35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Adaptive Sensing of ECG Signals using *R*-*R* Interval Prediction

Shogo Nakaya and Yuichi Nakamura

Abstract— **There is growing demand for systems consisting of tiny sensor nodes powered with small batteries that acquire electrocardiogram (ECG) data and wirelessly transmit the data to remote base stations or mobile phones continuously over a long period. Conserving electric power in the wireless sensor nodes (WSNs) is essential in such systems. Adaptive sensing is promising for this purpose since it can reduce the energy consumed not only for data transmission but also for sensing. However, the basic method of adaptive sensing, referred to here as "plain adaptive sensing," is not suitable for ECG signals because it sometimes capture the *R* waves defectively. We introduce an improved adaptive sensing method for ECG signals by incorporating *R*-*R* interval prediction. Our method improves the characteristics of ECG compression and drastically reduces the total energy consumption of the WSNs.**

I. Introduction

The worldwide population is progressively aging, and this inevitably causes great concern for the health care of many people. Consequently, there is growing demand for the systems capable of continuous and long-term monitoring of people's biomedical signals as they go about their normal daily lives without obstructing or annoying them. Ambulatory electrocardiogram (ECG) monitors provide particularly useful information on vital signs and have a long history as Holter devices.

A promising solution to meet the above demand is a system comprising tiny sensor nodes powered with very small batteries that acquire ECG data and wirelessly transmit the data to remote base stations or mobile phones over a long term.

To realize such systems, the use of electric power saving technology in the wireless sensor nodes (WSNs) is essential. Radio transmissions consume especially large amounts of energy, and therefore ECG data compression is considered an effective means of reducing the energy consumption. Much research has been done on ECG data compression. Time domain compression techniques such as AZTEC, CORTES, FAN, and TP [1]–[4] were proposed in the early stages of research. These technologies generally have low computational complexity and thus small energy consumption, but their compression performance is relatively low. The next-generation techniques involved transform domain compression, mainly with the help of wavelet transform [5]–[7]. Their compression performance was high, although they consumed a large amount of energy due to their high computational complexity. We respectively refer to the two stages of techniques as the first- and second-generation of ECG compression techniques in this paper.

The authors are with Green Platform Research Laboratories, NEC Corp., Kawasaki, Kanagawa, 211-8666, Japan (e-mail: s-nakaya@da.jp.nec.com).

Although a lot of research has been done on the ECG data compression, only a few analyses of energy consumptions in real WSNs have been conducted. Mamaghanian et al. [8] recently reported energy-consumption analyses of a WSN using Shimmer™ [9]. Their results indicated that sensing energy was a more important issue than transmission energy although the traditional (first and second generation) ECG compression techniques focus on saving only the latter.

In this work, we have focused on adaptive sensing techniques that reduce the amount of sensed data. These techniques can save the energy used for sensing as well as for transmission. Feizi et al. [10] researched these techniques in detail and applied them to ECG data compression. Although they called these techniques time-stampless adaptive nonuniform sampling (TANS), we refer to them as adaptive sensing because the first-generation compression techniques mentioned above are often referred to as adaptive sampling. We point out in this paper that plain adaptive sensing such as that in [10] is inadequate for actual ECG sensing because it sometimes capture *R* waves defectively. Therefore, we propose an *R*-*R* interval prediction scheme to compensate for this. In demonstrations, our method exhibited better compression characteristics than plain adaptive sensing, and it significantly reduced the amount of energy consumed by the WSNs than prior techniques.

The rest of this paper is organized as follows. Section II introduces adaptive sensing and a problem associated with it. Section III presents the improved adaptive sensing for ECG data. In Section IV, we present evaluation results of our method, and we conclude our paper in Section V.

II. Adaptive Sensing

A. Traditional Compression Techniques

Both the first- and second- generations compression techniques are processed according to the block diagram shown in Fig. 1. The processing flows from left to right in a forward direction only. A certain amount of data acquired through an analog to digital converter (ADC) is stored in a storage or memory device and compressed afterwards. In the first-generation compression techniques, ECG signals are scanned little by little, stored in the device, and then discarded except for important sample data featuring the ECG signals. The point is that the full amount of data must be acquired in the process. This is also true for the second-generation techniques. This means that these traditional compression

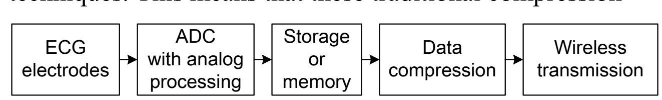

Figure 1. Block diagram of traditional data compression.

techniques cannot save any energy in the sensing process, although they can reduce the energy used for data transmission.

B. Plain Adaptive Sensing

Adaptive sensing is a time domain compression technique. However, there is a crucial difference between it and the first-generation techniques. Adaptive sensing adaptively determines the next sensing times in real time according to past acquired data, as shown in Fig. 2. Hence, data to be discarded later are not sensed, which is different from the first-generation techniques. Thus, it can save sensing energy as well as transmission energy.

Data are acquired until k-th sensing time t_k; the next sensing time t_{k+1} is computed by

$$t_{k+1} = t_k + \Delta(f(t_k)), \tag{1}$$

where $f(t_k)$ is a feature value to represent the steepness of the signal change at time t_k in some way. Since $f(t_k)$ is calculated from the acquired data until t_k , the sensing interval Δ is also calculated in the same way. This means that it is sufficient for the WSNs to transmit sensed data without any information about their intervals, because the intervals Δ can be restored from transmitted data. This advantage is what prompted Feizi et al. to call this technique time-stampless adaptive nonuniform sampling (TANS) [10].

We use the following definition as the feature value representing the steepness:

$$f(t_k) = a\cdot|v(t_k)| + b\cdot|g(t_k)|, \tag{2}$$

where $v(t_k)$ is the discrete derivative of signal $s(t_k)$:

$$v(t_k) = \frac{s(t_k) - s(t_{k-1})}{t_k - t_{k-1}} \tag{3}$$

and $g(t_k)$ is the discrete second derivative of $s(t_k)$:

$$g(t_k) = \frac{v(t_k) - v(t_{k-1})}{t_k - t_{k-1}}. \tag{4}$$

The a and b in (2) are positive constants. This type of feature value f has often been used in ECG analysis. In this paper, the time t_k and the interval Δ are measured in multiples of a minimum sensing interval T, and thus they are integers. We introduce the following linear equation as Δ:

$$\Delta(f(t_k)) = M - M\cdot U\cdot f(t_k), \tag{5}$$

where the positive constants M and U determine the upper limit of the sensing interval and the steepness of the dependence on the feature values f, respectively. The lower limit of Δ is 1.

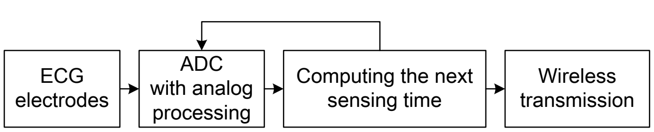

Figure 2. Block diagram of adaptive sensing.

Since the sensing interval should become shorter as the signal becomes steeper, Δ should be a decreasing function of the f. We adopted the simplest decreasing function (5) for Δ in contrast with Feizi et al. [10] because CPUs for WSNs generally have very low computing power.

After the ADC, a low-pass filter is applied to the ECG signal for smoothing, and the feature value f is then calculated from the smoothed signal. It should be pointed out that the derivative in the f calculation serves as a high-pass filter. As the low-pass filter, we use the so-called exponential moving average (EMA):

$$s(t_\kappa) = (1-\alpha)\cdot e(t_\kappa) + \alpha\cdot s(t_{\kappa-1}), \tag{6}$$

where $e(t_k)$ and $s(t_k)$ are the signals after ADC and after filtering the e, respectively. Here, α is the so-called forgetting factor between 0 and 1. The EMA filter has the advantage of saving memory because only the last single value $s(t_{k-1})$ is required. In general, the limited memory capacity in WSNs is an important matter.

C. Problem with Plain Adaptive Sensing

We applied the above plain adaptive sensing technique to actual ECG signals available on the Web and found a problem. Fig. 3 shows an example of sensing around an R wave in the ECG record s20031 obtained from the Long-Term ST Database [11]. Since the signal immediately before the R wave varies slowly, i.e. the feature value f is small, a long sensing interval is given for the next sensing. Therefore, the sensing fails to capture the major part of the R wave. This phenomenon occurs since R waves rise too suddenly and steeply to be captured by the adaptive sensing. R waves are the most important feature in ECGs, and it is a serious problem if they are defectively captured by the sensor.

III. ADAPTIVE SENSING WITH R-R INTERVAL PREDICTION

A solution to the above problem cannot be expected even if a more sophisticated feature value f and sensing interval

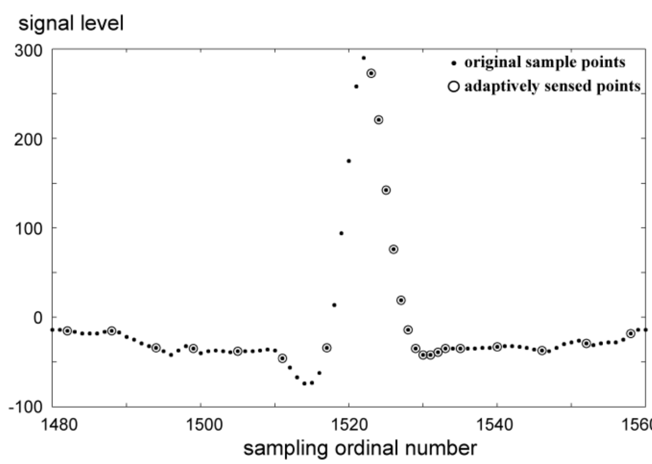

Figure 3. Example of defectively capturing R wave using adaptive sensing.

function Δ are used. Since R waves are too sudden and steep to detect them from the f, quite a different approach is required. In this work, we exploit an R-R interval prediction scheme for this purpose.

We adaptively predict R-R intervals by using the following EMA:

$$p[i] = (1-\beta)\cdot q[i] + \beta\cdot p[i-1], \tag{7}$$

where $q[i]$ and $p[i]$ are the last (i-th) R-R interval and the next predicted R-R interval, respectively. Here, β is the second forgetting factor between 0 and 1. Then, the upper limit M of the sensing interval Δ is changed from a large value to a small one at interval change point $\phi\times p[i]$ after the last R wave, where a margin factor ϕ is between 0 and 1. The smaller the ϕ is, the more robust the adaptive sensing is against R-wave prediction failure.

R-wave detection is necessary in order to acquire every R-R interval q. The detection is accomplished by comparing the feature value f with a threshold. R waves are detected if the f exceeds the threshold for a longer duration than a certain time width. To calculate the threshold adaptively, the peak value of the f in the next R wave is adaptively predicted using the third EMA:

$$z[i] = (1-\gamma)\cdot r[i] + \gamma\cdot z[i-1], \tag{8}$$

where $r[i]$ and $z[i]$ are respectively the f's peak value in the last R wave and the predicted peak value in the next R wave. Here, γ is the third forgetting factor between 0 and 1. Then, the threshold to detect the next R wave is given by $\zeta\times z[i]$, where the threshold factor ζ is a value between 0 and 1.

IV. Evaluation

The above improved adaptive sensing captures ECG signals with fine sensing intervals in the neighborhood of R waves and coarsely in the rest, and consequently enables the WSNs to save a lot of energy and preserves good signal fidelity. We demonstrated the effects of this sensing method using 10 ECG records: s20021, s20031, s20061, s20081, s20101, s20141, s20161, s20201, s20401, and s20651 in the Long-Term ST Database [11]. We evaluated the compression performance using the settings for the aforementioned parameters as shown in Table I. These values were decided to optimize the following indices as much as possible.

We employed two indices as compression characteristics: percentage root mean square difference (PRD) and compression ratio (CR). PRD measures the distortion between original data $e[j]$ and data $y[j]$ reconstructed from the adaptively sensed data and is defined as

TABLE I. Parameter Value s used in Evaluation.

a	b	U	α	β	γ	ζ	ϕ
1	2	1/8	3/8	3/4	7/8	1/3	2/3

$$PRD = 100\times\sqrt{\frac{\sum_j (e[j]-y[j])^2}{\sum_j (e[j]-\underline{e})^2}}, \tag{8}$$

where $\underline{e}$ is the average of signal e. The reconstructed data y is given by linear interpolation of the adaptively sensed data. The CR indicates compression performance based on the definition:

$$CR = \frac{\textit{the amount of original data}}{\textit{the amount of compressed data}}. \tag{9}$$

For example, CR=3 means that the amount of the compressed data is 1/3 that of the original data. In general, a lower PRD and higher CR are pursued for better performance.

The PRD versus CR of the plain and improved adaptive sensing is plotted in Fig. 4. In the case of the plain adaptive sensing, the number given at each plot mark indicates the upper limit M of the sensing interval Δ. In the case of the improved sensing, these numbers represent the M before the interval change point mentioned above; the M after that point is 3. Each PRD and CR value was averaged over the 10 ECG records. This result demonstrates that the improved adaptive sensing gives a lower PRD for the same CR or a higher CR for the same PRD than the plain sensing method.

This difference between the two techniques was expected to become larger in the neighborhood of R waves. To confirm this, we used an R-wave PRD that was defined only between 80ms before the annotated R-wave times and 120ms after them. Fig. 5 presents the R-wave PRD versus CR for the same conditions as Fig. 4. As expected, the improved adaptive sensing gives much lower signal distortion than the plain sensing in the neighborhood of R-waves.

In our method, the upper limit M changes to a small value after the interval change point $\phi\times p$ for the R-wave ready mode. The margin factor ϕ determines the total compression ratio and error tolerance for the next predicted R-R interval p. Fig. 6 depicts the PRD and CR as functions of ϕ, where M=8 before the interval change point. A value of ϕ=1 means there

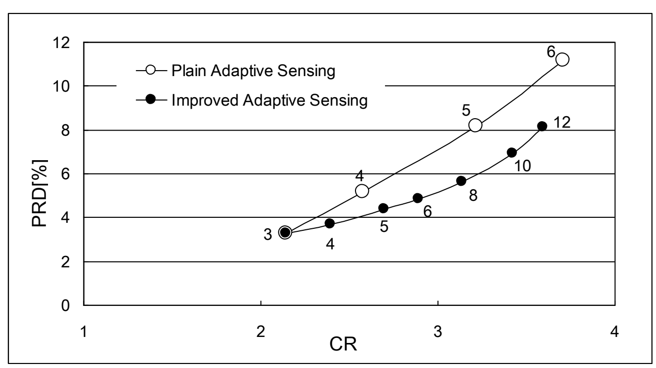

Figure 4. PRD versus CR of plain and improved adaptive sensing.

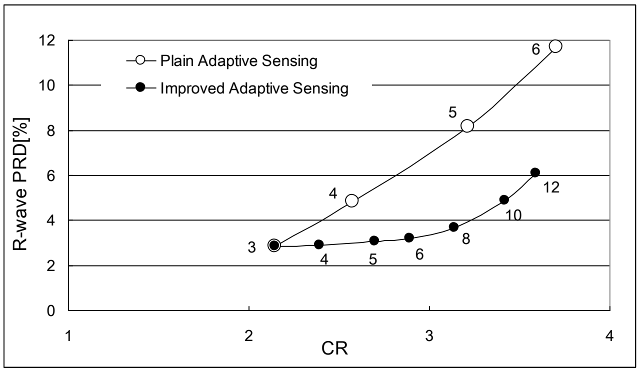

Figure 5. *R*-wave PRD versus CR for plain and improved adaptive sensing.

is no margin for the prediction, and the smaller the ϕ is, the larger the margin is. However, a high compression ratio requires a small margin. It is clear in Fig. 6 that ϕ=2/3or 3/4 gives a high CR with a good margin.

In terms of *R*-wave detection performance (sensitivity and specificity), significant differences between the plain and improved methods were not observed since such indices are insensitive to imperfectness of *R* waveforms.

Based on the results of the reference [8], we estimated the energy consumption of the WSN [9] that processes the improved adaptive sensing. The WSN has an ultra low-power microcontroller (MSP430F1611 at 8MHz by Texas Instruments) [12]. We analyzed our algorithm using the IAR Embedded Workbench [13] and found that the average number of clock cycles for processing an original data sample was 512 under the conditions listed in Table I and M=8 for the *R*-wave ready mode. The same estimation for the compressed sensing (CS) and wavelet-transform (WT) based compression gives 390 and 9048 clock cycles respectively, according to [8]. Here, the so-called "good" reconstruction quality of compression, i.e. PRD < 9% [14], was used as a reference. We used the above analysis and CR values to estimate the consumption energy for processing 512 original samples. The results and comparison with [8] are summarized in Table II.

The processing energy of our algorithm had only a slight impact on the result. Although our CR was not very high, its energy saving effect was far greater than that of the other methods because our method saves sensing energy.

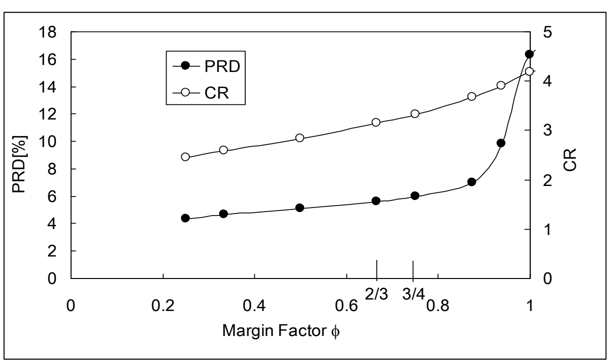

Figure 6. PRD versus margin factor ϕ.

TABLE II. ESTIMATION AND COMPARISON OF ENERGY CONSUMPTIONS

	Our method	CS [8]	WT [8]	No compression [8]
Compression ratio	3.14	3.45	10	1
Processing time [ms]	32	25	580	0
Processing energy [mJ]	0.13	0.1	2.95	0
Transmission energy[mJ]	0.46	0.35	0.12	1.15
Sensing energy [mJ]	2.1	6.6	6.6	6.6
Total energy [mJ]	2.7	7.05	9.67	7.75

V. CONCLUSION

We proposed a method of improved adaptive sensing for ECG compression. Although the adaptive sensing in itself is effective in reducing energy consumption, the plain method of adaptive sensing is not applicable to ECG. To overcome the defective *R*-wave problem, we incorporated an *R-R* interval prediction scheme into the adaptive sensing. The compression characteristics were demonstrated to improve by applying this scheme. The demonstration showed that our method drastically reduced the total energy consumption of WSNs.

REFERENCES

[1] J. R. Cox, F. M. Nolle, H. A. Fozzard, G. C. Oliver, "AZTEC, a Preprocessing Program for Real-Time ECG Rhythm Analysis," *IEEE Trans. Biomed. Eng*., vol. 15, pp. 128–129, Apr. 1968.

[2] J. P. Abenstein and W. J. Tompkins, "A new data reduction algorithm for real time ECG analysis," *IEEE Trans. Biomed. Eng*., vol. 29, no. 1, pp. 43–48, Jan. 1982.

[3] D. A. DiPersio and R. C. Barr, "Evaluation of the fan method of adaptive sampling on human electrocardiograms," *Med. & Biol. Eng .& Comput.* vol. 23, pp. 401–410, Sep. 1985.

[4] K. Kato and S. Sato, "Data Compression of a Gaussian Signal by TP Algorithm and Its Application to the ECG," *IEICE Trans. Inf. & Syst.* vol. E76-D, no. 12, pp. 1470–1478, Dec. 1993.

[5] M. Hilton, "Wavelet and wavelet packets compression of electrocardiogram," *IEEE Trans. Biomed. Eng*., vol. 44, no. 5, pp. 394–402, May 1997.

[6] Z. Lu, D. Y. Kim, and W. A. Pearlman, "Wavelet compression of ECG signals by the set partitioning in hierarchical trees algorithm," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 7, pp. 849–856, Jul. 2000.

[7] B. A. Rajoub, "An efficient coding algorithm for the compression of ECG signals using the wavelet transform," *IEEE Trans. Biomed. Eng.*, vol. 49, no. 4, pp. 355–362, Apr. 2002.

[8] H. Mamaghanian, N. Khaled, D. Atienza, and P. Vandergheynst, "Compressed sensing for real-time energy-efficient ecg compression on wireless body sensor nodes," *IEEE Trans. Biomed. Eng.*, vol. 58, no. 9, pp. 2456–2466, Sep. 2011.

[9] Shimmer Research. [Online]. Available: http://shimmer-research.com

[10] S. Feizi, G. Angelopoulos, V.K. Goyal, M. Médard, "Energy-Efficient Time-Stampless Adaptive Nonuniform Sampling," *IEEE Sensors 2011 Conference*, pp. 912–915, Oct. 2011.

[11] The Long-Term ST Database. [Online]. Available: http://www.physionet.org/physiobank/database/ltstdb/

[12] Texas Instruments. [Online]. Available: http://www.ti.com/lsds/ti/microcontroller/16-bit_msp430/overview.page

[13] IAR Systems. [Online]. Available: http://www.iar.com/jp/Products/IAR-Embedded-Workbench/TI-MSP430/

[14] Y. Zigel, A. Cohen, and A. Katz, "The weighted diagnostic distortion (WDD) measure for ECG signal compression," *IEEE Trans. Biomed. Eng.*, vol. 47, no. 11, pp. 1422–1430, Nov. 2000.