Efficient Health Data Compression on Mobile Devices

Amit Pande, Eilwoo Baik and Prasant Mohapatra
Department of Computer Science
University of California, Davis, CA 95616, USA
{ pande, ebaik, pmohapatra}@ucdavis.edu

ABSTRACT

There is an increase rise in the usage of mobile health sensors in wearable devices and smartphones. These embedded systems have tight limits on storage, computation power, network connectivity and battery usage making it important to ensure efficient storage/ communication of sensor readings to centralized node/ server. Frequency Transform or Entropy encoding schemes such as arithmetic or Huffman coding can be used for compression, but they incur high computational cost in some scenarios or are oblivious to the higher level redundancies in signal. To this end, we used the property of periodicity in these naturally occurring signals such as heart rate or gait measurements to design a simple low cost scheme for data compression. First, a modified Chi-square periodogram metric is used to adaptively determine the exact time-varying periodicity of the signal. Next, the time-series signal is folded into Frames of length equal to a pre-determined period value. We have successfully tested the scheme for good compression performance in ECG, motion accelerometer data and Parkinson patients samples, leading to 8-14X compression in large sample sizes (6-8K samples) and 2-3X in small sample sizes (200 samples). The proposed scheme can be used stand-alone or as pre-processing step for existing techniques in literature.

Categories and Subject Descriptors

I.4.2 [**Compression (coding)**]: *approximate methods, exact coding*

General Terms

Performance

Keywords

Data compression, mobile health applications

1. INTRODUCTION

There is an increasing rise in the usage of mobile health sensors in wearable devices, Body Area Networks (BANs) and smartphones. Wearable devices such as Nike+ Fuelband[1], Fitbit[2] and the rumored iWatch monitor personal fitness of an individual using accelerometer and other passive sensors. A number of smartphone apps use phone inertial sensors and GPS for fitness-tracking of mobile users, although they achieve lower accuracy than dedicated wearable devices. Body sensors such as Wahoo heart-rate monitor[3] and Nike+ shoe sensors[4] are also gaining significant market. The LifeWatch-V Android phone can monitor body temperature, ECG, body fat, stress, blood glucose and saturation[5]. Increasing overall cost of medical care and advances in wireless technology has also paved way for cost-effective remote monitoring of patients using wireless devices. These devices, the stand-alone equipment or body-sensors or smartphone sensors, are typical embedded systems with tight limits on storage, computation power, network connectivity and battery usage. Although newer smartphones are now equipped with Quad or Oct core processors, battery life is a serious concern in these devices. Continuous streaming of sensors' data must be done in a cost-effective manner, in order to avoid battery drainage. Apart from this, efficient compression is helpful to reduce the transmission cost of data-uploads in cellular networks. A number of healthcare researchers are using these sensors for pilot health intervention programs that study the impact of health monitoring on patient health. A wide variety of patient population suffering from obesity [21], cardiac rehabilitation [2] and diabetes [22] have benefitted. Locomotion monitoring is useful in gait analysis, early diagnosis of cognitive impairments like dementia [18], AlzheimerâĂŹs disease [1], ParkinsonâĂŹs disease [15] and detection of autistic disorders in infants. Frequency transform such as Fourier series or DWT or Entropy encoding schemes such as arithmetic or Huffman coding or codebook based LZW coding schemes are efficient for data compression, however, they are not suitable for mobile medical data for two reasons:

1. The computational complexity of these schemes may be still high for many scenarios. For example, the arithmetic coding scheme requires a multiplication operation per encoded bit.
2. These bit-level schemes may fail to capture the higher level redundancies in human signals. For example, the heartbeat pattern and human walking pattern are periodic by nature.

In this paper, we develop a simple, cost-efficient scheme for compressing such sensor measurements. A modified Chi-square periodogram metric is used to adaptively determine exact time-varying

MobileHealth'13, July 29, 2013, Bangalore, India.

[1] `http://www.nike.com/us/en_us/c/nikeplus-fuelband`
[2] `http://www.fitbit.com`
[3] `http://www.wahoofitness.com/Products/`
[4] `http://store.nike.com`
[5] `http://www.lifewatchv.com/`

periodicity of the signal. This scheme is found to be more cost-effective than auto-correlation-based or Fourier-based approaches to periodicity detection. Next, the time-series signal is folded into 'Frames' of length equal to pre-determined period value. A set of consecutive 'Frames' are group together (we call them Group of Frames (GOF)). The first Frame in a GOF is intra-coded (Primary or P frame) while remaining frames are matched to P-Frame and residual frames are then constructed by subtracting current frame from P Frame. This frame is called as Secondary (S) frame. The residue is then quantized. The residue and P-frame can be further compressed using other procedures reported in existing literature, or skipped (in case of low computational capacity of device). We have successfully tested the scheme for good compression performance in ECG data, EMG data, accelerometer data from Parkinson patients and healthy individuals.

The paper is organized as follows: Section 2 gives a brief review of existing work. Section 3 gives details of proposed algorithm. Section 4 gives an overall discussion of proposed approach, its applications and limitations and directions for future work.

2. RELATED WORK

Lots of research in bio-medical data compression has focused on ECG signal. AZTEC [5] achieves a high compression ratio but loses a lot of signal fine-grain information. Discrete Cosine Transform [3, 4], Discrete Legendre Transform [17] and Wavelets [11, 9] based techniques have been proposed which transpose the signal to frequency domain followed by quantization and entropy encoding procedures. Many schemes also depend on accurate QRS detection (peak in ECG signals). Philips [16] model ECG signal using a polynomial of order n. However, all these scheme do not consider the computational complexity of the base algorithm.

The transform domain approaches (such as DCT or DWT) use the fact that higher frequency components are insignificant and can be truncated without loss in major information conveyed by the signal. This assumption is generally true, however the quantization threshold for high frequency content should be carefully derived. The entropy coding techniques are lossless schemes which try to assign shorter (even fractional) codewords to symbols in the bit-stream to approach Shannon's limit for information compression. Nabar et al. [12] uses a model driven approach to compress ECG signals. This approach is template-driven and restricted to ECG signals. The computation cost of generating the signal parameters can be high for low power sensors. Quite different from these approaches, we model this problem as a generic problem of compression a generic quasi-periodic signal (not limited to ECG data). We determine the period of available sensor output, divide it into 'Frames' and obtain the residues, as will be discussed next. The DCT, DLT or DWT based approaches can be used to encode the residues. Our work draws analogy from video compression standards such as MPEG [20] where video is divided into Frames which are then matched and a residue is formed.

In case of a video, frames are matched using motion compensation and estimation procedure on block (8×8 pixel group within a video frame) level and is quite cumbersome. Plus, intra-coding or residue coding is done using frequency transform (Discrete Cosine Transform) followed by quantization and entropy encoding. However, the frame matching procedure in our case is different and much simpler. Unlike video frames which have constant size, our frames have variable size (depending on human activity). But they are simple 1-dimensional signals and no block-matching is required.

Periodicity detection is the first step in our approach. Parthsarthy et al. [14] use a combination of time-frequency and auto-correlation analysis. This is, by far, most popular approach for periodicity detection. Plus, a Kalman filter is used to track changes in periodicity with time. Elfeky et al. [7] model this problem as an approximate string matching algorithm. Indyk et al. [10] uses a dimensional reduction technique. These techniques have high computational cost. Auto-correlation and frequency analysis is also inaccurate, both in terms of resolution offered by frequency transforms and our experimental results. We use a modified χ^2-periodogram based approach, adapted from the approach presented in [19, 8] to reduce its computational overheads.

3. ALGORITHM

In this section, we give an overview of our compression scheme. We introduce the term 'Frame' which refers to one period of time-series data under consideration. The scheme is divided into the following steps:

1. Frame segregation: The periodicity of the given time-series is determined from the peak of computed modified χ^2- periodogram. The period is updated periodically using a local update mechanism.

2. Frame packaging: The input signal is split into a Group of Frames. The first frame in each group is chosen as reference and called as P-frame. The later frames are called S-frames and are predicted from P-frame. They are first aligned to P-frame and then subtracted from it to obtain a residue.

3. Residue coding (optional): The residue and P-frame can be encoded further using standard data compression techniques. First, a frequency transform operation (such as Discrete Cosine or Wavelet Transform) can be used to transform the signal into frequency domain. It has been observed that most natural occuring signals have significant low frequency component. This property has been used in signal, image and video processing algorithms to truncate or quantize the higher frequency terms from the frequency transform coefficients, obtaining significant compression ratios with insignificant losses. Entropy coding procedures such as arithmetic and Huffman coding can be used to compress the quantized coefficients to the Shannon's compression limit. These stages may incur high computational cost and have been well established for image, videos and ECG signals (see literature review). We don't make any contribution to this stage, thus we skip the description in this paper. We use direct quantization (without frequency transform or entropy encoding schemes) which requires no computations.

3.1 Frame segregation

Figure 1 shows sample output from health and medical sensors for ECG, diseased EMG and gait signals. The EMG and Parkinson disease gait samples were obtained from Physionet[6] database. The main idea behind this illustration is to show that many sensor readings from human subjects and behavior are periodic to a great extent. Thus, we need an algorithm for automatic detection of period of the signal. Autocorrelation function is the most popular approach to estimate the periodicity of a given signal. One can take a segment of signal (X) and obtain its autocorrelation as follows:

$$R_P = \frac{\mathrm{E}[(X_m - \mu)(X_{m+P} - \mu)]}{\sigma^2}, \tag{1}$$

[6] http://www.physionet.org/physiobank/database/

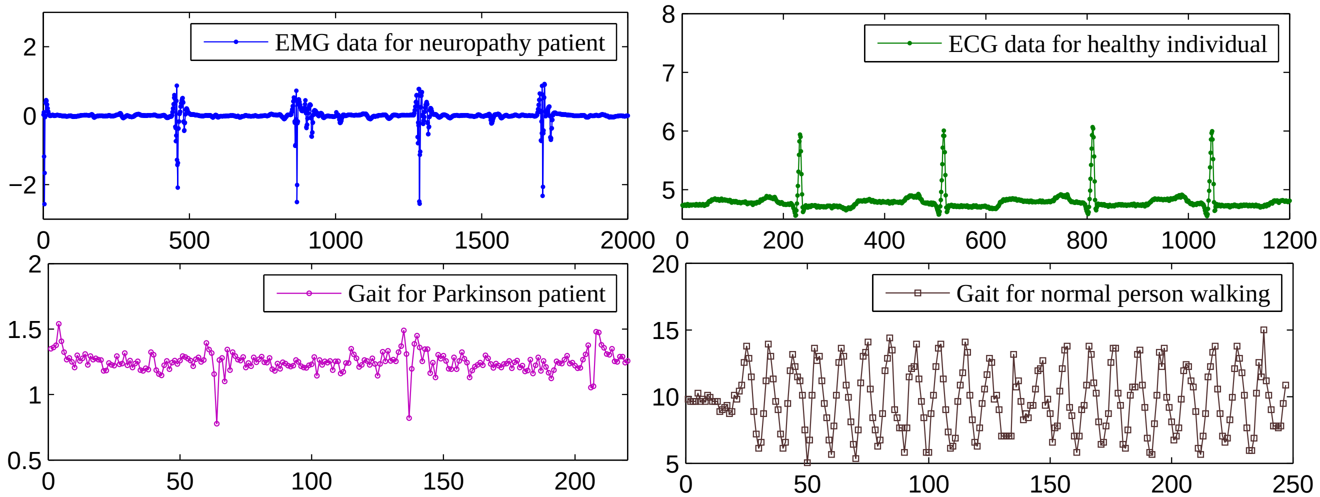

Figure 1: Illustration of data collected from (a) EMG signals from neuropathy patients, (b) ECG signals from normal person, (c) Gait (accelerometer) of Parkinson patient, and (d) Normal person walking. The x and y axes are not normalized.

Table 1: Relative computational performance of Period detection algorithms in Matlab (ms)

Signal	X1	X2	X3	X4
Autocorrelation R_P	193.7 ± 2.1	232.5 ± 2.1	$33 \pm .22$	33.25 ± 1.2
Discret Cosine Transform C_P	$62.3 \pm .04$	124.1 ± 2.5	$\mathbf{3.6 \pm .09}$	$\mathbf{3.7 \pm .09}$
χ^2-Periodogram χ_P	$52.1 \pm .1$	90 ± 6.1	$4 \pm .09$	$4.1 \pm .08$
Modified χ^2-Periodogram $\overline{\chi}_P$	$\mathbf{46.9 \pm .06}$	$\mathbf{83.8 \pm 1.1}$	$\mathbf{3.7 \pm .16}$	$\mathbf{3.7 \pm .08}$

where μ is mean of the signal X and σ^2 is the variance. The function R_P is maximum at the point corresponding to the period of input signal. This approaches, however, requires computing second order statistics (both numerator and denominator of equation 1). Fourier analysis can also be used to obtain the period of signal X, however the output signal is a complex number. Discrete Cosine Transform is therefore preferred, as it produces real coefficients from real valued inputs. It can be computed as follows:

$$C_P = \sum_{n=0}^{N-1} X_n \cos\left[\frac{\pi}{N}\left(n + \frac{1}{2}\right)P\right] \qquad P = 0, \ldots, N-1$$

The peak in DCT frequency diagram corresponds to major harmonic of the

signal, which can be converted to obtain the period of signal. However, we encountered some practical difficulties in this approach:

1. Signal noise leads to inaccuracies in detection of correct peak.
2. Frequency domain representation is quantized in intervals of sampling frequency, thereby blurring the time-domain resolution of determined period.

Implementing the cosine term requires time-series expansion which may be slow in embedded devices. If we divide signal X into K Frames of an arbitrary period P, the χ^2-periodogram approach [19, 8] uses the following metric χ_P to calculate the period.

$$\chi_P = \frac{KN\sum_{h=1}^{P}(\mu_h - \mu)^2}{\sum_{h=1}^{N}(X_i - \mu)^2}$$

where μ is the mean of signal X_i and μ_h is the mean of K values under each time unit of the period length. χ_P is maximum for the period P of the sequence. Since we are interested in P corresponding to the maximum value of χ_P over range of values, we modify this metric to ease the computations:

$$\overline{\chi}_P = K\sum_{h=1}^{P}(\mu_h - \mu)^2$$

This approach leads to lesser computations than the above mentioned approach without affecting accuracy. The relative computational requirements of these algorithms on a Desktop (using 2.8 GHz single core on core-i7 processor) are given in Table 1. Values are reported for all the four test signals mentioned above. We use samples of length 1000, 2000, 200 and 200 for EMG, ECG, Parkinson and normal walk signals. Average values over 25 trials is reported for all 4 test signals. We expect an orders of magnitude improvements in the results using low-level C implementation (on an iPhone), which will remove overheads of function calls and interpretation.

We ran our experiments over all the four types of signals (ECG, EMG, Parkinson and normal gait) and observed that modified $\overline{\chi^2}$ periodogram scheme gives accurate detection of signal period as compared to other two schemes. Figure 2 illustrates the efficacy of using modified χ^2 periodogram ($\overline{\chi_P}$) over DCT and auto-correlation function. The DCT coefficients are plotted in frequency domain and the peak in frequency domain can be back-translated to time domain. The peak for EMG and ECG signals and Parkinson gait don't correspond to visible periodicity in the time-series, which we desire to obtain for compression purposes. We attribute this to the fact that these signals are not exactly sinusoidal and hence detection of sinusoidal frequency component is difficult. Normal walk signal, in this case is sinusoidal and peak is correctly detected in DCT domain. The auto-correlation function also performs well only for

Table 2: Energy of compressed coefficients (Percentage of original signal energy

Signal	X1	X2	X3	X4
With Frame Packaging	7.06	0.23	12.18	.69
With Frame Packaging+Quant.	3.27	0.10	6.85	.25

normal gait. There is no distinct peak observed for other signal types. It can be seen that our scheme gives correct period length for these signals. There is a distinct peak for each of the four signal types.

3.2 Frame Packaging

Once the period is determined, frames can be segregated from the original signal and grouped together into 'GOF' or Group of Frames. The first frame is used as a reference and called as P-frame or Primary Frames, while other frames are predictively encoded with reference to P frame by subtraction operation. They are called as Secondary or S-frames. However, frame subtraction is not always trivial, because of time-varying periodicity and noise of these signals. There are a number of sequence alignment techniques for bioinformatics and other sequences [6], but they incur significant computational cost. **Episodic Data:** Data from human subjects is periodic but the period may vary with time. For example, while walking a person takes rhythmic steps which are recorded as quasi-periodic time-series from accelerometer sensors but depends on walking speed. This is the same for heart-rate and Electromyograms (not always though, due to added noise). The rhythmicity or periodicity varies with time. For example, a person may be walking or running which will change the period for accelerometer or ECG readings. Whenever needed, we align multiple frames using a simple heuristic - matching their maxima and minima, instead of matching the entire frame. The lag is stored and transmitted separately (if it exist). To update the period of a time-varying signal, [14] propose using an adaptive Kalman filter. We run the period detection algorithm in the local neighborhood of past values to minimize our computation time.

After frame matching, the current frame is subtracted from P Frame to obtain S-residue frame. The Frame packaging operation is straight-forward as it involve subtraction of S-frames from P-frames, and doesn't involve much computational complexity.

3.3 Residue Coding

The residue thus obtained can be quantized to remove the non-significant values and obtain further compression. It is then possible to terminate the operation, or use existing approaches (such as DCT, DWT, arithmetic or Huffman encoding; discussed in related works section) to achieve further compression. This choice depends on the availability of computational resources in the sensor. Figure 3 shows sample residues from the four test signals. It can be seen that the residues have significantly lower energy than original signal. Most of the residues are zero values requiring no value for transmission. Thus, the mean energy of residue is much less than the original signal. This can be seen in Table 2 which gives energy of output signals as a percentage of input signals.

In this paper, we quantized the coefficients from residue whose magnitude was less than 1% of maximum signal value. We have not used any post-processing technique like wavelets or arithmetic coding. Using them will complement our approach and improve the compression efficiency, at the cost of computational complexity.

Table 3 gives the compression performance of the proposed approach. The EMG and ECG traces were of long duration, and hence we obtain much higher compression ratio than with gait traces, which were short length. We obtain 8-14x compression for long periodic sequences such as EMG and ECG signal. The signal length for the four signals were 6000, 8000, 200 and 200 samples.

Table 3: Compression Efficiency of proposed approach. (file size is reported in bytes)

Signal	X1	X2	X3	X4
Original signal	39619	43334	2381	2563
With Frame Packaging (FP)	6971	9735	1336	1360
With FP+ Quantization	4922	3182	839	822

When no quantization is done, there is no loss in signal values (lossless coding). We reconstructed the signal in case of quantization and the values are plotted in Figure 4 for a small sample of all four signals. It can be seen that quantization leads to insignificant losses in compression efficiency (less than 3% in all cases).

4. DISCUSSION & FUTURE WORK

In this paper, we presented an algorithm to achieve high compression of health sensors' time series data in mobile devices. The algorithm is low-cost, making it suitable for low-power embedded devices. It achieves 8-14X compression for long datasets in our experiments done using Matlab platform on Windows workstation.

The algorithm is compatible with existing Wavelets, Fourier, Arithmetic or Huffman based approach and complements their performance. Thus, as needs permits, these approaches can be integrated to yield further compression.

As a future work, we would like to implement this scheme in our portable wearable sensors such as Shimmer platform and use with ECG/ Accelerometer sensors to measure savings in real-world implementation. We would also like to investigate the use of cost-effective Wavelet Transform implementations [13] to further reduce our computational cost of period detection using its property of multi-resolution analysis.

5. REFERENCES

[1] AVVENUTI, M., BAKER, C., LIGHT, J., TULPAN, D., AND VECCHIO, A. Non-intrusive patient monitoring of alzheimerâĂŹs disease subjects using wireless sensor networks. In *2009 World Congress on Privacy, Security, Trust and the Management of e-Business* (2010).

[2] AYABE, M., BRUBAKER, P. H., DOBROSIELSKI, D., MILLER, H. S., ISHI, K., YAHIRO, T., KIYONAGA, A., SHINDO, M., AND TANAKA, H. The physical activity patterns of cardiac rehabilitation program participants. *Journal of Cardiopulmonary Rehabilitation and Prevention 24*, 2 (2004), 80–86.

[3] BATISTA, L., CARVALHO, L., AND MELCHER, E. Compression of ECG signals based on optimum quantization of discrete cosine transform coefficients and golomb-rice coding. In *Proceedings of the 25th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (2003), vol. 3, IEEE, pp. 2647–2650.

[4] BENZID, R., MESSAOUDI, A., AND BOUSSAAD, A. Constrained ECG compression algorithm using the block-based discrete cosine transform. *Digital Signal Processing 18*, 1 (2008), 56–64.

[5] COX, J., NOLLE, F., FOZZARD, H., AND OLIVER, G. AZTEC, a preprocessing program for real-time ecg rhythm analysis. *IEEE Transactions on Biomedical Engineering*, 2 (1968), 128–129.

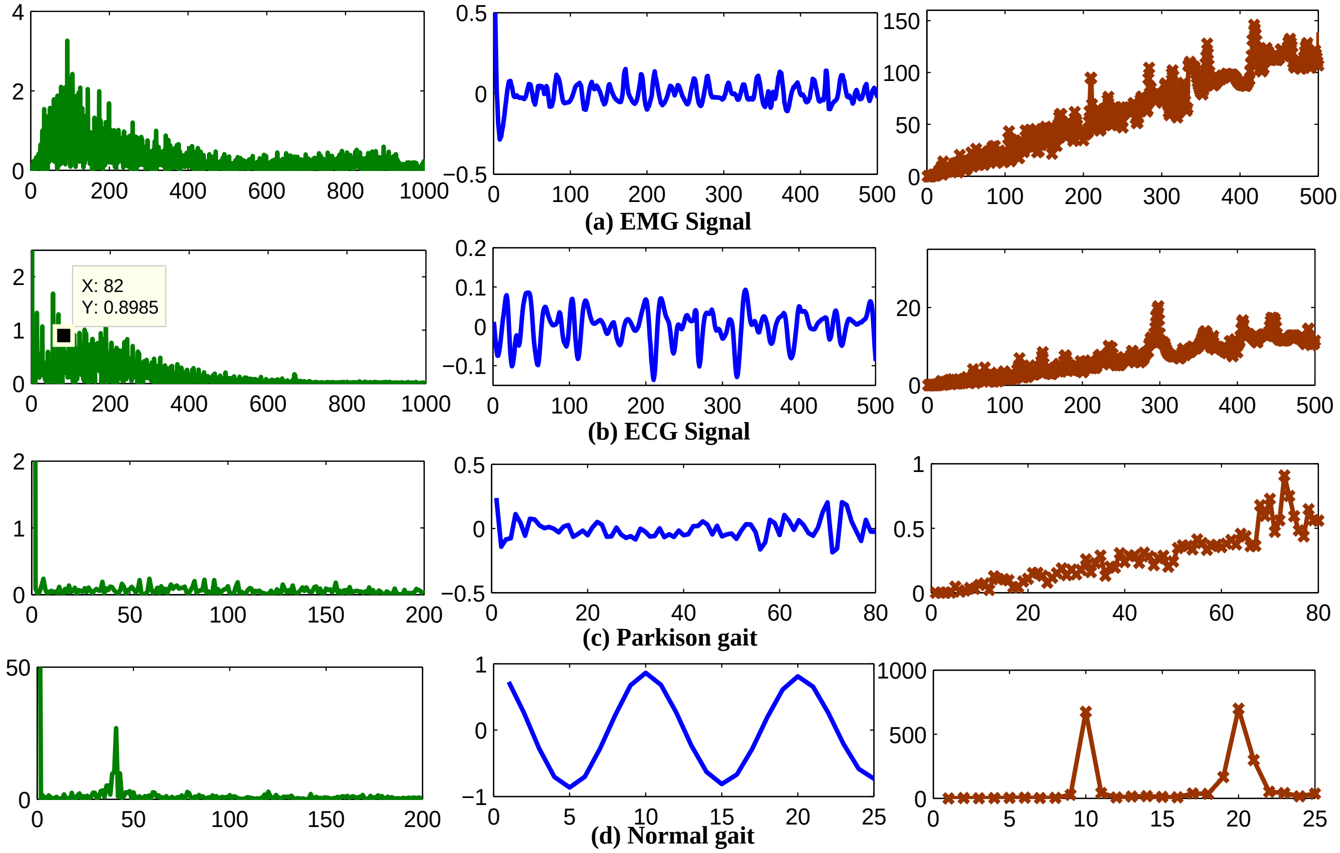

Figure 2: Extracting period length from mobile health sensor values using different methods. Left- Right (1) Discrete Cosine Transform (green), (2) Autocorrelation (blue) and (3) χ^2-periodogram (brown) method. Top to bottom - a. EMG signal (length 2000 samples, period 400); b. ECG signal (length 1000 samples, period 298); c. Parkinson signal (length 200 samples, period 70) and d. normal walk (length 200 samples, period 10). χ^2-periodogram (brown) plot shows distinct peaks at 400 (for EMG), 298 (for ECG), 70 (for Parkinson) and 10 (for normal gait). Other two schemes work only for normal gait signal with no error, but they lead to huge errors in other cases.

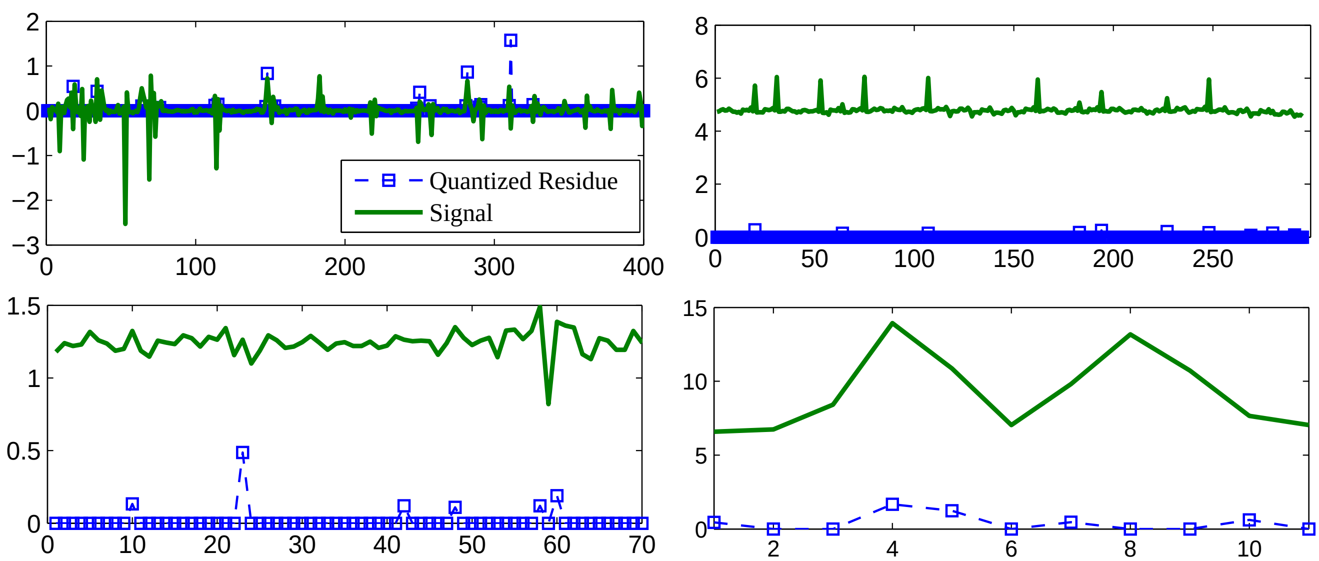

Figure 3: Plot of quantized residues obtained from our approach vs. original signal, for one Frame of corresponding signal.

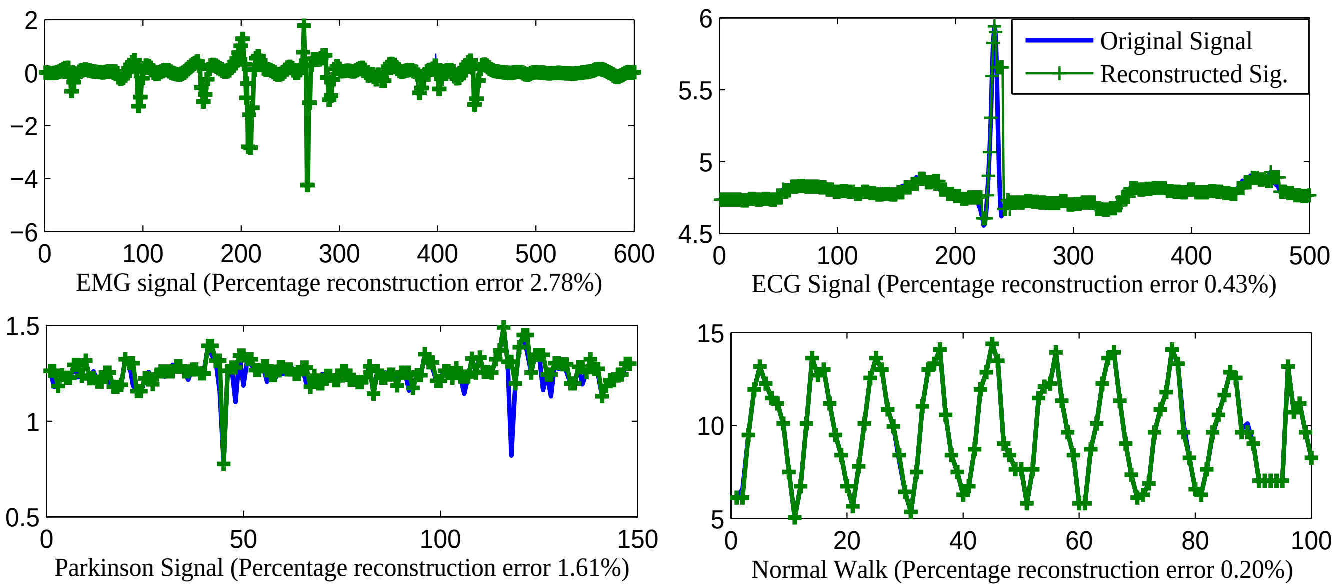

Figure 4: Plot showing original signal and the signal reconstructed after quantization and compression. It can be seen that less than 3% error is introduced in the signals without any loss in visual performance. The basic scheme (frame segregation and packaging) doesn't introduce any losses.

[6] EDGAR, R. C. Muscle: multiple sequence alignment with high accuracy and high throughput. *Nucleic acids research 32*, 5 (2004), 1792–1797.

[7] ELFEKY, M. G., AREF, W. G., AND ELMAGARMID, A. K. Periodicity detection in time series databases. *IEEE Transactions on Knowledge and Data Engineering 17*, 7 (2005), 875–887.

[8] ENRIGHT, J. The search for rhythmicity in biological time-series. *Journal of theoretical Biology 8*, 3 (1965), 426–468.

[9] HILTON, M. L. Wavelet and wavelet packet compression of electrocardiograms. *IEEE Transactions on Biomedical Engineering 44*, 5 (1997), 394–402.

[10] INDYK, P., KOUDAS, N., AND MUTHUKRISHNAN, S. Identifying representative trends in massive time series data sets using sketches. In *Proceedings of the 26th International Conference on Very Large Data Bases* (2000), pp. 363–372.

[11] LU, Z., KIM, D. Y., AND PEARLMAN, W. A. Wavelet compression of ECG signals by the set partitioning in hierarchical trees algorithm. *IEEE Transactions on Biomedical Engineering 47*, 7 (2000), 849–856.

[12] NABAR, S., BANERJEE, A., GUPTA, S. K., AND POOVENDRAN, R. GeM-REM: Generative model-driven resource efficient ecg monitoring in body sensor networks. In *International Conference on Body Sensor Networks (BSN)* (2011), IEEE, pp. 1–6.

[13] PANDE, A., AND ZAMBRENO, J. Poly-dwt: polymorphic wavelet hardware support for dynamic image compression. *ACM Transactions on Embedded Computing Systems (TECS) 11*, 1 (2012), 6.

[14] PARTHASARATHY, S., MEHTA, S., AND SRINIVASAN, S. Robust periodicity detection algorithms. In *Proceedings of the 15th ACM international conference on Information and knowledge management* (2006), ACM, pp. 874–875.

[15] PATEL, S., LORINCZ, K., HUGHES, R., HUGGINS, N., GROWDON, J., STANDAERT, D., AKAY, M., DY, J., WELSH, M., AND BONATO, P. Monitoring motor fluctuations in patients with parkinson's disease using wearable sensors. *IEEE Transactions on Information Technology in Biomedicine 13*, 6 (2009), 864–873.

[16] PHILIPS, W. ECG data compression with time-warped polynomials. *IEEE Transactions on Biomedical Engineering 40*, 11 (1993), 1095–1101.

[17] PHILIPS, W., AND DE JONGHE, G. Data compression of ECG's by high-degree polynomial approximation. *IEEE Transactions on Biomedical Engineering 39*, 4 (1992), 330–337.

[18] REEVES, A., ET AL. Remote monitoring of patients suffering from early symptoms of dementia. In *Intl. Workshop on Wearable and Implantable Body Sensor Networks, London, UK* (2005).

[19] REFINETTI, R. Non-stationary time series and the robustness of circadian rhythms. *Journal of theoretical biology 227*, 4 (2004), 571–581.

[20] RICHARDSON, I. E. H. 264/MPEG4 part 10. *H. 264 and MPEG-4 Video Compression: Video Coding for Next-Generation Multimedia* (2003), 159–223.

[21] THATTE, G., LI, M., LEE, S., EMKEN, A., NARAYANAN, S., MITRA, U., SPRUIJT-METZ, D., AND ANNAVARAM, M. Knowme: an energy-efficient multimodal body area network for physical activity monitoring. *ACM Transactions on Embedded Computing Systems (TECS) 11*, S2 (2012), 48.

[22] TUDOR-LOCKE, C., BELL, R., MYERS, A., HARRIS, S., ECCLESTONE, N., LAUZON, N., AND RODGER, N. Controlled outcome evaluation of the first step program: a daily physical activity intervention for individuals with type ii diabetes. *International journal of obesity 28*, 1 (2003), 113–119.