dependent pressure measurements taken over thousands of steps using five human subjects. We normalize this data and extract the aforementioned gait characteristics measured collectively by all 99 sensors as well as measured by the individual sensors independently of one another. 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 function. We separate our data into a training subset that consists of 80% of the raw data and metrics and a testing subset consisting of the remaining 20%.

1.4.4 Metric Prediction

Traditional approaches to sensor reduction in multisensory systems remove redundant sensors from the original array while maintaining full sensor predictability [37]. However, in application specific devices, such as in medical sensing, sensor predictability (i.e. raw data prediction) is not necessary. The essential information that the device is intended to measure is the application-specific metrics themselves (e.g. gait characteristics in medical shoes). Thus, it is only necessary that prediction accuracy of these metrics is maintained during sensor selection and subsampling. It is also often the case that the information relevant to the application domain is easily derived from the raw data and can hence be computed with minimal energy overhead on the mobile device.

Ultimately, the pressure measurements recorded by the Hermes platform are unimportant for medical diagnoses. Rather, only the balance and instability metrics that are easily computed from these pressure measurements need be recorded. Our sensor selection and subsampling techniques capitalize on these properties. Thus our procedure is best applied to those applications with the following characteristics:

- The important metrics can be easily derived from the raw sensed data
- The raw data is ultimately unimportant
- Measurement of important metrics utilizes a multisensory array[1]

1.5 Cost and Energy Optimization

We minimize the energy demands and expense of medical wearable sensing devices by accomplishing the following tasks: (i) reducing the sensor array through a bottom-up sensor selection process that retains metric prediction accuracy and precision; (ii) physically or electronically combining adjacent sensors to decrease the energy lost to excessive sampling at the cost of reducing localized resolution; and (iii) subsampling individual sensors in the reduced array at significantly lower frequencies while maintaining metric prediction accuracy and precision.

[1]This characteristic is not necessary for our sub-sampling technique.

1.5.1 Sensor Placement

Sensor Selection

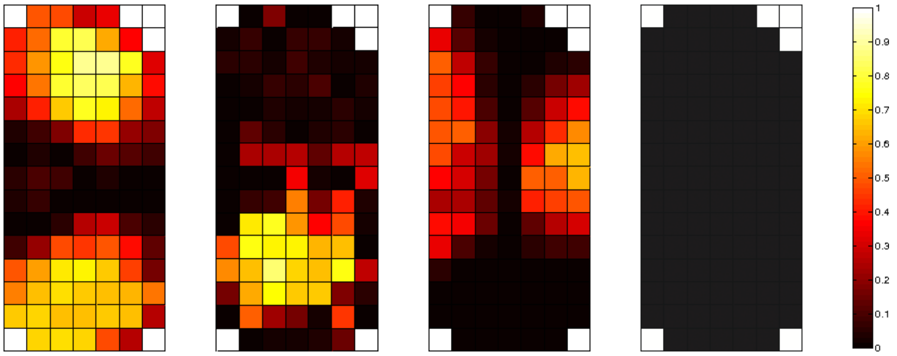
A key observation in Figures 1.1 and 1.2 is that while clear correlations might exist between the measurements of a few individual sensors and the metrics individually, between each set of four figures it is not immediately apparent which subset of sensors can predict all metrics simultaneously well. We also recognize that there is a distinct discrepancy in the coefficients of determination between those measurements for a single subject and those of a group of subjects. Therefore, we can customize our sensor selection for a single individual or generalize the design for a wider population, while in each case retaining prediction accuracy and precision; of course, we observe less error in the individually customized design.

Algorithm 1 Single iteration of sensor selection (without pruning)

```
Input: S_i, 1 ≤ i ≤ K
For 1 ≤ i ≤ K
    For all sensors s not in S_i:
        Create set T_j = S_i ∪ s
        Compute error for prediction of relevant metrics by sensor set T_j
Rank T_j ∀j by prediction error, ascending
Output: T_j, 1 ≤ j ≤ K
```

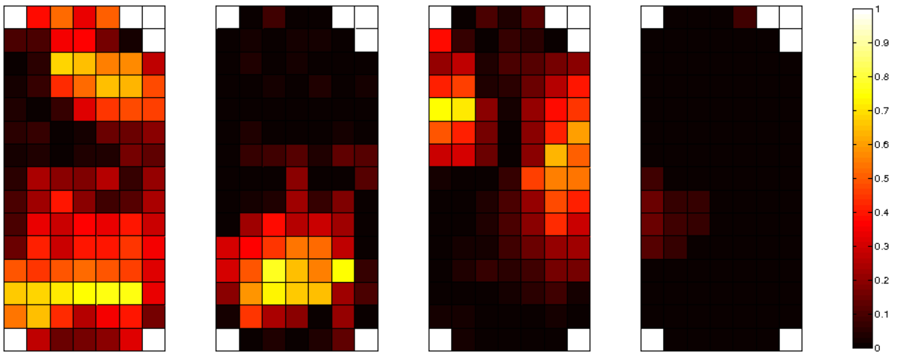
In sensor selection, we perform this very task of systematically selecting the best groupings of sensors until we find a minimal subset that accurately predicts the given metrics. Sensor selection is an iterative process; at iteration i, the K strongest-predicting sets of i sensors are returned. Each iteration proceeds as described in Algorithm 1.

The prediction error of some of these sensors can vary from metric to metric. In fact, due to the very application-specific nature of these metrics, some are inherently hard to measure (such as change in step stride), while others are very well suited to the sensor design (such as maximum average 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 prediction error to a normalized value, relative to the rest of the sensor 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.



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

Figure 1.1: Individual sensor coefficient of determination for (a) average maximum step amplitude, (b) change in step stride, (c) lateral pressure difference, and (d) guardedness. The correlations are constructed from samples of the left and right feet from a single subject. The lighter the sensor, the more correlated it is to the metric.



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

Figure 1.2: Equivalent to Figure 1.1, constructed from both feet from all test subjects.

Sensor Combination

To further optimize cost and energy reduction, we add a new dimension to our approach that enables adjacent sensors to be physically or electronically combined with one another to create a single, larger sensor that measures an average pressure over the new area. Unfortunately, there are 2^{99} possible sensor combinations. Coupling the number of sensor combinations with the number of sensors that can be chosen in selection creates an exponentially

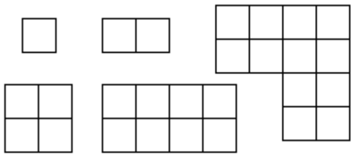


Figure 1.3: All rotations of the sensor combinations are pre-computed and applied across the Pedar shoe mapping prior to training.

large search space.

Therefore, we use application specific knowledge to pre-construct a number of sensor combinations. The correlations of determination for the metrics reveal that some spaces of high correlation are square, rectangular, and L-shaped. From the existing 99 sensors, we construct five new shapes depicted in Figure 1.3, effectively adding 544 abstract sensors to the list of sensors from which to perform sensor selection. We ensure during sensor selection that no two selected sensor combinations overlap one another.

Pruning

With 643 sensors, both real and abstract, and each sensor being considered as an addition to K sensor sets at each iteration (Algorithm 1), sensor selection can be 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. Our key observation is that if two sensors give similar predictions for each metric, then there is likely no benefit in having them in the same predictive set.

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. Therefore, we augment line 3 of Algorithm 1 to read: For all sensors s not in S_i and not having edges to any sensor in S_i.

1.5.2 Sampling

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 [37] [53].

Based on the first two observations, we add a sensor that covers the entire insole and sample it at the full rate (60 Hz) solely to detect the start and end times of steps. Note that this sensor is large and subsequently subject to a high signal-to-noise ratio, and therefore is not effective 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 can formulate the subsampling 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 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 selected sensors times the number of samples in the largest step. Therefore, the only modification is in line 4, which now reads: Create set $T_j = S_i - \{s\}$, where S_i is a top predictive sensor-sample set and s is the sensor-sample being removed. Note that in this approach, each sensor can have a different sampling rate since only one sample of one sensor is removed at each iteration. Furthermore, the same strategy for pruning, as described for sensor selection in Section 1.5.1 above, can be applied for sampling, with nodes replaced by sensor-samples.

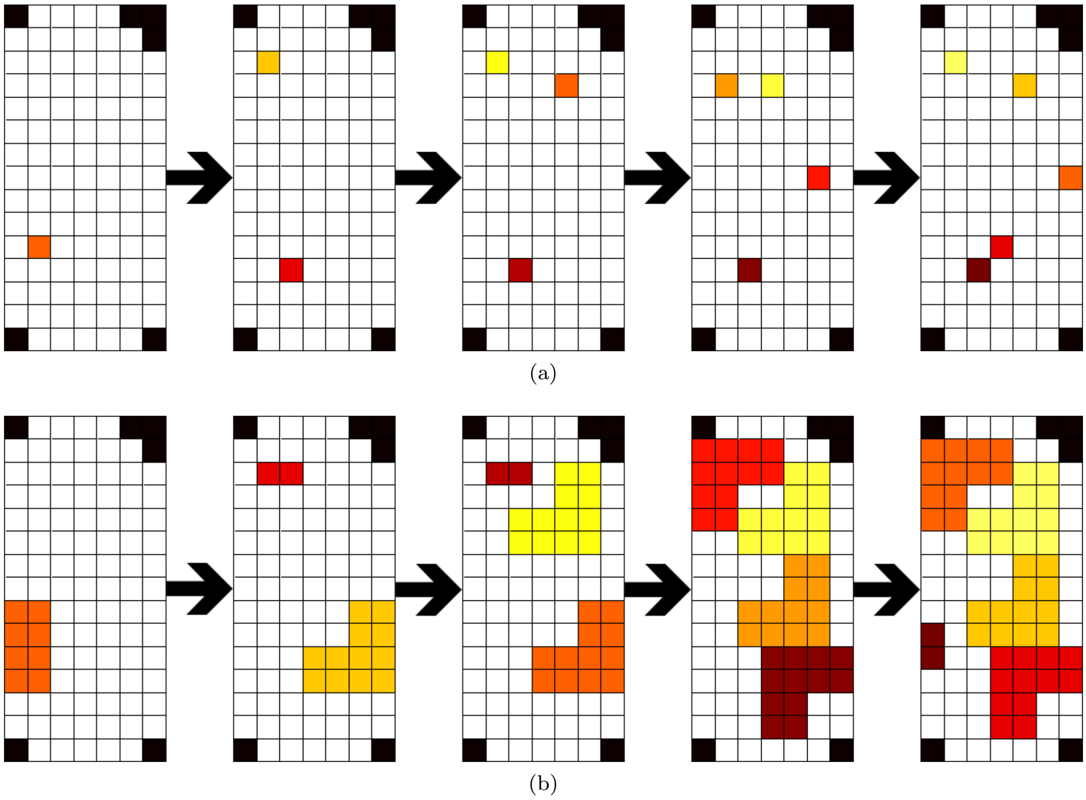


Figure 1.4: Top sensor configurations at iterations 1 through 5 for a single subject, trained on both feet. (a) The solution that limits sensor selection to individual sensors. (b) The solution that includes sensor combinations.

1.6 Results

1.6.1 Selected Sensors

We perform our sensor selection algorithm on individual sensors only, then include sensor combinations, and compare our results to traditional sensor selection that maintains sensor predictability [37]. While selection of individual sensors performs better than traditional selection, the best sensor configurations include sensor combinations. In three of the metrics we see significant improvement over the results of traditional sensor selection. Figure 1.5 shows that we can reduce cost and energy consumption by 97%, 93%, or 90%, while maintaining error corresponding to selecting 3, 6, or 9 sensors, respectively.

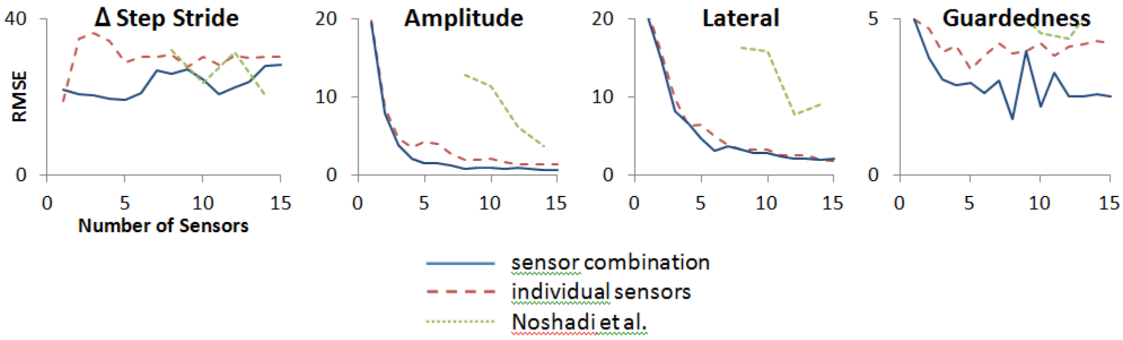


Figure 1.5: Testing error for solutions to single sensors, sensor combinations, and results from [37].

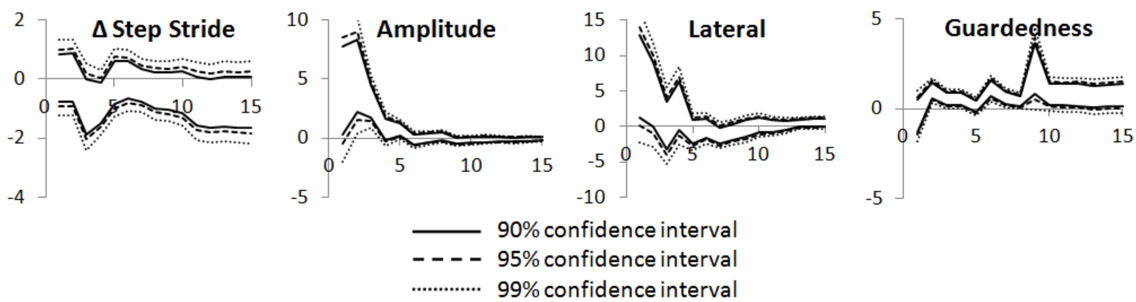


Figure 1.6: Confidence intervals for the gait metrics. The horizontal axis is the number of sensors used in prediction and the vertical axis is the root mean squared error of those predictions.

1.6.2 Prediction Confidence

As the number of sensors increases during sensor selection, the confidence interval of the average maximum amplitude and lateral difference predictions tend toward higher accuracy and higher precision. On the other hand, the change in step stride and guardedness metrics are harder to train for, due in part to the low variance of the actual metric values and high variance of the individual sensor values. This may be motivation to apply non-linear models to such metrics to better model the relationship between the individual sensor measurements and the overall metrics.

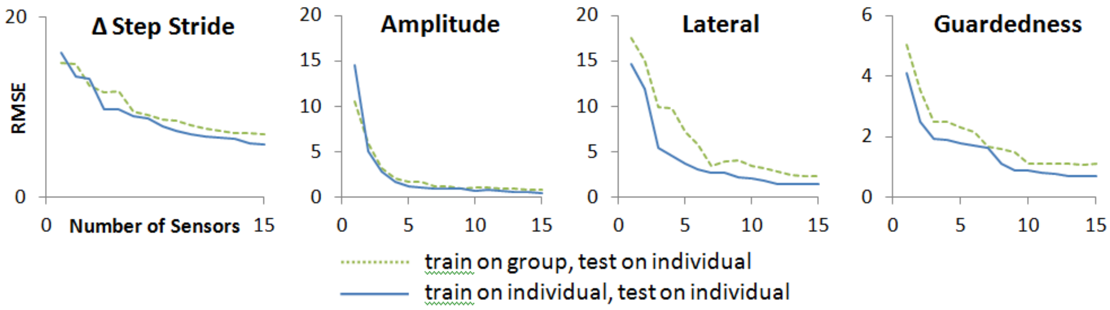


Figure 1.7: Testing error for customized (solid line) and general (dotted line) sensor selection.

1.6.3 Customization

Our sensor selection methodology not only works for the general case, but can also be used for more personal customization. The generic shoe, in which we do sensor selection based on the data of many subjects, has low error, but with customization (i.e. sensor selection based on the data of a single subject), we are able to reduce that error even further. Figure 1.7 shows the general trend that customized sensor selection produces lower error than general sensor selection. Likewise, customization can also be applied to the left and right feet so that if increased accuracy is required over each foot, then a customized low energy, low cost shoe for each foot can also be designed.

1.6.4 Sampling

Figure 1.8 shows the effect of removing sensor-samples on prediction error of the gait metrics for 8 selected sensors. We see that out of a total of 1656 sensor-samples in a given step the error does not begin to increase until 94% of sensor-samples 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 [37] [53].

Assuming that we add one sensor, as described in Section 1.5.2, that is sampled at the full sampling rate, using our subsampling approach we can reduce energy consumption by 83% in addition to the savings gained by sensor selection without increasing error. Note that by increasing our error threshold we can further increase our energy saving.

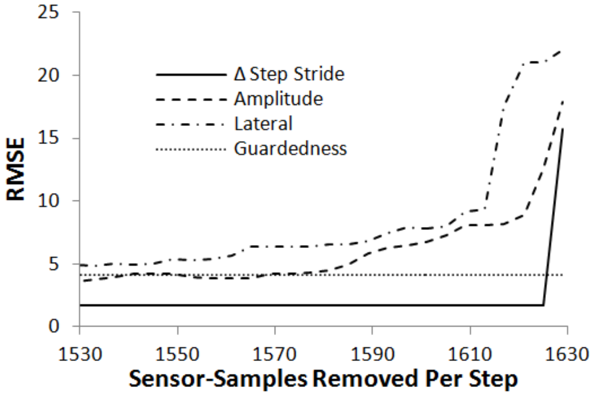


Figure 1.8: Using 8 sensors selected using our algorithm, the graph depicts accuracy lost for the energy gained through subsampling.

1.7 Conclusion

We have presented a novel approach for cost and energy reduction in localized multisensory systems for medical diagnostics through application-driven 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 92% and an energy reduction of 98.6% over the original system design.

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