

Volleyball Spike Quality

BACHELOR THESIS

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Abstract

The trend of using technology in sports is on the rise, where volleyball is the 5th most popular sport in the world. The aim of this research is to analyse whether the quality of a spike can be determined with the use of an IMU sensors and machine learning. This helps to improve volleyball when it comes to smart sport. IMU sensors are placed to certain parts of the body, where the output of the IMU will be used in machine learning. The quality of the smash is rated using “good” or “bad”. The results of this studies show that the quality of the smash can be detected. Thus, the conclusion is that the quality of a volleyball smash can be detected.

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1. Introduction

Smart sports hold in the use of modern technology in sports (How Technology in Sport is Changing the Game, 2016). The trend of using technology in sports is rising rapidly. In this paper the use of smart sports is implemented in the sport of volleyball.

1.1 Motivation

Volleyball is the 5th most popular sport in the world (M.Bird, 2016) and the third most participated team sport in the Netherlands (contributors, Wikipedia, 2020).

Selecting volleyball as a sport to investigate smart sport exercises will provide big opportunities when it comes to resources and market value. The sport volleyball requires some essential skills and techniques such as: serve, smash shot (or a spike), dig shot, set shot and block shot (Volleyball smash shot - Volleyball - essential skills and techniques - GCSE Physical Education Revision - Edexcel - BBC Bitesize, n.d.). In volleyball, the shoulder is the third most injured body part and this correlates with losing 40% of male volleyball athlete's training and competition time in the English first-division (Jonathan C. Reeser, Glenn S. Fleisig, 2010). In this research the focus is placed on performing a proper spike. Improving the spike technique by using modern and advanced technology might open the doorway for many athletes towards injury prevention and skills development.

1.2 Related Work

Determining the quality of a pitch using IMU sensors and machine learning is not covered extensively in different literature. However, there are multiple studies related to the quality of a pitch in volleyball. A study done by Li-Fang Liu (Li-Fang, Liu and Gin-Chang, Liu., 2008) investigated the proper body coordination and timing during a spike. Li-Fang used a camera and players at an elite level and intermediate level as test subjects. The average time of a proper spike resulted in 0.6 to 0.8 seconds in the air by intermediate players and 0.3-0.6 seconds by elite players. The difference between range of motion between the two test subjects were on average 60 degrees, which can be seen as a significant difference.

Ciapponi, Teri, Hudson and Jackie investigated the balance and skill when approaching the ball (Ciapponi, Teri and Hudson, Jackie, 2000). This approach phase involves gaining the right amount of speed before jumping and hitting the ball. Here the use of both elite and intermediate level players was used as test subjects. Video as well as a 3D software was used. The two jump approaches which were investigated were the hop step approach and the step close approach as seen in Figure 1.

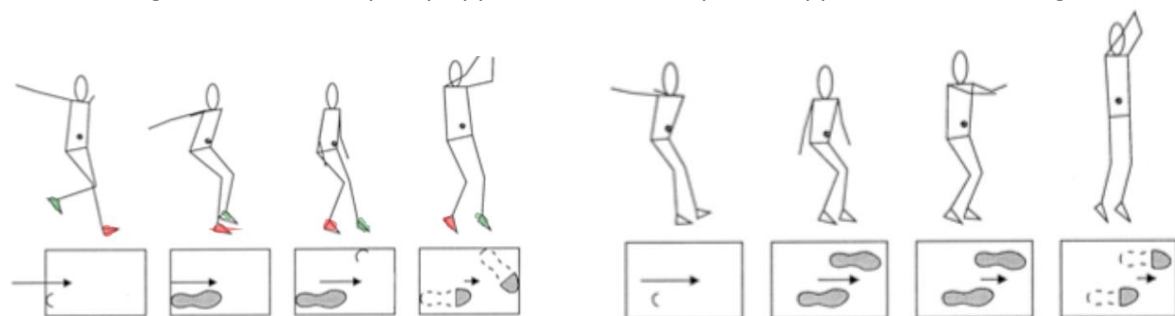


Figure 1 Hop step approach (right) and step close approach (left)

The result of this study shows that there is an inverse relationship between mobility and stability these two approaches. Here the advanced players had better stability and were better in decreasing their mobility. Most test subjects are more familiar with the step close approach and therefore that one was chosen to be the approach for this study to standardize the measurement.

Yufan Wang, Yuliang Zhao, Rosa H. M. Chan³ and Wen J. Li used IMU sensors and machine learning to differentiate between elite, sub-elite and amateur volleyball players (WANG, 2018). This study uses a high-speed camera, IMU sensors and machine learning. The difference between this study and Yufan is that in this study the focus is placed on one skill level, which is the amateur level.

1.3 Project Scope

First an analysis of the volleyball spike is done and afterwards a method to assess the volleyball quality is developed.

The test subject wears the sensors and performs a spike. The data out of the IMU sensors is analysed and converted into readable data, using signal processing of factors such as: roll, pitch, yaw, speed of the arm, angle of the arm. From this data an analysis is done to determine parameters such as the threshold, standard deviation. This data is applied to machine learning to determine the quality of the spike. The performance of the spike was filmed for the purpose of validation.

1.4 Research Question

The research question for this thesis is as follows:

Can the quality of a spike in the sport of volleyball be detected using IMU sensors and machine learning?

2. Context

2.1 Volleyball

Volleyball is a sport played by two teams of six players (contributors, Wikipedia, 2020). These two teams are playing in a court seen in Figure 2 Volleyball court , which is separated by a net that acts as a barrier for the ball. The goal of both teams is to ground a ball on the opponent's side of the court in order to score points.

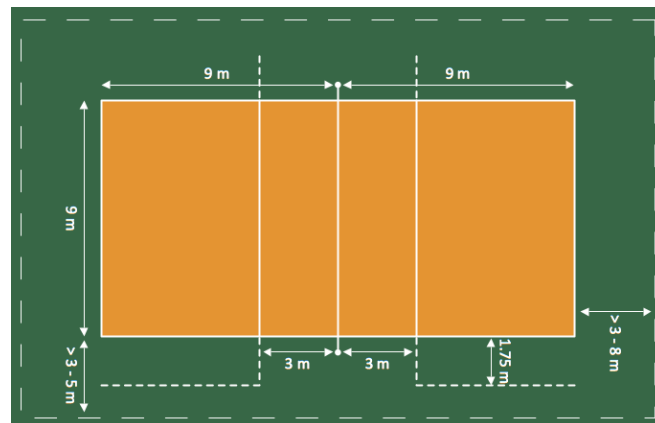


Figure 2 Volleyball court (Sport Field Plans, n.d.)

2.2 Volleyball Pitch

The most challenging part for the opponent during a game is when a spike is performed, which creates a lot of tension and excitement throughout the game (Roque, 2012). The steps to perform a spike are illustrated in Figure 3. The spike is used as a strategy to score a point, where the ball is sent to the other side in such a way that it is difficult to return the ball to the initial side (Basics, n.d.). This difficulty is caused by the speed in which the ball enters the opponent's side. Spiking a ball requires a great amount of skills, which needs to be gained over the course of time. The quality of the spike progression is accelerated when feedback is given by either a trainer or another observer (Roque, 2012).

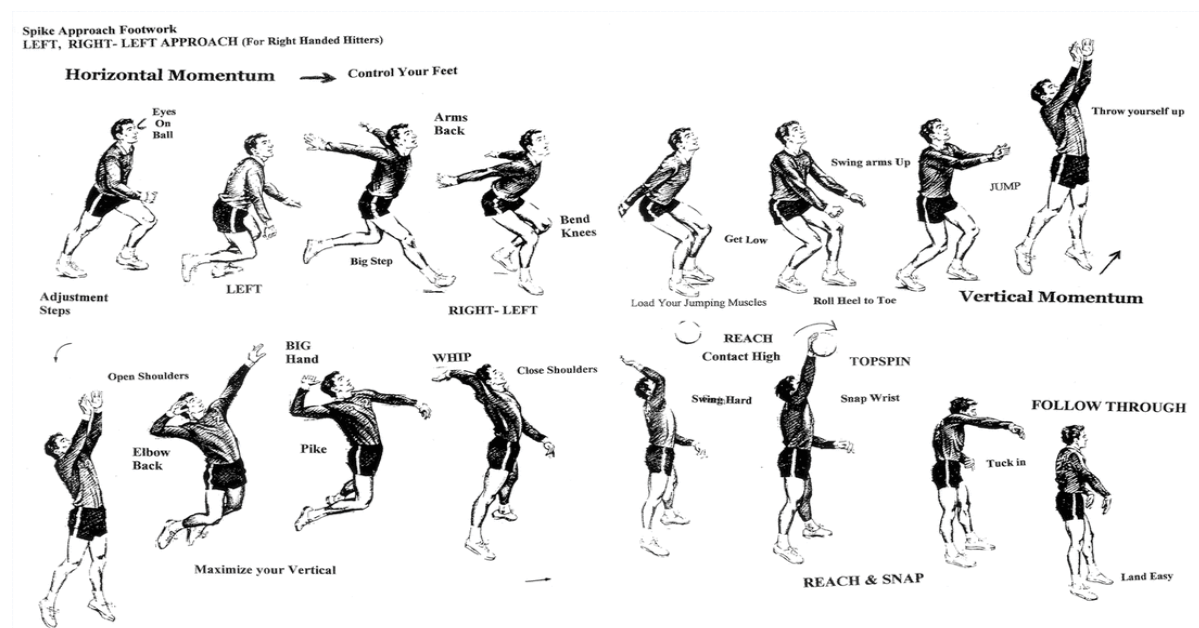


Figure 3 Spike performance (Basics, n.d.)

2.3 IMU Sensors

An Inertial Measurement Unit or IMU has the capability to do various measurements on a body (contributors, Wikipedia, 2020). There are IMU with the size small enough to fit in the user's hands and also lighter than 100 grams (Inertial Sensors: IMU, GPS-INS, AHRS, MRU for UAVs & Robotics, 2020). These measurements include angular rate and acceleration. Nowadays IMU sensors come with a magnetometer and humidity sensor (contributors, Wikipedia, 2020).

2.4 Machine Learning

Machine learning is used for the classification of the quality of the pitch. Hereby training and test data are necessary, whereby both first need to be labelled. Predicting what label/class the unknown data has is done by using classification through machine learning or the alternative deep learning (Classification with Neural Networks: Is it the Right Choice?, 2020). Terms involving machine learning are explained below, which are used throughout the report.

Instances

The classifier needs data of an observation in order to classify them, where one example of the data is considered an *instance*. An instance includes a number of attributes.

Class

The classifier will classify the given instance by labelling the result of each instance. A class can be a certain action like: sitting down, running or standing.

Attributes/Feature

Machine learning needs measurable properties or characteristics of the phenomenon being observed. These individually measurable properties are called *features* (contributors, Wikipedia, 2020). Features are also referred to as attributes. Features can be data such as velocity of an object, position or the standard deviation of the velocity. Some features are less effective when it comes to classifying. This can be determined using a feature available in the WEKA software – the software used for classification. The more attributes each instance contains, the more accurate the classifier model will become.

Training data/test data

A classifier needs both *training data* and *test data*. Here the data will have one or more instances. The difference between these two types of data is that the classifier usually uses the training data to train the classifier model and at the end the test data will be used to test the classifier accuracy.

Example:

Checking whether a person is “walking” or “running” using the data from his smart watch. In this case the *class* will be “walking” and “running”. A sample of the data where he is running is called an *instance*. The smart watch will give data such as acceleration or location, which are called *features*. The data which includes the class, so noted if he is running or not, is considered the *training data* or *test data*.

Classification Algorithm

There are different algorithms available for classification, such as linear classifier, decision trees, neural networks, etc (M.Sidana, 2020).

Confusion Matrix

After the classification algorithm and features are selected, the performance of the classifier can be determined. This performance can be determined using a confusion matrix. This is done by comparing the outcome of the classifier, done using the training set, with the test data.

3. Methodology

3.1 Volleyball Pitch Analysis

3.1.1 Biomechanics of a Volleyball Spike

According to Wang (WANG, 2018) and Rogue (Roque, 2012), the factors which affect the spike in volleyball are:

1. Linear and horizontal velocity of the spiker
2. Rotation of the arm swing, wrist snap and the torso rotation
3. The specification of the wrist itself

These factors are taken into account when determining the performance of the volleyball spike. A spike can be done using a hop-jump or by a step-close jump (Hu, Lin Huan and Sheu, Tai Yen, 2002) (Roald Bahr, Jonathan C. Reeser, 2003). In terms of reaching a certain height, both jumps show equal results (Hu, Lin Huan and Sheu, Tai Yen, 2002) (Roald Bahr, Jonathan C. Reeser, 2003). In terms of the amount of stress on the knee and ankle, it shows that the hop step jump has more stress on the knee and ankle (Hu, Lin Huan and Sheu, Tai Yen, 2002) (Roald Bahr, Jonathan C. Reeser, 2003). An advantage of the step-close jump is that the jump decreases the response time for the opponent, which is favourable. Because of those two advantages the step-close jump has over the hop step approach and due to the amount of research available on that type of jump, this study focuses only on the step-close jump.

The volleyball spike can be divided into 4 different phases: approach, arm cocking, arm acceleration and follow-through. These steps can be seen in Figure 4.

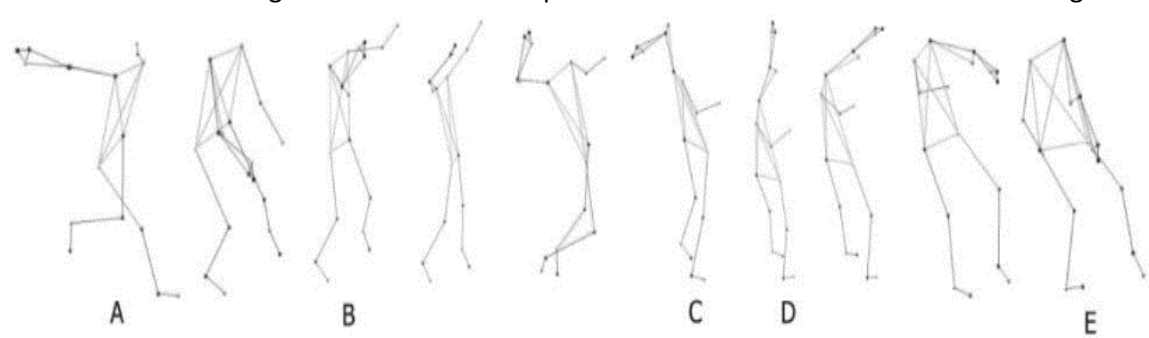


Figure 4 The 4 phases of the volleyball spike: A->B approach, arm cocking (B -> C), arm acceleration (C -> D), and follow-through (D → E) (Jonathan C. Reeser, Glenn S. Fleisig, 2010)

3.1.2 Approach

During the approach phase the spiker will fix his gaze on the ball, to make an estimation of the ball's location. Using the estimation, the spiker will adjust his steps according to the direction of the spike. To reach the highest jump the spiker extends his arm to his back. While extending his arm to the back, a step is made by using his right leg. This increases the potential energy prior to the jump (Roald Bahr, Jonathan C. Reeser, 2003). After the spiker reaches his back with his arm, the second left step follows and his arms swing to the front. While swinging down with his arms and taking a step with his left leg, the spiker gets ready for the jump by bending his knees. This will destabilize and decelerate the spiker body's center of mass, causing to translate the spiker's horizontal velocity into a vertical velocity. The faster the transition phase between the preloading and the jumping phase, the higher the jump will be (Roald Bahr, Jonathan C. Reeser, 2003).

3.1.3 Arm Cocking

In this phase the spiker focuses on hitting the ball. The amount of power that goes into hitting the ball is relative to the range of motion prior to hitting the ball (Roald Bahr, Jonathan C. Reeser, 2003). The arm cocking phase can be divided into 3 different phases namely: back swing phase, turn swing phase and forward swing phase (Roald Bahr, Jonathan C. Reeser, 2003). These steps are illustrated in Figure 5.

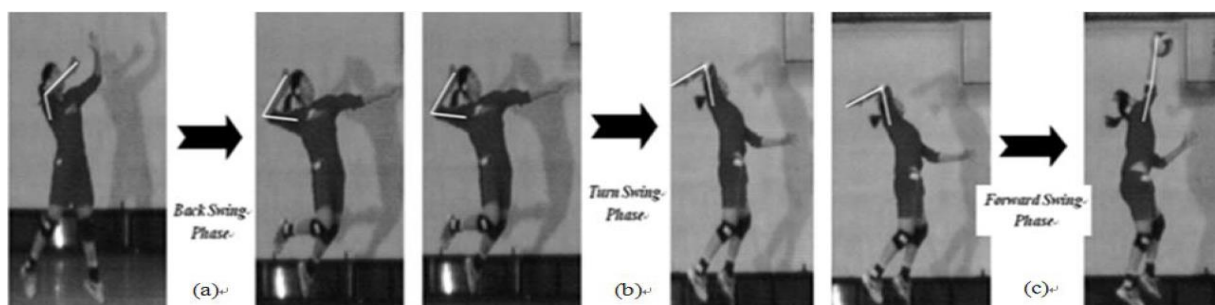


Figure 5 Arm cocking phases. Back Swing phase (a), Turn Swing Phase (b) and Forward Swing Phase (c) (Roald Bahr, Jonathan C. Reeser, 2003)

In the beginning of the back-swing phase the spiker has both of his hands up, where his dominant hand will reach his back by rotating his shoulder to the back. An elite athlete's range of motion goes back up to 120 degrees, whereas intermediate athletes reach 62 degrees (Roald Bahr, Jonathan C. Reeser, 2003). The range of motion of the spiker's dominant hand can be increased by setting the spiker's hand into a whip position. When swinging the dominant hand to the back the angular momentum of the body is destabilized, which is compensated by a counter movement. The main movement for compensating is by contracting the legs to the back and swinging the opposite hands to the front (Roald Bahr, Jonathan C. Reeser, 2003).

3.1.4 Forward Swing Phase

In the forward swing phase, or the phase where the ball is being hit, most of the kinetic energy built up by the dominant hand is being transferred to the ball. As analysed the ball should not be exactly hit while jumping to the ball, but rather while falling.

3.2 Spike Quality

The method for this assignment to determine the quality of the volleyball spike includes determining if certain movements are performed and if they are in line with the movement sequence of other body parts. For the sake of time and simplicity the focus of movements is placed on the jump and if the arm movements are done in the right sequence, so without analysing the whip movement of the hands. A grading system is made where a point is given if each movement is done correctly. A spreadsheet of the movement sequences and the grading system can be seen in Appendix A in Table 3. Each movement by each body are dependent on each other in order to increase the quality of the spike. The dependency of each activity during the spike can be seen in Appendix A in Table 4.

The quality of a spike can be judged in different ways, such as: the velocity of the ball, the ball hitting the aimed target, if a point is made, etc. These requirements can be mastered if the spike is performed properly. Therefore, the quality of the spike for this research is determined by the technique of the player. The factors required to do a proper spike include the right speed and right coordination of the legs, feet, arms, wrists and hips. If the run-up is performed poorly, then the pitch might be considered a poor pitch. Mastering the right technique can be time consuming if not all factors are combined properly. In the current situation volleyball players are given feedback from their trainers and next to that training is also done by using online tutorials. Providing additional data can automatically help a player practice independently or remotely which can decrease the necessity of a volleyball trainer. One of the methods to observe and analyse the behaviour of volleyball players during a spike is the vision base solution in combination with machine learning and signal processing. An alternative is using IMU sensors in combination with machine learning and signal processing as done by Yufan (WANG, 2018). This alternative solution is easily available and more in line with the skillset of an electrical engineer student.

3.3 Technology Used

3.3.1 IMU Sensors

The Inertia Measurement Unit or IMU sensor used during this assignment is a NGIMU from *x-io Technologie* Figure 6. This sensor is necessary for the kinematics of the spiker. The NGIMU sensor contains a gyroscope, accelerometer, magnetometer, pressure, humidity and temperature sensor (NGIMU, 2020). The NGIMU IMU sensor has also the possibility to be used wirelessly. The alternative of interconnecting the NGIMU is by connecting all of them together in a single computer. This requires a lot of cables and affects the player comfort. Thus, choosing the wireless option of the NGIMU sensor to interconnect all IMUs together. The NGIMU sensor comes with its own software to retrieve its data in excel format. This data is easily transferred into MATLAB.

The sample rate of the NGIMU can be set, which is set to 258 Hz. The maximum sample rate of this device is 400Hz. Higher sample rate decreases the battery level faster and therefore a lower sample rate is chosen. 258Hz is chosen after a trial and error during the analysis of the code.



Figure 6 NGIMU sensor from IO-Technologies (NGIMU, 2020)

3.3.2 Ground Truth Device

The volleyball pitch is recorded and the recording is used as the ground truth data. There is no method developed for this project to synchronize the timing of the pitch. The solution for this problem is that the timer is recorded in the same shot as the pitch.

The requirement for the ground truth device is that the device should be able to record in slow motion, because a spike has a duration of around 2-3 seconds where multiple observations need to be done into the milliseconds.

The device used for the ground truth is an iPhone XS. This device has the option to record video in slow motion up to 240 fps in 1080p HD (Arena, 2020).

3.3.3 Software

Data processing is done using the software **MATLAB**. In MATLAB the data is loaded and manipulated using signal processing. Several features are necessary for machine learning and pattern recognition. Machine learning is done using the software **Weka**. Weka is filled with different classifiers out of which the J48 algorithm has been used. The J48 algorithm makes use of decision trees (contributors, Wikipedia, 2020) (contributors, Wikipedia, 2019).

3.4 IMU Placement

This section explains the comprehensive setup of the IMU sensors with the measurement plan for data retrieval. In each relevant body part, an IMU sensor is placed (Figure 7). First it is determined which the dominant hand is. The body parts on which a sensor is placed are decided by using the analysis made from the biomechanics of a volleyball spike. A table is made from the analysis (Appendix A, Appendix B), where it can be seen what movements are necessary from each body part in order to do a proper spike.

1. Head: During a spike the head will barely move or rotate. This IMU will be used as a reference point, because the head has not the capability to move as much as other body parts. An alternative would be using the IMU sensor on the test subject's stomach.
2. Left wrist: In combination with the head's IMU and the left arm, the angle of the left arm can be estimated.
3. Right wrist: In combination with the head's IMU and the right arm, the curl and angle of the arm can be estimated.
4. Dominant upper arm: This is useful when it comes to detecting the curl of the arm (Thomas Seel, 2014).
5. Left and right ankles: The steps, velocity and positions of the test subjects can be detected (Sebastian O.H. Madgwick, 2011)

The left upper arm does not get an IMU sensor, because there are less movements than in the dominant arm. The movement made by the left arm does not include much curling as seen in Figure 3 Spike performance .



Figure 7 Sensor placement

3.5 Experimental Setup

The setup for the measurement of data facilitates a systematic retrieval of data. The setup is as follows:

1. Setting the volleyball at a convenient height of around 3 meters using ropes. A volleyball net is between 2.22 meters and 2.43 meters depending on which gender plays (Dimensions.com, 2020). A height of 3 meters is sufficient to do a proper spike. The height of the ball is adjusted to the player to be both comfortable as well as slightly challenging. However, the height of the volleyball for every participant was between 1.78 and 1.85 (Table 1).
2. The court of a volleyball field is 18 meters long (9 meters each side). The spike can be performed with a horizontal or vertical jump. Setting a run-up of around 5 meters is sufficient for both types of jumps. The starting position is indicated using a line.
3. The test subject is in a resting position before performing a spike. This is due to no mechanism available to initiate the spike data retrieval. Detecting a stationary position using data processing gives an indication that the user is standing still and vice versa.

3.6 Participants

The test subjects are chosen with respect to their experience in volleyball in order to widen the gap between a good and bad pitch on an amateur level. The test subjects are asked to rate their skills between 1 and 5 if they would be in an amateur volleyball team. Each participant performs 6 pitches, after a couple of warming up pitches.

The information of the test subjects is seen in Table 1 Test subject info.

Participant #:	Skill level from 1-5 (low to high)	Height (m)	Ball height (m)	Distance to the ball (m)
Participant 1	4	1.85	2.45	3.43
Participant 2	3	1.83	2.85	3.43
Participant 3	1	1.72	2.2	3.43
Participant 4	2	1.78	2.62	3.43

Table 1 Test subject info

3.6.1 Instruction for the Participants

Prior to the data retrieval instructions were given to each participant. The instruction given to the participants were:

- Prior to the data collection stretch and do at least 3 pitches.
- Stand still with the hands down till the command is given.
- Stand behind the line.
- Run a straight line towards the ball

4. Data analysis

4.1 Annotation

The classifier requires an excel file including each feature with the results (depends if it's the training set or data set). Each feature is calculated in MATLAB, which are then placed into an excel file. All features have the same number of rows.

The labelling of the data is done by watching the video recording of each pitch and labelling the quality of a movement of each body part during each phase of a spike using 1 (proper movement) or 0 (improper movement). This is done as the first step in assessing the quality of the pitch before using the table in Appendix A. From the result of every body part an array is made with the same length as the features in MATLAB, so that this can be merged into the excel file with the exact same rows.

4.2 Pre-Processing

The recorded data includes the movement before, during and after the pitch. The users were said to stand still. However, during the analysis of the IMU data it is seen that the data had noise, which was a result of the slightest movement, for example if the pitcher was ticking with his feet while waiting for the command. This phenomenon can be seen in Figure 8, where the black lines indicate where the user was moving. Since slightest movement was considered being noise the data was cut, removing everything except for the pitch itself.

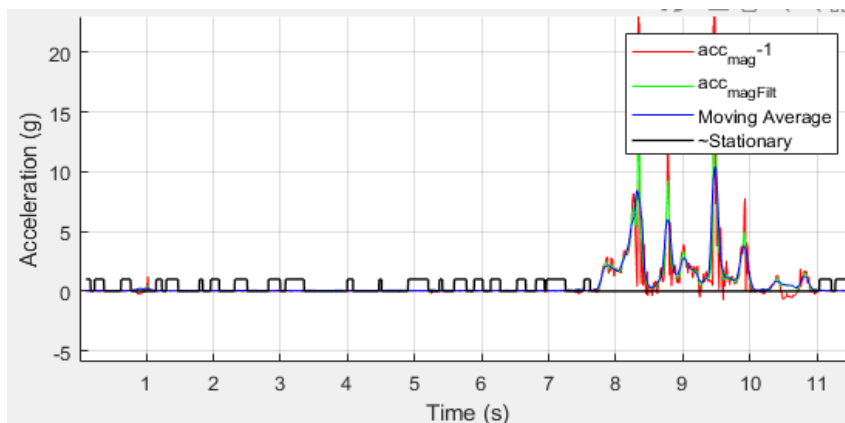


Figure 8 Indication of where the pitcher was standing still and moving. Start time = 6 seconds, stop time = 9 seconds

4.3 Data Processing

The data of the IMUs are processed using data signal processing. The raw data of the IMU sensors includes the acceleration on three axes, namely the x, y and z axis. Integrating the acceleration will result in the velocity and double integrating will result in the position of the IMU with respect to the start of the IMU's data collection. These parameters are easier to read and understand than only using the acceleration data, this type of data makes it then easier to verify with the video recording (ground truth data). The raw data from the IMUs are transferred into MATLAB.

The raw data used for data processing are the acceleration of each axis and the quaternions of the IMU. The types of signal processing are calculating the velocity, velocity drift, roll, pitch, yaw, magnitude of the acceleration, RMS, acceleration moving average and the difference in acceleration between the different body parts. Each parameter is explained in the sections below.

4.3.1 Velocity

Each measurement is filmed so that the processed data can be verified. Acceleration is equal to 0 in case where the velocity is 0 and constant and therefore using the velocity as another parameter is more practical. From the IMU sensor acceleration signals from the 3 axes (x, y and z) are given. Integrating these signal results in the linear velocity in the corresponding direction.

$$v = \int a dt \quad (4.1)$$

V = VELOCITY (M/S)

A = ACCELERATION (M/S²)

The output of the IMU sensors are discrete signals. Eq.(holds only for continuous signal, whereas for discrete signals the equation holds:

$$v(t) = v_{t-\Delta} + a(t)\Delta t \quad t > 0 \quad (4.2)$$

v_0 = Initial velocity(m/s)

a = acceleration (m/s²)

Δt = sample period (s)

Eq. (4.2) is placed into the code for the retrieval of velocity.

4.3.2 Velocity Drift

Velocity drift can be caused by various noise factors as well as by small sample rates. If the sample period in eq.(4.2) is small enough then this will help to decrease velocity drift. A solution for velocity drift is the use of a threshold in order to determine where the spiker was stationary. With the stationary signal the drifting acceleration can be removed, thus only resulting in acceleration where the spiker was moving.

The stationary signal can be retrieved using the resultant of the acceleration signals (x, y and z) using eq.

$$Mag(t) = \sqrt{a_x^2 + a_y^2 + a_z^2} \quad (4.3)$$

a = acceleration in the corresponding direction (m/s²)

$mag(t)$ =resultant of the acceleration vector(m/s²)

The frequency for running is on average below 10 Hz. The data is filtered through a Butterworth filter which has the advantage that it makes the frequency response as flat as possible (W.Storr, 2018).

Using a threshold, the samples below the threshold can be discarded leaving only a signal where the spiker was moving. When comparing the samples of the stationary signal and the velocity signal, the stationary samples can be removed from the velocity signal.

Integrating the velocity will result in the position of the IMU sensor, using eq (4.4).

$$r(t) = r_0 + \int v dt \quad (4.4)$$

4.3.3 Roll, Pitch and Yaw

The orientation of the fixed body parts can be described using the Euler angles with respect to a fixed coordinate system (contributors, Wikipedia, 2020) . Movements such as curling the legs and arms can easily be detected by the roll, pitch and yaw. The roll, pitch and yaw of the arm can be seen in Figure 9.

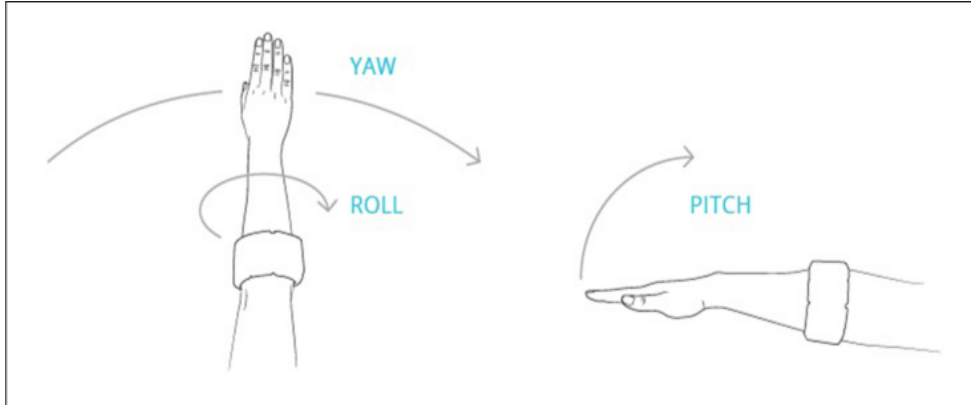


Figure 9 Roll, pitch and yaw of the arm

The IMU sensor has as output quaternions, which can be used to convert to Euler angles. The roll, pitch and yaw are retrieved using the “*quat2angle*” function of MATLAB itself. Here the function has as argument the quaternions, which are the output of the NGIMU sensor itself.

4.3.4 RMS

The Root Mean Square (RMS) of the accelerometer is calculated using eq. (4.5).

$$x_{RMS} = \sqrt{\frac{1}{N} \sum_{n=1}^N |x_n|^2} \quad (4.5) \text{ (Root-mean-square level - MATLAB rms, n.d.)}$$

x_{rms} = scalar rms value

x_n = sample n of the signal

MATLAB contains a function, which calculates the moving RMS of the signal. Here a window size is selected with the size N in eq.(4.5).

4.3.5 Moving Average

The accelerometer signal of the IMU contains a lot of noise. The moving average is a technical analysis tool, which helps to smoothen out the signal. The equation for calculating the average is equal to eq. (4.6)

$$\mu = \frac{1}{N} \sum_{i=1}^N A_i \quad (4.6) \text{ (Moving mean, 2020)}$$

The moving period uses a sliding window, which has been chosen to be 0.1 seconds. 0.1 seconds was the optimal window length for as little data loss as possible.

4.3.6 Difference between Signals

Each individual activity is dependent on each other in order to build up to a proper spike. Therefore, it is necessary to have signals which indicate the correlation between those two. The difference

between the magnitude of each signal is calculated. The magnitude of the signal indicates the resultant of the velocity, which gives the difference in speed relatively to each other. Subtracting one body part's magnitude with the magnitude of another body part gives the relative velocity which they are moving from each other. An alternative would've been using the correlation between the two signals.

4.4 Classes

In this project the classes which are used are: true or false, so the classifier determines if the instance is a proper spike or not. The classifier used in this assignment is a binary classification, which has only two groups (correct order/incorrect order).

4.5 Classification Algorithm

There are different algorithms available for classification, such as linear classifier, decision trees, neural networks, etc (M.Sidana, 2020). The classification algorithm used in this project is the J48 algorithm. The J48 algorithm uses a decision tree, where the data set broken down into smaller subsets and meanwhile a decision tree is made (M.Sidana, 2020) (contributors, Wikipedia, 2020).

4.6 Feature selection

The features used for the classifier are (as how they are named in the files):

- `acc_mag` : the magnitude of the acceleration
- `accXmean`, `accYmean`, `accZmean`: the mean of each axis
- `accXRMS`, `accYRMS`, `accZRMS` : RMS of each axis
- `accXstd`, `accYstd`, `accZstd` : Standard deviation of each axis
- `vel_X`, `vel_Y`, `vel_Z` : velocity of each axis
- `pitch`, `roll`, `yaw` : roll, pitch and yaw of the corresponding body part
- `diffWR` : difference in acceleration between the *right wrist* and the corresponding body part
- `diffWL` : difference in acceleration between the *left wrist* and the corresponding body part
- `diffArm` : difference in acceleration between the *right arm* and the corresponding body part
- `diffH` : difference in acceleration between the *head* and the corresponding body part
- `diffAR` : difference in acceleration between the *right ankle* and the corresponding body part
- `diffAL` : difference in acceleration between the *left ankle* and the corresponding body part
- `WL_Result` : result of the pitch in the corresponding instance.

There is no difference in acceleration between a body part and itself, thus removing that feature from each IMU's data. The total amount of features per body part/IMU are 22.

Weka has the possibility to rank these features from most effective to the least effective for the classifier. This is beneficial for reducing processing time by eliminating unnecessary data (less features) into the classifier.

4.7 Validation

The model is validated using the cross-validation method. Here the data set is divided into a certain amount of sets k . So, a k -fold of $k=10$ means that the data set is divided into 10 subsets (J.Brownlee, 2020). The $k-1$ sets are used as training data and this process is repeated k times (each subset set is used as a training set). This is useful when not a lot of data is available. Afterwards the use of a confusion matrix is used to determine the performance of the classifier.

5. Results

5.1 Measurement Result

In Appendix B the results of each individual body part from all the test subjects are seen. These results are assessed by observing the recorded pitch of each individual body part using the table in Appendix A.

5.2 Data Processing Result

The raw data of the acceleration contains oscillation shown in Figure 10. This signal is used for further calculation, such as the calculation of the velocity and moving average as well as to determine where the user was stationary.

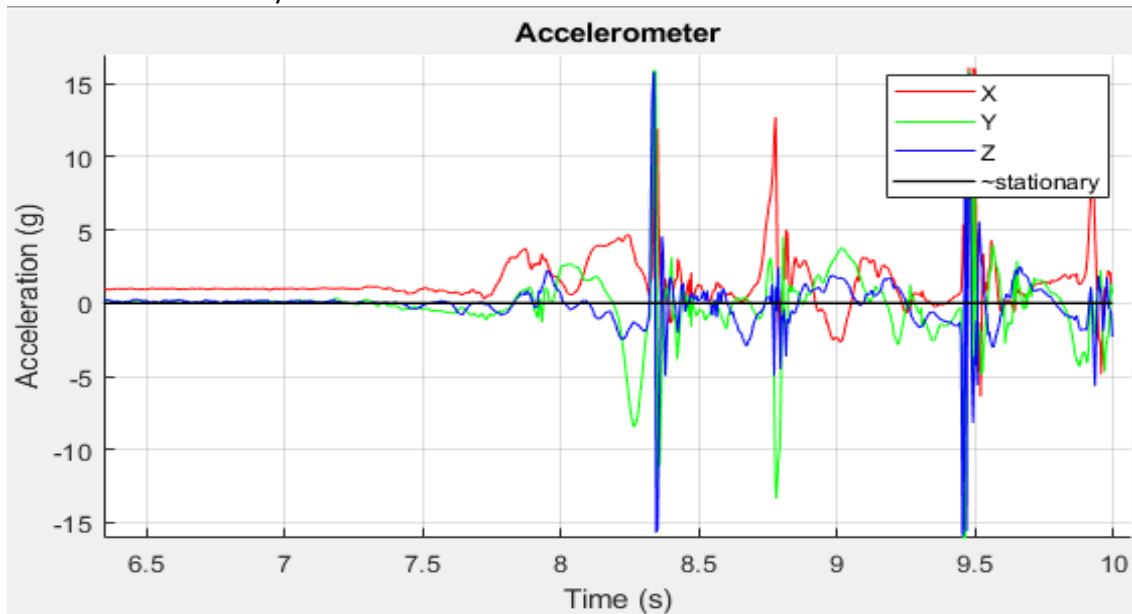


Figure 10 Raw acceleration data

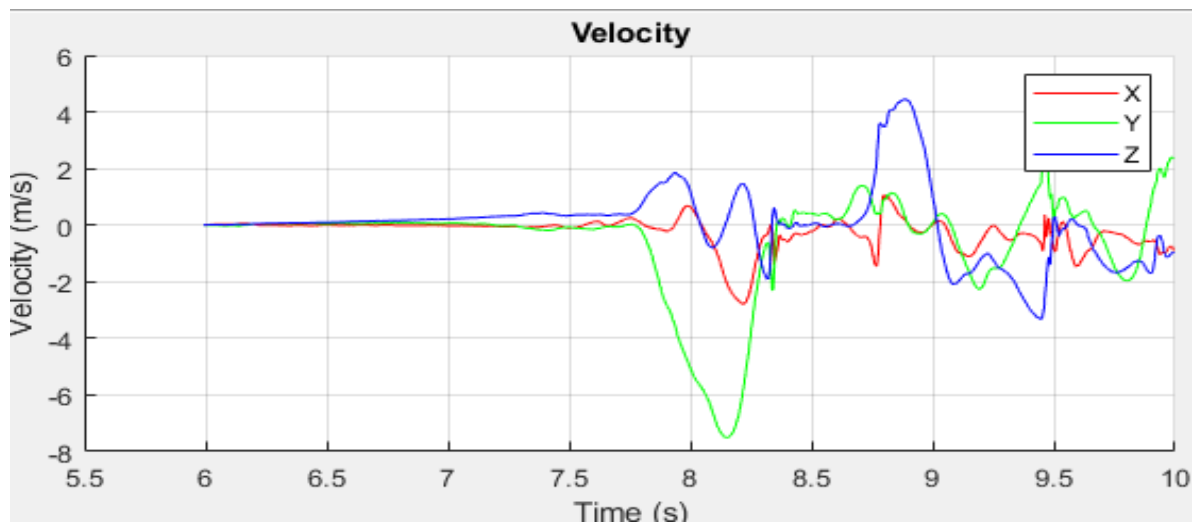


Figure 11 Velocity of a pitch in all direction

Applying the acceleration data from Figure 10 in eq (4.2).results in velocity seen in Figure 11.

The result for using the moving average on an accelerometer data can be seen in Figure 12. From Figure 12 it can be more easily determined where the user was stationary due to less oscillations.

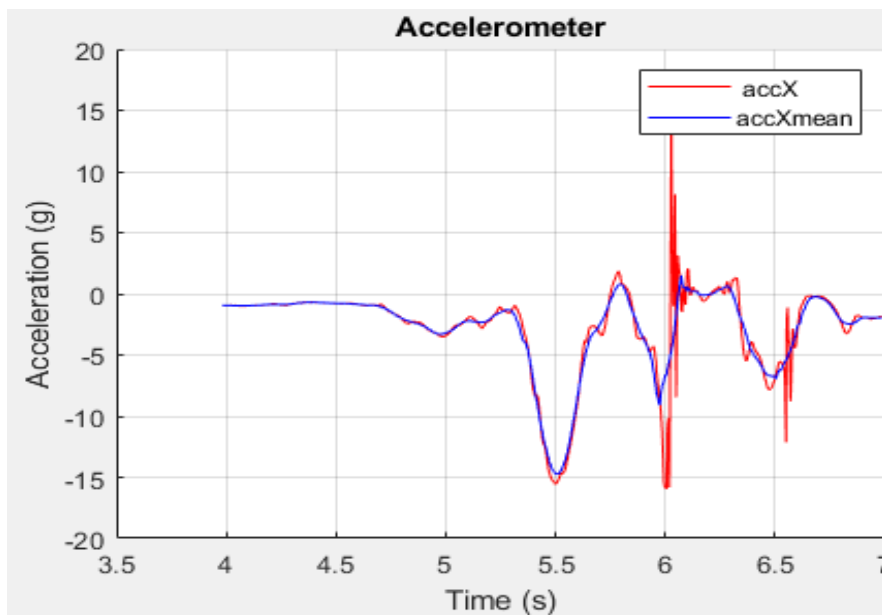


Figure 12 Accelerometer data vs average mean of the accelerometer

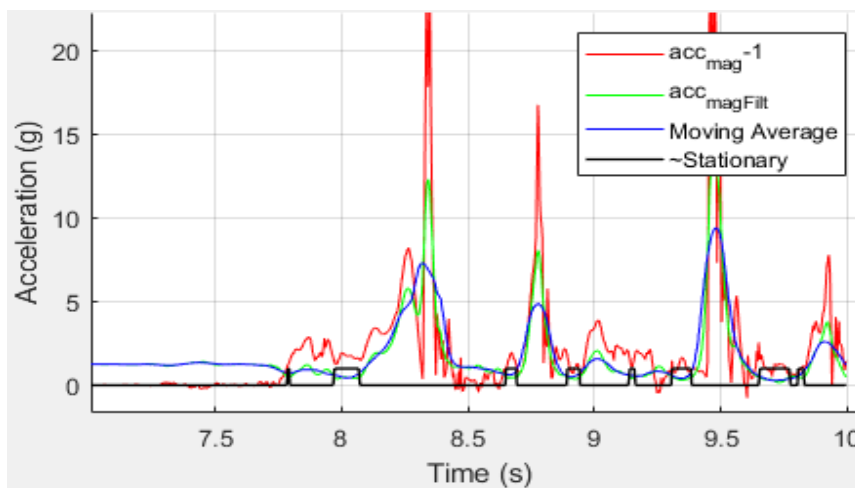


Figure 13 Unfiltered (red), filtered (green), stationary and moving average (blue) of the magnitude of the acceleration data

In Figure 13 the *stationary signal* indicates where a velocity drift occurs.

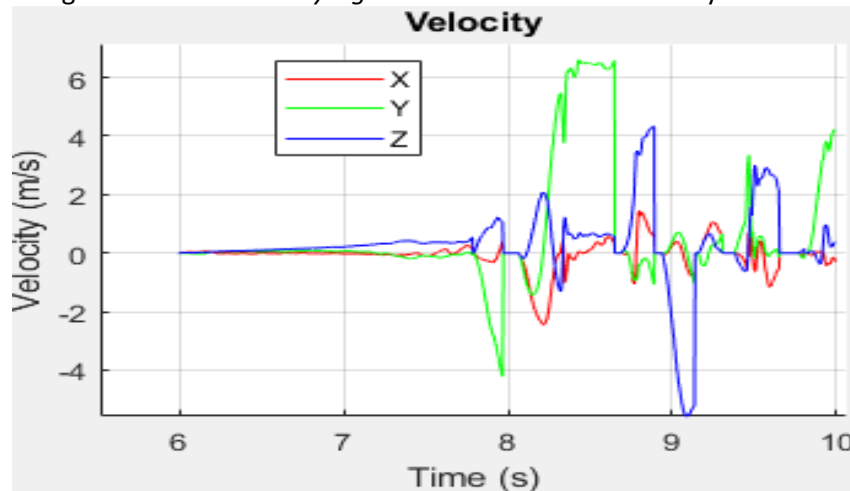


Figure 14 Velocity of the acceleration signal in Figure 13.

The result of the position of the IMU sensor can be seen in Figure 15.

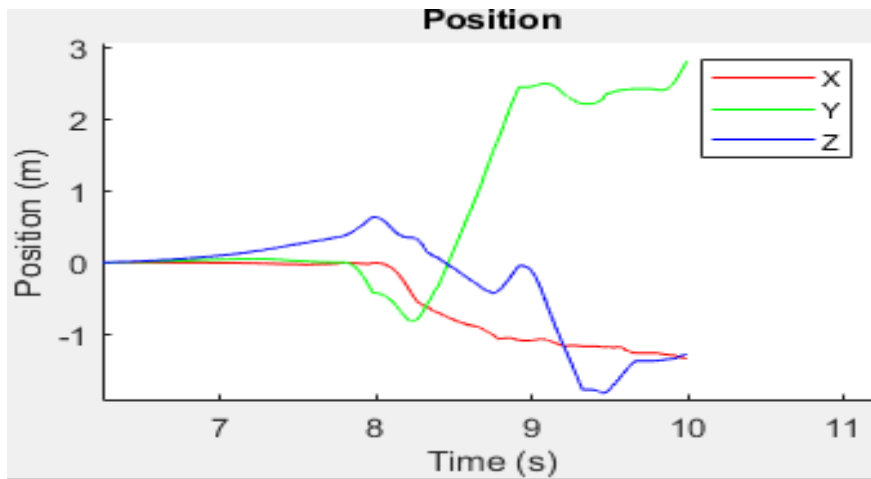


Figure 15 Calculated position of the IMU using eq. (4.4) and the velocity signal in Figure 14.

From Figure 15 it is seen that the velocity signal still consists of a velocity drift, since the IMU is going up and not coming back. This can be solved by other types of signal processing. It has been decided to not use the position as a feature for the machine learning classification, due to being faulty. The stationary signal is used to remove the velocity drift partially.

5.3 Machine Learning Results

After importing the data, each set of features was ranked from most important to least important for the classification of the quality of the pitch. While processing the data, the result of the right arm has been discarded due to faulty assessment of the pitch. In Table 2 the results of the top ten features per body part can be seen.

Rank	Ankle Left	Ankle Right	Arm Right	Head	Wrist left	Wrist right
1	DiffArm	AccXmean	-	accXmean	roll	Roll
2	vel X	pitch	-	pitch	vel X	accXmean
3	roll	diffArm	-	diffArm	yaw	accMean
4	vel Z	yaw	-	diffH	vel Y	Yaw
5	DiffWR	roll	-	yaw	vel Z	pitch
6	DiffH	diffH	-	roll	diffH	accYmean
7	Pitch	accYmean	-	accYmean	diffArm	accZTRMS
8	Yaw	vel X	-	diffWL	AccYmean	diffWL
9	DiffAR	vel Y	-	vel X	pitch	diffAL
10	AccyMean	accZmean	-	diffAL	diffWR	vel Y

Table 2 Top ten features for each sensor, rated from most important to least important

Afterwards the data has been classified using the J48 classifier. The incorrect and correct instances in percentage can be seen in Table 3. In Table 3 all features are used for the detection of the activity. Even after all features except the top 3 have been removed, the classifier has still a high accuracy and even higher for most features than when all instances were taken into account.

	Incorrect classified instances(%)	Correctly Classified Instances(%)
Ankle Left	0.634	99.366
Ankle Right	0.634	99.366
Arm Right	-	-
Head	0.506	99.494
Wrist left	1.3578	98.6422
Right wrist	1.5371	98.4629

Table 3 Incorrect and Correct classified instances in percentage of each body part, using the J48 algorithm

6. Conclusion

The answer to the research question is that yes, the quality of the pitch can be detected using IMU sensors and machine learning. This answer is supported by the results of the confusion matrix and also the accuracy of the classifier. This research is considered to be a success due to a high accuracy in classification.

The features were rank from most important to least important and when removing all but the top 3, then it still resulted in a high accuracy. Hence, it can be concluded that most of the signal processing was not necessary. This can make future work in this area easier, because less features need to be taken into account.

6.1 Limitations

For the sport volleyball only the volleyball spike was assessed because analysing other movements would have gone beyond the constraints of this paper. However, there are other types of movements in volleyball. An important factor which plays a role in the quality of the volleyball spike is the whip of the dominant hand. This has not been taken into account because of the lack of expensive wearable material proper mounting gear.

Another factor is the timing whenever the ball is hit. The IMU sensors are sufficient to detect when the ball is hit. Yet this aspect has not been taken into account because of a lack of time and knowledge.

An alternative way to detect the timing of when the ball is hit, is using microphones.

During the corona period there were not enough participants available for data gathering which led to fewer data sets available for classifications.

6.2 Further Work

For further research it is advised to include other IMU data as much as possible when determining the quality of a specific body part, mainly because the quality of a pitch depends on the full body movement.

In this research the whip of the volleyball has not been taken into account, which has a big impact on the quality of the pitch. Also, the timing of the ball impacts the quality of the pitch. Taking these two factors into account for further research might improve the quality of the pitch.

	initial state	arm cocking		
Body part/step	0	1	2	3
Arms rotation	270°	270°-340°	340°-280°	280°-168°
Head	Eyes on the ball	Eyes on the ball	Eyes on the ball	Eyes on the ball
Right arm	Resting position	swing front	swing front	swing back
Right wrist	Resting position	swing front	swing front	swing back
Left wrist	Resting position	swing front	swing front	swing back
Left foot	back of right foot	adjust steps	medium step front	idle
Right foot	front of left foot	adjust steps	idle	big step front
total		6	6	6

arm acceleration									
4	5	6	7	8	Back swing phase				
168°-190°	190°-225°	225°-315°	315°-340°	340°-60°	9	10			
Eyes on the ball	Eyes on the ball	Eyes on the ball	Eyes on the ball	Eyes on the ball	Eyes on the ball	Eyes on the ball	rotate elbow to the back	rotate elbow to the back	Eyes on the ball
swing front	swing front	swing front	swing front	swing front	•rotate elbow to the back	keep pointing to the ball	Back of head		
swing front	swing front	swing front	swing front	swing front	start going down	concentric	idle		
small step front	get low	get low	jump	keep legs straight	concentric	idle			
•idle	get low	get low	jump	keep legs straight	concentric	idle			
•start bending knees	get low	get low	jump	keep legs straight	concentric	idle			
6	6	6	6	6	6	6			6

Turn phase					Forward swing phase				
11	12	13	14	15					
Eyes on the ball	Eyes on the ball	Eyes on the ball	Eyes on the ball	Eyes to the ground					
close the shoulder	arm straight with wrist	Rotate downwards	Rotate downwards	Rotate downwards					
wip the hand to ball	wip the hand to ball	Rotate downwards	Rotate downwards	Rotate downwards					
go down	idle	idle	idle	idle					
eccentric	idle	idle	idle	land					
eccentric	idle	idle	idle	land					
6	6	6	6	6					6

7. Appendix A

Table 3 Volleyball Pitch sequences

Head	1. Eyes on the ball 2. Eyes to the ground					
Right arm		1. Resting position 2. swing front 3. swing back 4. rotate elbow to the back and open shoulder 5. close the shoulder 6. swing to the ball 7. Rotate downwards	1. Resting position 2. swing front 3. swing back 4. keep pointing to the ball 5. hit the ball 6. Rotate downwards			
Right wrist						
Left wrist				1. Resting position 2. swing front 3. swing back 4. start going down 5. idle		
Left foot	1. get low 2. jump 3. keep legs straight 4. concentric 5. eccentric			6. adjust steps 7. medium step front 8. idle 9. small step front		
Right foot	1. start bending knees 2. get low 3. jump 4. keep legs straight 5. concentric 6. eccentric				7. adjust steps 8. idle 9. big step front	

Table 4 dependency of each individual activity

8. Appendix B

	Ankle Left	Right Ankle	Arm Right	Head	Wrist Left	Wrist Right
Kevin_pitch_1	1	1	1	1	1	1
Kevin_pitch_2	1	1	1	1	1	1
Kevin_pitch_3	1	1	1	1	1	1
Kevin_pitch_4	1	1	1	1	1	1
Kevin_pitch_5	1	1	1	1	1	1
Kevin_pitch_6	1	1	1	1	1	1
Marius_pitch_1	0	0	0	1	1	0
Marius_pitch_2	1	1	1	1	0	1
Marius_pitch_3	1	1	0	1	0	0
Marius_pitch_4	1	1	0	1	0	0
Marius_pitch_5	1	1	0	1	1	0
Marius_pitch_6	1	1	1	1	1	1
Yash_pitch_1	1	1	0	1	0	0
Yash_pitch_2	1	1	0	1	0	0
Yash_pitch_3	1	0	0	1	1	0
Yash_pitch_4	1	0	0	1	1	0
Paul_pitch_1	1	1	1	1	1	1
Paul_pitch_2	1	1	1	1	1	1
Paul_pitch_3	1	1	1	1	1	1
Paul_pitch_4	1	1	1	1	1	1
Paul_pitch_5	1	1	1	1	1	1
Paul_pitch_6	1	1	1	1	1	1

Table 5 Table of result. Which are asses by observing the recorded pitch and asses each individual body part using the table in Appendix A.

9. Appendix C

```

Number of Leaves :    54

Size of the tree :    107

Time taken to build model: 0.84 seconds

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances      15515          99.366 %
Incorrectly Classified Instances      99          0.634 %
Kappa statistic                    0.7342
Mean absolute error                  0.0073
Root mean squared error              0.078
Relative absolute error              28.6589 %
Root relative squared error          69.2152 %
Total Number of Instances           15614

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                0.998   0.308   0.996     0.998   0.997     0.736   0.863    0.996    true
                0.692   0.002   0.790     0.692   0.737     0.736   0.863    0.616    false
Weighted Avg.   0.994   0.305   0.993     0.994   0.993     0.736   0.863    0.991

=== Confusion Matrix ===

      a      b  <-- classified as
15376   37 |      a = true
   62  139 |      b = false

```

Figure 16 Right ankle classifier confusion matrix

```

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances      15515          99.366 %
Incorrectly Classified Instances      99          0.634 %
Kappa statistic                    0.7342
Mean absolute error                  0.0073
Root mean squared error              0.078
Relative absolute error              28.6589 %
Root relative squared error          69.2152 %
Total Number of Instances           15614

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                0.998   0.308   0.996     0.998   0.997     0.736   0.863    0.996    true
                0.692   0.002   0.790     0.692   0.737     0.736   0.863    0.616    false
Weighted Avg.   0.994   0.305   0.993     0.994   0.993     0.736   0.863    0.991

=== Confusion Matrix ===

      a      b  <-- classified as
15376   37 |      a = true
   62  139 |      b = false

```

Figure 17 Right ankle classifier confusion matrix

```

=== Stratified cross-validation ===
=== Summary ===

```

```

Correctly Classified Instances      15535          99.494 %
Incorrectly Classified Instances      79          0.506 %
Kappa statistic                    0.9795
Mean absolute error                  0.0056
Root mean squared error              0.0698
Relative absolute error              2.2493 %
Root relative squared error          19.8784 %
Total Number of Instances           15614

```

```

=== Detailed Accuracy By Class ===

```

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.997	0.016	0.997	0.997	0.997	0.980	0.994	0.998	true
	0.984	0.003	0.981	0.984	0.982	0.980	0.994	0.978	false
Weighted Avg.	0.995	0.015	0.995	0.995	0.995	0.980	0.994	0.995	

```

=== Confusion Matrix ===

```

```

      a      b  <-- classified as
13321   42 |      a = true
   37 2214 |      b = false

```

Figure 18 Head classifier confusion matrix

```

=== Detailed Accuracy By Class ===

```

	TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	ROC Area	PRC Area	Class
	0.991	0.052	0.991	0.991	0.991	0.939	0.979	0.993	true
	0.948	0.009	0.947	0.948	0.948	0.939	0.979	0.927	false
Weighted Avg.	0.985	0.046	0.985	0.985	0.985	0.939	0.979	0.984	

```

=== Confusion Matrix ===

```

```

      a      b  <-- classified as
13196  121 |      a = true
   119 2178 |      b = false

```

Figure 19 Wrist left classifier confusion matrix

```

=== Stratified cross-validation ===
=== Summary ===

Correctly Classified Instances      15402           98.6422 %
Incorrectly Classified Instances     212           1.3578 %
Kappa statistic                     0.9668
Mean absolute error                 0.015
Root mean squared error             0.1148
Relative absolute error              3.6644 %
Root relative squared error          25.3604 %
Total Number of Instances           15614

=== Detailed Accuracy By Class ===

                TP Rate  FP Rate  Precision  Recall   F-Measure  MCC      ROC Area  PRC Area  Class
                0.992    0.028    0.989     0.992    0.990     0.967    0.986    0.989    true
                0.972    0.008    0.981     0.972    0.976     0.967    0.986    0.971    false
Weighted Avg.   0.986    0.022    0.986     0.986    0.986     0.967    0.986    0.984

=== Confusion Matrix ===

      a    b  <-- classified as
11030   86 |      a = true
    126 4372 |      b = false

```

Figure 20 Wrist Right classifier confusion matrix

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