The Classification of Skateboarding Trick Manoeuvres: A *K*-Nearest Neighbour Approach

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Abstract. The evaluation of skateboarding tricks is commonly carried out subjectively through the prior experience of the panel of judges during skateboarding competitions. Hence, this technique evaluation is often impartial to a certain degree. This study aims at classifying flat ground tricks namely Ollie, Kickflip, Shove-it, Nollie and Frontside 180 through the use of Inertial Measurement Unit (IMU) and a class of machine learning model namely *k*-Nearest Neighbour (*k*-NN). An amateur skateboarder (23 years of age ± 5.0 years' experience) executed five tricks for each type of trick repeatedly on a customized ORY skateboard (IMU sensor fused) on a cemented ground. A number of features were extracted and engineered from the IMU data, i.e., mean, skewness, kurtosis, peak to peak, root mean square as well as standard deviation of the acceleration and angular velocities along the primary axes. A variation of *k*-NN algorithms were tested based on the number of neighbours, as well as the weight and the type of distance metric used. It was shown from the present preliminary investigation, that the *k*-NN model which employs $k = 1$ with an equal weight applied to the Euclidean distance metric yielded a classification accuracy of 85%. Therefore, it could be concluded that the proposed method is able to classify the skateboard tricks reasonably well and will in turn, assist the judges in providing more accurate evaluation of the tricks as opposed to the conventional-subjective based assessment that is applied at present.

Keywords: Skateboarding tricks · Machine learning · *K*-Nearest Neighbour · IMU sensor

1 Introduction

Skateboarding is classified as a form of action or extreme sport will debut in the 2020 Summer Olympic Games, Tokyo and it is worth noting that this sport is associated with an industry that is worth amounting USD 4.8 billion [1]. Moreover, with the recent

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introduction of the skateboarding in the 2018 Asian Games, implies that this sport is increasingly popular and necessitates the scouting of such talents at an early stage. Nevertheless, it is worth noting that the evaluation of the tricks is often carried out subjectively by judges based on prior experience that in turn, more often than not prone to a certain degree of biasness, if not erroneous assessments.

To date, there exist limited literature with regards to the classification of the tricks Groh et al. [2] utilised five different machine learning algorithm namely *k*-Nearest Neighbor (*k*-NN), Support Vector Machine with a radial-basis kernel (RBF-SVM), Linear Support Vector Machine (LSVM), Naïve Bayes (NB) and Random Forest (RF) to classify only one skateboarding trick i.e., Ollie via data obtained from both IMU sensors as well as motion capture system. Eleven skateboarders were recruited for the study (age: 23 ± 4 years, height: 179 ± 5 cm, stance types: 5 goofy; 6 regulars). It was shown from their investigation that the RBF-SVM yield the best classification accuracy of 89.1%.

In an earlier investigation, Groh et al. [3] carried out an investigation employing different machine learning models in classifying six tricks (Ollie, nollie, kickflip, heelflip, pop shove-it and 360-flip) through data acquired via IMU sensors as well as motion capture system. Seven experience male skateboarders (age: 25 ± 4, stand: 4 goofy, 3 regular) participated in the study. A number of time-series data features were extracted namely, mean, variance, skewness, kurtosis, dominant frequency, bandwidth, the correlation between x-y-axis, x-z-axis and y-z-axis. It was shown from the investigation that the NB and SVM obtained a relatively high classification accuracy of 97.8%.

A study was carried out by using IMU and machine learning in classifying snowboarding tricks [4], a sport which is similar in nature with skateboarding. The IMU was placed to the top right side of the snowboard using the attachment device and fit tightly with fast mounting. Eleven male snowboarders were recruited for data collection for part A (event) and B (tricks) to perform two tricks categories with three tricks classes. In the feature extraction, thresholds were defined from magnetometer signals. Nine gyroscopes signals extracted from the total rotation, rotation of half trick, rotation of half trick. Four classifiers: NB, *k*-NN, SVM and C4.5 were compared. The Leave-One-Out cross-validation (LOOCV) technique was used to evaluate the recall and precision evaluation metrics. For event detection, recall and precision gained 99.0% and 36.8%, respectively. Conversely, for the trick category, grind obtained 96.6% and 88.5% for recall and precision, respectively. In addition, for airs trick, recall and precision gained 97.4% and 91.0%, respectively.

It is worth noting, although limited studies have been conducted with regards to skateboarding, nonetheless, other sporting activities that have used IMU sensors, as well as machine learning, has been well-documented [5–12]. This paper aims at evaluating a variation of *k*-NN models based on selected IMU signals in classifying Ollie, Kickflip, Shove-it, Nollie and Frontside 180 tricks that is absent in the literature. This outcome of this investigation may serve useful to a more objective based evaluation by the judges as well as providing a means for skateboarders to further improve their performance.

2 Methods

2.1 Instrumented IMU Device

Figure 1 illustrates the instrumented IMU device designed using CATIA V5. The device is printed with a Zortrax M200 Plus 3D printer and the material used for printing the instrumented IMU device is Acrylonitrile butadiene styrene (ABS). ABS is used due to its desirable mechanical properties, namely high impact strength and good shock absorbing as the device is susceptible to impacts and shocks from the performed tricks. The instrumented IMU consists of an IMU unit (MPU6050), a Bluetooth Module (HC-05), a microcontroller (Arduino Pro Mini) as well as a 3.7 V Lithium Polymer Battery. The tricks are detected based on the readings extracted from the accelerometer and gyroscope in terms of acceleration (m/s^2) as well as the angular velocity (°/s), respectively that is then sent to a personal computer (PC) for further processing. Figure 2 depicts the placement of the instrumented IMU device on the nose side of the skateboard deck. The device is placed in such a way that it does not impair the movement of the skateboarders whilst performing a given trick as well as reducing the damage risk of the device during the data collection process.

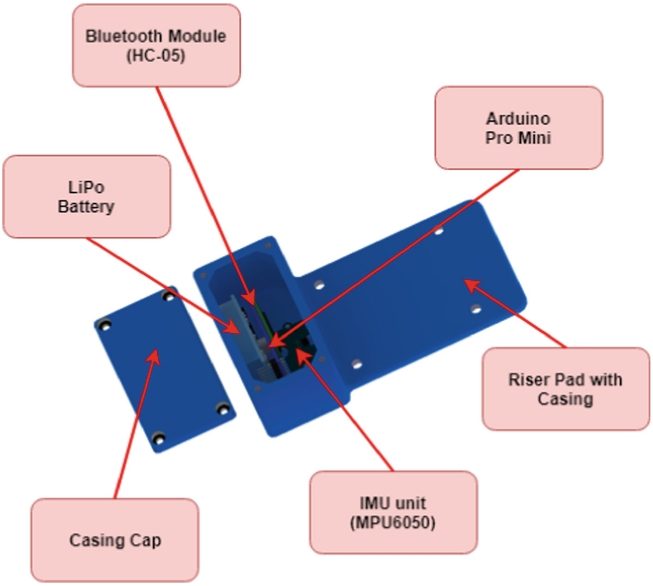

Fig. 1. The developed instrumented IMU device

2.2 Data Collection

One armature skateboarder (23 years old, 170 cm and 54 kg) was recruited from the University Malaysia Pahang (UMP) skatepark. The skateboarder is required to perform five different tricks (as shown in Table 1) and to be repeated 5 times per trick. The

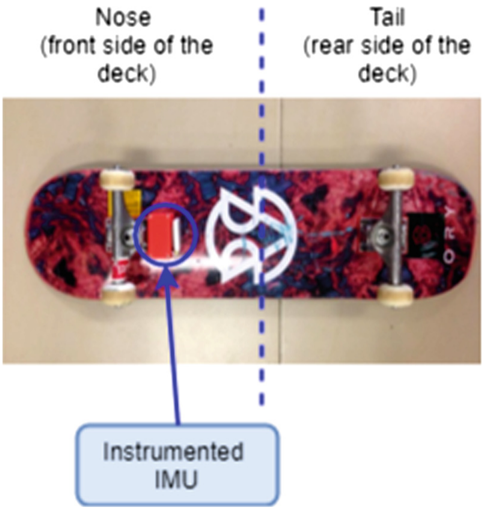

Fig. 2. The attachment of the instrumented IMU on the deck

tricks were chosen based on experience of the skateboarder. The axis of the rotation is referring to goofy stance direction.

Table 1. List of the skateboarding tricks evaluated

Trick name	Orientation (angle and axis)
Ollie (O)	Board incline about x-axis (Approximately 45º + y)
Nollie (NFS)	Board incline about x-axis (Approximately 45º − y)
Frontside 180º (FS180)	Clockwise rotation about z-axis (180º − z)
Pop Shove-it (PS)	Clockwise rotation about z-axis (180º + z)
Kickflip (K)	Clockwise rotation about y-axis (360º + x)

2.3 Machine Learning

The raw signals extracted from the IMU are then processed by using MATLAB 2016b in order to obtain the following statistical features, namely mean, skewness, kurtosis, peak to peak, root mean square as well as standard deviation for all the readings (all six degrees of freedom). A variation of *k*-NN models based on the number of neighbours, distance metric selected as well as the weight of the distance are evaluated in this investigation towards its efficacy in classifying the tricks. The details pertaining the models are listed in Table 2. The mathematical treatment of the models is provided in [12]. The classifiers are evaluated based on its classification accuracy (CA) as well as Cohen's kappa coefficient (κ). The fivefold cross-validation technique was employed in the present investigation owing to its ability in mitigating the notion of overfitting [12].

Table 2. Evaluated *k*-NN models

k-NN models	Number of neighbours	Distance metric	Distance weight
Model 1 (Fine)	1	Euclidean	Equal
Model 2 (Medium)	10	Euclidean	Equal
Model 3 (Cosine)	10	Cosine	Equal
Model 4 (Cubic)	10	Minkowski (Cubic)	Equal
Model 5 (Weighted)	10	Euclidean	Squared Inverse

3 Results and Discussion

A total of 40 trick events were carried out by the skateboarder and the success rate of the landings were recorded. From the 40 tricks, only 20 tricks were found to be successful and the data obtained were used to develop the models. In this investigation, all the features listed in the preceding section are used in order to develop the model. It could be observed from Table 3, Model 1 or the fine *k*-NN model is able to achieve a classification accuracy (CA) of 85% followed by Model 5, i.e. the weighted *k*-NN with a CA of 80%. A strong agreement of the categorical items demonstrated by the κ value of Model 1, further suggests the efficacy of the model in classifying the skateboarding tricks with reasonable accuracy. Nonetheless, it could be seen that the other models do not fare that well due to the inherent nature of the models in understanding the data provided.

Table 3. Efficacy of the developed *k*-NN models

k-NN Models	CA (%)	κ
Model 1(Fine)	85	0.812
Model 2 (Medium)	25	0.062
Model 3 (Cosine)	50	0.375
Model 4 (Cubic)	20	0
Model 5 (Weighted)	80	0.75

Further inspection on the confusion matrix of both the fine and weighted *k*-NN models (Figs. 3 and 4, respectively), revealed that the misclassification recorded by the fine *k*-NN model came from the NFS trick that was misclassified as FS180, whilst the O trick was misclassified as either FS180 or K. In addition, the misclassifications recorded by the weighted *k*-NN model were the K, NFS and O which were misclassified as FS trick that was misclassified as FS180, K as well as FS180 and PS, respectively. The misclassification may be due to the similar motion of the deck along the y-axis for FS180, O and NFS. The misclassifications may be improved by increasing the data collected, evaluating the sensitivity of the features selected towards classification accuracy as well as optimising the hyperparameter of the developed model.

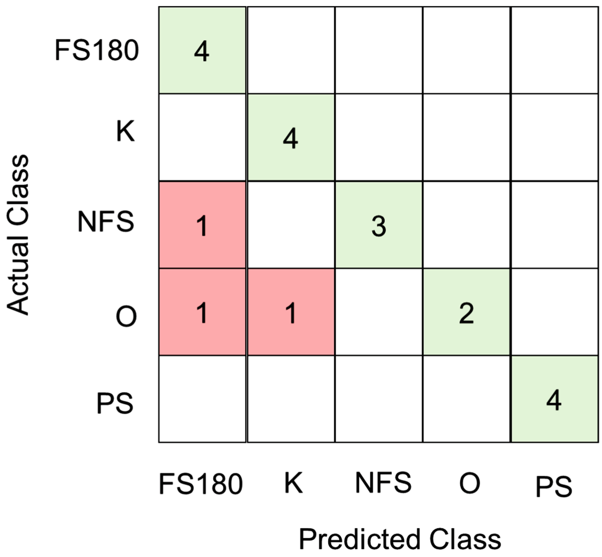

Fig. 3. Model 1 confusion matrix

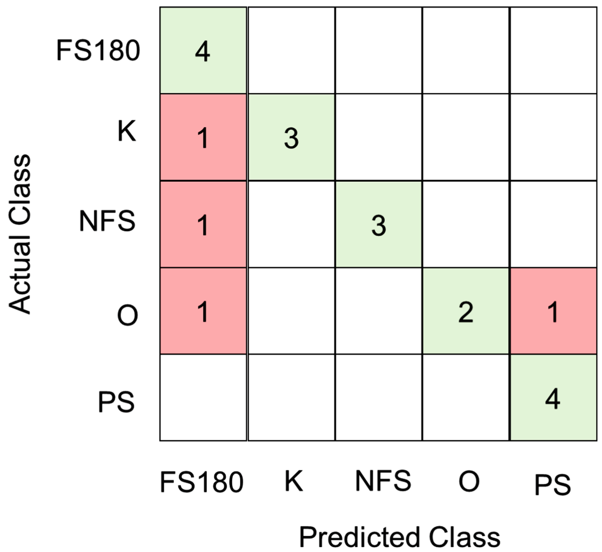

Fig. 4. Model 5 confusion matrix

4 Conclusion

In this preliminary investigation, an offline skateboarding tricks classification system was developed. It was shown from the investigation that the selected features and the fine as well as the weighted version of the *k*-NN models are able to provide a reasonable classification accuracy of the evaluated skateboarding tricks. Future study will be carried out by including more subjects, engineering different features and evaluating its sensitivity, as well as performing hyperparameter optimisation on the best model *k*-NN model. The preliminary results further suggest the applicability of the proposed system in providing an objective based judgement on skateboarding tricks. This will assist the judges in providing a more accurate evaluation of trick performance as opposed to the conventional subjective based assessment that is currently been applied in this sport.

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