Energy Saving using Scenario based Sensor Selection on Medical Shoes

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***Abstract*—Cost and energy have become the bottleneck of many medical embedded systems. It is mainly due to the fact that wireless medical devices used in wireless health applications normally employ a large number of sensors, which are both expensive as well as consuming a considerable amount of energy. In this paper, we have developed a cost and energy saving scheme by reducing the number of required sensors in the medical devices. We have used a popular medical shoe with 99 pressure sensors for demonstration. With the goal of reducing the number of required sensors without influencing the diagnose accuracy, we have proposed algorithms to select only a small subset of the sensors while still maintaining an almost same diagnostic performance compared to using all the 99 sensors. Our results indicate that on average, our sensor selection can save as much as 88% of the total sensors. We also analyze the effect of using the medical shoes under different scenarios on the results of sensor selection. For example, we have analyzed the scenarios of walking, jumping, running and slow walking. Based on our sensor selection algorithm, it turns out that there exists different subsets of sensors to best recover the diagnostic performances for different scenarios.**

I. Introduction

The growing prospective of wireless sensor networks have imposed new and practical healthcare applications. More recently, the remote sensing and remote monitoring of wireless sensor networks on human bodies have enabled novel types of medical applications, among which the most successful one is remote medical diagnosis. These wearable sensor systems allow doctors to eliminate the constraint that they must rely on in-person patient checkups in order to diagnose patient illness. Using the sensor systems on patient bodies, the doctors are able to remotely collect and analyze the patients' health data from sensors on a regular basis.

However, such wearable sensor systems are both costly as well as energy consuming, which directly prevents them from being widespread use in real life. On one hand, the sensor systems usually employ large number of sensors in order to collect enough and accurate information. For example, a commercial medical shoe designed by Hermes [1] consists as many as 99 pressure sensors, which leads the cost of a shoe to be more than a thousand dollars. On the other hand, the large number of sensors also requires a large amount of energy to collect and to transfer the data, which by nature is contradict to the properties of wireless sensor networks. For example, due to the mobility and the restricted battery life, the applications on wireless sensor network must be lightweight in terms of both energy and bandwidth.

To leverage the problem of high cost and high energy in medical sensor networks, we have proposed a new approach of sensor selection on the platform of medical shoe. Our goal is to select a subset of sensors in the sensors networks in such a way that the new set of sensors can still keep a same diagnostic performance compared to using all the sensors. The intuition is that the patients/doctors will not care about how many sensors are used for diagnose as long as the number of sensors is enough to offer an accurate diagnostic performance. Therefore, we optimize the number of required sensors within the restriction that the diagnostic performance should never be changed.

We evaluate our sensor selection algorithm on the Hermes shoe platform, which is designed to assess balance and instability in patients [1]. It consists of 99 pressure sensors distributed in each insole and integrated with a common computing platform. The special features of a person's gait which are highly correlated to his/her risk of falling as shown by Maki [2] are used for diagnose metric. However, an important issue in sensor selection of medical shoe is that the selection result highly depends on the scenario of using the medical shoe. For example, when a patient is walking, the selected subset of sensors will be different from the subset of sensors selected when running. It is due to the fact that the frequency and the focus of sensors touching ground are different under different scenarios. Thus the doctors need to focus on a different set of sensors to retrieve an accurate diagnose. To solve this, we apply our sensor selection algorithm under various scenarios including walking, running, jumping, and slow walking, then we summarize to compare the sensor selection results for different scenarios.

To summarize the contribution of our paper: 1) we have proposed a novel approach of sensor selection to reduce the cost and energy of medical sensor networks, more specifically, a medical shoe with pressure sensors. Instead of purely focusing on maintaining full predictability of the original sensor array while reducing the sensor count, our sensor selection algorithm targets at keeping a consistent diagnostic performance while reducing the number of sensors. Our approach is more high level and touches the essence and purpose of sensor selection. 2) Wendt et al. have proposed a similar approach for sensor selection which is defined by them "semantic driven" sensor selection [3]. We are one step forward compared to their

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work since we further consider the sensor selection under different scenarios. We analyze and compare the difference in sensor selection when patients are under different activities. Besides, we have also proposed our algorithm for scenario identification.

II. Implementation Procedure

Our procedure of implementation is shown in Figure 1. The first step is scenario identification where the goal is to identify the current scenario using the readings of pressure sensors. To achieve this goal, on one hand, we have designed an algorithm to identify the scenarios with sensor readings, on the other hand, we have also proposed to only use a subset of sensors (subset A) for the purpose of identification to save the required number of sensors. The second step is to apply sensor selection on different scenarios for the purpose of diagnose. The diagnose is based on the standard gait characteristics of patients. The key idea is that for an individual scenario i, only a subset of sensors (subset B_i) is needed to accurately calculate the gait characteristics.

To summarize the above steps, in a real use case, as long as the user starts using the medical shoe, subset A of sensors are used to identify the scenario. After the identification, subset B_i is applied to diagnose the user based on the identified scenario i. The energy saving comes from the fact that sensors will be dynamically turned on/off for different scenarios/individuals, which means that at one time point, only a subset of sensors need to be activated while all the rest sensors are turned off. If we assume that each sensor consumes the same power, then the ratio of energy saving equals to the ratio of number of sensors saving. Consider that the users will dynamically switch the scenario when wearing the shoe, the process of scenario identification should be regularly repeated.

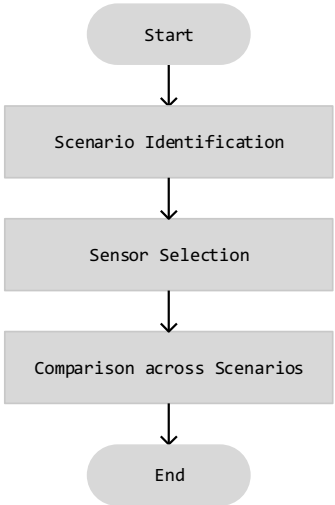


Fig. 1: The procedures of implementation.

III. Related Work

The rapid growth of wireless medical devices and corresponding techniques have attracted a great deal of research attention. Many efforts have been emphasized on reducing cost and energy consumption on medical devices. Among them, there are two most popular approaches. The first approach is sensor selection which targets at reducing the number of required sensors as well as energy consumption. The second approach is lightweight hardware design which employs low-energy hardware structure on medical devices [4][5][6].

Investigations have also been made into the application of gait analysis in wearable sensing systems such as sensor-equipped medical shoes. In terms of gait analysis, the efforts have been made along the line of diagnosing the risk of falling using sensor pressure of each gait [7]. Besides this, most of the work on the gait analysis for energy optimization are preliminary and target to predict other sensor pressures using a limited number of sensor subsets [8]. More recently, Wendt et al. and Yan et al. have proposed semantic driven sensor selection on the medical shoes to reduce energy consumption [3][9][10].

In terms of scenario identification, Parkka et al. have proposed to use real data from wearable sensors to classify activities [11]. Noshadi et al. have further done the work along the line of using unsupervised learning for activities identification [12].

IV. Preliminaries

A. Medical Shoe

We evaluate our sensor selection scheme on the Hermes medical shoe platform which consists of 99 pressure sensors distributed on the bottom of the show. The shoe also has a processing unit, a flash memory, a radio, and an analog-to-digital converter (ADC). The processing unit samples data from these pressure sensors at 50 Hz using a 16-bit ADC.

B. Data Set

The data is collected using the pressure sensors of the medical shoes when worn by volunteers. For each individual volunteer, our tested dataset includes pressure readings over all the 99 sensors for each shoe sampled at 50hz. The process of data sampling lasts for 5 minutes which results in 15000 pressure values for each pressure sensor. The pressure readings are collected for four different scenarios namely walk, jump, run, and slow walk. For each time point in those scenarios (at the frequency of 50hz), the readings of all the 99 sensors are recorded. The resulting time-dependent pressure mappings are used to calculate the below mentioned gait characteristics from the full dataset.

C. Gait Characteristics

In most cases, a doctor is not concerned with the raw measurement of the sensors, but rather, more concerned with the medical information derived from those data. Many potential diseases can be diagnosed using the pressure sensors on the

medical shoe, in this paper, we focus on the diagnose of predicting the risk of falling.

VanSwearingen et al. [7] have observed the gait characteristics of a patient highly correlates to a number of ailments and diseases in the elderly and directly contribute to the prediction of risk of falling in this population. Maki [2] has proposed that it is actually the variability in the gait characteristics has a strong correlation with the risk of falling. For a healthy person, the gait characteristics should be consistent with one another, however, if a person has the risk of falling, he/she will behave in a much more inconsistent way, only to best keep the body balance. In this paper, we take into consideration the gait characteristics as the metrics. For example, we use maximum pressure, stride period, guardedness (pressure difference between toes and heels), and lateral pressure difference to help in predicting the danger of falling. Table I shows the definition of all 4 characteristics we consider in this paper. We take the following parts to explain how we retrieve the above 4 characteristics using the sensor pressure data.

Maximum pressure	The variation of maximum pressure for each step
Stride period	The variation of time period spend on each step
Guardedness	The variation of pressure difference between toes and heels on each step
Lateral Difference	The variation of pressure difference between left side foot and right side foot on each step

TABLE I: The definition of 4 gait characteristics metrics.

Maximum pressure consistency is taken into account by computing the average of differences between the maximum pressure of two consecutive steps. If the patient is not able to walk with consistency, the maximum pressure of each step will change a lot. That means the patients are normally at higher risk of falling. Hence higher the variation; higher is the instability. In order to calculate the maximum pressure of each step with the help of our dataset, we generate the waveform of the total pressure of a patient's left foot within 600 time slots when walking as shown in Figure 2. The peak with the highest pressure in this waveform represents the moment of maximum pressure of each step. We measure the variation between all the maximum pressures and use it as the metric of maximum pressure.

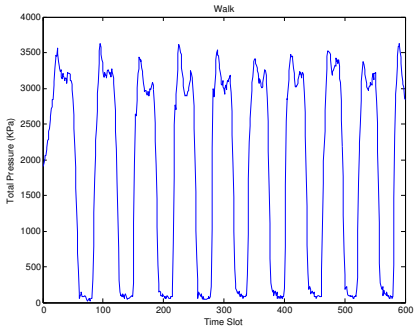


Fig. 2: The waveform of total pressure of a shoe in walking.

Note that all of the above metrics focus on the variation of the data. This is due to the fact that different patients have different style of moving, but regardless of the style, consistency is always crucial to guarantee that the patient can keep his/her balance. Combining the above 4 metrics, the overall instability of a patient can be calculated using Equation 1. In the equation, each $Metric_i$ takes a partial weight w_i, where each w_i serves as two major functions. The first is to decide the importance of each individual metric. The detail weight can be adjusted by the doctor or customized based on the condition of a patient. The second function is to normalize between different metrics. For example, the metric maximum pressure is calculating the variation of pressure difference while the metric stride period is calculating the variation of time difference. By properly assigning the weight w_i, all the four metrics can be normalized to a same scale, e.g., 0-1.

$$Instability = \sum_{i=1}^{4} w_i * Metric_i \tag{1}$$

D. Scenarios

We consider four scenarios in this paper, respectively walking, running, jumping, and slow walking. We have tested the sensor pressures of the four scenarios separately. In Figure 2, Figure 3, Figure 4, and Figure 5, we show the total pressure of a shoe over 800 time slots in the four scenarios. We can clearly see that they have totally different pressure distribution both horizontally and vertically. Starting from the next section, we will first propose our algorithm of sensor selection, then based on the algorithm, we will test and compare the sensor selection results of the 4 scenarios respectively.

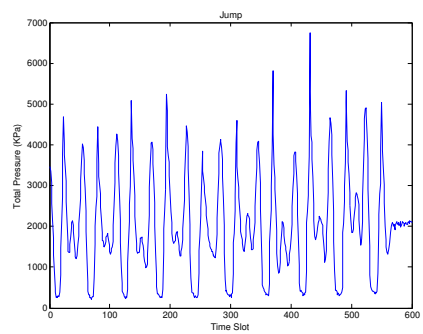


Fig. 3: The waveform of total pressure of a shoe in jumping.

V. Scenario Identification

In this section, we explain our algorithm for scenario identification. The key idea is to use only a subset of sensors to first identify the current scenario, then in the next step to apply scenario specified sensor selection. In the process of identification, our key idea is to split 80% of the data as training and 20% of the data as testing. Using the training data, we extract the features of each scenario, then use the testing data to find a subset of sensors that can best correlate to the features of each scenario. For example, we identify

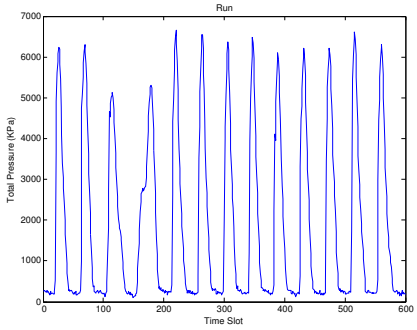


Fig. 4: The waveform of total pressure of a shoe in running.

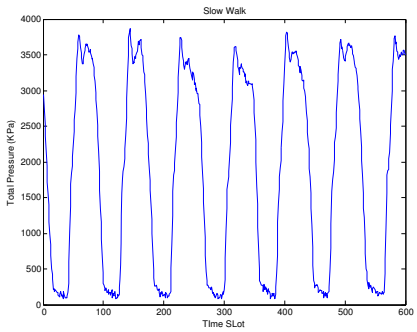


Fig. 5: The waveform of total pressure of a shoe in slow walking.

the following features for each scenario, maximum pressure, derivative of pressure change, period of stride, and number of peeks per step. Algorithm 1 shows the flow of scenario identification. The key idea is to iteratively increase the size of sensor subset that used for scenario identification until the test error is smaller than the threshold error.

Algorithm 1 Scenario Identification

Input: S-overall set of sensors.
Input: S_0-set of sensors being used for scenario identification.

```
while testerror≥thresholderror
    for all sensors s_i in S − S_0
        if Identifytesterror(s_i + S_0) is the smallest
            S_0.append(s_i)
            break
        end if
    end for
end while
```

Output: S_0

Our results have indicated surprisingly high correlation between the pressure of a single sensor with the total pressure of the 99 sensors. For example, as shown in Figure 6, we find and plot the pressure of a single sensor which provides the smallest test error and find that its waveform is highly correlated to the waveform of the total pressure of 99 sensors in the scenario of running.

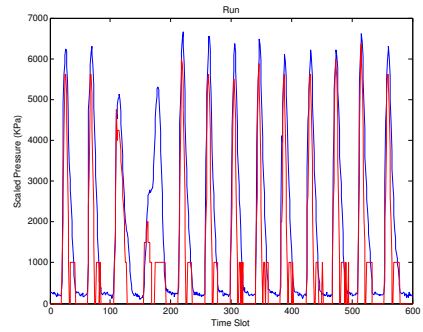


Fig. 6: The scaled pressure distribution of a single sensor (in red) compared with the total pressure distribution (in blue) in the scenario of running.

VI. Sensor Selection

A. Goals and Challenges

The major goal of sensor selection is to save both cost and energy by reducing the number of sensors used in the medical shoe. In terms of cost, it is directly proportional to the number of pressure sensors used in the shoes. In terms of energy, the saving comes from both reducing the number of sensors as well as reducing the energy spent transferring the sensor data. However, the largest challenge in sensor selection is to select a subset of sensors in such a way that the diagnostic performances will not change. For example, in the medical shoe, the diagnostic performance corresponds to the "instability" value of a person. Therefore, we convert the problem into an optimization problem where the goal is to minimize the number of sensors and the constrain is to always maintain a same diagnostic performance.

Another challenge is due to the fact that different metrics have different sensor selection results. For example, the metric of guardedness requires to use sensors that best correlate to the pressure difference between toes and heels. Therefore, the best sensors to select will be the ones near heels or toes. However, the metric of lateral difference focuses on the pressure difference between left side and right side of a foot, thus the best sensors to choose will be the ones on both sides of shoes. Comparing the above two metrics, it is obvious that different metrics require very different subset of sensors depending on the focus of the metrics. Our solution to this is to union each subset of sensors for individual metrics to generate an overall subset S as shown in Equation 2.

$$S = \sum_{i=1}^{4} S_{metric-i} \tag{2}$$

In the following parts, we propose two sensor selection algorithms from two different angles, respectively iterative selection and probabilistic selection .

B. Iterative Selection

The basic idea of iterative selection is to iteratively seek for a currently optimal solution. In every iteration, we add one more sensor in our selection in such a way that the predicted "instability" is closest to the real "instability" using all the 99 sensors. We continue this process for multiple iterations until the error between the predicted "instability" and the real "instability" is smaller than the threshold. Since the worst case is to include all the 99 sensors in the sensor selection, thus the algorithm is guaranteed to generate a sensor selection that meets the constrain.

Algorithm 2 Iterative Selection

Input: S-overall set of sensors.
Input: S_1-set of sensors being selected.
Input: $diff$-the difference between instability tested using S_1 and the real instability tested using all 99 sensors.

```
while diff≥thresholddiff
    for all sensors s_i in S − S_1
        diff=abs(Identifyinstability(s_i + S_1)-realinstabilty)
        if diff(s_i + S_1) is the smallest
            S_1.append(s_i)
            break
        end if
    end for
end while
```

Output: S_1

C. Probabilistic Selection

Probabilistic sensor selection approaches the problem from a different perspective. The key idea is to first randomly choose subsets of sensors that can generate "instability" value close enough to the real "instability". Then we summarize the generated subset of sensors and find out the sensors that frequently appear in majority of the subsets. We claim that these sensors should also be included into the final sensor selection group. Our intuition is that if a sensor is highly correlated to reveal the real "instability", that means the sensor has high likelihood to be included in the subsets of different sensor combination that produce a "instability" close to the real one. Correspondingly, if a sensor always appear in such subsets, then it means this sensor has high correlation to the real "instability".

VII. Evaluation

A. Scenario Identification Evaluation

The evaluation result for scenario identification is shown in Figure 7. The figure shows that top sensor configuration for scenario identification from iteration 1 to 3. At iteration 3, the error of feature identification is smaller than the threshold value, thus the algorithm terminates. As the result shows, it only requires 3 sensors to identify the scenario, and the sensors distribute over different locations of the shoe.

Algorithm 3 Probabilistic Selection

Input: S-overall set of sensors.
Input: S_i-random set of sensors that generate instability close to the real instability tested using all 99 sensors.
Input: T-set of sensors being selected.
Input: $diff$-the difference between instability tested using S_i and the real instability tested using all 99 sensors.

```
for each sensor group S_i
    diff=realinstability
    while diff≥thresholddiff
        Randomly select sensor s_j
        S_i.append(s_j)
        diff=abs(Identifyinstability(S_i)-realinstabilty)
    end while
end for
for each sensor group S_i
    for each sensor s_j in S_i
        count(s_j)
    end for
end for
T.append(topcount(s_j))
```

Output: T

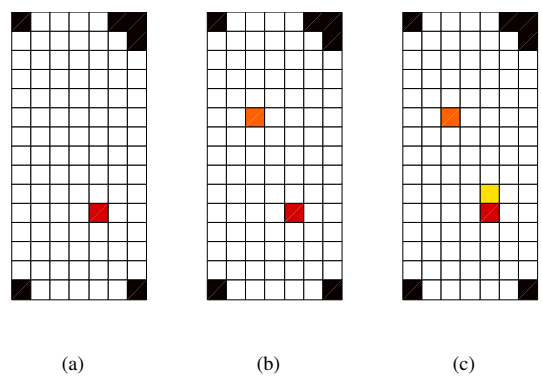
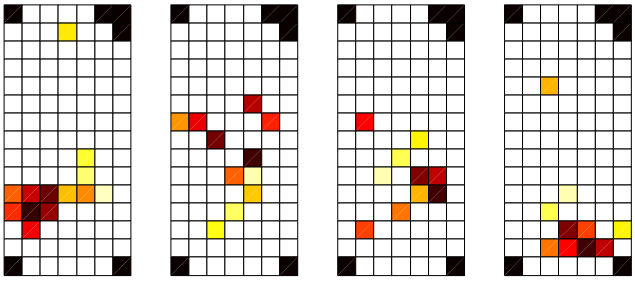


Fig. 7: The sensor selection for scenario identification from iteration 1 to 3. In each iteration, 1 more sensor is added into the sensor subset. The sensor in darker color is added into the selection subset earlier than the sensor in lighter color.

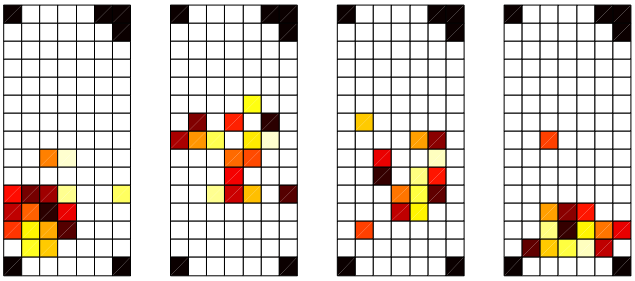
B. Sensor Selection Evaluation

We respectively evaluate the results of iterative selection and probabilistic selection. Figure 8 shows the sensor selection results for the four scenarios, where in every iteration, we introduce a new sensor in the total sensor selection group. Figure 9 shows the results of probabilistic selection for the four scenarios, where we include the sensors with high frequency to appear in the sensor selection result.



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

Fig. 8: The sensor selection results using iterative selection in different scenarios. (a) walk, (b) jump, (c) run, (d) slow walk.



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

Fig. 9: The sensor selection results using probabilistic selection in different scenarios. (a) walk, (b) jump, (c) run, (d) slow walk.

C. Discussion

From the results, if comparing horizontally, we can clearly see that no matter which algorithm we are using (iterative selection or probabilistic selection), the four scenarios have very different sensor selection. This is due to the intrinsic difference between the scenarios. But all the scenarios reduce a considerable number of sensors. The average number of sensors in each subset is around 12, which saves around 87 sensors from the total 99 sensors (88%). Note that this percentage of saving is equivalent to the ratio of energy saving since we dynamically activate/deactivate the sensors and assume that each sensor consumes the same power. If we compare vertically, the two algorithms offer similar results in such a way that the major location of sensors keeps the same given the same scenario.

VIII. Conclusion

In this paper, we have explored the possibility to reduce the number of sensors required for medical diagnose in such a way that the cost and energy is saved. Due to the fact that different scenarios have their own unique pressure distribution properties, we consider the sensor selection for 4 scenarios, respectively walking, jumping, running, and slow walking. Our sensor selection flow includes scenario identification as well as two of our proposed sensor selection algorithms, respectively iterative selection and probabilistic selection. The results of sensor selection indicate that different scenarios indeed have very different sensor selection results. But regardless of the scenario, our sensor selection algorithm can achieve an average saving (both number of sensors as well as energy) to as much as 88%.

IX. Acknowledgement

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