Volleyball Setting Technique Assessment Using a Single Point Sensor

Ann-Kathrin Holatka
Karlsruhe Institute of Technology
Karlsruhe, Germany
a.holatka@gmail.com

Hirohiko Suwa
Nara Institute of Science and Technology
Ikoma, Japan
h-suwa@is.naist.jp

Keiichi Yasumoto
Nara Institute of Science and Technology
Ikoma, Japan
yasumoto@is.naist.jp

***Abstract*—The correct technique is one of the main aspects for semi-professional athletes training their volleyball skills. Traditional training and movement assessment though, might not yield the best result to improve the capabilities of a player. Hereby problems or sub-optimal executions of a movement from a technical point of view are often not easily detectable by a coach or without technical support. We investigate the usage of an IMU (inertial measurement unit) combined with an EMG sensor in form of a 'Myo' Sensor unit [16], to classify the setting action of a volleyball player to afterwards judge the technical qualities of the movement and suggest improvements like a digital coach. We look into the framework to gather a suitable ground truth and detect the sequence of the actual setting in the datasets. This is then used in combination with a machine learning model to classify the movement. Results show that a subjective direct description of the inaccuracies of the movement as a ground truth is sufficient for this approach. An additional scored function is designed to classify allowed setting actions by the international Volleyball rules [6]. The sequence selection shows optimal results for 54.4% of the samples, 26.6% of the selected sequences show minor displacements. The classification of the setting action shows best results for labels with 2, 3 and 4 classes with an F1-score of 0.74, 0.64 and 0.35, respectively. The classification results are overall reasonable and are especially interesting for the scored function, giving feedback for beginner players. Using the classification model, feedback for the player is created directly through the ground truth labeling.**

***Index Terms*—Sensor Systems, Data Analytics, Recurrent Neural Network, Machine Learning, Sport Activity Recognition**

I. Introduction

The correct technique is one of the main aspects for semi-professional athletes training and improving their volleyball skills. Traditional training and movement assessment though, might not yield the best result to improve the capabilities of a player. Hereby problems or the sub-optimal execution of a movement from a technical point of view is often not easily detectable by a coach or without technical support, e.g., through camera tracking of the movement. A sensor which is monitoring more than just the visual aspects of a video, but instead the actual movements of the arm and muscles can give more valuable insight into the actions during the interaction of the player with the ball. Through this, direct and very detailed feedback can be given, as well as suggestions for improvements. The setting action of a ball, relates to the volleyball specific action of passing the ball over the head without catching it. As the setting of the ball is a very important action of a volleyball match, it is interesting for all levels of volleyball skills as a support for the player as well as for the coach in a training setup. In competitive volleyball games, incorrect technique while setting a ball, will result in a point for the opposing team, according to the international volleyball rules [6]. Additionally, the setting action is the base for most forms of attack during a game, and therefore very strong technique capabilities are indispensable. Sensors used for this task are combined in one appliance which is fastened with an armband in an unobtrusive way just below the elbow.

In previous research, many applications have been developed to support volleyball sport through sensors and other analytical support. For most of these applications, the jumping activity has been in focus [8], [10], [17]. The 'Altathlon' system is discussing an application to give feedback on the arm movements while the player is passing or setting the ball [1], [2], [3] and therefore considered closest to this suggested application. Due to the invasive nature of the 'Althatlon' sensor and without gathering EMG data, this paper is going beyond this approach and creates room for different insights. The overall conclusion of the previous research is that IMU sensors are very commonly used in volleyball activity recognition or tracking. In these cases the usage is often focused on analyzing the foot and leg movement. The same sensor has also been used for arm applications even though the combination of tracking the arm, hand and wrist movement in an unobtrusive way, to give insight about the technique of the setting action, is not available. This would be especially useful, to analyze a mostly undisturbed movement through an unobtrusive application using a comparatively cheap sensor which is affordable even for small sports clubs, delivering detailed information of the hand and arm.

In this paper, we cover the question, whether it is possible to identify the hand and arm movements in detail so that the reason for technical inaccuracies can be identified and explained to the player. This overall goal is broken down into three main questions. Firstly, how can the setting movement be divided into classes in a consistent and usable way, so that a ground truth congruous to volleyball technique standards and rules, can be gathered. Secondly, can the setting action be identified in the recorded data, so that the relevant sequences can be selected. Thirdly, can the technique of the setting action be classified, so that the player can get usable feedback.

Using a 'Myo' sensor armband by Thalmiclabs [16], multiple setting actions of 35 persons were gathered and preprocessed. Additionally, those actions were videotaped to compile the ground truth labels. The video data for each dataset was analyzed to see in detail which part of the arm, wrists, hand and fingers are moving in which way during the setting action. The ground truth should represent this in a way, that the player can get feedback on how s/he can improve his/her setting actions quality wise, to increase performance. In order to achieve this, the movement was labeled subjectively in relation to the 'correct' performance for a setting action as one would explain to a player, as a coach. This is therefore especially interesting, e.g., for semi-professional players to perfectly orchestrate the team. The ground truth should also represent problems in the movements, which result in a direct point for the opposing team. For this purpose, a scoring method was designed, summarizing the subjective labels into 'allowed' and 'not allowed' actions. The scoring function is most relevant for beginners, who do not know how to correctly set a ball, according to volleyball rules.

To detect the areas of interest as subsets of the time sequences, these datasets are being analyzed for their characteristics. Therefore, a set of base rules were defined, which decide on the areas characterizing the setting action in the datasets, based on the flow of the curves. After manually defining these sets of rules, a sliding window approach in combination with the basic variance per window is used to statistically identify the described windows. The selected sequences in combination with the labels are used to classify the setting action. As most volleyball related applications are different to this project, suitable algorithms were compared to the human movement classification which use multimodal time sensitive data. A deep convolutional neural and LSTM recurrent network [12] capable of multimodal wearable activity recognition is being used in our approach. The classification of the setting movement can then directly be used to explain to the user how s/he can improve his/her setting skills.

The subjective as well as the scoring labels could cover the basic movements which are interesting for the setting action. Compiling the labels for the samples showed that through limitations of the video data as well as the hazard of subjective decisions the consistent labeling is a challenge. In regard to the sequence selection, a sliding window approach in combination with the variance metric is used. Results show that the correct area can be detected, according to the previously defined rules, and it is therefore possible to navigate through the samples time wise. Of the analyzed samples 54.4% of the selected windows were perfectly aligned with the defined rules, 26.6% showed slight differences. The machine learning model is evaluated using the F1 measure and is computed for the separate labels, for each EMG data and acceleration, gyroscope and orientation (AGO) data, due to the different sampling rates. The classification result shows that for labels containing 2, 3 and 4 classes, F1-scores of 0.74, 0.64 and 0.35 can be achieved, respectively. *Acc*, *gyr* and *or* data show best results for the labels. Using these results to make recommendations to the player is directly possible due to the setup of the classes. Overall best results are achieved by the scoring labels. In future, the model could be used in combination with a user interface used by beginners as well as semi-professional players to train their skills using the 'Myo' Sensor and the developed model. This paper shows a viable approach to prepare the data sequences, compute descriptions of the movement in form of ground truth labels and compute the classes using a machine learning model. Even though there is room for improvement on the accuracy of the model results, the capabilities for the preparation of the data is widely discussed and gives a solid starting point to extend and improve the model.

In the following, volleyball related background is provided to understand how a setting action is theoretically executed in section II-A. After this, in section II, approaches in literature for similar problems are discussed. This is followed by an explanation of the data collection setup as well as an explanation of the ground truth design in section III. The methodology and model design are subsequently discussed for the sequence selection in section IV, as well as for the movement classification in section V. The results for both are then discussed in terms of accuracy in section VI, followed by the conclusion and further research.

II. Background and Related Work

A. Setting Technique in Volleyball

The setting movement, which is also called overhand pass, is a very important volleyball technique for all players and is used as the standard way to pass the ball between the players. Especially for the position of the setter, the player needs to master the setting technique perfectly to be able to orchestrate the offense of the team. The setter therefore needs to pass the ball to the attacking players very precisely and with the correct timing. The official rulebook dictates the base on which the setting action is defined [6]. These rules are, among others, that "The ball must not be caught and/or thrown" and it is forbidden to "contact various parts of his/her body in succession" with the ball [6]. These rules have multiple consequences for the actual playing of the ball. The restraint to not catch the ball while playing implicates therefore, e.g., that the contact to the ball needs to be very swift and delicate. This means the movement of the hands and wrists is very central. Therefore, the official rules are translated to the players to guide them, e.g. "Push the ball outwards using your wrist," to ensure the correct movement. These rules aim on the one hand to help the player to play the ball correctly in relation to the official rules, but on the other hand to guide the player to play in a way that they get full control over the ball in order to pass it to an attacking player precisely. To perform a setting action therefore, the technique is very important.

B. Analytics in Volleyball

Volleyball is already supported through many digital technologies, starting with basic video material capture and manual analysis or aided by software [18], [15]. The analysis of the visual data might not lead to optimal suggestions though, as the problems in the performance depicted through the detailed views and angles are not necessarily identifiable. Also more sophisticated approaches exist, using sensor data.

Kautz et al. [11] concentrated on collecting information on arm movements through a single point sensor. The suggested method is to use inertial sensor data through a wrist band, which is not perceived as intrusive, as the study states. The collected data is then used to identify player actions during the game or practice. Another similar approach was introduced by Cuspinera [5]. In this approach, the player wears a glove which is fitted with a gyroscope sensor. This is then used to identify the serving technique of the player. This application comes closest to the suggested usage for technique improvement feedback for the setting action. A similar armband is used to track arm and shoulder movement by Rawashdeh [14] which is fitted with an IMU unit. The data captured is then used to identify the action of serving a ball. The studies show that the use of the IMU unit has been successful in the past to analyze volleyball movements, also for technique analysis applications. As the capture of the hand data with the IMU unit is difficult, in this study, we add the EMG sensor to this setup. Lastly, the 'Altathlon' system is tackling similar areas of giving feedback on the arm movements while the player is passing or setting the ball [1], [2], [3]. Hereby a rather intrusive sensor combination including a glove, flexion sensors as well as electric contacts covering the elbow, forearm, wrist and hand is being used. This gives more insight into the passing and setting technique of the athlete and creates the possibility of giving recommendations. The aim hereof is similar to the application suggested by this paper, though the expected advantages will be improved practicability and lower costs.

C. Multimodal Multivariate Time Series Activity Classification

To classify the setting action, a multimodal time series activity classification for multivariate classes needs to be designed. As a similar setup, Human Activity Recognition (HAR) algorithms are examined to identify a suitable algorithm for this problem. With a wide area of applications, also in the area of HAR, simple models like the SVM or Random Forest model are being used [7], [13]. Due to the importance of the relationships and the very time sensitive data, we decided to design a machine learning algorithm. As a similar approach, the results of Ordonez et. al. [12] were taken into account, where a deep convolutional and LSTM recurrent neural network system for multimodal wearable activity recognition is discussed. This system, which is suitable for multimodal wearable sensors, can perform sensor fusion naturally and does not require expert knowledge in designing features and explicitly models the temporal dynamics of feature activations. This falls in line with the setup of this paper, therefore this approach has been taken as a model for our classification.

III. Activity Recording

The data is collected using a 'Myo' gesture control armband, developed by Thalmiclabs [16], which is incorporating 'Medical Grade Stainless Steel EMG sensors, highly sensitive nine-axis IMU' [16], with a sampling rate of 200Hz in the unit 'activation'. The EMG data shows the muscle activation per electrode. This means there is no direct mapping between the muscles and each node [16]. The 'Myo' also collects acceleration (acc) data in the unit 'gravitational force,' gyroscope (gyr) data in the unit 'radians' and orientation (or) data represented by 'quaternions' with a sampling rate of 50Hz each. All data is collected with a laptop through a Bluetooth interface. The ball that was used is a regular FIVB training volleyball Mikasa MVA330 [4]. The data of 35 persons (22 m, 13 f) between 16 and 51 years old was collected, while they were passing a regular FIVB training volleyball [4] about 5-10 times each. Of the 35 subjects, 19 were beginners with little to no volleyball experience and 16 were competitive players in various upper skill levels. The distance played per set is roughly 2m each. The setting action was additionally recorded using two video cameras focusing on the hand movements in order to enable the model building process. The recordings are on average 5s in length. This data was then used to identify and translate the data points of the various sensors into practical movements.

A. Ground Truth Model

As described in the first research question, we needed to define a framework in which a setting movement could be classified in a consistent and usable way, so that a ground truth congruous to volleyball technique standards and rules, could be gathered. This is necessary to train the machine learning model and classify the movement of the player in later stages.

1) Subjective Approach: There are several basic problems typical for sport analytics, in designing feasible ground truth labels. Especially for volleyball technique the distinction between targeted movement executions is very small, which makes it difficult to describe the movement in detail in an objective way to classify it. As an alternative, the movement executions are described in whole, directly related to possible problems by the following labels:

1) Arm Movement: Too low, too far in front, correct, too far back
2) Hand Movement: played with palm, played partly with fingertips, played with fingertips
3) Wrist Movement: smooth, medium, inflexible
4) Timing: correct, incorrect
5) Standing while playing: yes, no

Using this setup, the classes are directly related to the problems and yield direct feedback for the player.

2) Scoring Method: As a second option, we wanted to classify whether a setting action can be considered 'allowed' or 'not allowed' using a scoring function. In competitive volleyball games, incorrect technique while setting a ball, will result in a point for the opposing team, according to the international volleyball rules [6], so the player will get this feedback through the system. We used the already available information of the subjective labels and scored their outcome. Here the aim was to have a less fragmented movement description but a full movement assessment which identifies

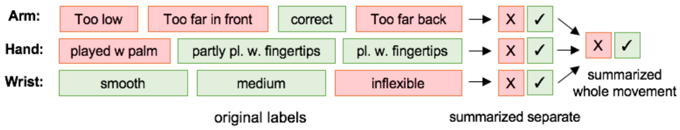

Fig. 1. Score structure, green 'allowed', red 'not allowed'

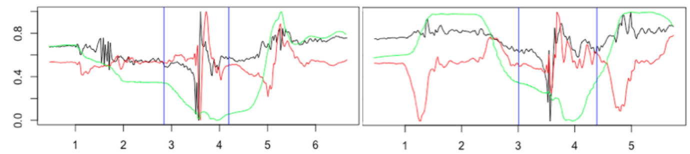

Fig. 2. Sum curve of acc (red), gyr (black) and or (green). The blue vertical lines mark the areas selected by the variance selection with a window length of 60 (about 1.2s), y-axis normalized to 1, x-axis in seconds

unaccepted movements of the player. Therefore, the subjective labels 'arm movement,' 'hand' and 'wrist movement' as well as the label describing whether the player is 'standing while playing' are being broken down further into an 'allowed' and a 'not allowed' action as can be seen in Fig. 1. This means the all arm movement classes but 'correct' result in a 'not allowed' class. For the hand movement, played with palm results in a 'not allowed' class, all others in 'allowed'. The wrist movement is scored accordingly. The other introduced labels aim on the quality, not the correctness of the setting action and are not included in the scoring function. If all three areas result in 'allowed', the setting action is considered 'allowed' as no rule breaking mistakes were made. In the results section, the summarized separate classes are used as shown in Fig. 1. The results of the three separate labels can be summed up to determine the overall 'allowed' class as a second step.

IV. Sequence Selection

A. Methodology

To support the classification algorithm, it is necessary to get an understanding on which areas show the actual setting action. This is important as the datasets also contain additional arm movements from before and after the setting action. Comparing the datasets and crosschecking them with the video tape time line, it is clear that the main area of interest is located where the strongest deviation occurs, as can be seen in Fig. 2. The challenge hereby is, that there is not necessarily only one time window with strong peaks but multiple per sample, of which only one depicts the actual setting action. Additionally, the border locations of the window are not clearly definable as the areas vary to some extent over the different datasets.

1) Data Preprocessing: The datasets provided by the 'Myo' sensor are preprocessed to be used in the next computational steps. This processing includes the adjustment of all axes to the same length if individual package losses occurred and the exclusion of defect datasets after, e.g., losing connection to the sensor.

1) For further computations, the data is also divided into windows using a sliding window approach. The windows have lengths of 1.2s of recorded data, for all data types and are moved in steps of 0.2s over the whole set.
2) The sums of each data type for *acc*, *gyr* and *or* data are computed over the time line for the absolute values.

2) Model Design: For the sequence selection, we use the normalized sum of all axes over all sensor types separately, as discussed in section IV-A1. When comparing the curves over the samples, there are three main characteristics we can distinguish, as can be seen in Fig. 2. Firstly, the *acc* curve as well as the *gyr* curve show one very volatile area, which overlaps time wise. Additionally, the orientation curve shows a very pronounced bulk with a very small dip around the center. This is usually also overlapping with the strongly volatile area of the other two curves. Preceding and following this area, the gyroscope data especially shows a bulk which frames the area. A clear border selection is not possible in our case as the window length needs to be the same length for all samples to be usable for the machine learning model. The lengths of the setting actions however vary to some degree. The window is correctly placed in a way that the volatile area is center of the window or slightly in front, if the windows do not match perfectly. Using these insights, we summarize the characteristics as:

1) Very volatile area, at least partly overlapping for *acc* and *gyr* curves
2) Strong bulk with small dip for the orientation curve

The vertical lines in Fig. 2 show a sequence selection example, according to the defined rules.

3) Variance Selection: After theoretically establishing the sequence selection we next discuss the computational approach to select this area over all samples. Firstly, the variance in relation to the full dataset is computed for each window of *acc* and *gyr* data. The following steps are taken to select the window.

1) The window X with the highest variance is pre-selected per sensor type j.
2) After selecting the windows with the highest variance per sensor type for *acc* and *gyr*, the average window location between the two types is being computed.
3) The selected windows are then transformed to a sampling rate of 200Hz so that they are also usable for the EMG data.

This selection of the setting action in the set enables us to select the same area in every dataset. Of this selection, a sub-length can be selected which depicts, e.g., different phases of the setting movement.

V. Movement Classification

The selected sequences of the data sets are used for the movement classification. Only the computed sequence borders are used to subset the un-normalized datasets. As introduced in section III-A there are two sets of labels which are being tested to classify the movement of the player in the following.

A. Model Design Convolutional Neural Network

The machine learning model is built similarly to the model suggested by Ordonez [12], in which a deep convolutional and LSTM Recurrent neural network for multimodal wearable activity recognition is introduced. The model is built in a recurrent LSTM architecture which is a special kind of recurrent network application, capable of learning long term dependencies [9]. The features of the model are extracted by one dimensional convolutional layers. There are four convolutional layers set in a row, creating layers 2-5. Those recurrent layers are used to model the temporal dynamics of the activation of the feature maps. This means they process the input only along the axis representing time [12]. The convolutional layers use rectified linear units (ReLUs) as an activation, computing the feature maps using the sigmoid function. Results of Ordonez et. al. show that a depth of at least two recurrent layers is beneficial when processing sequential data [12]. Therefore, two dense layers are added as layer six and seven. The last layer is computed as a dense layer using a softmax activation. The filters are the same for every convolutional layer, being defined as 5 $\times$ D, where D is the number of channels.

The model is built separately for acc, gyr and or data as well as for the EMG data as the sampling rates differ, which leads to different time lines of the datasets. The suggested model by Ordonez [12] is used in combination with a sliding window approach as the data is collected in a constant stream. In this case, the actual setting action is already preselected, so no further window function is used.

1) Input Data: Through the usage of the 'Myo' sensor, we obtain multimodal time series data of four different types. Using the previously discussed sequence selection, we were able to select the same data sequences for all sets. The different setups for the window lengths can be found in Sect. VI-B.

The acc, gyr and or datasets can be stacked by their time line, as they have the same sampling rate. For the EMG data, with a higher sampling rate, all 8 nodes are stacked as a second set. For both, the raw data is being used in the selected sequence. The datasets are matched with the according ground truth labels, which are discussed in Sect. III-A. The datasets are split into 70% trainings data as well as 15% validation and test data each. As the labels are not equally distributed, the classes are oversampled to avoid over-fitting. The samples of the minority classes are therefore chosen randomly and copied.

VI. Results

A. Ground Truth Labels

1) Subjective Labels: The subjective labels directly depict correct or incorrect movement, including its magnitude. This approach can more easily be challenged in its correctness as it is a personal impression of the movement of a domain expert using coaching rules. When doing this, multiple movements are summarized to one label containing different manifestations. The labeling process is simpler than a more hierarchical and objective approach, as the differences between the classes on the video data are better distinguishable. This is therefore also expected to increase consistency.

2) Scoring Function: As discussed, there are only two manifestations per subjective label summarized into the information, which is whether the setting action has been 'allowed' or 'not allowed'. The information is less detailed than with the before mentioned labels. On the other hand, consistency is improved, as there are fewer classes to differentiate when using the video data. Depending on the skill level of the player, we suggest that for beginners the scoring function should be sufficient. The more advanced the skills of the player, the more important detailed information about the problems of the action is required.

B. Sequence Selection

The variance selection is used on the full dataset to gather the correct sequence. These pre-selected windows are manually checked to evaluate the results in comparison to the rules defined in Sect. IV-A2. Of all 383 used sample datasets 54.4% show perfect results, 26.6% of the selected sequences show minor displacements of about one window length, which is 200ms. The remaining 19.3% show an average displacement of 518ms. Perfect alignment means the volatile area of the acc and gyr data was placed in the middle of the window. If the spacing did not allow perfect alignment, the window was placed in favor of the earlier time steps. An example of a correctly selected phase can be seen in Fig. 2. The selected window is used for orientation in the dataset. The actual window borders are extended from this selected area as a starting point to a length of 2s. The variance selection is an easy way to get a sufficient first sequence selection. Adding further statistical features or a machine learning model in the future will be a promising and easy way to improve the results as well as incorporate these insights into a real-time selection. The sequence selection is corrected manually and perfectly selected sequences are used for the classification. Through this first variance selection, we can establish a way to coordinate through the dataset. This means we can select the same area with a certain sub-length in every dataset.

C. Movement Classification

The two preceding results, concerning the ground truth and the sequence selection of the setting action are now used to classify the movement. From the result of the ground truth set up, we learned that both ways of labeling are interesting if a sufficient number of samples is available in the set. The results of the sequence selection show that we are capable of capturing the important sequence through the variance selection. This selection can now be used to get a sub-length, which optimizes our classification result for each label.

In the following the results of the machine learning model are evaluated in terms of the F1-score for the optimal sub-lengths of the data.

D. Range Evaluation for Machine Learning

Even though we are capable of navigating in the data sets through the sequence selection, we still do not have further insight on whether the full sequence is yielding best results or a sub-length of the movement. Therefore, a test has been set up in a way to evaluate sub-lengths of the sequence selection, using the machine learning model. This consists of the following steps:

TABLE I
BEST SUB-LENGTH IN DATAPOINTS (DP) OF MAXIMUM LENGTH OF 100DP/2S OF AGO DATA. CORRESPONDING F1-SCORE OF BEST AGO SUB-LENGTH AND ST. DEV. BETWEEN THE RESULTS PER STEP OF 3DP/60MS. BEST SUB-LENGTH F1-SCORE OF EMG DATA.

	Best sub-l. AGO	F1-score AGO sub-l.	Std. Dev. all windows AGO	Best F1-Score EMG
Subj. Labels				
Arm P.	0:23	0.35	0.05	0.32
Hand	0:41	0.64	0.06	0.38
Wrist	0:47	0.48	0.06	0.48
Timing Arms	0:80	0.74	0.08	0.60
Moving/Sta.	0:35	0.69	0.07	0.64
Scoring				
Score A	0:95	0.64	0.07	0.58
Score W	0:98	0.72	0.08	0.65
Score H	0:83	0.72	0.08	0.62

1) A sub-length of the selected sequence is computed, starting with a minimum length of 400ms from the start of the selected sequence
2) These shorter samples are being used to train, test and validate the model as defined in Sect. V
3) Extend the sub-length by 60ms and run the model again

Results of this technique provide information on whether a sub-length of the sequence selection yields best results in terms of the F1-score or if this does not influence the results. Table I shows the results in terms of the best F1-score as well as accuracy and recall for each label and dataset. Looking at all results per range and label shows, that the F1-scores of the sub-length windows are overall only marginally better than the full window selection. The standard deviation between the different ranges is very small and there are only small changes of the achieved F1-score. Especially looking at the variance between the F1-scores in the ascending window length, it shows that there is no clearly distinguishable trend. Still, the results for specific windows do yield better result in some cases, even though this can not necessarily be tied to the above-mentioned theory. The EMG data sub-length results show similar outcomes. Overall, the results per label are not as good as the usage of the acc, gyr and or data. Some differences can be seen in the sub-length. Of the full length of 400 data points, the majority of best sub-lengths are located in the first half of the dataset.

VII. FURTHER RESEARCH

This preceding research leads way for further analyses. For the ground truth gathering, a more objective approach could be designed to have less bias concerning the labeling. Furthermore, the impact of individual differences between the players e.g. height or arm length on the results, could be further investigated. For the sequence selection, a more sophisticated model which can detect a setting action in a dynamic environment including data streams instead of separate datasets would be an advancement. So far, the identification of the setting action is limited to the same length, further investigations about exact identifications would be beneficial. Also, the classification algorithm did yield feasible results which, however, leave room for improvement through a different setup e.g. using acc, gyr and or data in combination with EMG data.

VIII. CONCLUSION

The paper shows, that it is feasible to describe the setting action with IMU and EMG sensors and the usage of performance classes, which are directly related to the mistakes made. Especially the scoring function led to good results. The sequence selection is an important part in the activity recognition and is, in combination with the machine learning model, a feasible approach to classify the setting action technique which can be directly used as feedback for the player.

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