Automatic Classifications of Solos and Kicks in Gaelic Football Using Accelerometer Data

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Declaration of Authorship

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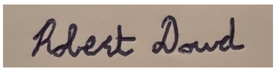
Signed: 

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Abstract

Gaelic football is a uniquely Irish football field sport where the round football can be caught, kicked or hand passed. Four steps can be taken while holding the ball in your hand. Each time you take four steps, you must bounce the ball or solo it, which involves lowering the ball to your foot and kicking it back into your hand. You are not allowed to bounce the ball twice in a succession (GAA, 2015). It would be very useful for coaches and players to be able to keep track of solos over time because they are a good indicator of a player's possession of the ball. Likewise, knowing how many shots or kicks were taken and when they were taken would be very helpful for managers and players to analyse the shot or pass rate and identify areas for development.

The purpose of this research is to employ signal processing and machine learning to classify Gaelic football solos, shots or kicks obtained from accelerometers strapped to players' legs. This research describes both support vector machine and random forest classification methods to automatically recognise solos, kicks, or shots using accelerometer data and validates the techniques by comparing automatically detected actions to manually labelled actions using data collected from four unique individuals. The accelerometer data was collected from four healthy adult volunteers while they ran and took solo, kicks and shots at random.

The validation results demonstrate that the system can reliably identify kicks or shots with a very low rate of false positives and false negatives, achieving sensitivity and precision ratings of 0.933 and 1.00 for both the support vector machine model and the random forest model, respectively, when using three of the subjects for model training and a different unique subject for model testing. The validation outcomes for our models developed to identify solos were less spectacular as the random forest model had a sensitivity of 0.676 and precision of 0.641 and the support vector machine model had a sensitivity of 0.757 and precision of 0.571 with again three subjects for training the models and one subject utilised for testing the models.

Project Description

Introduction

In the expanding subject of sports analytics, athletes' performance can be evaluated through the use of data. Wearable electronics and sensors are capable of gathering this data, but it is our responsibility as data analysts to evaluate this information so athletes can understand where they need to improve. Metrics from on field data can assist management and players with decision making and how to enhance game plans and boost athletes' performance. The increased usage of sports analytics is a result of the availability of wearable performance devices and sensors. Accelerometers/gyroscopes, pedometers, and global positioning system (GPS) devices are just a few of the movement sensors that are currently in use (Li et al., 2016).

The analysis of human activity using accelerometers is gaining significant attention among academics nowadays. Accelerometers were initially utilized in medical studies to examine fundamental body movements using uniaxial accelerometers (Veltink et al., 1996). This important piece of medical research led to the adoption of accelerometers in sporting settings. When the results of the accelerometer measurements were compared to those obtained through kinematic analysis based on the optical concept, the findings and conclusions confirmed the belief that accelerometer data is extremely reliable and accurate for field observations in both clinical and sporting settings (Mayagoitia et al., 2002).

Gaelic football is one of the last surviving completely amateur sports in the world with players, coaches, and managers not permitted to receive any kind of payment. This is one of the key causes of the delayed development of sports analytics in Gaelic football, and it explains why there aren't any reliable electronic wearables or software to identify solos, kicks, or shots in the game today. The objective of this project is to classify Gaelic football solos, kicks or shots using accelerometer data obtained from a wearable device affixed to players' legs using signal processing and machine learning.

Research Questions and Objectives

This project will use data gathered from accelerometers on a player's leg to identify and categorise the solos, kicks and shots of Gaelic Footballers. We plan to develop machine learning models using a support vector machine which is a supervised machine learning algorithm and a random forest which belongs to the ensemble learning family to detect solos or shots in Gaelic football.

Football players or coaches can use this project to assess a player's possession of the ball, and the quantity of solos, kicks and shots completed throughout a training practice or game.

In consideration of this, the following are the project's research questions:

- What are potential durations and predictive characteristics of solos, kicks or shots?
- Can we build a machine learning model using support vector machines and random forests that will classify Gaelic players solos, kicks or shots?
- How accurate are these models and can they be used in practice?

In consideration of this, the following are the project's objectives:

- Identify potential durations and predictive characteristics of solos, kicks or shots.
- Build a machine learning model using support vector machines and random forests that will classify Gaelic players solos, kicks or shots
- Assess the quality of the models and compare them

Project Outline

The outline of this project or steps taken to complete the project were as follows:

1. Collect accelerometer data from four individual players
2. Create an algorithm to select and reduce potential windows of actions
3. Manually label these static windows as actions or not actions
4. Gather characteristics of these potential windows
5. Create support vector machines and random forests models
6. Assess the models performance

Literature Review

Since Gaelic football is a uniquely Irish football field sport, it was difficult to obtain publications that were directly relevant to our research regarding Gaelic football, and we were unable to find literature outlining how to detect solos, kicks or shots in Gaelic football. However, we were able to locate comparable research studies that were conducted on player activities for rugby union, soccer, and Australian football. We have chosen to adopt similar approaches for our methodologies because the techniques and methods used in these research projects were extremely similar and were found to be effective.

In this rugby union study (Kelly et al., 2012), collisions in top-level rugby union are detected using accelerometer data collected via a wearable accelerometer device. The strategy presented in this research study is remarkably similar to the method we want to use, even though detecting tackles in rugby union and detecting solos and shots in Gaelic football appear to be completely different objectives. The article goes into great detail about the approach, and this project's data would have included a lot of noise from other actions, which is comparable with solos in Gaelic football while a player is sprinting.

They suggested using a simple linear threshold on peak magnitude values to filter out any impact peaks that were less than 5.2G, which was the lowest G-Force for a tackle that they could find in their data analysis. This was done in an effort to identify probable collisions. The static windows that were obtained in the first step were then subjected to analysis. The maximum point, minimum point, mean, variance, kurtosis, and skewness were the feature metrics investigated during the analysis of these static windows.

They then used an SVM to try and forecast collisions. To gauge the effectiveness of their endeavour, they assessed the recall and precision of the outcomes. The classifier's capacity to choose collisions from the entire collection of data is referred to as recall or precision. Low false negatives and high true positives are the results of a high recall. Low false positive rates and high true positive rates are indicators of high precision. With a precision and recall score of 0.761 and 0.631, respectively, the SVM trained on static window features, the best-performing standalone model, achieves rather low performance. These findings suggest that learning the intricate connections between source and target data is challenging for a single model. It demonstrates that developing a complementing collection of classifiers, each of which learns a different component of the tackle actions, outperforms trying to train a single classifier to learn every facet of the tackle motions.

In this soccer study (Ahmadi et al., 2014) they use the wearable accelerometer sensor to detect different actions in soccer training. In this study they analysed the average, min, max, and magnitude of accelerometer data across each for cycle. They measured and classified activities such as agility course, walking, jumping on box, jogging, sprinting, kicking.

The training session activities were successfully classified with up to 98% overall accuracy by the suggested system, which combined a random forest training algorithm and a DWT feature extraction technique. For every activity the recall, precision and f measurement were all very close to 1. Therefore we can conclude that a random forest algorithm is another extremely effective classifier when it comes to classifying human activities.

In this study on Australian football (Cust, 2020), kicks are identified using accelerometer data obtained from a wearable accelerometer device. They identified potential static windows that might be kicks by calculating the magnitude of the accelerometer data and using peak detection over every 250 data samples or 0.5 seconds. They measured kick characteristics including the mean, median, standard deviation, variance, minimum, and maximum as well as skewness and kurtosis, just like the rugby union study we previously covered.

They also discussed and contrasted several classification algorithms, including neural networks, support vector machines, and random forests. The weighted F1-score was used as a single evaluation metric to balance precision and recall for each class, as opposed to classification accuracy, which has a tendency to underestimate the classifier's performance on the smaller classes when there is a class imbalance. For each model under the 4-Kick condition, the train and test F1 scores were: KNN train 0.70 and test 0.70; SVM train 0.74 and test 0.72; and RF train 0.72 and test 0.76. We may conclude that all of the classifier algorithms under discussion are capable of accurately detecting kicks.

This analysis leads us to the conclusion that a support vector machine and random forests are effect machine learning algorithms for detecting kicks. Finding probable windows for player actions can be done by using a sliding window, peak detection, and the magnitude value of the accelerometer data. Then, with the use of support vector machines and random forests, we can classify player actions using the predictive features of such actions, such as maximum point, minimum point, mean, variance, kurtosis, and skewness. Following that, calculations like those for recall, precision, and F values will be used to gauge the model's accuracy

Methodology

We will describe our suggested method to automatically detect solos, kicks, or shots in this section.

1. Collect accelerometer data
2. Identify potential windows that could be an action
3. Gather characteristics of these potential window
4. Create SVM and Random Forest models using these characteristics
5. Assess the models performance

Data Analytics Lifecycle

The Data Analytics Lifecycle provides a methodical approach outlining the key steps required to manage data so that it may be transformed into information and used to achieve organisational and project objectives. The data lifecycle is not always a linear process and can involve combinations of certain stages or loops back to the previous stages. The key stages involved in the data analytics life cycle are business understanding, data mining, data cleaning, data exploration, feature engineering, predictive modelling and data visualisation.

Business Understanding

The main purpose of this research is to develop SVM and random forest models that can identify solos, shots, and kicks in Gaelic football using accelerometer data from an accelerometer attached to a player's leg. This project can then be used by football players or coaches to evaluate a player's possession of the ball and the number of solos, kicks and shots made during a practise or game. There are numerous further uses for this project, including the possibility of utilising it in other sports to recognise different sorts of players' movements.

Data Mining

The accelerometer data used for this project was gathered using an accelerometer attached to 4 individual player's legs when the player was running while soloing, kicking, and taking shots at random for roughly 5 minutes.

Data Cleaning

When the accelerometer is stationary and pointed upwards, we need to calculate the gravitational impact on it and divide the original accelerometer data by this value to convert the data to gravitational force. The gravitational acceleration on Earth, which is around 9.8 m/s/s, is equivalent to a gravitational force of 1G.

Data Exploration

In order to help with labelling, the primary stage in data exploration involved using a Butterworth filter on the raw data and peak detection to identify action features that are visually distinctive while players are standing.

Feature Engineering

The feature engineering stage involves a number of steps, including the creation of a sliding window with a period duration of the length it takes for the specific action to identify prospective windows for actions, manually labelling these prospective windows and defining characteristics for these windows that we can use to train and test our models. The characteristics we from the raw accelerometer data on the x axis, include the standard deviation, variance, maximum value, minimum value, interquartile range, skewness, and kurtosis.

Predictive Modelling

Predictive modelling involves the creation of SVM and random forest models. We will take two approaches to build and test our models. The first approach using accelerometer data from 3 subjects using 70% for training and the remaining 30% for testing our model. The second approach using accelerometer data from 3 subjects for training and the other subject for testing our model. If we determine that our characteristics are not linear separable which is technically a data exploration step, then we must return to the feature engineering phase and apply a kernel trick to our SVM model. Lastly, we need to evaluate and compare our models' performances.

Data Visualisation

Finally, to complete our project we will visually present our finding through a visual presentation which will cover all the steps involved in our research as well as our conclusion and findings.

Accelerometer Data

Acceleration of the human body is frequently employed as a measure of everyday physical activity. Movement, gravity, and noise are the three fundamental components of raw acceleration signals (van Hees et al., 2013). We need to calculate the gravitational influence on the accelerometer when it was motionless and pointed upwards. We then need to divide the original accelerometer data by this value to remove this from our raw data. A GPS receiver is built inside the device, which records player position coordinates at a rate of 5 Hz, and a three-axis accelerometer, which records player accelerations in the X, Y, and Z planes at a rate of 100 Hz as seen in (Figure 1).

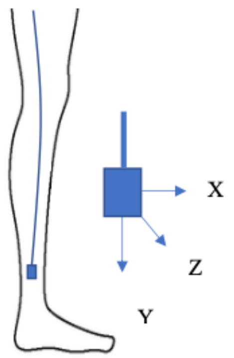

Figure 1: Accelerometer placement on the players leg and axes orientation (Cust, 2020).

Sliding Window

Identifying characteristics of the accelerometer data that refer to a solo, kick or shot is a challenging undertaking. Peaks in acceleration can be caused by a variety of activities, such as running, jumping, and falling, which introduces noise into our data and makes it challenging to spot a solo. The objective of this study is to automatically identify all instances that are related to a solo, kick or shot and ignore all others. There are a variety of potential markers that could be utilized to recognize a solo, kick or shot, according to a manual investigation of the acceleration signals for numerous different solos, kicks, and shots.

The first characteristic measurement we looked at was the magnitude of the accelerometer data, which refers to the total strength of the acceleration being measured in the X, Y, and Z axes. The magnitude can be calculated using the following calculation, $Mag = \sqrt{X^2 + Y^2 + Z^2}$. This feature metric proved to be effective in automatically identifying tackles in rugby union (Kelly et al., 2012), and analysing the performance of Australian rules kicks using accelerometer data as we discussed earlier (Cust, 2020). The sliding window will shift alone periods of 1.5 seconds for detecting solos, kicks, or shots. We then can analyse characteristics in each sliding such as magnitude to extract potential action windows. The characteristics of the static sliding windows we will be interested in are standard deviation, variance, max value, min value, interquartile range, skewness, and kurtosis, which will then be put into a support vector machine and random forest models for classification.

Butterworth Filter

The Butterworth filter is one of the most frequently applied types of low pass filters particularly in digital signal processing. High frequency noise or undesirable signal elements can be eliminated with the use of Butterworth filters. The required frequencies relating to the solo, kick or shot can be preserved while undesirable frequencies and noise are removed from the accelerometer signal using a Butterworth filter. This can help to increase the precision of our solo and kick detection algorithm and decrease the number of false positives. A Butterworth filter can be helpful for analysing accelerometer data, but to improve the precision of solo, kick or shot identification, other signal processing and machine learning approaches should also be applied (Davis, 2016).

Peak Detection

The argmax function determines where the maximum values are located in a smoothed version of the accelerometer data, which is expected to be a function of time. A smooth curve is initially fitted to a set of data points using the loess function. With the aid of this smooth curve, it is possible to see the trend in the data and anticipate the points between the initial data points. In order for this method to function, a small subset of data points close to each point in the dataset are fitted using a separate weighted regression line. A rolling window that is centred at each point of this moving curve is then created using the rollapply function from the zoo package. By locating array indexes that are less than or equal to 0, the function finally determines where the peaks, or maximum values, are located (Meng, 2016).

Support Vector Machine (SVM)

Often employed for classification and regression analysis, the Support Vector Machine (SVM) is a well-known supervised learning technique. SVM operates by identifying the ideal boundary, which is also referred to as the decision boundary, that divides the various classes in the data. Data is represented in a SVM as points in a multidimensional space, where each point represents an observation, and the number of dimensions reflects the number of characteristics in the data. The optimal hyperplane is the one that maximizes the margin, or the separation between the hyperplane and the nearest data points for each class, these points are known as support vectors. The SVM algorithm's performance depends heavily on the distance between the hyperplane and the support vectors.

Many aspects, like the kind of kernel being used, the regularization parameter, and the kernel coefficient, might have an impact on how well SVM performs. To achieve the greatest performance, these parameters need to be tweaked which is very much an iterative process. SVM provides a number of benefits, including high accuracy, robustness to noise, and although it is primarily designed for binary classifications where characteristics are linearly separable, we can also use a kernel trick when the characteristics are not linearly separable.

As seen by the example in (Figure2) below, if we convert the non-linear data from 2-dimensional to 3-dimensional space, we will be able to identify a decision surface that distinguishes between various classes with clarity. The amount of processing required by the machines increases as more and more dimensions are needed, which raises the cost. This is the key reasoning for using the kernel, as it enables us to work in the original feature space without having to compute the coordinates of the data in a higher dimensional space (Zhang, 2018).

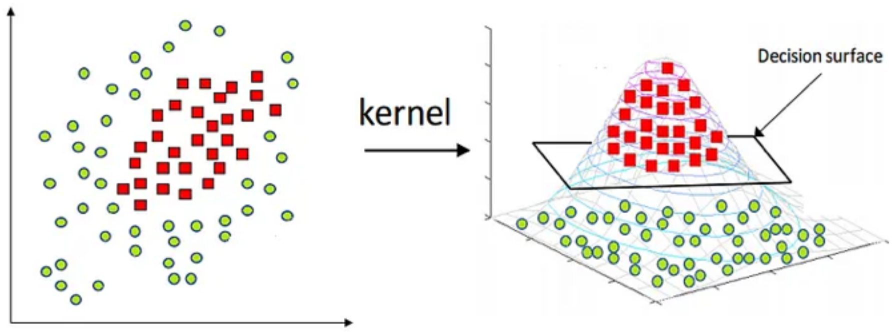

Figure 2: Example of Support Vector Machine Kernel Trick (Zhang, 2018).

As we previously observed support vector machines are more than capable of categorising players actions in a wide range of sports which is why we chose them for this project. The data is split into a training set and a test set with a ratio of 70:30 in order to train and test an SVM model. We use the test set to assess the model's performance after training it on the training data with calculations such as sensitivity which is sometimes called recall and the precision.

Random Forest

A common machine learning method for classification is the random forest. It is an ensemble learning technique that builds several decision trees during the training phase and then combines their predictions to produce final predictions. In a random forest, each decision tree is trained using a different subset of the original data that is sampled with replacement. Additionally, only a random subset of features is considered for the decision at each split in the decision tree and because of this, we'll keep the seed value at 150 throughout the project to guarantee that the results we describe in this report hold true.

In general, random forest models are more resistant to noisy data than SVM models. They can efficiently capture intricate non-linear relationships in the data without much feature engineering unlike SVM models that require the use of the kernel trick to adjust for non-linearly separable data. We chose random forests for this project because, as we've seen in the past, they're excellent at classifying player actions across a wide range of sports.

The random forest model performance is measured the same as the SVM model described early while using the same data and a seed of 150 so that when we compare their results, we can make a fair and justified comparison between the two different model types.

Research Analysis and Findings

Project Data Collection

For this study, an accelerometer that was fastened to a player's leg was used in two main phases of data collecting. In order to recognise and grasp how solos, kicks or shots look so that we could effectively classify data obtained from players while running, we first needed to collect data from a player soloing and kicking a ball while standing which was 9 solos and 9 shots in total. This allowed us to distinguish key characteristics that we could use to identify potential periods of time that could contain these actions and also assist us with the visual inspection to ensure we label these potential windows correctly before training and testing our model. The second phase of data collection was gathering accelerometer data from four players while they were running, soloing, and kicking the ball at random for roughly 5 minutes each. Every player's activity was recorded throughout the data collection phase with the players consent to use as a reference when labelling the potential windows of actions.

An instrument used for player tracking that can capture GPS and accelerometer data was used to gather the accelerometer data while strapped to a player's leg. Each accelerometer value represented the acceleration over 100^{th} of a second. Kodaplay Limited, a company based in Dundalk, County Louth, Ireland, produced the Playertek device that was used for this project. We calculated the gravitational influence on the accelerometer when it was motionless and pointed upwards, and the result was 82. We divided the original accelerometer data by 82 to remove this from our raw data which have us g-force measurements. A gravitational force of 1G is equal to the gravitational acceleration on Earth which is about 9.8 m/s/s. The device employed for this project records player accelerations in the X, Y, and Z planes at a rate of 100 Hz as seen in (Figure 1) as seen earlier.

Exploratory Analysis

Sliding Window

It was found that solos happen within a time window that can vary from 1 to 1.25 seconds following the initial manual inspection of solos that were recorded while a player was stationary as seen by the 3 solos shown in (Figure 3). We made the decision to create an initial sliding window based on this information, one that contains feature measurements throughout a 1.5 second period to ensure that we do not miss any important information in case solos were longer than the 1.25 second period. It is possible to have two solos within a 1.5 second period and therefore having the sliding window set to 1.5 seconds ensures the inclusion of all solos. A 1.5 second period is 150 frames in our case, as each line represents data that was collected for every 100th of a second. After analysing our solos, we discovered that all the solos had a magnitude value over 2G. This stage assists us in assembling possible static solo windows that we can later further analyse and categorise as solo or non-solo but just to be sure we do not remove any potential solos we will have a cut-off of 1.5G.

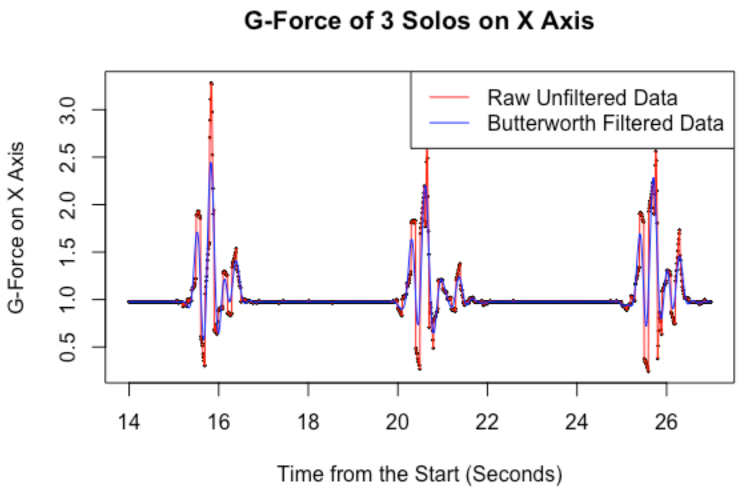

Figure 3: G-Force of 3 Solos on X Axis showing the Raw Unfiltered Data and the Butterworth Filtered Data

As shown in (Figure 4) below, using the Butterworth filter improves the readability of our data much better compared to the raw unfiltered data. This is a crucial filtering method that will be highly beneficial to us when it comes to manually labelling solos, shots, or kicks.

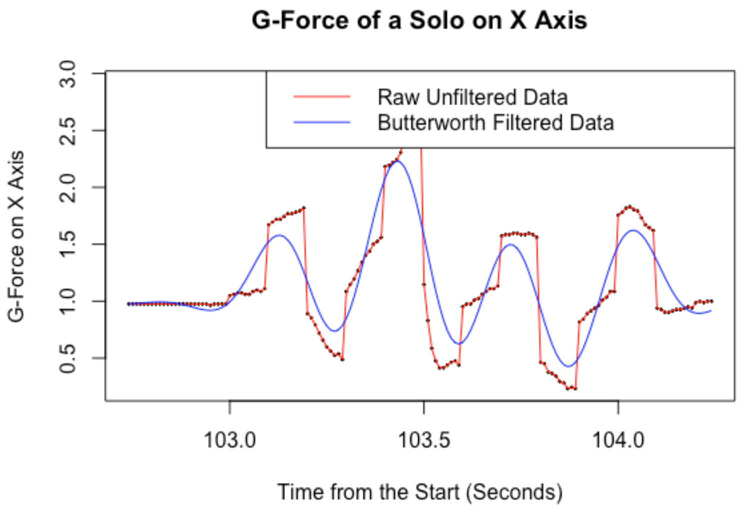

Figure 4: G-Force of a Solo on X Axis showing the Raw Unfiltered Data and the Butterworth Filtered Data

We found that after the initial manual assessment as shown in (Figure 5), kicks or shots occur within a time span of 1 second. Even though they seem to occur over a 1 second period this could potentially change when running so we created an initial sliding window when detecting kicks or shots of 1.5 seconds, but we will re-evaluate the window size before we provide the data of the predicter variables to our models. We were able to locate potential peak points where kicks or shots might have been taken and they all appear to be over 5G, but we have to remember that this was a very small amount of data gathered for the exploratory phase and kicks can of course have a lesser magnitude than this. This stage assists us in gathering possible static kick or shot windows that we can later further analyse and categorise but just to be sure we do not remove any potential kicks or shots we will have an initial cut-off of 3.5G.

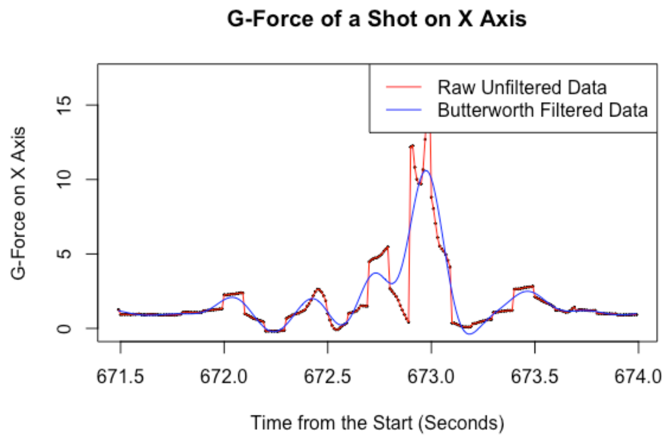

Figure 5: G-Force of a Shot on X Axis showing the Raw Unfiltered Data and the Butterworth Filtered Data

Characteristics of a Solo

The major objective of this study is to create a model that can recognize solos and non-solos automatically. The system that is proposed in this study is built on a starting set of manually labelled solos and can automatically distinguish between solos and non-solo passages. The manual labelling method has the potential to produce inaccuracies if done incorrectly so it is crucial that we label our data correctly to produce accurate results. To accurately classify solos and non-solos in the preliminary research for this work, manual labelling was accomplished by comparing acceleration data signals with video recordings of the occurrences.

After we are capable of recognizing a solo from a non-solo visually, we must undertake univariate analysis on characteristics that might be distinctive to a solo so that the machine can correctly identify the solos. The variables that may be of interest are standard deviation, variance, max point, min point, the interquartile range, skewness, and kurtosis.

As we previously mentioned, when we examined the raw acceleration data, we found that some solos featured four to five peaks. To solve this problem, we applied the Butterworth filter to the acceleration data, which effectively eliminated the extra peak that was not desired. As it must include at least four peaks as seen below in (Figure 6), this is one of the qualities we could be looking for in a prospective solitary static window to reduce the number of windows we need to analyse and label.

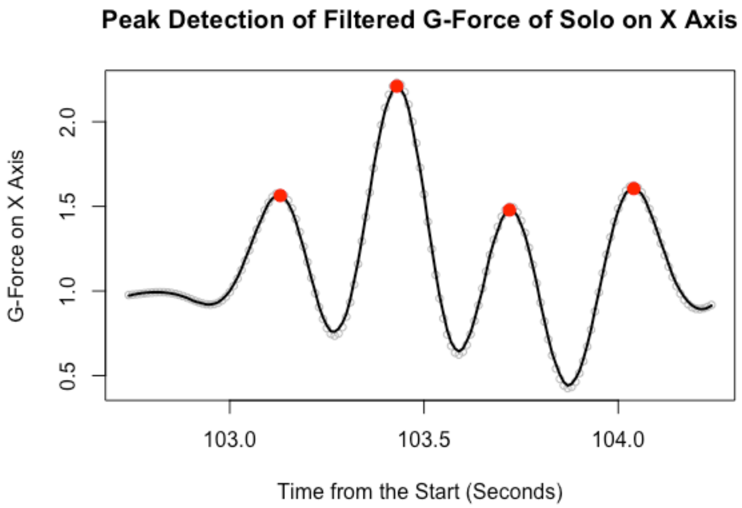

Figure 6: Peak Detection on Butterworth Filtered G-Force of a Solo on X Axis

Labelling Potential Windows for Solos

We started the labelling process by creating an algorithm to find potential single windows for solos. The main goal of this algorithm was to identify windows that not only were solos but also ensured their inclusion. This particular project stage was crucial but an extremely rigorous time-consuming step. It’s importance stems from the fact that any mistakes or flaws made during this process would have negatively impacted the accuracy of both our random forest and SVM models. Additionally, it would have made it more difficult for us to accurately gauge the models' effectiveness. Therefore, guaranteeing the algorithm's correctness was crucial for getting accurate results. We will now outline the various stages of our algorithm and use subject A to illustrate how effective each stage was for selecting and reducing potential windows using our sliding window technique.

We looked for 1.5 second windows that contained peak points exceeding 1.5G for the Butterworth filtered magnitude of the x, y, and z, which is the total strength of all the axes, using the peak detection function that was previously described. We gathered 714 distinct windows that might be solos after applying this process to subject A's data.

Then, using the Butterworth filtered data received from the x axis, we applied our peak detection method once more to search these prospective windows while maintaining the window width of 1.5 seconds for more than 3 peaks. The reason for this is that solos should have three or more peaks, as determined by our exploratory investigation. Using subject A's data, we applied this process to find 387 distinct windows that might be solo encounters.

We realised that, despite the fact that these two phases successfully included all solos, there were some duplicate windows or partial duplicate windows, which is not what we wanted because it would mean we would be counting the same solo twice. In order to fix the duplicate window issue, we looked at the windows to make sure that each had a unique time for the maximum point, and we also removed any windows that were within 0.3 of a second from this time as the smoothing filter technique used in our peak detection function (Meng, 2016) sometimes caused the maximum value to correspond to a slightly different time. This stage reduced our potential windows for subject A's data even further to 209 distinct windows that could be a potential solo which contained all actual solos.

As soon as we had this algorithm established, we began the labelling process by classifying each window as a solo or non-solo. This required a manual examination of each window and the use of our solos that were recorded with the player standing as a model for how a solo should look. It took a lot of time to complete as the real time clock inside the accelerometer was not always accurate, but with the knowledge we gained about solos from our exploration analysis and the video footage of the players' movements, we were able to make sure that no solos were missed and that the solos were appropriately labelled. Only 35 of the 209 potential windows were solos, with the remaining windows containing noise coming from other actions like running, jumping, kicking, or shooting.

We did see that some solos lasted longer than 1 second and that certain solos, particularly for subject B, may last up to 1.25 second or slightly longer. We did attempt to design characteristics over a 1.25 second period to account for their extended solo period, but for the other 3 subjects, our models produced a sensitivity result of 0, as the solos lasting less than this time contained data that was not a solo. Despite the fact that doing so might decrease the accuracy for capturing solos for subject B, we chose to build our predictor characteristics from these potential windows for a duration of 1 second as it would yield better results for the majority of the participants.

Labelling Potential Windows for Kicks or Shots

The labelling process for kicks or shots was much simpler than labelling solos because they were easier to recognise visually because they contained a large max point, as we observed in our explanatory analysis phase. We began the labelling process by developing an algorithm to find potential single windows for kicks and shots. We will now describe the different phases of our algorithm and utilise subject A to show how successful each phase was at identifying and minimising potential windows using our sliding window technique.

Using the peak detection function previously described, we searched for 1.5 second windows containing peak points over 3.5G for the Butterworth filtered magnitude of the x, y, and z, which is the total strength of all the axes. Using this approach on subject A's data, we got 71 different windows that could be kicks or shots.

We came to the realisation that, even though this phase successfully included all kicks or shots, there were some duplicate windows or partial duplicate windows. This was not what we desired because it would have resulted in counting the same kick or shot twice. In order to resolve the duplicate window problem, we examined the windows to make sure that each had a distinct time for the corresponding maximum point and also eliminated any windows that were within 0.3 of a second from this time as the smoothing filter technique used in our peak detection function (Meng, 2016) sometimes caused the maximum value to correspond to a slightly different time. This stage reduced our potential windows for subject A's data even further to 57 distinct windows that could be a potential kick or shot. The number of potential kick or shot windows for subject A's data was reduced further at this step, to just 57 different windows.

Once this algorithm was in place, we started the labelling process by categorising each window as a kick or other activity. The knowledge we gained about kicks and shots from our exploration analysis and the video footage of the players' movements allowed us to manually inspect each window and ensure that no kicks or shots were missed and that the kicks or shots were labelled correctly. Only 15 of the 57 potential windows were kicks or shots, with the remaining windows containing noise coming from other actions.

Labelled Solos, Kicks or Shots

We have given a visual representation of a segment of data obtained from subject A displaying 3 solos and 1 shot as seen in (Figure 7), as the labelling process can be challenging to comprehend.

The red background serves as a clear indication of the chosen 1 second solo windows, but it also draws attention to how the solos can vary significantly while they are in use. Since it looks that the first solo is longer than the other two solos we can see, a chunk of the solo is shown in this visualisation with a yellow background to reflect the missing portion of the solo when the window is set to 1 second. However, if we were to widen our window to accommodate this solo's additional time period, it is obvious that the other solos would then gather a decreasing portion of the data that is not a solo. Therefore, leaving the window at 1 second was the best choice, although it is not ideal, having the window at 1 second did produce better results for the vast majority of the data gathered for this project.

Figure 7: G-Force of 3 Solos and 1 Kick using Butterworth Filtered Data from Subject A.

Model Design

Model Data

After labelling each of our possible windows, we developed the predictor or characteristic factors for each of these windows. For each conceivable window, we established variables from the raw accelerometer data on the x axis, including the standard deviation, variance, maximum value, minimum value, interquartile range, skewness, and kurtosis as these characteristics were successfully used in the past as discussed earlier to identify kicks in Australian football (Cust, 2020) and identifying collisions in rugby union (Kelly et al., 2012).

After inspecting the pairs plots and correlation matrix of the data, we could see that there was multicollinearity between the standard deviation and variance variables which was expected as the standard deviation is the square root of the variance, so we opted to remove the variance variable from our data. The model is made simpler and more stable by removing the variance variable. Although there was a high correlation between the maximum value and standard deviation, they are still considered significant and relevant to the classification issue. We chose to include both variables even though they may be highly correlated because each one still offers distinct and useful information that aids in the categorisation process.

Models for Classifying Solos

Since SVM models are primarily intended for binary classification situations where the classes can be split using a linear boundary, we must first determine whether the data is linearly separable before we can build our SVM models. The characteristic variables for the solos for subjects B, C, and D are shown in a pairs plot below (Figure 8), and it is evident that the solo data cannot be linearly separated. Consequently, in order to classify solos, we must apply the kernel trick for our SVM model. We used the radial kernel function to overcome this problem with the data not being linearly separable. The data's inability to be separated linearly was a challenge that was solved using the radial kernel function.

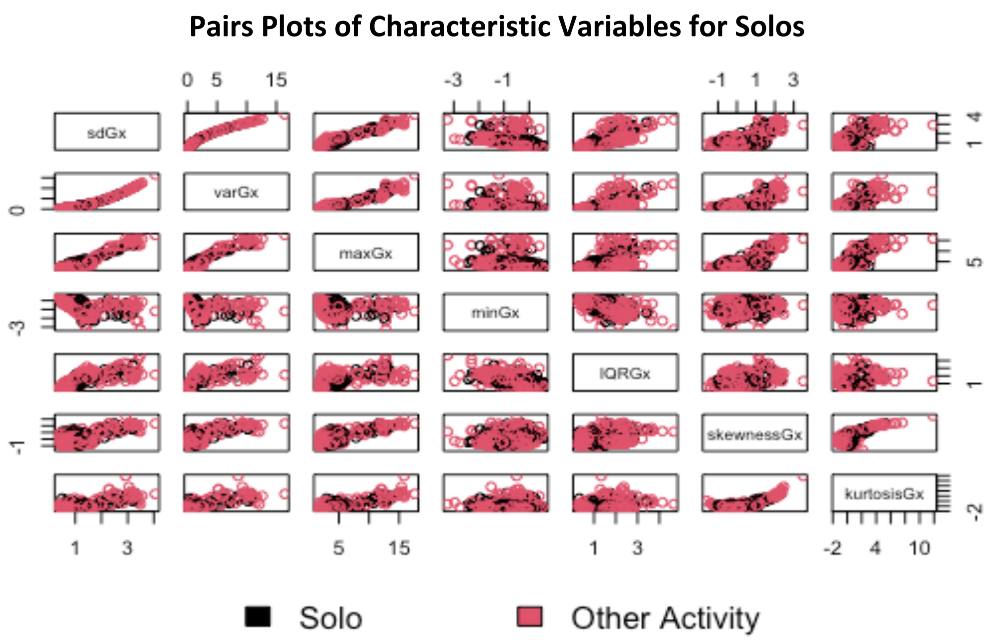

Figure 8: Pairs Plots of Characteristic Variables for Solos for Subject B, C and D.

We adjusted the SVM model's accuracy by considering the ideal gamma and cost tuning parameters. The gamma parameter, which can take values between 0.001 and 1000 in our model, governs how each training sample affects the decision border. The cost parameter establishes the trade-off between restricting the margin and minimising the training error. It considers the vector values we gave it, which were 0, 0.1, 1, 10, 100, and 1000. A low-cost parameter value denotes a higher margin, which could result in classification errors.

Our random forest model was more simple than the SVM model as it used the default parameters provided by the randomForest() function and because random forests can handle non-linearly separable data without the use of feature engineering.

We made the decision to build two models using the SVM and random forest modelling techniques. The first model employed the data from individuals B, C, and D, training the models on a random 70% of potential windows which contains 141 windows that are solos and 329 windows that contain other activities and testing the models on the remaining 30% which contains 55 windows that are solos and 146 windows that contain other activities. The second model was tested using data from subject A which contains 37 windows that are solos and 172 windows that contain other activities and trained using data from subjects B, C, and D which contains 196 windows that are solos and 475 windows that contain other activities.

Although specificity and accuracy aren't particularly important when presenting the project's findings as these calculations involve true negatives which has no true meaning, it's always pleasant to include all calculations for the reader, therefore we chose to do so. Specificity evaluates a classifier's aptitude to correctly classify actions that are not of interest as negatives which is important, but to measure the success of these models for this project we are more interested in the results for sensitivity and precision.

Sensitivity, sometimes referred to as recall or true positive rate, measures the percentage of instances that are actually solos and are correctly classified as such by the classifier. Precision, sometimes referred to as positive predictive value, estimates the percentage of solos that are actually solos while considering false positives or solos that were classified as solos but were not solos.

Sensitivity = TP / (TP + FN)
Precision = TP / (TP + FP)

As can be seen from the results shown in (Figure 8) below, when 70% of subjects B, C, and D were used to train the model and 30% were used to test it, both the SVM and random forest models had the same sensitivity value of 0.5636 and the SVM model had a slightly better precision value of 0.5961 compared to the random forest model, which had a precision value of 0.5535.

According to the results shown in (Figure 9) below, when subjects B, C, and D were used to train the model and subject A was used to test it, in comparison to the random forest model, which had a sensitivity value of 0.6757 and a precision value of 0.641, the SVM model had a better sensitivity value of 0.7568 but a worse precision value of 0.5714. Both precision and sensitivity values are equally important but with a higher precision value the random forest model performs better at reliably labelling events as positive which we could subjectively argue is the most important of the two calculations and therefore the random forest is the better model in this scenario. Having said that, more data is needed to fully test these models and draw a more conclusive judgement about whether one model is superior to the other.

Model Results for Solos

SOLOS	Accuracy	Sensitivity	Specificity	Precision
3 Subjects (70 Train : 30 Test)				
SVM	0.7761	0.5636	0.8562	0.5961
Random Forest	0.7562	0.5636	0.8288	0.5535
3 Subjects Train and 1 Subject Test				
SVM	0.8565	0.7568	0.8779	0.5714
Random Forest	0.8756	0.6757	0.9186	0.641

Figure 9: Model Results for Solos

Although we can clearly see that the random forest performed better when subject A data was used to test the model trained on subjects B, C and D as it had a higher precision and sensitivity value than the random forest model when 70% of subjects B, C, and D were used to train the model and the remaining 30% were used to test it. This can also be confirmed by viewing a ROC (Receiver Operating Characteristic) curve which can be used to access this binary classification model, as the area under the curve is larger for the model using subject A as test data. This may be due to the fact that subject B's solos lasted longer than the other subjects as we discussed earlier during the labelling process and with the window set at 1 second it is missing vital information to predict that subject's solos accurately. ROC curves can be contrasted to access random forest models as they are probabilistic and can't be used with SVM models as they are not probabilistic as they don't provide probability estimates.

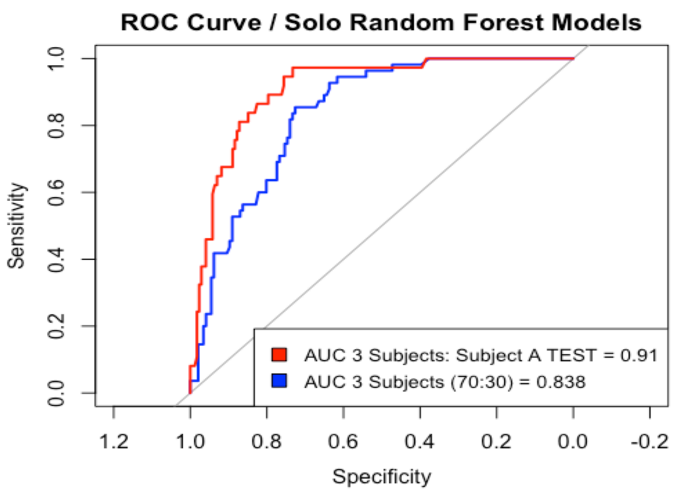

Figure 10: ROC Curve of Solo Random Forest Models

Models for Classifying Kicks or Shots

We must first establish whether the kick and shot data are linearly separable before we can create our SVM models, just like we did before with classifying solos. The characteristic variables for the kicks or shots for subjects B, C, and D are shown in a pairs plot below (Figure 11), and it appears that the kicks or shot data can be separated linearly. Consequently, there is no need to categorise kicks or shot using the kernel trick like we employed when classifying solos. Just like all our models the seed value is set to 150 for reproducibility purposes and the tuning process for SVM and random forest models follows the same method used when classifying solos.

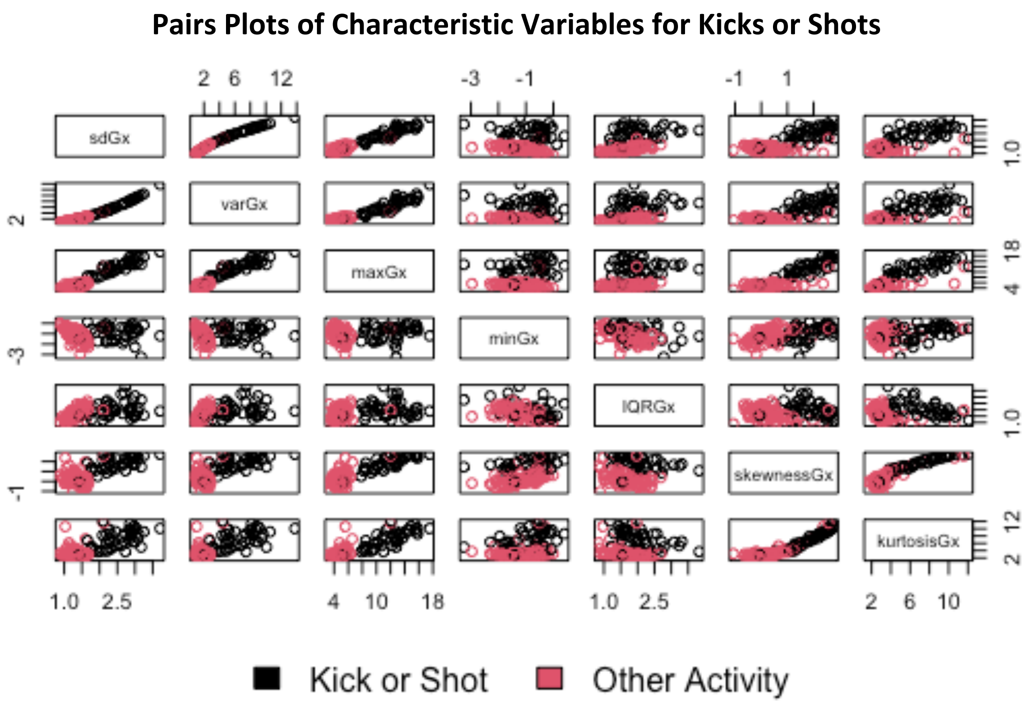

Figure 11: Pairs Plots of Characteristic Variables for Kicks or Shots for Subject B, C and D.

Like previously, we decided to use the SVM and random forest modelling techniques to create two models for each. The first model employed the data from individuals B, C, and D, training the models on a random 70% of potential windows which contains 29 windows that are kicks or shots and 61 windows that contain other activities and testing the models on the remaining 30% which contains 14 windows that are kicks or shots and 24 windows that contain other activities. The second model was tested using data from subject A which contains 15 windows that are kicks or shots and 42 windows that contain other activities and trained using data from subjects B, C, and D which contains 43 windows that are kicks or shots and 85 windows that contain other activities.

It is evident from the results in (Figure 12) that when it comes to categorising kicks and shots in Gaelic football, both our SVM and random forest models perform equally well, as they have the same values across the board for accuracy, sensitivity, specificity, and precision. These outcomes are nearly perfect because they are all extremely close to the ideal outcome, which is 1. Although these results are impressive and demonstrate that these models can be used to classify kicks and shots, further study with more data, such as perhaps different kick types or kick distances, is necessary.

Model Results for Kicks or Shots

SHOTS or KICKS	**Accuracy**	**Sensitivity**	**Specificity**	**Precision**
3 Subjects (70 Train : 30 Test)				
SVM	0.9737	1	0.9583	0.9333
Random Forest	0.9737	1	0.9583	0.9333
3 Subjects Train and 1 Subject Test				
SVM	0.9825	0.9333	1	1
Random Forest	0.9825	0.9333	1	1

Figure 12: Model Results for Kicks or Shots

Conclusion and Recommendations

Gaelic football players face increasing physical demands, and as the competition between the opposing sides intensifies, there is an increased need for performance analysis in order for teams and players to improve and develop. Management and players can use metrics from on-field data to help with decision-making, how to improve game strategies, and how to improve athletes' performance. The main goal of this project was to build machine learning models using support vector machines and random forests that would classify Gaelic players solos, kicks, or shots accurately. The research covered in this paper demonstrates how accelerometer readings from a single sensor worn on the player's leg can be used to automate solo, kick, or shot recognition.

In this report, we outlined all the procedures needed to recognise solos, kicks, and shots in Gaelic football. These procedures included signal processing, the use of a sliding window, and peak detection to gather potential windows of interest. Our findings demonstrated that utilising SVM and random forest models, accelerometers are very proficient at distinguishing kicks or shots. The validation results show that the system can accurately identify kicks or shots with a very low rate of false positives and false negatives. When using three of the subjects for model training and a different unique subject for model testing, the sensitivity and precision ratings for the support vector machine model and the random forest model, respectively, were 0.933 and 1.00.

The validation results for the solo identification models we developed were less impressive, with the random forest model having a sensitivity of 0.676 and precision of 0.641 and the support vector machine model having a sensitivity of 0.757 and precision of 0.571, using subject B, C and D for training and subject A for testing. This relatively mediocre accuracy was primarily caused by how much a solo's duration may vary, from about 1 to 1.25 seconds as well as the fact that accelerometer data for solos appears to be extremely similar to the accelerometer data for running actions. The solos recorded for subject B were particularly long compared to the other 3 subjects and the data was collected on a different pitch and different day. We can only speculate as to why this is, and additional research is required. For example, is the time period greater if a player is moving slower, is it because the ground is soft from rain, and so forth.

Future research with a bigger sample size could examine more thorough classification of solos, kicks or shots. One way to boost performance might be to increase the number of players the system is trained on. Not only should more external validation tests be performed with a larger number of people but also with various age groups and over the course of a match. Despite the fact that our results for solos when using subject A as an external validation of our solo models seem to be rather decent, it is important to keep in mind that this data was collected over a 5-minute period while they were primarily running and in possession of the football most of the time. As we know, throughout a match, a player runs without the ball a lot more often than they would with it, which in our situation would bring a lot more false positives for solos. Therefore, in order to evaluate whether these models are practical for use, they would need to be tested throughout a match.

This research was the first attempt to categorise actions in Gaelic football, and Australian football was found to be the most comparable study. As a result of this research, it is now clear that while kicks can be accurately identified, more intricate moves, such as solos, are far more challenging. Another investigation could be carried out to enhance our solo models using information acquired from gyroscopes as it has been demonstrated to effectively recognise similar low-detailed motions such as recognising running, walking, walking upstairs or walking downstairs (Miao et al., 2015). It is also very important to acknowledge that this project research can be used to recognise other various actions in other sports as well as provide a stepping stone for anyone else who is willing to improve wearable technology in the area of Gaelic football. An extremely reliable kick or shot detection system may also be provided by applying the techniques suggested in this study to kicks and shots in other sports.

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