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著者	Xu Tongtong
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Analysis and Modeling of Temporal Features in Data Streams from Multiple Wearable Devices

Tongtong Xu
Graduate School of Computer and Information Sciences
Hosei University
Tokyo 184-8584, Japan
tongtong.xu.66@stu.hosei.ac.jp

***Abstract*—Time is a vitally important issue in the coordination of multiple wearable devices. Theoretically, wearable applications should require data streams to be synchronized with the necessary degree of precision. However, in the available applications, this critical issue has not been well considered. Actually, time discrepancies exist among data streams, resulting in certain decrease of data analysis and fusion accuracy. The study of time discrepancy is rarely found in the literature, and there is no specific model to describe temporal features. In this dissertation, we first analyze several temporal issues in multi-wearable system and the source of time discrepancy. Then, by taking into account temporal features, we propose two typical models, which provide statistical methods for describing time discrepancy and its distribution. Furthermore, the accuracy of the models is verified by a set of experiments. Finally, we demonstrate the application of the proposed models through a case study, in which the adaptive frequency strategy is adopted. Experimental results show that the strategy can not only guarantee the completeness of the data, but also reduce redundancy compared with the static frequency method. Our models and experiments of time discrepancy can be a basis for further research on the time synchronization of data from multiple wearable devices.**

Keywords—time discrepancy; temporal features; statistical model; synchronization; wearable device

I. Introduction

Recent technological advances in wearable computing, low-power integrated circuits, and wireless communications have enabled the design of low cost, miniature, lightweight, and intelligent sensors. These sensors, capable of sensing, processing, and communicating, can be used to detect user's location [1] and daily activity, and can even be incorporated into ambience to monitor the environment status. In addition, some wearable devices containing biosensors such as heart rate sensor, electrocardiogram (ECG) sensor, and blood pressure sensor have been developed. One or more vital signs from these wearable devices can be seamlessly integrated into wearable applications and further can provide users with health status such as nutrition, stress, relaxation, heartbeat and sleep quality.

The design and development of wearable biosensor systems for health monitoring [2] have gained much attention in the academic community and the industry. Over the last years, various healthcare applications have been developed in several research activities [3], following an integral approach in human physiology and focusing on the continuous detection of the health status.

In these applications, coordinating multiple devices to achieve the health monitoring target requires data fusion from various devices. Therefore, to improve the accuracy of the monitoring, many studies have focused on high-level multi-device fusions [4]. But in the process of data fusions, one aspect that cannot be ignored is that given a multitude of devices, combining data to derive valuable information requires them to work together with minimal time discrepancy. Especially in a multi-wearable system, such as [5], where the number and status of wearable devices are dynamically changed. Theoretically, applications should require data streams to be synchronized with necessary degrees of precision. However, traditional applications directly deal with original data, regardless of whether there are discrepancies, resulting in insufficient reliability of the analysis results.

To the best of our knowledge, there are only few relevant studies on the time discrepancy of the data from multiple wearable devices, and there is no specific model to describe temporal features. This dissertation strives to analyze the source of time discrepancy and find the temporal features of the data streams from multiple wearable devices. Based on temporal features, we propose two typical models, which provide statistical methods for describing time discrepancy of data streams from multiple wearable devices. In addition, we experimentally demonstrate the effectiveness of the proposed models in improving the quality of data. Our study of time discrepancy will provide a theoretical and experimental basis for further research on personal data collection [6] and time synchronization of data from multiple wearable devices.

The rest of this dissertation is organized as follows. In the next section, several related studies found in the literature are reviewed. In Section III we give an overview of temporal issues in multi-wearable system as well as the sources of time discrepancy. In Section IV, two temporal models are proposed based on the temporal features in data streams from multiple wearable devices. The accuracy and usability of the proposed models are demonstrated through the case study in Section V. Finally, Section VI summarizes our research achievements and briefly describes the future research issues.

Supervisor: Prof. Jianhua Ma

II. Related Work

Time issues in wireless sensor networks (WSN) and multimedia have been studied deeply in the past few years, and various protocols and schemes have been proposed and experimentally evaluated to achieve time synchronization between data streams. These time synchronization schemes are devised to adjust the local time of network nodes to the same reference value, thus ensuring that there is no time discrepancy between the node data.

A survey of time synchronization mechanisms can be found in [7], from which we can find several factors that affect the time issues. The Network Time Protocol (NTP) proposed by Mills is a traditional approach to synchronize the time of nodes in networks [8]. Elson et al. proposed a novel approach called Reference Broadcast Synchronization (RBS) for sensor networks [9], in which the general idea is to use a "third party" for synchronization, rather than directly synchronizing between the sender and a receiver. Ganeriwal et al. proposed a time synchronization protocol called Timing-Sync Protocol for Sensor Networks (TPSN) based on traditional sender-receiver synchronization methods, which can realize synchronization in the whole networks [10]. A number of techniques for higher synchronization accuracy have been proposed in the literature, while a novel approach put forward by Greunen and Rabaey was aimed at minimizing the complexity of the synchronization [11]. Maróti et al. proposed a similar TPSN protocol known as the Flooded Time Sync Protocol (FTSP) for large-scale multi-hop networks [12].

The classical example of multimedia synchronization is the synchronization between the audio stream and the associated lip movements in a speech, which is called lip-synchronization or lip-sync [13]. While in a distributed multimedia presentation (DMP) system, which integrates multiple media streams, e.g., audio, video, image, and text media, and possesses timeliness requirement of media units with respect to the presentation. It is necessary to ensure flexibility and good quality of service (QoS) for multimedia data presentation. To realize flexible and satisfactory presentation of multimedia data, a collaboration between sources, networks and receivers must be carefully designed to transfer the data to receivers. A comparison of time synchronization mechanisms in the multimedia can be found in [14], in which the concepts of intra-stream and inter-stream are illustrated in detail.

This dissertation strives to provide an overview of temporal issues in multi-wearable system and analyze the source of time discrepancy, and in this context, find the temporal features of the data streams from multiple wearable devices. Based on temporal features, we propose two typical models, which provide statistical methods for describing time discrepancy and its distribution. In addition, we experimentally demonstrate the effectiveness of the proposed models in model matching and data quality improvement. Our study of time discrepancy will provide theoretical and experimental basis for further research on personal data collection and time synchronization of data from multiple wearable devices.

III. Temporal Issues in Multi-Wearable System

Our research is mainly based on the multi-wearable system, as shown in Fig. 1, the basic structure consists of three layers. In the wearable layer, a variety of devices such as bracelets, smart watches, rings and other intelligent items are used to collect the user's activity data, which are then fused when they reach the gateway layer. The specific application installed on the gateway will calculate and exhibit personal characteristics, e.g., steps, energy burn, sleep status to the user. These types of information will be uploaded to the cloud layer as historical data and can be shared with others based on the user's settings.

However, different levels of factors, such as clock drift, processing delay and network latency can be found, which will result in time discrepancies, i.e. the timestamps of data for different devices are inconsistent even if they are collected at the same time.

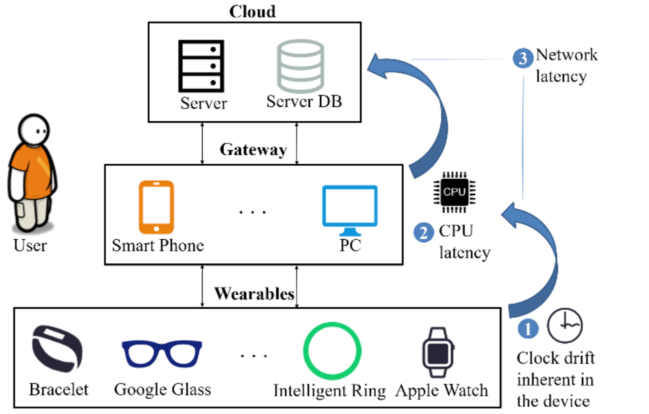

Fig. 1. Temporal issues in multi-wearable system

With these above-mentioned factors in our system, time discrepancies can be manifested in the data streams from multiple wearable devices in two ways, namely intra-stream and inter-stream. The temporal relationship between data streams is illustrated in Fig. 2, where the time of the left data item is the real time when the raw data is generated, and the right side is the actual stamp time. From this diagram, we can see that, assuming the data transmission time from the wearables to the gateway is the same, even if the data items are generated simultaneously, they will also obtain a variety of timestamps, where the time discrepancy varies depending on intra-stream or inter-stream.

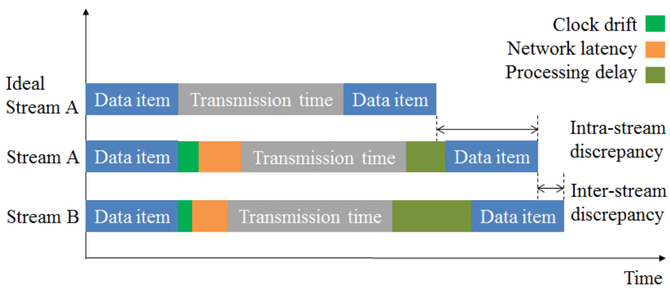

Fig. 2. Time discrepancy of data streams

According to the analysis results from 12 kinds of data, different wearable devices transfer data with different strategies, which can be divided into two categories, i.e., *static frequency* and *dynamic frequency*. When we try to use statistic methods to analyze these data, we find that although the device data is given at a static or dynamic frequency, but in fact they follow certain rules. The features of data streams can be described from the perspective of *intra-stream* and *inter-stream*. However, even with the features, we still cannot reduce the impact of time discrepancy. In such context, we present two typical temporal statistical models based on the time features of data streams from multiple wearable devices.

IV. Temporal Statistical Models

In this section, we propose two typical statistical models based on time interval features, which provide mathematical methods for describing time discrepancy and its distribution.

A. *Single-Modal Normal Distribution (SMND)*

In our experiment, 491 heartbeat data items were gathered from Polar H6. Ideally, the data should be transmitted at a *static frequency* and the time interval of the adjacent data should be 1 second if the time accuracy is required to second. However, when we consider time accuracy as milliseconds, only a small fraction of the data fit the expected static frequency. As shown in TABLE I, the time interval of the adjacent data varies from 993 milliseconds to 1002 milliseconds. We can find from the table, the 998 milliseconds time interval account for the largest proportion, with its distribution centered at 997 milliseconds and 998 milliseconds, and then exhibits a decreasing trend to both sides.

TABLE I. Time Distribution of Heartbeat Data (Polar H6)

Time-interval (milliseconds)	*Count*	*Proportion*	*Model probability density*	*Model error*
993	5	1.02%	0.25%	-0.77%
994	14	2.85%	1.65%	-1.20%
995	34	6.92%	6.68%	-0.24%
996	77	15.68%	16.80%	1.12%
997	105	21.38%	26.28%	4.90%
998	125	25.46%	25.54%	0.08%
999	70	14.26%	15.42%	1.16%
1000	28	5.70%	5.79%	0.09%
1001	10	2.04%	1.35%	-0.69%
1002	7	1.43%	0.20%	-1.23%

Factors that influence the time discrepancy have been discussed before, and it is these elements that lead to such a distribution of time interval. In probability theory, the central limit theorem (CLT) establishes that, for the most commonly studied scenarios, when independent random variables are added, their sum tends toward a normal distribution even if the original variables themselves are not normally distributed. Based on this, normal distribution model can be used to describe the distribution features of time interval.

As in (1), T stands for the time interval of the adjacent heartbeat data, and its distribution features follow the Single-modal normal distribution. μ is the mean and σ^2 is the variance of the collected data.

$$T \sim N\left(\mu,\ \sigma^2\right) \tag{1}$$

Equation (2) is the probability density function (PDF) of the time interval distribution and is used to specify the probability of the time interval falling within a particular range of values.

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}}\ exp\ (-\ \frac{(t-\mu)^2}{2\sigma^2}) \tag{2}$$

The cumulative distribution function (CDF) as in (3) is used to describe the probability distribution of time interval, which is the integral of the probability density function.

$$F(t;\ \mu,\ \sigma) = \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{t} exp\left(-\frac{(t-\mu)^2)}{2\sigma^2}\right)dt \tag{3}$$

When we use the existing model to estimate the experimental data, the confidence interval with a significance level of α can be calculated by (4), where $Z_{\alpha/2}$ is the bilateral quantile of normal distribution.

$$\left[\bar{T} - \frac{\sigma}{\sqrt{n}}Z_{\alpha/2}, \bar{T} + \frac{\sigma}{\sqrt{n}}Z_{\alpha/2}\right] \tag{4}$$

The degree of fitting of the model to the actual data distribution can be reflected by the correlation coefficient. As in (5), where R represents raw data from the wearable device and M means model data. *Cov(R, M)* is the covariance of R and M, *Var[R]* is the variance of R, and *Var[M]* is the variance of M.

$$r(R,\ M) = \frac{Cov(R,M)}{\sqrt{Var[R]Var[M]}} \tag{5}$$

Using the single-modal normal distribution model, we can combine Polar H6's heartbeat data to calculate the parameters and the corresponding values as listed in TABLE II. In addition, the probability density corresponding to each time interval can also be computed, as shown in the fourth column of TABLE I. In the Fifth column, the model error is the difference between the probability calculated by (2) and the actual proportion, which can initially reflect the degree of fit between the model and the actual data.

TABLE II. The Parameters and Values of SMND

Parameter	*Symbol*	*Value*
Data quantity	n	491
Mean	μ	997.44
Variance	σ^2	2.10
Standard deviation	σ	1.45
Significance level	α	0.05
Confidence level	1-α	0.95
Sampling average error	$\sigma/\sqrt{n}$	0.07
Bilateral quantile	$Z_{\alpha/2}$	1.96
Allowable error	$\sigma/\sqrt{n}\ *\ Z_{\alpha/2}$	0.14
Lower confidence limit	$\bar{X} - \sigma/\sqrt{n}\ *\ Z_{\alpha/2}$	997.30
Upper confidence limit	$\bar{X} + \sigma/\sqrt{n}\ *\ Z_{\alpha/2}$	997.58

We can use the model to fit the actual time interval distribution, as the results shown in Fig. 3. The horizontal axis represents the time interval between adjacent data items, and the vertical axis shows the corresponding probability or proportion. The blue histogram represents the distribution of the actual time interval, and the red solid line reflects the fitting curve of the model. The correlation coefficient can be used to judge the correlation between the model data and the raw data. In this case, the correlation coefficient obtained by (5) is 0.9938, which means that the model data is in agreement with the original data.

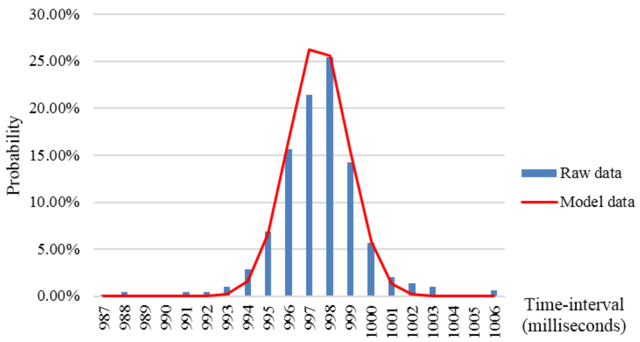

Fig. 3. Time interval distribution and model fitting curve of heartbeat data

In this section, we propose a model called single-modal normal distribution based on the temporal features to describe the time interval distribution of heartbeat data. Through the above analysis, we can draw the conclusion that the proposed model can accurately reflect the actual distribution. It should be noted that this model is constructed based on the time interval features of heartbeat but not limited to this kind of data. Among the wearable devices we analyzed, if the data features exhibit a single peak distribution, the model can be used to describe it, but for the different cases, the model parameters need to be adjusted. In addition, with this statistical model, the existence of time discrepancy and the its size can be determined. More details about how to calculate the time discrepancy and how to improve the data quality will be illustrated in the case study.

B. *Multi-Modal Normal Distribution (MMND)*

We collected 3694 step data from Apple Watch, and the time interval between each adjacent data seemed to be different. Theoretically, the step data of the Apple Watch changes as the user's status changes, so the data will be generated at a *dynamic frequency*. However, when statistics are made on the frequency of each time interval, we find that even if the frequency changes dynamically, it follows a certain law. As shown in TABLE III, part of the time interval distribution of step data. According to the definition of a small probability event, we will no longer consider such time intervals whose probability of occurrence is less than 1%. Depicted from the TABLE III, the time interval of the adjacent data is changed from 0 minutes to 12 minutes, and the count and proportion represent the corresponding amount and percentage of overall data. The features of the time interval distribution can be extracted, and the curve of the data shows bimodal structure. The distribution centered at 1 minutes and 10 minutes, and then exhibits a decreasing trend to both sides.

TABLE III. TIME DISTRIBUTION OF STEP DATA (APPLE WATCH)

Time-interval (minutes)	*Count*	*Proportion*	*Model probability density*	*Model error*
0	35	0.70%	4.39%	3.69%
1	2939	59.08%	59.37%	0.29%
2	468	9.41%	10.46%	1.05%
3	252	5.07%	0.02%	-5.04%
4	160	3.22%	0.01%	-3.21%
5	116	2.33%	0.08%	-2.26%
6	102	2.05%	0.39%	-1.66%
7	81	1.63%	1.38%	-0.25%
8	77	1.55%	3.36%	1.81%
9	88	1.77%	5.65%	3.88%
10	355	7.14%	6.56%	-0.58%
11	97	1.95%	5.24%	3.30%
12	57	1.15%	2.89%	1.75%

It is obvious that the previously proposed model called single-modal normal distribution is no longer suitable to describe the time interval distribution of step data because there are two salient points. Further analysis shows that the data distribution is centered at each salient point and subject to a normal distribution respectively. Based on above analysis, we propose a new model called multi-modal normal distribution, as described in (6), where μ_i and $\sigma_i{}^2$ represent the mean and variance of each normal distribution. The value of parameter i can be 1 and 2 since there are two peaks in this case.

$$T \sim N\ (\mu_i,\ \sigma_i{}^2)\ \ (\mathrm{i} = 1,\ 2) \tag{6}$$

Equation (7) is the probability density function (PDF) of the time interval distribution, where k_i represents the weight of the i-th normal distribution and the constraint relation is expressed as $\sum_{i=1}^{2} k_i = 1$.

$$f(t)\ =\ \sum_{i=1}^{2} \frac{k_i}{\sigma_i\sqrt{2\pi}}\, exp\ (-\ \frac{(t-\mu_i)^2}{2\sigma_i{}^2}) \tag{7}$$

The cumulative distribution function (CDF) as in (8) is used to describe the probability distribution of time interval, which is the integral of the probability density function.

$$F(t;\ \mu_i, \sigma_i)\ = \sum_{i=1}^{2} \frac{k_i}{\sigma_i\sqrt{2\pi}} \int_{-\infty}^{t} exp\ (-\ \frac{(t-\mu_i)^2}{2\sigma_i{}^2})\ dt \tag{8}$$

Using the multi-modal normal distribution model, combined with Apple Watch's step data we can calculate the parameters and the corresponding values, as listed in TABLE IV. The weights of the two normal distributions are 0.73 and 0.27 respectively. In order to be able to use the existing model to estimate the experimental data, the confidence intervals calculated by (4) with a significance level of 0.05 are also listed. In addition, the probabilities corresponding to each time interval are computed, as shown in the fourth column of TABLE III. In the Fifth column, the model error is the difference between the probability calculated by (7) and the actual proportion, which can initially reflect the degree of fit between the model and the actual data.

TABLE IV. THE PARAMETERS AND VALUES OF MMND

Parameter	*Symbol*	*Value*	
ID	i	1	2
Data quantity	n_i	2697	997
Weight coefficient	k_i	0.73	0.27
Mean	μ_i	1.10	9.90
Variance	${\sigma_i}^2$	0.23	2.69
Standard deviation	σ_i	0.48	1.64
Significance level	α	0.05	0.05
Confidence level	1-α	0.95	0.95
Sampling average error	$\sigma_i/\sqrt{n_i}$	0.01	0.05
Bilateral quantile	$Z_{\alpha/2}$	1.96	1.96
Allowable error	$\sigma_i/\sqrt{n_i} * Z_{\alpha/2}$	0.02	0.10
Lower confidence limit	$\bar{X} - \sigma_i/\sqrt{n_i} * Z_{\alpha/2}$	1.08	9.80
Upper confidence limit	$\bar{X} + \sigma_i/\sqrt{n_i} * Z_{\alpha/2}$	1.02	10.00

In this section, we propose a model called multi-modal normal distribution based on the time interval distribution of step data from Apple Watch. The fitting result is shown in Fig. 4. In this case, the correlation coefficient obtained by (5) is 0.9852, which means that the model data is highly consistent with the original data. We can draw the conclusion that the proposed model is applicable to data that is subject to multiple normal distribution. The model can well reflect the distribution of the actual time interval by adjusting the weight coefficients of each normal distribution.

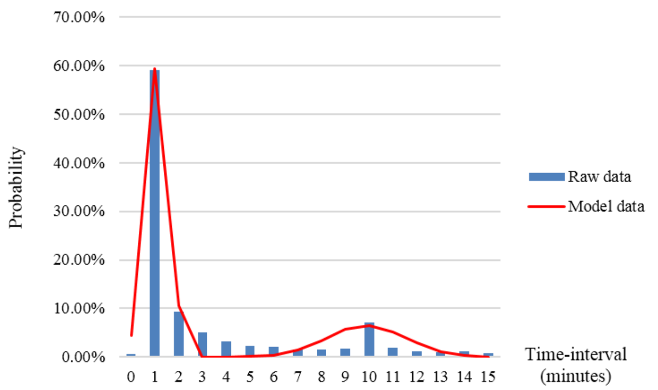

Fig. 4. Time interval distribution and model fitting curve of step data

V. EVALUATION AND CASE STUDY

To evaluate the performance of our proposed model, a series of experiments have been conducted to test its accuracy and usability.

A. *Evaluation of Model Accuracy*

3250 step data items were gathered from iPhone and the temporal features are shown in TABLE V. The time interval of the adjacent data varies from 0 minutes to 11 minutes, but is mainly distributed in 1 minute, 5 minutes and 10 minutes, accounting for 47.32%, 15.97% and 11.26% of the total respectively. The distribution of time interval can be described as the blue histogram in Fig. 5, from which we can see three peaks correspond to the three salient points.

TABLE V. TIME DISTRIBUTION OF STEP DATA (IPHONE6)

Time-interval (minutes)	*Count*	*Proportion*	*Model probability density*	*Model error*
0	12	0.37%	4.95%	4.59%
1	1538	47.32%	47.33%	0.01%
2	177	5.45%	5.89%	0.45%
3	99	3.05%	0.08%	-2.97%
4	84	2.58%	3.83%	1.25%
5	519	15.97%	16.03%	0.06%
6	121	3.72%	4.97%	1.25%
7	57	1.75%	0.11%	-1.64%
8	61	1.88%	0.08%	-1.80%
9	100	3.08%	3.89%	0.81%
10	366	11.26%	11.80%	0.54%
11	42	1.29%	2.23%	0.94%

We can find that the features of normal distribution are presented around each salient point, so it is more appropriate to use a multi-modal normal distribution to fit the raw data. Consequently, the distribution of time interval can be described by (6), where the value of parameter i should be 1, 2 and 3 corresponding to three peaks. The weights of the three normal distributions are 0.57, 0.25 and 0.18 respectively. The probability and model errors corresponding to each time interval computed by the model are shown in the fourth and fifth columns of TABLE V. The model fitting curve of step data from iPhone can be drawn as show by the red solid line in Fig. 5. The correlation coefficient obtained by (5) is 0.9892.

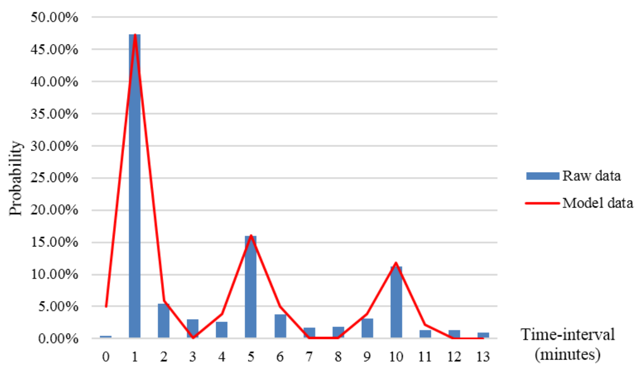

Fig. 5. Time interval distribution and model fitting curve of step data

B. *Case Study of Model Usability*

In this subsection, we attempt to use the proposed model to optimize the quality of wearable device data. Assuming in a health monitoring application, we need to read step data from the user's iPhone. However, the step data from iPhone is calculated by the application called Health Kit, the time interval is dynamic changed and subject to a certain distribution. In this case, if the application requests to obtain data from the Health Kit at a static frequency, it will result in data redundancy. For example, we selected a portion of the raw data from the Health Kit, as shown in TABLE VI. The data record is the step status of the user from 16:33:04 to 16:53:01. During this 20 minutes, 5 data records are generated.

TABLE VI. THE ORIGINAL STEP DATA SAMPLES

No.	***Start time***	***End time***	***Step***
1	0028-08-29 16:33:04	0028-08-29 16:34:19	62
2	0028-08-29 16:34:19	0028-08-29 16:39:25	450
3	0028-08-29 16:39:25	0028-08-29 16:43:28	245
4	0028-08-29 16:43:28	0028-08-29 16:53:01	618
5	0028-08-29 16:53:01	0028-08-29 16:57:54	324

If the Health Kit' step data is requested at a fixed frequency such as 5minutes, we can only get 4 data items during this period, which means that the *completeness* of the results cannot be guaranteed. However, if we read the data once every 2 minutes, 10 items will be recorded, resulting in high *redundancy*. An adaptive frequency data acquisition strategy is proposed in combination with the above model. After reading the first data, we add 1 minute based on the last read time. If the time does not exceed the previous time interval, we will add 4 minutes. If the time exceeds the last time interval, then read the next data item, otherwise add another 5 minutes. Follow this strategy until all the data is read and we get 8 data records, which ensures completeness and low redundancy.

We selected 6 days' data to verify the validity of the proposed adaptive frequency strategy by comparing the amount of step data collected under different approaches. The experimental results are shown in Fig. 6. We can see that, compared with the static frequency (every 5 minutes), the adaptive frequency strategy can reduce data redundancy.

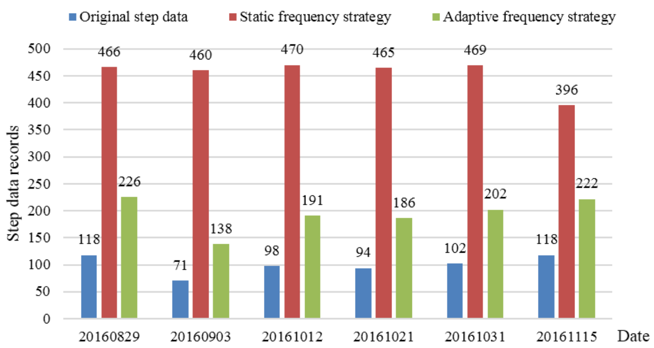

Fig. 6. Comparison of step data records under different strategies

In this case study, we demonstrate the accuracy and usability of the model. Based on the above analysis, we can find that when new wearable device data is collected, an appropriate model can be used to describe its temporal features. In addition, with the model, the adaptive frequency strategy based on the features of data can be adopted to collect data which can not only guarantee the completeness of the data, but also reduce redundancy.

VI. CONCLUSION AND FUTURE WORK

In this dissertation, we provide an overview of temporal issues in multi-wearable system, and in this context, analyze the source of time discrepancy. Our main contributions are (1) to analyze the temporal features in data streams from multiple wearable devices, and (2) to propose two statistical models of temporal discrepancy. By carrying out experiments, it is confirmed that the proposed models can accurately fit the actual data. In addition, we demonstrate the usability of the proposed models though a case study, in which the adaptive frequency strategy is adopted. Experimental results show that this strategy can not only guarantee the completeness of the data, but also reduce redundancy compared with the static frequency method.

In the future, the proposed temporal statistical models need to be further optimized to improve the accuracy of the actual data fitting. Moreover, the current models cannot fully describe the temporal features of all types of wearable device data, so new models should be established. Finally, with these models, novel schemes should be proposed to reduce the impact of time discrepancy.

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