Vol.2022-ASD-25 No.2
2022/12/2

Preliminary Trial of Activity Recognition of Medical Technicians using Accelerometers

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Abstract: In this paper, we recognize the activities of medical technicians using accelerometer data addressing the issues of timestamp duration and imbalanced data with segmentation technique and sampling. Research efforts mostly target patient and nurse activities while fewer studies are centered on medical technicians. Patient journey in hospitals often involves laboratory visits hence better comprehension of the medical technician routine is also vital. In this study, we investigate the activity recognition of 5 activities performed by a medical technician from Saiseikai Kumamoto Hospital by varying the overlapping segments and removing long-duration data. We compare the performance of balanced and imbalanced data. A 92% accuracy with 82% F1-score were achieved for the imbalanced data using 90 seconds window size and 40% overlapping using Random Forest algorithm while 84% accuracy with 78% F1-score for the balanced data using similar algorithm with 50% overlapping, removal of long-duration activities and random sampler.

Keywords: Human Activity Recognition, medical technician, accelerometer, Random Forest

1. Introduction

The application of Human Activity Recognition (HAR) in healthcare has continuously increased in recent years in efforts to understand the activity patterns of patients and medical staff to optimize healthcare. These research efforts mostly target activities of patients, nurses, and caregivers while fewer studies can be found centered on other medical staff including doctors, and medical technicians [1]. The majority of inpatient and outpatient journeys following clinical pathways or not, involve laboratory tests during hospital visits hence understanding the routine of medical technicians is also vital to improve patient care. Activity recognition remains a challenging task due to the limitations of real-world data with issues of data imbalance, missing timestamps, improper activity duration, and labeling [2] [3] [4] [5].

In this paper, we recognize the activities performed by a medical technician using accelerometer data. Specifically, we handle long-duration timestamps and investigate imbalanced data by: (1) performing segmentation with varying window sizes and overlapping rates; (2) removing false data with with respect to activity duration. We compare the performance of the Random Forest Algorithm in classifying balanced and imbalanced dataset.

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2. Related Literature

Wearable devices are common to HAR with nurses and caregivers as participants where users carry the sensors with them as they perform any activity [5] [6]. Data collection for HAR studies also use inertial, physiological, and environmental sensors [7] including barometric pressure sensor to distinguish simple activities such as sitting and standing [8] and complex activities [9]. Accelerometer is the most common type of sensor used in human activity recognition often deployed along with other sensors.

Smartphones are preferred over wearable devices considering software capability and integrated sensors allowing real-time data collection, and possibly all day long [10]. Smartphones are generally used for labeling and recording patient data in nursing care activity recognition [2] [3] [4] [5] to overcome manual writing and lessen incorrect timestamps.

The quality of data affects the performance of HAR systems. Pre-processing including data cleaning and segmentation is essential. Among the segmentation techniques in HAR are optimizing window size in grid search strategy [11], and sliding window [12] usually not more than 3 seconds [10]. In this study, we apply segmentation ranging in window size from 30 seconds to 90 seconds with 20% to 60% overlapping. We remove long-duration timestamps maintaining only 1.5 times the average duration and 80% of the middle duration. Lastly, sampling is applied to handle imbalance data.

3. Data Collection

The data comprised of activities performed by a single medical technician from Saiseikai Kumamoto Hospital collected from

September 15 to 16, 2022 using a smartphone with installed FonLog application. The participant was required to place the smartphone in the front right pocket of his uniform while performing the activities specifically electro-cardiogram, echocardiography, vascular echo, and report creation. Unspecified activities within the considered time duration were labeled as "others" for classification. The medical technician can perform inspection in sitting position as shown in Fig. 1 or in standing position depicted in Fig. 2 and Fig. 3 beside the patient.

Fig. 1 Sitting position, vascular echo (right) and echocardiography (left)

Fig. 2 Standing position performing electro-cardiogram

Fig. 3 Standing position performing echocardiography

Depending on the space in the patient's room and the presence or absence of Intravenous Fluid (IV) drips, the equipment used during the activity is placed in the most vacant place at that time, whether the patient is standing, standing, or sitting. When performing an echo, the medical technician operates the device including the probe with flexed hand. Echocardiography takes about 10 to 30 minutes while vascular echo lasts about 15 to 30 minutes or sometimes up to 30 minutes according to the medical technician. Both activities are performed at the bedside for each target patient with no significant movement during the examination aside from wandering around the patient's bedside.

Electro-cardiogram, on the other hand, takes about 10-15 minutes also performed at the bedside of patient with no significant movement aside from wandering around the bedside of the patient. The frequency of wandering is higher than during echocardiography and vascular echo.

Report creation is about 1 to 15 minutes or sometimes up to 30 minutes according to the staff usually done in a fixed location in the hospital with almost no movement aside from general desk work.

4. Methodology

4.1 Data Pre-processing

From the original data, we excluded one activity performed by a doctor which was rounds. Then, the timezone of the activity label and sensor data were matched.

Activity labels with lacking start-time and stop-time leading to undefined duration were filtered. Lastly, activity labels performed by the medical technician including "others" as the fifth class were annotated to the sensor data. 4 shows the total labeled sensor data per customer (patient).

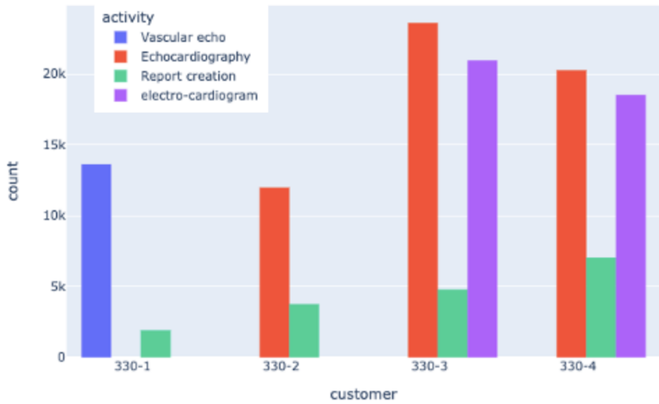

Fig. 4 Activity performed per customer, label annotated to sensor data

4.2 Feature Extraction

After pre-processing the data, seven statistical features were extracted specifically average, median, min, max, standard deviation, sum, and variance which were fed to the algorithm for activity recognition. We extracted the same features for all simulations.

4.3 Activity Recognition

For comparison, we simulated two different approaches to handle the data with balanced and imbalanced classes. For both approach, data was split into 70% to 30% ratio of training to testing set. With approach 1, all unspecified data (others) were used leading to highly imbalanced data. The window size was varied from 30 seconds to 90 seconds window with overlap rates of 20%, 40%, 50%, and 60%.

With approach 2, the unspecified data (others) was sampled using Random Under Sampler where 350 samples were maintained at 50% overlapping. We recognize that the duration of some events are especially longer than the majority of the events. Due to our hypothesis that these long events are the result of spurious factors, they need to be filtered out. False data with respect to activity duration was removed by (a) averaging, and (b) percentile matching.

A Random Forest classifier was used for both Approach 1 and 2 as it has been shown that this algorithm can handle effectively imbalanced data [13].

4.4 Performance Evaluation

To evaluate and compare the performance of each simulation approach, both accuracy and F1-score were measured and obtained respectively using the following equations [14]:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$F1 - Score = \frac{TP}{TP + 0.5(FP + FN)} \tag{2}$$

5. Result and Discussion

Table 1 displays the resulting performance of all simulations with imbalanced data using Approach 1. The highest accuracy of 92% with an F1-score of 82% was achieved with 90 seconds window size at 40% overlapping.

Table 1 Approach 1 with Imbalanced Data

Window size	Segmentation	Accuracy	F1-score
30 seconds	20% overlapping	84%	66%
30 seconds	40% overlapping	88%	76%
30 seconds	50% overlapping	86%	73%
30 seconds	60% overlapping	88%	75%
60 seconds	20% overlapping	86%	68%
60 seconds	40% overlapping	85%	66%
60 seconds	50% overlapping	84%	64%
60 seconds	60% overlapping	90%	79%
90 seconds	20% overlapping	34%	63%
90 seconds	40% overlapping	92%	82%
90 seconds	50% overlapping	91%	84%
90 seconds	60% overlapping	89%	76%

The resulting performance of Approach 2 is shown in Table 2 with balanced data using a Random Under Sampler. The highest accuracy of 84% with an F1-score of 78% was achieved with 350 samples at 50% overlapping where false data having duration outside the middle 80 percentile duration were removed.

Based on Fig. 5, a lower accuracy and F1-score were achieved using Approach 2 despite filtering long duration and efforts to solve data imbalance by using Random Under Sampler. This is attributed to fewer samples among classes, which is not enough to generalize the information of the data.

From Fig. 6 on the other hand, it can be observed that the accuracy and F1-score has increased in Approach 2 despite having an imbalanced data. The higher performance is attributed to higher number of samples and mis-classification of the minority classes to the majority class: others.

Table 2 Approach 2 with Balanced Data

False Data	Imbalance Handling	Accuracy	F1-score
Remove data having duration > 1.5 * average duration	Random Under Sampler	80%	73%
Remove data having duration outside the middle 80 percentile duration	Random Under Sampler	84%	78%

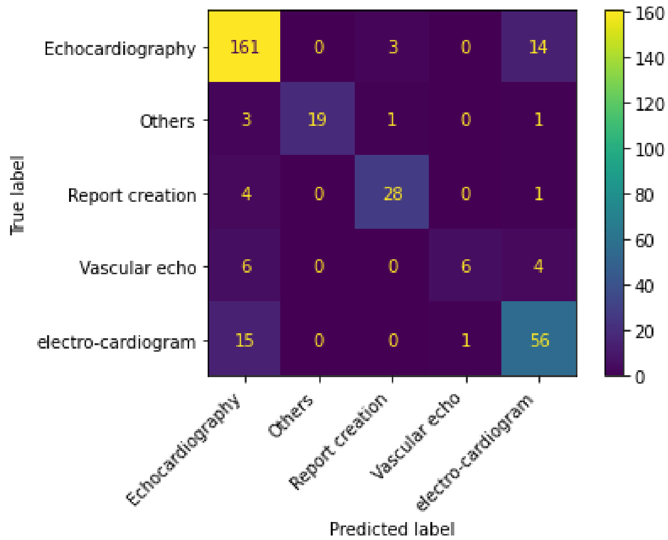

Fig. 5 Confusion Matrix of 5 classes, Balanced data with 50% overlapping, long-duration removed

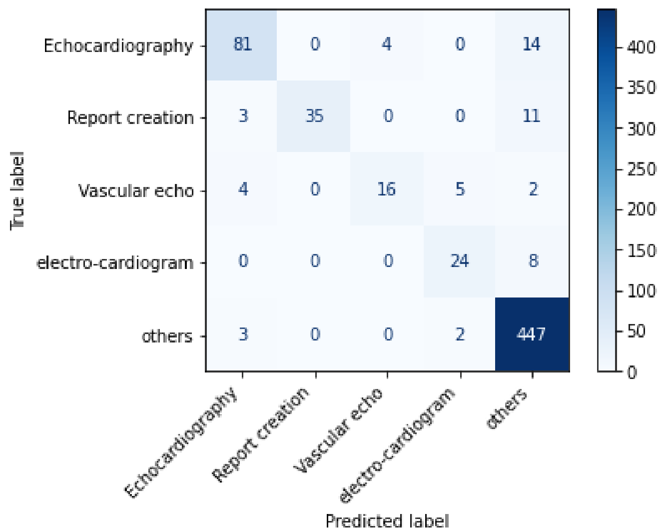

Fig. 6 Confusion Matrix of 5 classes, Imbalanced data with 90 seconds window with 40% overlapping

6. Conclusion and Future Work

Real-world data collected from hospitals are highly imbalanced. In this paper, we have shown that though imbalanced data is expected to lower the performance of activity recognition as it creates a biased learning model with lower accuracy for minority classes, this problem can be handled by sampling. However, too much sampling can result to very few samples resulting to overfitting. Data augmentation is another solution we can include in the scope of our future work. Furthermore, improper timestamp duration due to unfamiliarity of the device or application used in data gathering, device malfunction, or unstable network connection can add false data to the system. A high prediction rate of time series data is sensitive to correct timestamps. Filtering improper duration segments can effectively improve the performance of our learning model with real-world data. This improvement is very useful for future prediction [15] which supports the goal of not only classifying the real-time data but also predicting ahead activities so that we can help deduce meaningful hypothesis to balance the workload of medical technician, help monitor patient condition, and improve the delivery of healthcare. We aim to further investigate highly imbalanced data with more data from the field as we continue this work incorporating other sensors, more users, and much varied activities in the project.

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