A Method for Energy Saving on Context-aware System by Sampling Control and Data Complement

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Abstract

Although various systems use multiple accelerometers to recognize minute motions and states in the research area of context-awareness, a conventional architecture can be optimized from the viewpoint of its energy consumption and accuracy. In this paper, we propose a context-aware system that reduces the energy consumption by controlling the sampling frequency of wearable sensors. Even if the sampling frequency changes, no extra configuration is required because the missing data for the controlled sensors are complemented by our proposed algorithm. The evaluation results confirmed a power-reduction of 34.28% with keeping the accuracy. The energy consumption can be reduced without a large loss in accuracy using our system.

1. Introduction

Many context-aware systems with various kinds of sensors have recently been introduced in the research area of context-awareness. Context-aware systems are applied to various services i.e., health care. Though in these services, accelerometer plays an important roll, the architectures are not optimal in terms of power consumption. The number of sensors in conventional systems are predetermined and fixed. If the power supply and sampling frequency can be flexibly controlled, the power consumption can be reduced. Since the battery size is limited for wearability, reducing of power consumption is an important issue.

In this paper, we propose a method to conserve power in a context-aware system by decreasing the sampling frequency of the accelerometers. Our proposal complements the missing data caused by the sampling frequency control to maintain the accuracy. The sampling frequency of the data given to a context-aware system is kept constant. Therefore, neither extra training data nor a specific setting of the context-aware system are required. The energy consumption can be reduced without any large losses in recognition accuracy by using our proposal.

2. Related Work

Sensors of context-aware systems are used in the environment where battery size is limited. In addition, sensors with wireless transmission capubilities, such as Bluetooth, have recently been appearing. The Power necessary for transmitting data is large and power saving is required compared with wired sensors. Kang et al. proposed a system with only a minimum subset of multiple heterogeneous sensors that transmit to detect true/false threshold-based queries [1]. However, only threshold-based queries are supported, and whether each accelerometer is controlled and the recognition performance are unclear. Meanwhile, Murao et al. were able to reduce the energy consumption with keeping the accuracy by turning sensors off and by complementing data for the shut-off sensors according to the tolerance of the accuracy indicated by the users or applications [3]. In addition, Van Laerhoven et al. presented a low-power node with nine tilt switches and an accelerometer. While the tilt switches do not change, the accelerometer is turned off [4]. However, these systems turn sensors only ON/OFF and do not finely control the power, such as by controlling the sensors' sampling frequency. Generally, although detailed movement can be detected and the recognition accuracy rises with a high sampling frequency, much of the power is consumed for sampling and transmitting data to a computer. Andreas et al. proposed a system that reduces the energy consumption by controlling the sampling frequency of one accelerometer [2]. However, this system is not general because it implements a unique stand-by state that stops the processor between samplings. Moreover, simply reducing sampling frequency requires additional recognition models which has learned data captured with the sampling frequency after control since feature values change according to the sampling frequency. However, this is unrealistic to make models of all possible frequencies.

In this paper, we propose a context-aware system that flexibly controls trade-off between energy consumption and recognition accuracy by sampling control and data complement.

3. Proposed Method

3.1 Sampling frequency control

We propose the following two methods for reducing the production of data samples.

The Constant Reduction Method (CRM) controls the frequency by sampling the data once every n times, as shown in Figure 1. The sampling frequency when $n = 1$ is called the base frequency. For example, when the base frequency is set to 100 Hz, the sampling frequency becomes 50 Hz when $n = 2$. However, n should be a divisor of the base frequency.

The Burst Reduction Method (BRM) intermittently samples data, as shown in Figure 2. Let us assume time is $t = T$, then variance σ_T over N sample data sequence $W_T = (x_{T-N+1}, \cdots, x_T)$ is calculated. If $|\sigma_T - \sigma_{T-N}|$ runs over the threshold Th, the subsequent N samples W_{T+N} are captured. Otherwise, W_{T+N} are not captured and W_{T+2N} are captured. This method would effectively reduce the number of data samples, because human continues same context for certain period.

3.2 Data complement

The recognition algorithm learned the data in advance without missing any data. If the sampling frequency of the data for testing differs from that for training, the contexts are not well recognized since the feature values differ as the sampling frequency changes. Making recognition models for all the sampling frequencies is not realistic since there are a lot of combinations. Therefore, by complementing the missing data, the sampling frequency of the data fed to the recognition algorithm is kept constant. Six methods of data complement are described in the following paragraphs.

The Up Sampling Method (USM) resamples data with higher sampling rates. Any missing data in the obtained data sequence are replaced with 0 and FFT takes place for the sequence. Then, the LPF to cut the frequency over a half of the sampling frequency (Niquist frequency) is applied, and then the FFT is conducted. If we use this method with BRM, the recognition accuracy obviously goes down since the amount of data is continuously lacking. Therefore, this method is used with CRM.

The Same Value Complementation Method (SVCM) complements the missing data using the preceding sampled value. This method is used with CRM for the same reason as for USM.

The Liner Complementation Method (LCM) complements the missing data using the data on the line connecting the preceding sensing data and the adjacent complemented data. This method is used with CRM for the same reason as for SVCM.

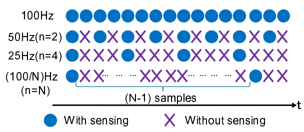

Figure 1. CRM

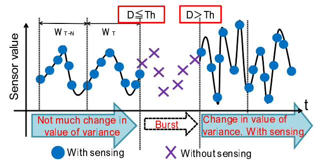

Figure 2. BRM

The Window Copy Method (WCM) complements the missing window data by using BRM with the window data of the preceding sampling, as shown in Figure 3. This method is used with only BRM because continuous data are needed.

The Pair Database Method (PDM) complements the missing data according to the values of the other sensors that have captured data when multiple accelerometers are used. Figure 4 illustrates the flow of PDM. For the sake of simplicity, three 1-axis sensors are used in this example. The system has collected complete sensed data (pair-data) for all the contexts and constructed a database of pair-data (pair-database) in advance. When the input data (15, 90, -) contains missing data, the missing data is removed. We call the remaining part (15,90) a recognition vector. Then, the system finds the pair-data in the pair-database that is nearest to the recognition vector by using the k-NN method, and the pair-data (20,100,100) is the nearest one. Finally, the data for the missing data are replaced by that from the extracted pair-data (100). A complemented vector (15,90,100) is generated and will be the input for the context-aware algorithm.

The Enhanced Pair Database Method (EPDM) is similar to PDM, but each pair-data has two continuous data. The procedure for EPDM is shown in Figure 5. Let us assume time $t = T$ now, and the input data of $t = T$ (-, 30, 70) and $T - 1$ (-, 10, 90) are used to create the recognition vector, and then the nearest pair-data is extracted from the pair-database as well as by using PDM. As a result, the missing data of $t = T$ is complemented using the data in the extracted pair-data corresponding to the missing data (30) and the complemented vector (30, 30, 70) is generated. The missing data of $t = T - 1$ is not complemented at that time since the data is already complemented at time $t = T - 1$. If all the sensors did not capture data at the same time, PDM and EPDM cannot be used. In that case, an exceptional process is carried out, which calculates the correct features by taking into consideration the number of captured data in the window. Both methods of sampling control are used since PDM and EPDM do not depend on how the data are missed.

4. Evaluation

This experiment provided data from nine activities captured from one test subject who wore three-axis wireless accelerometers [5] on his right ankle, right wrist, and waist. Obtained nine contexts are *Walking*, *Running*, *Ascending*

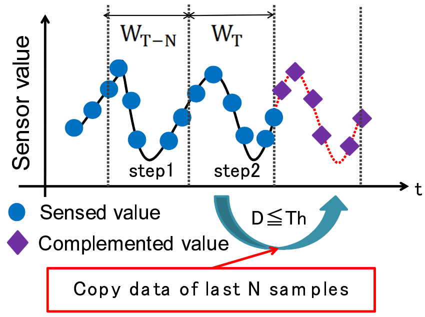

Figure 3. WCM

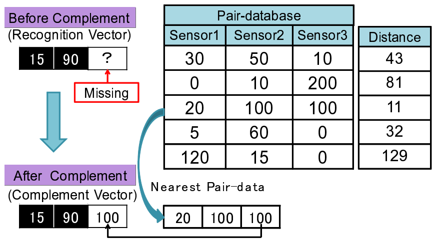

Figure 4. PDM

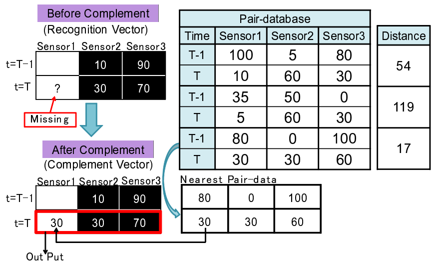

Figure 5. EPDM

Table 1. Trade-off between sampling and energy

Sampling frequency	Operation time	Energy consumption
200 Hz	210 min	243 mW
100 Hz	428 min	119 mW
50 Hz	490 min	104 mW
10 Hz	551 min	92 mW
1 Hz	570 min	89 mW

stairs, *Descending stairs*, *Lying*, *Kneeling*, *Sitting*, *Standing*, and *Biking*. There were 10000 samples of captured data at 150 Hz for each context, and 100 samples of which were used for training and the remaining one are used for testing. The correct contexts are manually labeled. USM, SVCM, LCM, PDM, and EPDM are applied to the data whose sampling frequency is reduced to 75 Hz, 15 Hz, and 1.5 Hz by CRM. In addition, WCM, PDM, and EPDM are applied to the data whose sampling frequency is reduced by BRM. The base frequency is set to 150 Hz. The System uses the average and variance as its features. We adopted SVM as a recognition algorithm from viewpoint of performance.

4.1 Sampling v.s. energy

Before going on the experiments, we measured the operation time of the sensors for different sampling frequencies to clarify the trade-off between the sampling frequency and energy consumption. From the results listed in Table 1, the energy consumption goes down as the sampling frequency decreases. Thus, it is clear that we can conserve energy by changing the sampling frequency. The same kind of tendency has been reported in [2]. Although the number of trials of data complement increases as the number of missing data increases, since even PDM consumes much less power than for sensing and transmitting [3], the sampling frequency control can conserve energy.

4.2 Performance of data complement

In this section, the sampling frequency of one sensor is reduced by CRM and the remaining two sensors are not controlled in order to observe the performance of the data

Table 2. Recognition accuracy for each complement method

Complement method			Recognition accuracy (%)			
ankle	wrist	waist	150 Hz	75 Hz	15 Hz	1.5 Hz
-	-	-	97.40	-	-	-
W/O C	-	-	-	93.82	90.92	81.42
SVCM	-	-	-	96.12	93.07	83.11
LCM	-	-	-	96.13	93.51	83.86
USM	-	-	-	96.12	93.07	83.01
PDM(C)	-	-	-	94.78	91.92	90.84
EPDM(C)	-	-	-	95.85	92.19	90.81
-	W/O C	-	-	94.41	92.34	86.65
-	SVCM	-	-	96.40	96.30	89.98
-	LCM	-	-	96.41	96.42	90.27
-	USM	-	-	96.40	96.30	89.98
-	PDM(C)	-	-	95.94	94.09	93.58
-	EPDM(C)	-	-	96.43	93.89	92.87
-	-	W/O C	-	93.36	91.82	75.09
-	-	SVCM	-	96.37	94.93	80.41
-	-	LCM	-	96.34	94.67	80.85
-	-	USM	-	96.37	94.93	80.45
-	-	PDM(C)	-	95.67	94.50	94.27
-	-	EPDM(C)	-	96.17	94.21	93.70

complement methods. The averages of the recognition accuracy over ten trials are listed in Table 2. The top line shows the result without sampling control. "W/O C" means "Without Complement" and "(C)" means "using CRM". The recognition accuracies are kept high regardless of the frequency compared to the results without data complement. A t-test (significance level 5%) is applied to these results. As a result, there is not significant difference between the complement methods at 75 Hz. However, we did confirm that there is a significant difference between PDM or EPDM and the other methods at 1.5 Hz. This is because the intervals of sampling elongate and the complemented values differ from the actual values, while PDM and EPDM complement well since the current values of the other sensors are used.

4.3 Combination of sampling control and data complement

Table 3 lists the recognition accuracy when the frequency control methods and the data complement methods are individually applied to each sensor. Each row shows the combination of the methods satisfying the required accuracy. The numbers in the parenthesis in the reduction rate column represent the power-reduction rates when W/O C is

Table 3. Recognition accuracy and power-reduction rates

Required accuracy (%)	Method			Power-reduction rate (%)				Recognition accuracy (%)
	ankle	wrist	waist	average	ankle	wrist	waist	
97	LCM75	SVCM15	WCM100-10^5	34.28	29.73	43.37	29.73	97.04 (81.51)
96–94	LCM75	SVCM15	SVCM15	38.82	29.73	43.37	43.37	96.12 (83.24)
93–90	EPDM(C)15	PDM(C)15	SVCM15	43.37	43.37	43.37	43.37	93.00 (79.83)
89–85	EPDM(C)15	PDM(C)15	EPDM(C)1.5	43.84	43.37	43.37	44.78	89.43 (74.56)

applied at the same sampling rate. In the table, the sampling frequency of CRM and the threshold of the window N and variance Th of BRM are written after the name of the complement methods. The power-reduction rates in Table 3 are calculated from the results listed in Table 1. It is confirmed that at least 34.28% of the power-reduction rate on average is achieved when the required recognition accuracy is more than 85%. CRM achieves this high power-reduction rate by setting the sampling frequency while the power-reduction rate of BRM achieves 29.73% at most. Therefore, CRM occupies the results at a high degree of accuracy. It is confirmed from the results of t-test in Section 4.2 that all the complement methods are allowed high sampling rates since a significant difference is not seen among them. Meanwhile, intelligent algorithms such as PDM and EPDM are needed at low sampling rates because there is a significant difference between them and the others.

The data used in the evaluation were obtained in laboratory environment, which means the variance does not fluctuate. We also evaluated all of this on a 24-hour data set to test whether a long-term deployment has a significant difference on the reported results, and found only minor differences.

4.4 Uniformization of power-reduction

Seeing the results when the required accuracy is 94-96%, the power-reduction rate of the ankle sensor is only 29.73% while the others are 43.37%, which means the ankle sensor stops first, and the cases for 85-89% are as well. For practical use, uniformizing the energy of all the sensors extends the lifetime of the system. Therefore, by combining the two methods for each region, the lowest power-reduction rate for the sensors that has been bottle-neck is improved. In order to find the optimal combination, all the combinations of the two methods are simulated by changing the proportion of each method. Compared with the results in Table 3, when the recognition accuracy is in the ranges of 94-96% and 85-88%, the power-reduction rate is improved by 4-10.8% and 0.28-1.22%, respectively.

4.5 Comparison with power control

This section compares our sampling frequency control with the sensor power control proposed in [3]. When only one sensor is used, the recognition accuracy is 87.00% and the power-reduction rate is 36.33%. On the other hand, when two sensors are used, the recognition accuracy is 92.54% and the power-reduction rate is 27.10%. From the results in Table 2 and that of the two sensors, power control is superior to the sampling control from the viewpoint of the power reduction. Although its recognition accuracy severely decreases, the flexible control can be conducted by using the proposed method. In addition, when comparing the power-reduction rate of one or two active sensors on average with that listed in Table 3, the controlling sampling frequency is superior. From this viewpoint, the controlling sampling frequency methods refrain from the drop in accuracy and have a higher degree of power-saving.

5 Conclusion

We have proposed a method of energy saving for context-aware systems using a sampling control and the data complement in this paper. Although the recognition accuracy was 97.40% without any control, 34.28% of the power was reduced with keeping a 97% accuracy. In addition, we proposed a method to make the power consumption uniform by combining two methods to cover the low power-reduction rate of each one. As future work, we plan to propose a method to extend a window size of BRM as data is continuously cut.

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