Abstract—Wireless sensors with accelerometers are widely used in various studies on human body movements. The most challenging problem in a small body-attachable sensing unit is how to maximize the battery lifetime. Previously, the preferred approach was to reduce the number of transmissions through data compression. Compressed Sensing (C-S) is an emerging alternative approach that aggressively reduces the samples yet permits the reconstruction of the original analog signal. C-S has the great potential to be extremely effective due to the universality and lower complexity of sensor implementation. In this paper, we investigate the nature of various human body movements. We examine the performance of the C-S framework in terms of the energy savings in a real testbed. Our experimental results show that the C-S framework can save up to 40% of energy in the sensing unit, compared with the traditional data compression scheme.

I. INTRODUCTION

Accelerometers have enabled a more convenient investigation on human body movements. Research using accelerometers began in the 1950s; however the expensiveness, large-size, and unstableness were obstacles to the wide employment in the early stages. In the past decade, the advance of MEMS (Micro-Electro-Mechanical Systems) technology made remarkable changes in this research area. The form-factor of the accelerometer device has been small enough to be attached on the human body without irritation, the manufacturing cost of the device has been affordable enough to be commonly used, and the accuracy has improved to analyze various human activities. The accelerometer is used in many areas such as gait analysis, balance evaluation, fall detection, activity monitoring, and so on.

More recently, research on human body movements using accelerometers is shifting to the new paradigm. As both wireless communication and micro-processor technologies advance, radio communication modules and micro-controllers have been getting not only smaller but also cheaper, which has resulted in a tiny wearable sensor can continuously collect human kinetic information and wirelessly transmit the data. Since neither tangled cables nor an additional controlling unit is necessary, it is possible to collect individual’s movement information everywhere and anytime in daily living without restrictions to the designated laboratory or a particular time. Wearable human activity monitoring systems [1] [2] or home rehabilitation applications [3] [4] are gaining interest in recent years.

The most challenging issue in battery-operated wireless sensing applications is how to achieve efficient power management at sensing unit side. The primary premise of successful realization is that the sensing unit never inconveniences people’s daily activities. Therefore the size of the sensing unit must be small, with the result that the sensing unit has extremely limited battery capacity and computing power. Under this condition, it is essential to use a simple scheme to prolong battery lifetime.

One straightforward scheme for energy saving on the sensor mote unit is to compress the sensed data to reduce the number of transmissions. In general WSN applications, the bulk of power usage lies in the transmitter. Thus much energy can be saved if an appropriate compression algorithm for the data and the hardware is used [5]. However, in the case of body-area short-range communications, the impact of the transmission on energy consumption inevitably shrinks because it is not necessary to transmit data with high power.

The wireless sensing unit consists of three major energy-consuming parts; 1) accelerometer, 2) processor, and 3) transmitter. Since energy consumption takes place at all three parts, we take all the three parts into account to maximize the battery lifetime.

Compressed Sensing (C-S) theory has been gaining great attention in the area of signal sensing and compression [6] [7]. C-S promises that certain signals can be well reconstructed from a small number of measurements without a priori knowledge of the signal structure; usually the number of measurements is much less than the number of samples required for the Nyquist rate. C-S has the great potential to reduce energy consumption when it is used in the small low-performance sensing units in which collecting signals consumes a bunch of energy. Since it is not necessary to sample signals at a high rate, the energy consumption for sampling can be reduced. Moreover it does not require data processing after sampling to lower the data size, thus the energy consumption induced by processing can be totally omitted. Finally, the power consumption for data transmission can also be reduced because the amount of sensed data is initially small.

In this paper, we investigate the characteristics of human body movements, and we examine the advantage of the C-S framework in terms of energy saving when it is applied to the wireless accelerometer data transfer system. The performance of energy saving is evaluated on the sensing unit side. Through extensive experiments, we show that the movement data collected by accelerometers on several parts of human body is sparse enough to be compressed by C-S. The comparison be-
between the C-S-applied scheme and the traditional compression scheme is also analyzed. The goal of this paper is to investigate the feasibility that C-S framework can reduce energy consumption more than the previous methods at the sensing units without increasing the implementation complexity so it can be used in various real applications.

II. COMPRESSED SENSING

This section presents the brief background of C-S theory and the advantages when it is used in accelerometer-aid human body movement studies. Figure 1(a) illustrates the basic scenario of an application that transfers daily human movement data. Multiple sensors, which are attached on the human body, are capable of capturing body movements via accelerometers and transmitting the data wirelessly to an intermediate gathering device, such as a smart phone. The collected data is transferred to a remote monitoring center so that it can be analyzed.

Figure 1(b) and (c) show how the traditional “Sensing and Compression” scheme and the “Compressed Sensing” scheme work in this scenario, respectively. Let x be a certain body movement signal that is sampled by the accelerometer. Assume that N size of information is necessary for the analysis. In the formal case, each sensing unit is required to record N size of data. Then the sensing unit may compress the captured data before transmitting it to the remote center in order to save energy consumption by wireless transmission. Now the data size is reduced to K, and the transmitter sends K size of data to the remote center. Upon receiving the packet at the remote center, the K size of data is decompressed. Finally the original signal x is recovered with size of N. In this system, major energy consumption of the sensing unit takes place in all the three steps: 1) signal sampling, 2) data compression, and 3) wireless transmission.

In the latter case, instead of capturing N size of data, only M size of information is collected where typically M is much less than N. In C-S, this step is called measurement. Next, the M size of data is directly sent to the remote center without the compression step. Upon receiving, the data is reconstructed to the original signal x. Depending on the size of M, the method of measurement, the characteristics of the signal, and the reconstruction algorithm, the accuracy of the reconstructed signal x’ varies. In the following subsections, we briefly explain the two phases of C-S framework, Measurement and Reconstruction.

A. Measurement

Signals can be said to be K sparse if the signal is expressible with a linear combination of the basis functions. Let \( \Psi = \{ \psi_1, \psi_2, ..., \psi_N \} \) be a basis or a dictionary of vectors, then the given signal x can be represented as:

\[
x = \sum_{i=1}^{K} a_n \psi_{n_i}
\]

where \( K \ll N \). According to C-S theory, an \( M \times N \) measurement matrix \( \Phi \) can be constructed. Thus if the sensing unit takes M non-adaptive linear measurements, then the measured signal y can be written as:

\[
y = \Phi x
\]

In the measurement process, the measurement matrix \( \Phi \) must be incoherent with the dictionary \( \Psi \). The incoherence can be provided by a random matrix such as Gaussian entries or the Bernoulli matrix. Hardware that supports direct construction of the measurement matrix makes possible the elimination of the effort to sample signals at the Nyquist rate [8] [9] [10].

B. Reconstruction

Such a measurement matrix \( \Phi \) enables any signal that is sparse in the dictionary \( \Psi \) to be recovered by the C-S framework with high probability. Many algorithms that reconstruct the original signal x from the measurements y have been proposed. The reconstruction algorithms are generally categorized into two approaches. The canonical approach [11] [6] [7] utilizes the linear programming to find the solution for the following \( l_1 \) minimizing problem.

\[
\arg \min_a \|a\|_1 \text{ subject to } \Phi \Psi a = y
\]

This method generally requires fewer measurements; however, it needs a relatively higher computation complexity. Another reconstruction approach [12], which is greedy-based, such as Matching Pursuit(MP) or Orthogonal Matching Pursuit(OMP) is also proposed. This method, in contrast to the canonical approach, requires fewer computations but more measurements.

III. ACCELEROMETER DATA OF HUMAN MOVEMENTS

This section presents the characteristics of accelerometer data of human body movements in terms of the applicability of C-S. To the best of our knowledge, it is the first study that explores human body movements from the perspective of C-S. The accelerometer signals of daily human activities, such as walking or running, reveal that they are sparse enough to be compressed by C-S.
A. Experiment dataset collection

To collect the experiment datasets, we strapped a 3-axis accelerometer sensing board, which can measure a range of ±2g, on 8 points of the human body. The circles in Figure 1(a) indicate the data collection points: chest, abdomen, shoulder, elbow, wrist, thigh, knee, and ankle. We recorded the 3-axis accelerometer data at 100Hz sampling rate at all 8 points for two cases: 1) normal walking and 2) light jogging.

For data analysis at the remote center, each axis data (i.e., x-axis, y-axis, and z-axis) can be assessed separately. However, the axis information is meaningless unless the orientation of the sensing unit is fixed on the human body. Thus the three-component data is usually combined into a single value to avoid the ambiguity that results from the orientation of the sensing unit. In this paper, we combined each value of the three axis data into a single magnitude $ACC_{mag}$ by the following equation:

$$ACC_{mag} = \sqrt{ACC_x^2 + ACC_y^2 + ACC_z^2}$$  \hspace{1cm} (4)

where $ACC_x$, $ACC_y$, and $ACC_z$ represent the values of the x, y, and z axis accelerometer, respectively.

The capturing precision for the human movement analysis differs from applications. For example, a pedometer only requires precision of step detection; however, more information may be necessary in many clinical researches. Figure 2 shows how much information can be lost as lower the sampling rate. A number of peaks are missing in the case of lower rate. Since our approach based on the C-S framework should also be applicable to sophisticated human movement researches, we select 100Hz for a high sampling rate.

Due to space restrictions, two examples of 16 human body movement datasets are presented in this section. Figure 3(a) and (b) show the $ACC_{mag}$ values at knee in the case of the normal walking and light jogging, respectively. Note that the base $ACC_{mag}$ value is adjusted to zero for easy calculation.

B. Sparsity of accelerometer data

To examine the compressibility of the accelerometer signals, we investigate the sparsity of the signals through DWT (Discrete Wavelet Transform) and DCT (Discrete Cosine Transform) bases, which are the most popular transforms used for image compression. Also, both transforms are suitable for audio signal separation [13]. For the first step of the investigation on the applicability of C-S to the accelerometer data, we start with the well-known bases. Figure 3(c) and (d) show the DWT coefficients of the accelerometer signals at transform decomposition level of 3. The DCT coefficients for the same accelerometer signals are illustrated in the Figure 3(e) and (f). The transforms are done by Matlab software, and the x-axes in Figure 3 are the entry numbers in vector, not indicating actual range of time or frequency.

The signal is sparse if it has many large coefficients and few small coefficients in the case of DWT, or if large coefficients of DCT are mostly located at low frequency. More sparsity leads higher compressibility. Figure 3 shows human walking and jogging signals can take advantage of the C-S framework. In fact, human body parts have their own unique movement patterns, and the patterns are repeated during normal activities. For example, when people walk, arms sway back and forth and legs do circular movements. Human body movements can be classified into three major patterns: 1) linear movement, 2) circular movement, and 3) swingy movement.

IV. Reconstruction Evaluation

In the previous section, we saw that the signals of body movements can be compressed by the C-S framework. This section presents the accuracy evaluation of various signal reconstructions using the real datasets of human body movements.
A. Evaluation method

The evaluation was conducted using Matlab software with the previously collected 16 datasets. For ease of computation, we adjusted all the datasets to the same size, 4 seconds-long (i.e. N=400). The measurement matrix $\Phi$ was constructed by random Gaussian matrices. As the dictionary $\Psi$, two different bases, DWT with the transform level of 8 and DCT, were used. For the reconstruction, we used an algorithm proposed in [14] [15].

B. Signal reconstruction

Figure 4 illustrates two examples of the signal reconstruction: 1) a walking signal at the thigh, C-S applied with dictionary of DWT, and 2) a jogging signal at the chest, C-S applied with dictionary of DCT. Figure 4(a) and (b) present the original signals. As shown in Figure 4(c) and (d), 100 measurements (i.e. 25%) for both the walking and jogging movements fail to reconstruct the original signals. In the case of walking, only 25% of measurements accurately picked most of the peak points in the original signal; however the magnitudes were not properly restored. In case of jogging, the magnitude and cycles of the reconstructed signal were not far different from the originals; however they had too much noise. As a result, 25% of the measurement is insufficient for accurate reconstruction.

For 50% of measurements, Figure 4(e) shows that the magnitudes of the peaks were accurately restored. However, the result seems that satisfactory reconstruction is still not achieved. Some parts of the signal are not as smooth as the original. For the chest signal of the jogging movement, as shown in Figure 4(f), much noise is eliminated compared to the case of the 25% measurement, but some noise still exists. Note that the actual accuracy requirement varies application by application, therefore reconstructed signals with 50% measurements may provide sufficient information for some applications.

Figure 4(g) and (h) show the reconstruction results where the both measurement ratios are increased to 75%. For the walking signal, the reconstructed signal is almost identical to the original. It is hard to find the erroneous points with the naked eye. The result of the jogging case is also much improved.

C. Reconstruction Accuracy

Figure 5 presents the reconstruction error in respect to the measurement ratio for all 16 datasets. The accuracy is represented by NRMSE (Normalized Root Mean Squared Error) value, which is calculated as follows:

$$\text{NRMSE}(X_{rec}, X_{ori}) = \sqrt{\frac{\sum_{i=1}^{n}(x_{rec,i} - x_{ori,i})^2}{x_{ori,\text{max}} - x_{ori,\text{min}}}}$$  \hspace{1cm} (5)

where $X_{rec}$ and $X_{ori}$ are the reconstructed and the original signals, respectively. $x_{ori,\text{max}}$ and $x_{ori,\text{min}}$ are the maximum and the minimum magnitude value in the original signal, respectively.

As shown in the Figure, the signals are reconstructed more accurately as the number of measurements increases for all datasets. For the movements of ankle, knee, and thigh, both DWT and DCT dictionaries present similar accuracy tendencies, which are almost linear. Neither the type of activity nor the type of dictionary actually affects the performance of the reconstruction results. The accuracy difference of the four pairs (i.e. walking-DWT, walking-DCT, jogging-DWT, and jogging-DCT) is insignificant.

For the movements of elbow and wrist, the DCT dictionary provides superior performance to the DWT. In case of both body part, only 40% of measurements restored the original signals with high accuracy (0.05 NRMSE) regardless of the type of activity. At the 40% measurements, the accuracy of DCT is at most 3 times higher than DWT for the walking movement and at most 4 times higher for the jogging movement.

For abdomen, chest, and shoulder, the accuracy improves linearly as the cases of leg movements (ankle, knee, and thigh) do. However the gap of reconstruction accuracy for each pair is relatively large compared to the leg movements where the measurement is below than 70%. Regarding to the signal reconstructions by body parts, more observations and analysis are presented in Section VI.

V. ENERGY CONSUMPTION COMPARISON

In this section, we compare a wireless human movement data transferring system that utilizes the C-S framework with
the same application that uses traditional “sensing and compression” scheme in terms of energy savings.

A. Evaluation method

For a realistic comparison between the two schemes, we performed a case study using a Mica2 Wireless Sensor Network mote [16] with MST310 sensor board [17]. We chose Mica2 as the experiment platform not only because it was an available programmable device but also because Mica2 was originally designed for low-power wireless sensing tasks. Mica2 with MST310 is equipped with an accelerometer, a low-power processor, and a low-power wireless transceiver. To measure the energy consumption for the data compression, we implemented two basic compression algorithms, Huffman and SF(Shannon-Fano) on Mica2 mote using TinyOS [18], and we measured the elapsed time for the completion of the compression. We also recorded the compressed data size. The results are shown in Figure 6. Since the Huffman algorithm outperforms the SF algorithm in both criteria (i.e. the elapsed time and the compressed size), we used the Huffman code for the evaluation. Note that the Huffman code is lossless algorithm and C-S framework is lossy scheme, thus two schemes cannot be compared directly. However, this paper focuses on the feasibility of C-S framework rather than specific performance comparison. We select the Huffman code since it is simple and efficient for the accelerometer data.

B. Power Consumption Model

Since a power measuring instrument was not available when we conducted the experiments, alternatively we calculated the power consumptions of two schemes using the proven experiment-based data. Table I presents the current dissipation data of Mica2’s core parts. The data have been acquired from actual measurements in [19].

In this paper, for simplicity, we calculated the power consumption only caused by the three parts (i.e. the accelerometer,
processor, and transceiver) which are the core parts in the sensing unit. The total power consumption $P_{total}$ during the time period of $T$ was calculated by Equation (6). The parameters of the power consumption model are explained in Table III. Note that in the case of the traditional compression scheme, additional power consumption may occur due to memory read/write operations. However, it is not included in our power consumption model because of lack of the detailed data.

\[
P_{total}(T) = (P_{acc} \cdot t_{acc} + P_{mcu-active} \cdot t_{compression} + P_{mcu-idle} \cdot t_{radio} + P_{mcu-standby}) + P_{tx} \cdot t_{tx} + P_{rx} \cdot t_{cs}) \cdot V
\]

(6)

### C. Energy consumption comparison

To evaluate how much energy the C-S framework can save, we calculated the total power consumption at the sensing unit for two schemes(i.e. C-S framework and traditional compression) using Equation (6) and parameter values in Table I and Table II. We set the compromising level of reconstruction error to 0.05 NRMSE. For example, in the event of elbow signals, a 0.05 NRMSE requirement is first satisfied by 40% of measurement for both walking and jogging activities if we use the DCT dictionary. In this case, the total energy consumption for 40% measurements and the packet transmissions is compared with the energy consumption for 100% measurements, data compression, and the transmissions of the compressed data.

For another example, in the case of shoulder signals, the 0.05 NRMSE requirement is first satisfied by 50% of measurements using DCT dictionary for walking activity and 70% of measurements using the DCT dictionary for jogging activity. Thus the energy consumption by C-S scheme for the cases of 50% measurements and 70% measurements are calculated and compared with the traditional scheme.

Figure 7 shows the energy consumption rates of both schemes where the energy consumption of the sensing without power saving scheme is 1. In the case of the traditional scheme, the buffer size for the data compression is set to 200 bytes. In other words, when the accelerometer samples 200 byte data, the processor performs the compression processing. Note that TinyOS 2.0 does not allow a single packet to have more than 115 bytes. Although we performed the evaluations based on the Zigbee platform, we did not restrict the platform to Zigbee. Thus we assumed that the packet size can be larger than 115 bytes.

The compression scheme constantly saves 12% energy compared to the non-scheme system. This is because the Huffman algorithm provides almost the same compression performance for all the datasets. Note that the 12% energy saving in the compression scheme may not be impressive. The reason that the compression scheme could not greatly reduce the energy consumption is because we set the transmission power to the minimum value. The current dissipation of the transmitter with the maximum power is 6 times larger than the case of minimum transmission power.

On the other hand, the C-S framework provides inconstant performance. Depending on the body parts and the type of human activity, the C-S scheme reduces more energy consumption than the compression scheme by from 5% for the jogging movement at the chest to 40% for the walking movement at the wrist. Only one case of the C-S scheme, which is the knee signal for jogging activity, fails to save more energy than the compression scheme. The results show that the walking movement is more compressible by C-S than the jogging movement. In the case of walking activity, on average, C-S saves 24% more energy than the compression scheme.

### VI. Discussion

In the previous sections, we examined the applicability of the C-S framework to wireless accelerometers for human body...
A. Human body movements

As shown in Figure 5, reconstruction accuracy by C-S varies depending on what activities humans are doing and where the sensing units are attached. In the case that the sensing unit is attached on the torso (i.e. chest, abdomen, or shoulder) of which the movement is mostly linear, the accuracy of signal reconstruction varies by not only the type of activity, but also the type of dictionary. In the case of leg movements (i.e. ankle, knee, or thigh), which are generally circular, neither the activity nor the dictionary makes any difference in the reconstruction. For arm movements (i.e. elbow and wrist), which are pendulum-like, the type of dictionary is a dominant factor that determines the accuracy, while the type of activity is not.

Different body parts have different characteristics (linear, circular, or swingy movements) in terms of the level of compressibility. Thus different strategies are required to maximize the performance when applying C-S to the accelerometer data of the human body movements. This paper investigates two cases of human activity. In future work, we will explore more diverse human activities (e.g. cycling, jumping, fast running, and so on.).

B. Dictionary

The dictionary $\Psi$ is a critical factor that determines the reconstruction accuracy. Figure 5(g) and (h) are the examples that show how the dictionary impacts on the results. For jogging activity in both cases, DCT provides over 150% improved accuracy compared to DWT at the 50% of measurements. For walking activity, DCT also reconstructs the original signals with at most 80% better accuracy at the same measurement level. On the other hand, no difference is shown between two dictionaries when the sensing unit is attached on ankle, knee, and thigh as presented in Figure 5(d), (e), and (f). This paper preliminarily examined two popular dictionaries. In future work, we will explore the other dictionaries to find the optimal ones for different body points and different human activities.

C. Reconstruction Algorithm

In addition to the type of dictionary, the reconstruction algorithm also affects the accuracy of signal restoration. Since it is not the scope of this paper to find the optimal algorithm, we used one reconstruction algorithm that has less implementation complexity. It may be possible, however, to improve accuracy with fewer measurements via the optimal algorithm. Reconstruction methods that can accurately and efficiently restore human body movement signals will be investigated in future work.

D. Application-specific hardware

For the energy consumption comparison between two schemes, we used a Mica2 sensor mote as an experiment platform. All the results are calculated based on the specifications of Mica2. However, much more energy than we presented in this paper can be saved with C-S for two reasons.

First, the computing power of the micro-processor of Mica2 is superfluous because it is designed for general Wireless Sensor Network applications. It should provide computing power for sensing, data processing, routing, and so on. However, wearable body sensors require no such complicated tasks. The two key tasks are 1) collecting accelerometer data and 2) transmitting the data to a device within one-hop communication range. If we can utilize the C-S framework, the processor does not necessitate any computing power for the data processing. Since a processor with extremely limited computing power is sufficient to perform the sensing task, we can save not only on power consumption but also on manufacturing costs.

Second, the transceiver power of Mica2 is also excessive. Since the data transmissions of the sensing units take place only within an individual body area, powerful transmission is not necessary. General purpose wireless transmitters such as Zigbee, Bluetooth, or Wifi, which have the communication range of tens to several tens of meters, consume at least several $mAs$. On the other hand, the target power consumption of transmitters specially designed for body area networking is less than $100\mu W$ [20] [21]. In real applications, thus, the impact of wireless transmissions on total energy consumption may be much less than the system that consists of Mica2 motes.
E. Energy consumption measurement

In this paper, we estimate the power consumption of the wireless accelerometer data transfer application with a simple model based on the specification of each part. The sensing unit does nothing but the assigned task (i.e. sensing, processing, and transmission), and the power consumption is extremely low when devices are not in active mode. Therefore, the estimated results may not be far different from the actual measurements. However, since many parts in the sensing unit are connected with each other, some factors that are not considered in the power consumption modeling may affect the total energy consumption. For an accurate comparison, it may be necessary to measure energy consumption with a power measuring instrument.

VII. Conclusion

In this paper, we investigate the characteristics of human body movements in terms of the C-S framework applicability, and examine how much energy C-S scheme can save compared to the traditional compression scheme where the wireless accelerometers are attached to the human body. We conclude our work as follows:

- We show that the accelerometer signals of human body movements are sparse in both DWT and DCT dictionaries using various datasets that are collected through real human activities.
- We evaluate the reconstruction accuracies for the 16 types of human body movements. We present that the reconstruction accuracy varies by not only the body part but also the human activity. The dictionary should be chosen with regard for the characteristics of the human body movements.
- We also investigate how much energy consumption the C-S framework can reduce in the real sensing platform, Mica2. The evaluation using realistic values shows that the basic C-S scheme can save up to 40% more energy than the traditional scheme.
- Most importantly, C-S still has further potential to save more energy. Transmitters designed for short-range body area networking consume much less energy than conventional transmitters. In the case that the low-power transmitter is used, the processor also becomes a major power-consuming part. Since C-S does not require complicated processing jobs by the sensing unit, the unit can perform its task with a processor that has extremely limited computing power. The low-energy and low-performance processor reduces not only the energy consumption but also the manufacturing cost.

In future work, we plan to explore other dictionaries and reconstruction algorithms to find the optimal pair that maximizes energy saving under the condition which tiny wireless accelerometers transfer the human body movements.

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