# Punch Detection and Classification Using Multiple IMUs

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**Abstract:** Physical exercise is essential for living a healthy life since it has substantial physical and mental health benefits. For this purpose, wearable equipment and sensing devices have exploded in popularity in recent years for monitoring physical activity, whether for well-being, sports monitoring, or medical rehabilitation. In this regard, this paper focuses on introducing sensor-based punch detection and classification methods toward the boxing supporting system which is popular not only as a competitive sport but also as a fitness standard. The proposed method is evaluated on 10 participants where we achieved 98.8% detection accuracy, 98.9% classification accuracy with SVM in-person-dependent (PD) cases, and 91.1% classification accuracy with SVM in person-independent (PI) cases. In addition, we conducted a preliminary experiment for classifying 6 different types of punches performed from both hands for two different sensor positions (right wrist and upper back). The result suggested that using an IMU on the upper back is more suited for classifying both hand punches than an IMU on the right wrist.

## 1. Introduction

Encouraging people to perform physical exercise regularly plays a key role in maintaining our health and quality of life. In fact, Hammer et al. found out that frequent physical exercise in a week reduce the risk of psychological distress [1]. However, in practice, maintaining a regular physical exercise a lifelong habit is challenging [2], [3]. As a result many people failed to maintain the recommended levels of exercise [4]. Some hindrances include location and time constraints, a lack of knowledge on appropriate exercise intensity, and poor performance and motivation due to monotony and fatigue. To solve these issues, wearable technologies can help. In recent years, the number of wearable devices available at a reasonable cost have increased including smartphones and smartwatches. This promoted the development of applications for tracking exercise to support people's health.The most used wearable device for people today is without a doubt smartphones. The smartwatch is also a wearable computing device that runs various applications to tracking exercise. In recent years, due to the growth in technologies such as the long-lasting rechargeable battery, high-performance central unit (CPU) and graphic processing unit (GPU), it has become possible to embed high-performance computers in watches making the demand of smartwatches increased. The smartwatch is also embedded with sensors that provide fitness or healthcare-related functionality, e.g., exercise tracking such as swimming, running, and cycling. Although the state of the art exercise tracking applications in smartwatches and smartphones and other wearable technologies can track exercise intensity from pedometer and heart rate monitor, there are only a limited types of exercise motion that smartwatch applications can detect, classify the activities. In this paper, we focused on boxing for punch detection. We propose a method for detecting and classifying shadow-boxing punches using multiple IMUs.

To validate the proposed method, we hired 10 participants and detect and classify 3 different basic punches of boxing (straights, hooks and uppercuts) using several algorithms. As a result, we achieved 98.8% detection accuracy, 98.9% classification accuracy with SVM in-person-dependent (PD) cases, and 91.1% classification accuracy with SVM in person-independent (PI) cases. In addition, we conducted a preliminary experiment with 1 participant to see the difference in classification accuracy between an IMU worn on the right wrist and upper part of the back for classifying 6 different types of punches performed from both hands. The result suggested that using an IMU on the upper part of the back is more suited for classifying both hand punches than an IMU on the right wrist.

## 2. Related Work

The most relevant previous work for punch recognition is that of Ovalle et al.[5], who classified 4 different taekwondo punches from IMU sensors attached to a right-hand wrist and a microphone. Their purpose of the research was to investigate if it is possible to recognize punches with bare hands and increase the recognition rate by adding audio input that is produced by hitting the mitt. They achieve 94.4% accuracy when using only the IMU sensor. However, the audio signal did not improve its performance. Even though they achieved high accuracy, they only had 3 participants and did not investigate person dependent case. Therefore, their research lacks credibility in punch recognition ac-

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curacy. They also did not test different sensor locations.

For the Boxercise related work, a Spanish start-up company VOLAVA [6] released Fitness Boxing kit in 2020 which includes a punching bag, gloves, an exercise mat, and an IMU sensor kit. The company made sensors that connect to the Volava boxing mobile app to analyze real-time data such as, number of punches, punch force, calories, and heart rate in order to connect sensor metrics with social interaction leaderboard. Their kit, however, includes 3 IMU sensors and requires boxing pieces of equipment which may be too expensive for some people. Their system also did not recognize the type of punches which may be significant information to evaluate the punching technique when creating mobile personal trainers in the future.

Another Boxercise related work is an exergame, Fitness Boxing [7] released by Nintendo Switch in 2018. They utilized Nintendo's Joy-Con motion Controllers for a player to perform punching and dodging maneuvers. In their game, players can personalize the workouts sessions by setting up their fitness goals. By making progress in the game, hit songs for background music and new personal trainers can be gradually unlocked. They can also estimate daily calories burn so that players can track their progress. However, the game only recognizes shadow-boxing punches when the controllers detected a certain motion threshold, and the type of the punch is not identified.

To sum up, the remaining problems of existing literature are poor credibility of punch recognition accuracy, lack of research comparing sensor position for punch recognition when applying real-world application, none of real-world application for boxercise identifying the type of punch. To solve these problems, our research utilized a single IMU sensor embedded in a smartwatch to achieve wireless communication and investigated if it is possible to recognize shadow-boxing movements and achieve high accuracy by testing person dependent cases with 10 participants.

## 3. Proposed Methods to Detect and Classify Punches

### 3.1 Overview

The end goal of this research is to build a sensor-based boxercise personal supporting system that can provide instruction, feedback, and gamified experience from boxercise motion and heart rate monitor. To achieve this, we first focused on the detection and recognition of boxercise movements in both real-time and non-real-time.

### 3.2 Target Activities

Although there are various types of exercise done in boxercise classes, shadow-boxing usually plays an important role for the class. Therefore, we focused on shadow-boxing punches first. According to Kasiri et al.[8] who recognized 6 different punches by using depth image, there are two type of boxer's stance (orthodox or southpaw) and 6 basic type of shadow-boxing punches shown in Figure 1. They includes straight, hook, uppercut for both lead and rear hands respectively. In this paper, we only focused on orthodox as the stance because it is the most commonly used stance in boxing. Thus, lead hand and rear hand means left hand and right hand respectively in this paper. We targeted the 6 types of the punches thrown from orthodox stance and described them below.

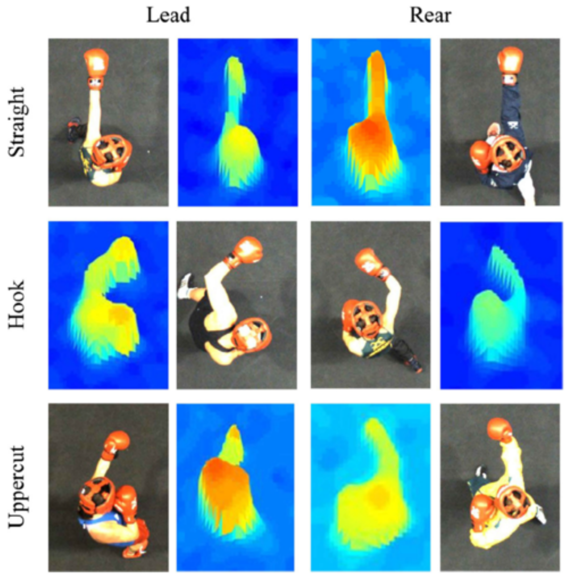


**Fig. 1** The six basic boxing punches captured using overhead depth and visible cameras. This includes the straight, hook, and uppercut punches thrown from both the lead and rear hands (quoted from [8])

(1) **Lead Straight (LS)** —Lead Straight is also known as jab and it is thrown with the lead hand from the guard position.
(2) **Lead Hook (LH)** —Lead Hook is a side power punch thrown with the lead hand from the guard position.
(3) **Lead Uppercut (LU)** —Lead Uppercut is a swinging upward power punch thrown with the lead hand.
(4) **Rear Straight (RS)** —Rear Straight is also known as cross and it is thrown with the rear hand from the guard position.
(5) **Rear Hook (RH)**—Rear Hook is a side power punch thrown with the rear hand from the guard position.
(6) **Rear Uppercut (RU)** —Rear Uppercut is a swinging upward power punch thrown with the rear hand.

In this paper, we first focused on recognizing three types of rear hand punches with an IMU embedded inside a smartwatch on rear hand wrist. In addition to this, we also targeted all six types of punches performed by both lead hand and rear hand for preliminary experiment.

### 3.3 Activity Detection

To detect the punching activity, the process of detection process is shown in Figure 2. The algorithm starts with a 3-D acceleration signal collected from an accelerometer. Since boxing punches contain both longitudinal and transverse motion, we calculated the synthetic acceleration, which is the norm of the 3-D signal. As shown in the second plot of Figure 2, the calculated norm contains noise. Thus, a low-

**Table 1** Extracted Features for each ax of raw 3-D acceleration and 3-D angular velocity

| Type of features |
|---|
| mean |
| median |
| standard deviation |
| min |
| max |
| 25% percentile |
| 75% percentile |

pass butterworth filter (order: 2 , cut-off frequency 1hz) is applied to smooth and emphasize the rapid change of punching motion. Finally, segmentation algorithms are applied to the preprocessed data.

Two kinds of thresholds are defined for segmentation shown as the horizontal line of the third plot in Figure 2. The lower threshold is set for detecting the starting point and ending point of an event. We set the value to 9.8 to ignore acceleration caused by gravity. The upper threshold is set to detect the rapid sensor motion. In this paper, we defined that any values above the threshold are a punch.

The segmentation algorithm starts with detecting the starting point every time preprocessed sensor value exceeds the lower threshold and saves the index of the data. After detecting the starting point, the algorithm looks for the sensor value to exceeds the upper threshold. If it did exceeds it, we set boolean value true, representing that upcoming sensor data is produced by a punch motion. If the boolean value is true and the preprocessed sensor value becomes lower than the lower threshold, the data point will be recognized as an endpoint of the punch, and the data between the saved starting point and endpoint is segmented as a punch. If the boolean value is false and the preprocessed sensor value becomes lower than the lower threshold, the starting point is simply deleted from memory which implies no punching event is detected. After segmenting a punch, the saved starting point and endpoint are also deleted from memory.

### 3.4 Activity Classification

We chose to use machine learning methods for classification and extracted statistical features from both raw 3-D acceleration and 3-D angular velocity for each axis within the segment. The features we extracted are shown in Table 1. We extracted 7 features for each axis, mean, median, standard deviation, min, max, 25% percentile, and 75% percentile in a total of 42 features for each segment. We also labeled each segment as a corresponding punch type. In this work, we compared three types of classifiers, multi-class Support Vector Machine (SVM), Random Forest (RF), K Nearest Neighbors (KNN) from scikit-learn a machine learning library for python. We chose to set all of the parameters of machine learning models to default values of scikit-learn. Before training data with classifiers we chose, for RF and KNN classifiers which calculate distances between different points in their algorithm, we normalized extracted features between [0; 1] to maintain proportional distances.

## 4. Validation of Proposed Method

### 4.1 Data Collection Method

To collect data for targeted activities, we set up two different configurations of sensors as follows:

- Sensor Configuration 1
  - Sensor position: Right Wrist (RW)
  - Measuring device: Smartwatch polar m600
    - Data: 3-D acceleration and 3-D angular velocity
    - Sampling frequency: 100hz
    - Target activities: 3 classes (RS, RH, RU)
  - Participants: 10 people (8 male and 2 female, age 27.8 ± 12.8)
- Sensor Configuration 2
  - Sensor position: Right Wrist (RW) and Upper Back (UB)
  - Measuring device for RW: Smartwatch polar m600 [9]
    - Data: 3-D acceleration
    - Sampling frequency: 100hz
    - Target activities: 6 classes (LS, LH, LU, RS, RH, RU)
  - Measuring device for UB: Movesense Sensor [10]
    - Data: 3-D acceleration
    - Sampling frequency: 26hz
    - Target activities: 6 classes (LS, LH, LU, RS, RH, RU)

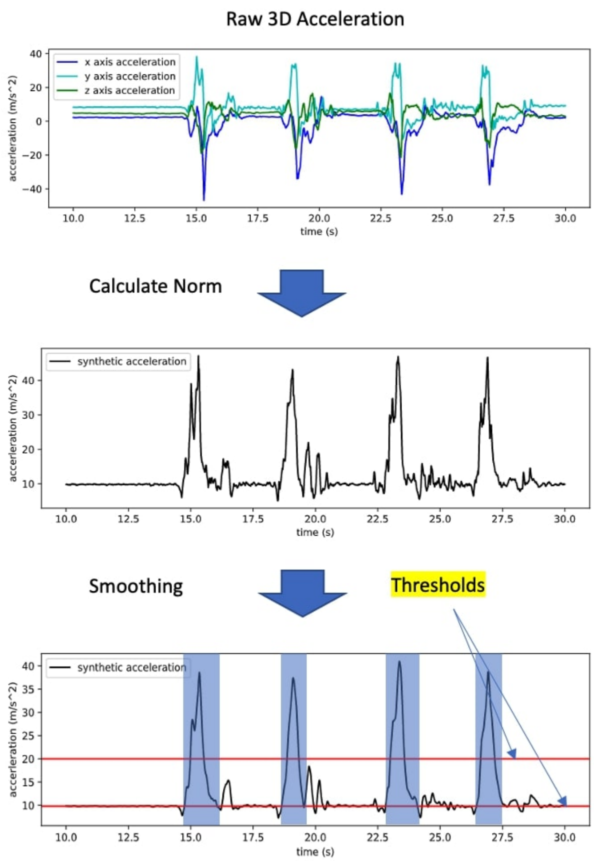


**Fig. 2** Example of punch detection processing flow applied to a 3D acceleration signal gathered during the execution of four consecutive lead hooks.

– Participant: 1 person (age 22)

For the sensor configuration 1, we chose an IMU sensor embedded in smartwatch polar m600[9] and developed a wear OS application. The app is used to collect acceleration and angular velocity of shadow-boxing punches from a smartwatch worn on a right hand wrist. When a user starts the application the user is asked to type their ID. After typing ID, the start button can be pressed whenever they are ready to start recording the sensor values. The user can press the stop button to stop recording and save sensor data as a comma-separated values format inside the device.

For the sensor configuration 2, we chose two types of IMUs for two different sensor locations shown in Figure 3 which are the right hand wrist and upper back to collect 3-D acceleration from the participant. There are two reasons why we chose the upper part of the back as the second sensor position. The first reason is that it is a more practical location when it comes to real boxing matches or sparring because the chance of getting hit to the upper back in boxing is low. The second reason is that we aim to compare the classification accuracy of different types of punches performed by both hands between the right wrist and upper back.

We assumed that it is more difficult to classify other hand punches from the sensor on the wrist than the sensor on the upper back. We also assumed that sensor on the wrist will score better than the upper back when it comes to classifying single hand punches because it is closer to the fist which includes more dynamic movement of the punch. For the right wrist, we used the same measuring device as configuration 1, and for the upper back, we used Movesense Sensor [10] which embeds an accelerometer with 26Hz sampling frequency. An android tablet was used to receive streaming sensor data via Bluetooth from the Movesense Sensor. We used Movesense Showcase Application [11] to collect data and converted it into comma-separated values format.

### 4.2 Experiment

For both of the sensor configurations, the participants were instructed to punch from a static boxing orthodox stance every 4 seconds. Participants were asked to take breaks every 30 punches to avoid degrading the quality of the punches due to fatigue. In this experiment, we excluded

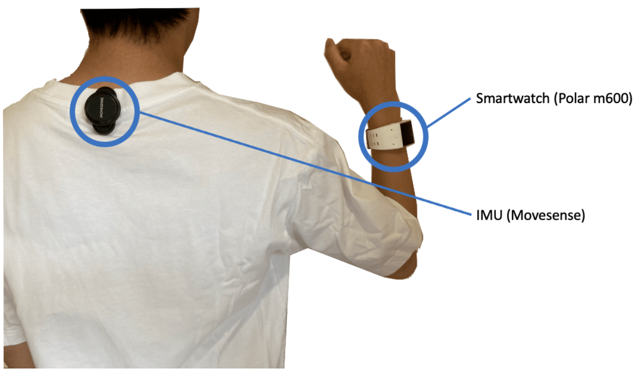


**Fig. 3** Sensors used for the experiments and their positioning (An IMU on right hand wrist and upper part of back)

boxing actions other than punches such as stepping forward or backward, slipping, and ducking by asking the participant to stay still while not performing punches.

The created dataset for sensor configuration 1 contains 924 punches with 3 types of rear hand punches (RS: 307 punches, RH: 308 punches, RU: 309 punches) performed by 10 participants. The participants' ages range from 17 to 53 years (8 male and 2 female, age 27.8 ± 12.8) and include 3 martial art experienced and 7 inexperienced persons. The ratio of created dataset for the punch classes and participants are shown in Figure 4.

The created dataset for sensor configuration 2 contains 212 punches with 6 types of punches (LS,LU,RS,RH,RU: 35 punches, LH: 37 punches) performed by one participant who has a year of experience in boxing. The ratio of created dataset for the punch classes and participants are shown in Figure 5.

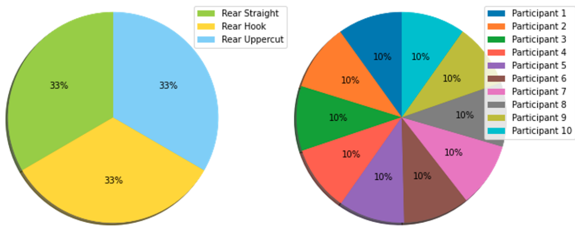


**Fig. 4** Ratio of the created dataset of sensor configuration 1 for the three types of punches (left) and the participants (right).

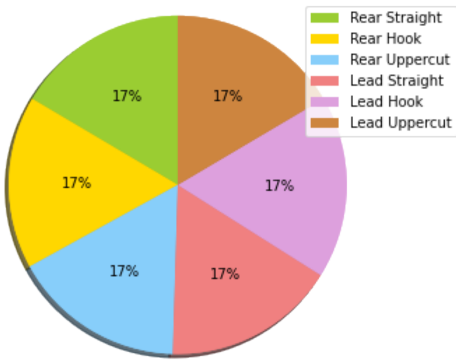


**Fig. 5** Ratio of the created dataset of sensor configuration 2 for the six types of punch punches

### 4.3 Activity Detection Result

For sensor configuration 1, out of 924 (307 rear hand straights, 308 rear hand hooks, 309 rear hand uppercut) detected punches, 913 punches were actual punches meaning that the overall accuracy was 98.8%. We had 1 false negative (predicted that the segment is not punched but actually it is) and we had 11 false positives (predicted that the segment is punch but actually it is not). Therefore, the precision of all punches detection was 98.8% and the recall of all punches was 99.9%. The accuracy, precision, and recall of each punch are shown in Table 4.

The result of detection method for sensor configuration 1 showed that it is possible to detect punches with high accuracy with the proposed method. Many of the false positives were caused by the participant's arm lowering movement when the experiment is done and they are asked to press and stop button of the data collection application. For the detection result on the right wrist of sensor configuration 2, we had 1 mistook error on LH resulting f1-score of 99.54%. For upper back as a sensor location, we had 1 mistook error on LH, LU, RS, RH resulting f1-score of 98.85%. The result of detection result on sensor configuration 2 is shown in Table 5.

**Table 2** The detection result for Sensor configuration 1

| | RS | RH | RU | Total Punches |
|---|---|---|---|---|
| Accuracy | 99.0% | 98.7% | 98.7% | 98.8% |
| Precision | 100.0% | 100.0% | 98.4% | 98.8% |
| Recall | 99.0% | 99.0% | 99.7% | 99.9% |

### 4.4 Activity Classification Result

For sensor configuration 1, we evaluated the three types of classifiers (SVM, KNN, RF) by two cases person-dependent case (PD) and person-independent case (PI). In the PD case, we conducted 10 fold cross-validation which shuffles the data randomly in each holds. This splits 25% of the data to testing data and 75% of the data to training data. The training data is used to train classifiers, and the trained classifiers are used to predict against the testing data. This process of splitting data and predicting is repeated 10 times and average accuracy is calculated. As shown in Table 6, we achieved 97.8% of f1-score (97.8% of accuracy) with RF, 99.0% of f1-score (99.0% of accuracy) with SVM, 98.5% of f1-score (98.5% of accuracy) with KNN. Therefore, in the PD case, we confirmed the SVM is the best classifier. The confusion matrix of the best classifier is shown in Figure 6.

In the PI case, we conducted leave-one-person-out cross-validation, wherein each fold, 9 participants are used for training, and the remaining one participant was used for testing. After calculating classification accuracy for each person. The average classification accuracy of 10 participants was calculated. As shown in Table 7, we achieved 85.9% f1-score (86.1% accuracy) for RF, 90.6% f1-score (91.1% accuracy) for SVM, and 85.8 f1-score (86.3% accuracy) for KNN. Therefore, in the PI case, we confirmed that the best classifier was the SVM. The confusion matrix of the best classifier is shown in Figure 7. The confusion matrix shows that the rear hook has the least true positive rate. It also shows the most confusion occurs when the model accidentally predicted the uppercut but the true label was the rear hook.

The result of the PD case showed that it is possible to

**Table 3** The detection result of each sensor location for Sensor configuration 2 (RW=Right Wrist, UB=Upper Back)

| | Precision | Recall | F1-score |
|---|---|---|---|
| RW | 100% | 99.1% | 99.5% |
| UB | 100% | 97.7% | 98.9% |

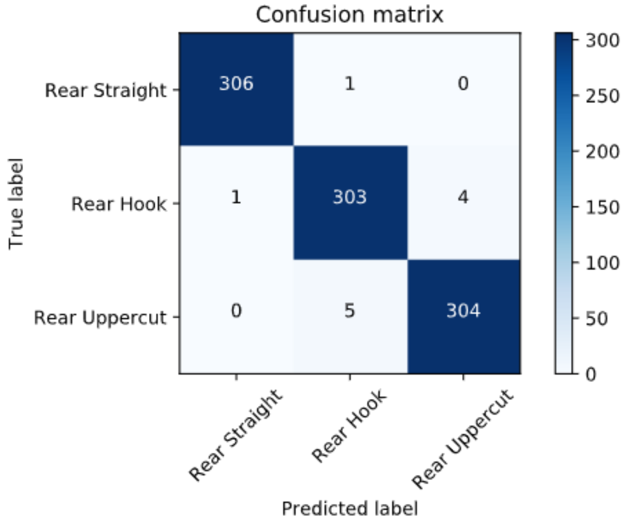


**Fig. 6** The confusion matrix of the best classifier (SVM) in person dependent case

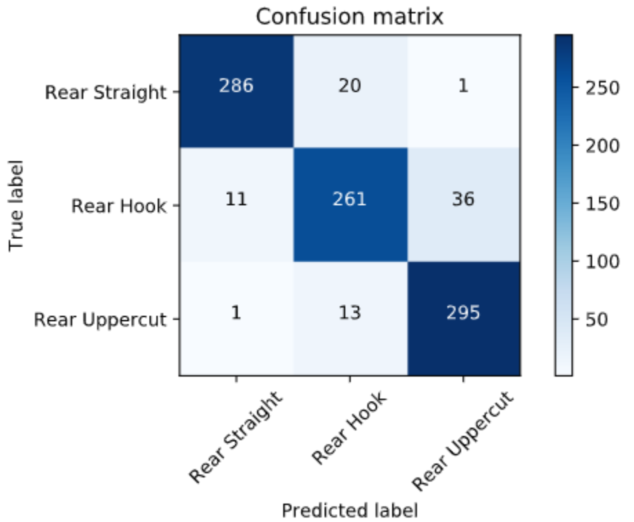


**Fig. 7** The confusion matrix of the best classifier (SVM) in person independent case

classify the 3 types of rear hand punches with high accuracy close to 100% in PD cases. The result of the PI case showed in table 6 that it is possible to classify the punches slightly over 90% despite a variety of the participant's age and gender.

**Table 4** The detection result for Sensor configuration 1

| | RS | RH | RU | Total Punches |
|---|---|---|---|---|
| Accuracy | 99.0% | 98.7% | 98.7% | 98.8% |
| Precision | 100.0% | 100.0% | 98.4% | 98.8% |
| Recall | 99.0% | 99.0% | 99.7% | 99.9% |

For sensor configuration 2, we evaluated the three types of classifiers (SVM, KNN, RF) by conducting 5 fold cross validation which shuffles the data randomly in each holds

**Table 5** The detection result of each sensor location for Sensor configuration 2 (RW=Right Wrist, UB=Upper Back)

| | Precision | Recall | F1-score |
|---|---|---|---|
| RW | 100% | 99.1% | 99.5% |
| UB | 100% | 97.7% | 98.9% |

**Table 6** Classification results of each models in PD case (sensor configuration 1)

| Method | Activity | Precision | Recall | F1-score |
|---|---|---|---|---|
| RF | Rear Straight | 97.5% | 99.7% | 98.6% |
| | Rear Hook | 97.7% | 96.4% | 97.1% |
| | Rear Upper | 98.4% | 97.4% | 97.9% |
| | Macro Average | 97.8% | 97.8% | 97.8% |
| KNN | Rear Straight | 99.0% | 99.4% | 99.2% |
| | Rear Hook | 98.1% | 98.1% | 98.2% |
| | Rear Upper | 98.4% | 98.1% | 98.2% |
| | Macro Average | 98.5% | 98.5% | 98.5% |
| SVM | Rear Straight | 99.4% | 99.7% | 99.5% |
| | Rear Hook | 98.7% | 98.4% | 98.5% |
| | Rear Upper | 99.9% | 99.0% | 99.0% |
| | Macro Average | 99.0% | 99.0% | 99.0% |

**Table 7** Classification results of each models in PI case (sensor configuration 1)

| Method | Activity | Precision | Recall | F1-score |
|---|---|---|---|---|
| RF | Rear Straight | 92.6% | 91.1% | 89.6% |
| | Rear Hook | 84.6% | 81.1% | 79.0% |
| | Rear Upper | 93.1% | 89.3% | 88.9% |
| | Macro Average | 90.1% | 87.1% | 85.9% |
| KNN | Rear Straight | 91.0% | 93.4% | 90.3% |
| | Rear Hook | 85.6% | 79.0% | 81.6% |
| | Rear Upper | 88.6% | 86.5% | 85.6% |
| | Macro Average | 88.4% | 86.3% | 85.8% |
| SVM | Rear Straight | 96.5% | 93.1% | 93.4% |
| | Rear Hook | 91.4% | 84.8% | 85.3% |
| | Rear Upper | 92.2% | 95.5% | 92.9% |
| | Macro Average | 93.4% | 91.1% | 90.6% |

for both sensor position of right wrist and upper back. As a result for the right wrist, we achieved the best accuracy of 96.7% with KNN when k = 5 (SVM=94.9%, RF=95.8%). As the best result for the upper back, we achieved an accuracy of 96.3% with SVM (KNN=95.4%, RF=94.9%). As the best result for a combination of the right wrist and upper back, we achieved 99.0% accuracy with KNN (SVM=98.6%, RF=98.1%) when k = 5. To compare the results by different sensor positions, the result of classification accuracy for sensor configuration 2 is shown in Figure 8. This figure implies that there is no much of a difference between the right wrist and upper back for classification accuracy when classifying punches from both hands. The confusion matrix of the best classifier (KNN) for the Six-Class punch activity classification result using features from an IMU on the Right Wrist (RW) is shown in Figure 9. The confusion matrix of the best classifier (SVM) for the Six-Class punch activity classification result using features from an IMU on the Upper Back (UB) is shown in Figure 10. The numbers of miss classified punches for rear (right) hands of Figure 9 and 10 supported our assumption that predicting single hand punches from wrist sensor score better than the sensor on the upper back. The numbers of miss classified punches for lead (left) hands of Figure 9 and 10 supported our assumption that predicting other hand punch from the wrist sensor will be more difficult than the sensor on the upper back. Thus, it can be suggested that using an IMU on the upper back is more suited for classifying both hand punches than an IMU on the right wrist, and using the wrist are more suited for single hand punches. We will test this on more participants for our future work.

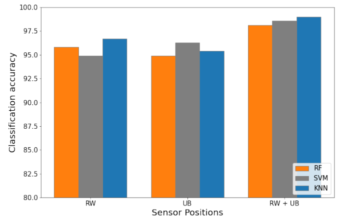


**Fig. 8** Six-Class punch activity classification result (sensor configuration 2) by accuracy for each IMU position and Machine learning algorithm (RW=Right Wrist, UB=Upper Back)

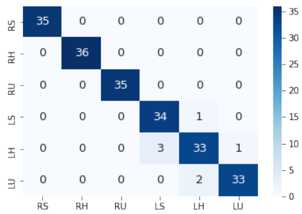


**Fig. 9** The confusion matrix of the best classifier (KNN) for Six-Class punch activity classification result (sensor configuration 2) using features from an IMU on Right Wrist (RW).

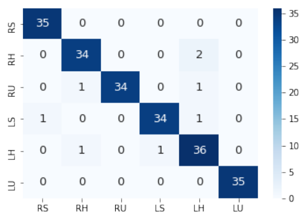


**Fig. 10** The confusion matrix of the best classifier (SVM) for Six-Class punch activity classification result (sensor configuration 2) using features from an IMU on Upper Back (UB).

## 5. Conclusion and Future Work

In this paper, we focused on boxing and proposed punch activity detection and classification methods using acceleration and angular velocity signals obtained by an IMU. The proposed method is evaluated on 10 participants aged between 17 and 53 years old (8 male and 2 female, age 27.8 ± 12.8). As a result, we achieved 98.8% detection accuracy, 98.9% classification accuracy with SVM in-person-dependent (PD) case, and 91.1% classification accuracy with SVM in person-independent (PI) case. In addition, we conducted a preliminary experiment for classifying 6 different types of punches performed from both hands for two different sensor positions. Furthermore, to develop our research into a boxing personal supporting system in future work, we estimated the real-time performance of classification methods. From the result of the experiment with 10 participants, we showed that it is possible to automatically detect a single punch with high accuracy and classify three basic types of punches in high accuracy with a machine learning approach. The result of the preliminary experiment suggested that using an IMU on the upper back is more suited for classifying both hand punches than an IMU on the right wrist.

Our aim for the future is to detect and classify boxing movements in real-time to give feedback to the user through the boxing supporting system. To achieve this, we will first investigate the best position of a single sensor by extending the preliminary experiment in this paper. Then, we will build a system that can run the methods in real-time on that sensor position and test their real-time validity by conducting the actual trial.

**Acknowledgments**
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