Preliminary Investigation on Band Tightness Estimation of Wrist-Worn Devices Using Inertial Sensors

Masayuki Hayashi(✉), Hiroki Yoshikawa, Akira Uchiyama, and Teruo Higashino

Osaka University, Osaka, Japan
{m-hayashi,h-yoshikawa,uchiyama,higashino}@ist.osaka-u.ac.jp

Abstract. Nowadays, wearable devices enable us to collect biological data from a massive number of people. However, the reliability of the collected data varies due to various factors such as band tightness and incorrect attachment. In this paper, we investigate the band tightness estimation by using an inertial sensor of a wrist-worn device. First, we analyze the relationship between the band tightness and the data reliability through a preliminary experiment. Then, we design the band tightness estimation as a classification problem based on frequency domain features. The evaluation results show the effectiveness of the frequency domain features, achieving the accuracy of 81.7% for the 3-class band tightness classification.

Keywords: Wrist-worn device · Inertial sensor · Machine learning · Tightness estimation

1 Introduction

With the recent rapid spread of wearable sensors, it has become possible to easily collect various biological data. For example, a wrist-worn device called empatica E4[1] enables us to obtain heart rate, sweating level (Electrodermal Activity), and skin temperature. Also, by using an earphone sensor called cosinuss°[2] One, heart rate and tympanic temperature (core temperature) can be recorded on a smartphone. Such biological data is expected to be used in various situations such as healthcare and sports [1].

In our research group, we have been developing a framework to construct big biological data using wearable devices from a massive number of participants. We assume they use various wearable sensors such as wrist-worn devices, chest heart rate devices, and ear-worn devices depending on their preference to collect their biological data in various environments such as gyms, parks, etc. as shown in

[1] https://www.empatica.com/en-int/research/e4/.
[2] https://www.cosinuss.com.

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Fig. 1. In such scenarios, we seldom assume that the participants wear the devices correctly because they wear the devices by themselves without enough knowledge. Even participants with the knowledge about the correct use of the devices may wrongly wear them by accident. Moreover, a wrist-worn device may slightly move on the wrist due to exercise, which results in the looseness. Obviously, the diversity of the appropriateness of the device attachment leads to the different reliability of the measured data. Therefore, the reliability of the collected biological data is non-uniform, which becomes a serious problem when we analyze the big data. In fact, many researchers and analysts have to start with data cleansing [2] since this problem is actually very common in big data analysis.

However, if we are able to know the reliability of the collected data at the time of data collection, it can be widely used for various purposes. For example, we may simply filter the data with low reliability before analysis. Furthermore, if we can detect the low reliability in real-time, we may send notifications to the subjects to check the device attachment. Based on the above idea, in this paper, we investigate band tightness estimation using inertial sensors by focusing on wrist-worn devices. To mitigate the effect of noise, many researchers have worked on noise filtering in the wearable sensing. For example, Refs. [4,5] propose methods to remove outliers of inter-beat (RR) interval (RRI). Also, Ref. [6] leverages the ECG (Electrocardiogram) patterns to calculate RRI. Ref. [3] filters the effect of body movement by focusing on the characteristic of Photoplethysmography (PPG) sensors. However, in spite of the continuous effort by many researchers and developers, commercial off-the-shelf (COTS) wrist-worn devices cannot detect the slight difference of the band tightness without special sensors such as strain gauges.

Therefore, our goal is to estimate the band tightness for COTS wrist-worn devices. We firstly investigate the relationship between the band tightness and the reliability of the measured heart rate through preliminary experiment. Then, we design a method to estimate band tightness based on machine learning by using the inertial sensor of the wrist-worn device. Our key idea is that different band tightness causes differences in vibration of the wrist-worn devices along with the arm movement. To capture the vibration difference, we employ frequency domain features extracted by FFT (Fast Fourier Transform).

To investigate the performance of our band tightness estimation, we collected data from two subjects with different band tightness in jogging. The result indicates that the frequency domain features are more effective than the others, supporting the appropriateness of our key idea. Overall, we have confirmed that our method can estimate the band tightness (i.e. *Loose*, *Medium*, and *Tight*) with accuracy of 81.7%, highlighting the usefulness of the inertial sensor for the band tightness estimation.

2 Preliminary Experiment on Band Tightness

2.1 Experiment Settings

To investigate the relationship between the band tightness and the quality of the heart rate measurement, we collected real data from one subject with five

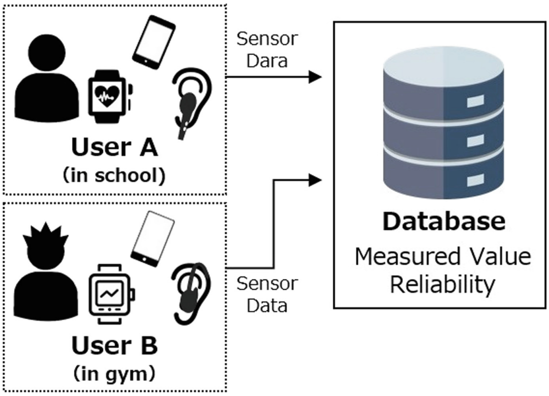


Fig. 1. Overview of Biological data collection platform

Fig. 2. Wrist-worn device: Polar Vantage V

levels of tightness. We used Polar Vantage V shown in Fig. 2 as a wrist-worn device. We note that Polar Vantage V is more tolerant to noise due to wrist movement since it employs a sophisticated sensor fusion technique by using a touch sensor, a 3-axis accelerometer, and multiple PPG sensors [7]. The subject jogged for two minutes for each tightness level. In total, we collected 10-min data with five tightness levels. We define the tightness level as shown in Table 1 according to the wrist size of the protruding bump of the wrist bone. We note that we attached an inertial sensor TSND151 to Vantage V as shown in Fig. 3 because it does not provide APIs to access to the raw inertial measurements. We set the sampling rate of TSND151 to 1,000 Hz for both of the 3-axis acceleration and the 3-axis angular velocity. For the ground-truth, we used a Holter monitor FM160 manufactured by Fukuda Denshi.

2.2 Result

Band Tightness and Heart Rate. Figure 4 shows the heart rates measured by the wrist-worn device and the Holter monitor. We see that the heart rate measured by the wrist-worn device is close to the Holter monitor in *Very Tight* and *Tight*. The peak and the trend are still similar in *Medium* tightness although we also see the difference slightly larger than *Very Tight* and *Tight*. However,

Table 1. Definition of band tightness

Tightness	Band length (0 cm = wrist size)
Very Tight	+1.0 cm
Tight	+1.5 cm
Medium	+2.0 cm
Loose	+2.5 cm
Very Loose	+3.0 cm

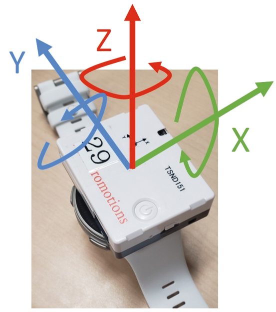


Fig. 3. Inertial sensor attached onto Vantage V

the difference between the wrist-worn device and the Holter monitor is clearer in *Loose* and *Very Loose*.

The result indicates that the band tightness is closely related with the reliability of the heart rate measurement. Especially, the measurement reliability is obviously low when the band is loose. Therefore, we conclude that the band tightness is one of the key indices to know the data reliability.

Band Tightness and Wristband Vibration. To investigate the cause of the low reliability when the band is loose, we analyze the relationship between the band tightness and the measurement of the wristband inertial sensor (i.e. 3-axis acceleration and 3-axis angular velocity). Specifically, we first analyze the variances of the inertial measurement because different band tightness may lead to different vibration of the wrist-worn device. Figure 5 shows the variances of the acceleration and the angular velocity in *Tight*, *Medium*, and *Loose*. The variances are calculated for a sliding window with a 10-s width and one-second slide step. We see some difference between different band tightness. The angular velocity of y-axis shows relatively clear difference between *Tight* and *Loose*. However, the variances cannot completely capture the differences between different tightness.

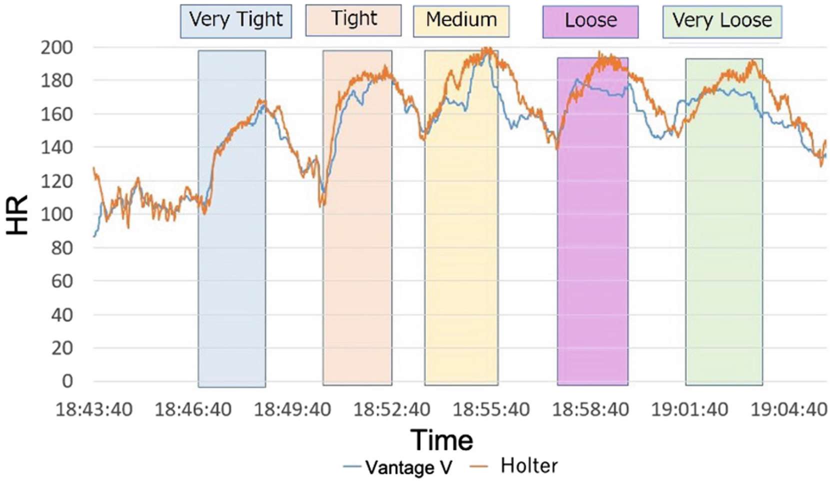
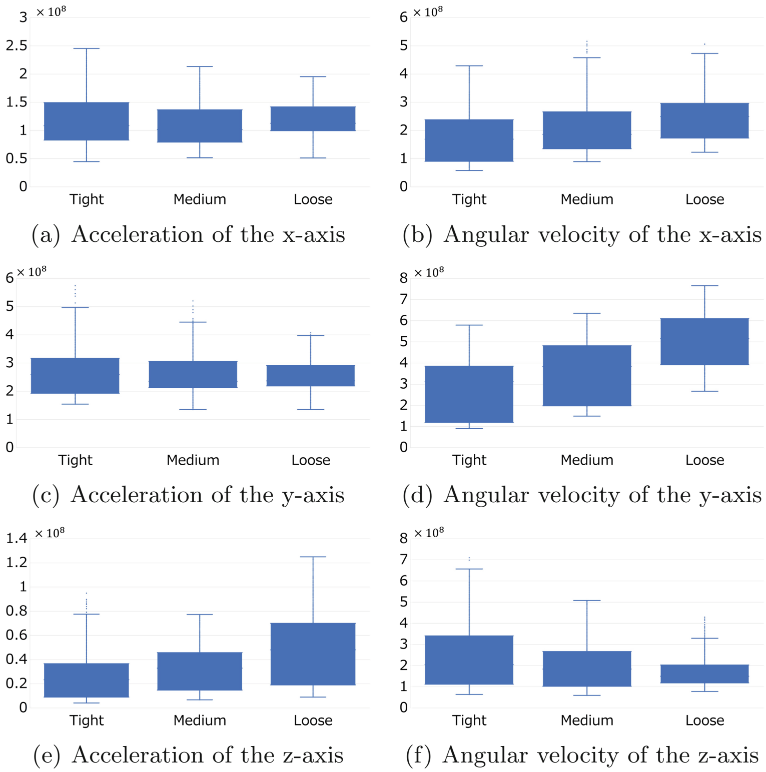


Fig. 4. Band tightness and heart rate

The vibration of the wrist-worn device is quite small compared to the arm motion during exercise. To separate the vibration due to the arm motion and the other factors, we apply Fast Fourier Transform (FFT) to the acceleration and the angular velocity. Figure 6 shows a frequency spectrum of the y-axis angular velocity in *Tight*. The clear peak around 1.5 Hz is close to the frequency of the arm motion. Actually, the vibration due to the other factors appears in the higher frequency. Figure 7 shows the scaled frequency spectrum for each band tightness. We see that the spectrum of *Loose* contains more high frequency components than *Tight*. Also, the peaks of the higher frequency appear around the frequencies of the integral multiple of 1.5 Hz (i.e. the arm motion frequency). This is because the arm motion causes the small vibration.

From the above observation, we have confirmed that the acceleration and the angular velocity of the wrist-worn device are useful for the band tightness estimation. In the following Sect. 3, we design the band tightness estimation method by using machine learning.



(a) Acceleration of the x-axis
(b) Angular velocity of the x-axis
(c) Acceleration of the y-axis
(d) Angular velocity of the y-axis
(e) Acceleration of the z-axis
(f) Angular velocity of the z-axis

Fig. 5. Variances of acceleration and angular velocity

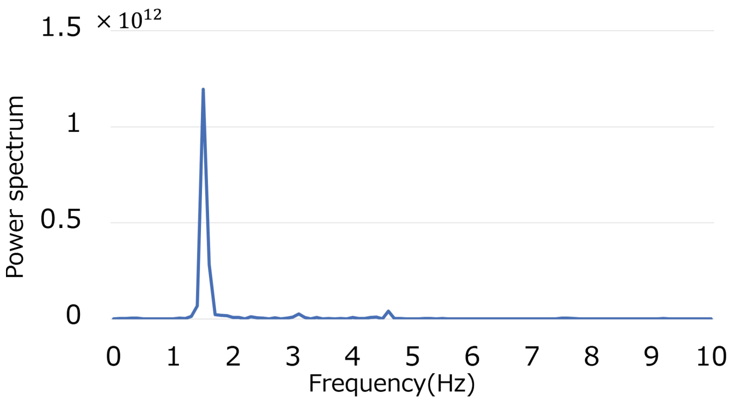
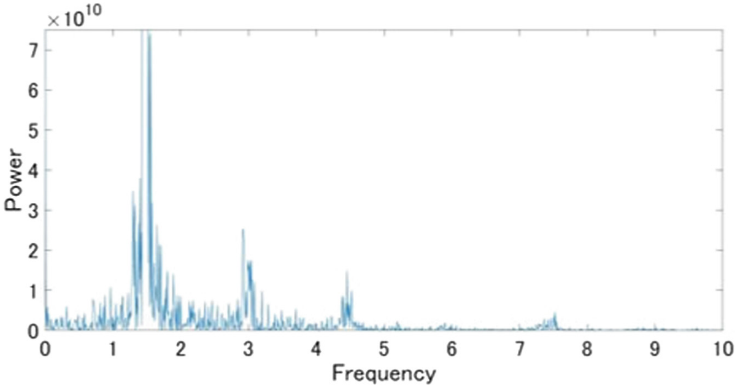
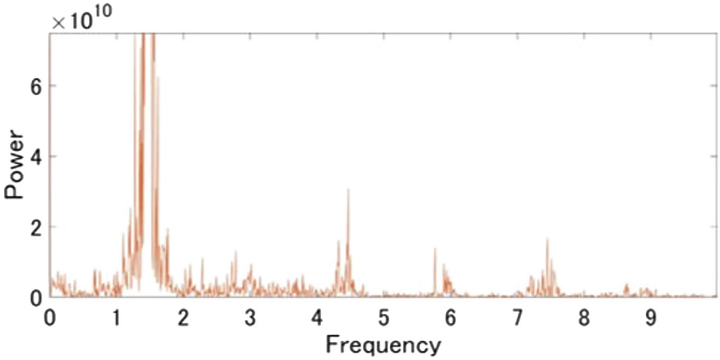


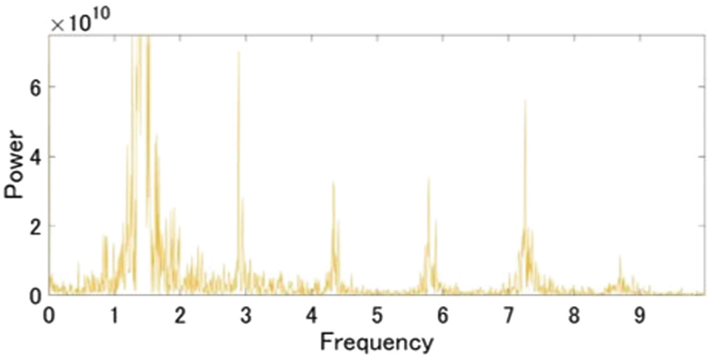
Fig. 6. Frequency spectrum of Y-axis angular velocity (*Tight*)



(a) *Tight*



(b) *Medium*



(c) *Loose*

Fig. 7. Scaled frequency spectrum of *Tight*, *Medium*, and *Loose*

3 Band Tightness Estimation

In our preliminary experiment, *Very Tight* and *Very Loose* are extreme conditions which seldom occur in the real environment. Therefore, in this paper, we focus on the other tightness categories: *Tight*, *Medium*, and *Loose*. Then, we design the band tightness estimation as classification based on machine learning using the acceleration and the angular velocity of the wrist-worn device.

Table 2. Feature candidates

Component (3-axes)	Feature
Acceleration	Mean, Median, Max, Variance
Angular velocity	Mean, Median, Max,Variance
Frequency component of acceleration	Mean, Median, Max, Variance
Frequency component of angular velocity	Mean, Median, Max, Variance

Table 2 lists the features used in the classification. We set a sliding window with the width of W and the slide step of one second for feature extraction. According to the result of the preliminary experiment, we also use the frequency domain features. First, we define the frequency f_1 due to the arm motion as the highest peak between 0 and 2.0 Hz. Then, we define the i-th frequency component f_i as if_1 $(i = 2 \dots 10)$. Finally, we extract features of f_i from the frequency spectrum between $[f_i - 0.5, f_i + 0.5]$ Hz. In total, we extract 264 features as candidates. We further apply feature selection based on the feature importance determined by Decision Tree algorithm.

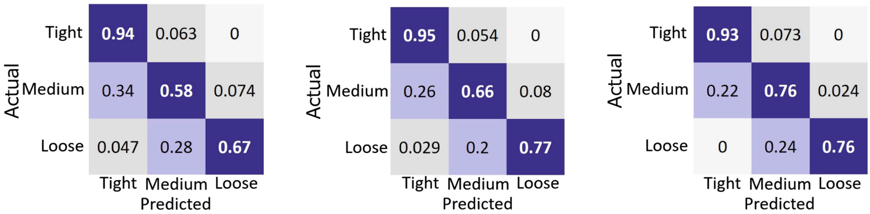
4 Evaluation

4.1 Settings

We collected the jogging data from two males aged 20's. For each session of data collection, each subject configured the tightness to *Loose*, *Medium*, and *Tight* and jogged two minutes for each tightness. We collected four sessions from one of the subjects and two sessions from the other subject on different days and/or times. We note that we did not control any motions such as arm swing styles.

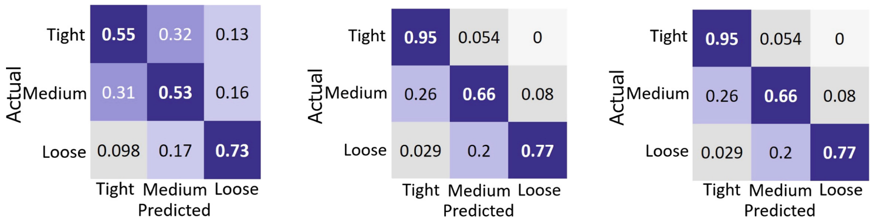
We conduct one-session-out cross-validation for evaluation. For the parameter settings, we use the window width $W = 10$ s unless otherwise stated. We compared SVM (Support Vector Machine), KNN (K-Nearest Neighbors), LR (Logistic Regression), and RF (Random Forest) for machine learning algorithms. In the following evaluation, we have used the best feature set for each algorithm.

4.2 Result



(a) 4 sec (SVM) (b) 10 sec (SVM) (c) 30 sec (SVM)

Fig. 8. Effect of window size W



(a) Stats. Features (KNN) (b) Freq. Features (SVM) (c) All Features (SVM)

Fig. 9. Confusion matrices of different feature sets

Effect of Window Size. The window size W is closely related with the realtimeness of the band tightness estimation. To see the effect of W, Fig. 8 shows the confusion matrices of different window size W. In all the cases, SVM performed the best for the machine learning algorithm.

We see that the accuracy increases with the increase of the window size. From the result, we have confirmed a larger window size is effective for the classification. However, we need to consider the trade-off between realtimeness and the classification accuracy.

Feature Comparison. Figure 9 shows the confusion matrices of different feature sets. To see the effect of frequency features, we have compared the classification performance of statistical features, frequency features, and all features. We define the statistical features as those except frequency features.

We note that the best machine learning algorithms are different for the different feature sets. KNN is the best for the statistical feature set while SVM is the best for the other feature sets. The classification by the statistical feature

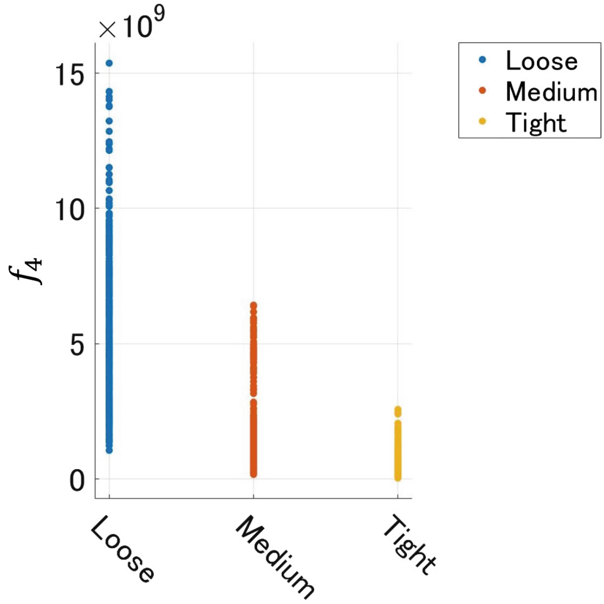


Fig. 10. Overlap of feature value

set achieves the accuracy of 60.3% while the classification by the frequency feature set shows the accuracy of 79.3%. Also, the result using all the features is equivalent to that based on the frequency feature set. This result indicates the effectiveness of the frequency features for the band tightness estimation. However, the accuracy of *Medium* is relatively low due to the confusion between the neighboring classes. To further investigate the cause of the low accuracy, Fig. 10 shows the distributions of the frequency feature f_4. The distributions of *Medium* and the other classes overlap to some extent, which is the main reason of the low accuracy. To improve the performance, we may further analyze the tiny movement of the wrist-worn device precisely.

5 Conclusion

In this paper, we investigate the design of the band tightness estimation using an inertial sensor of a wrist-worn device. Our key design is the frequency domain features based on the key observation that different band tightness causes difference in vibration of the wrist-worn devices. The evaluation results show the effectiveness of our design, achieving the accuracy of 81.7% for 3-class tightness classification.

Our future work includes further evaluation by collecting more data samples. We are also planning to investigate other factors related with the reliability of the biological data.

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