IMU-BASED ACTIVITY RECOGNITION OF THE BASKETBALL JUMP SHOT

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The skill and performance of athletes is more and more represented by numbers. Technical devices are utilized to assist and monitor practices and games. In this regard, the objective of this study was to develop an IMU-based algorithm to recognize jump shots in arbitrary basketball motion sequences. For the extraction, a convolutional neural network was trained on the classification task. The leave-one-subject-out cross-validation of the network showed values of over 0.970 for recall and precision and an area under the curve of 0.995 for the receiver operating characteristic curve. The recognition algorithm represents the first step towards future motion analysis incorporated in a tool which may enable the individual player to self-evaluate their shooting mechanics and improve their shooting performance.

KEYWORDS: IMU, basketball, human activity recognition, convolutional neural network.

INTRODUCTION: There is an undeniable passion for sports in human beings. Be it for reasons of competition, fitness, health or aesthetics. It is mainly driven by the deeply manifested desire to improve. This consumer interest is met by a constantly growing market of wearables to monitor performance and progress (Aroganam et al. 2019). One of these wearables is the inertial measurement unit (IMU) which is mainly applied for two tasks regarding human movements: human activity recognition (HAR) and motion analysis. Compared to the camera-based gold standard in motion capture, IMUs provide several advantages. On the one hand, they allow location-independence and in-field measurements due to portability based on their small size. On the other hand, the low price makes them affordable and attractive for the individual consumer (Picerno et al. 2011). As a result, the objective of this study was to design an algorithm to classify jump shots in arbitrary basketball motion sequences in order to provide samples for later analysis. The jump shot is the primary way to score in basketball and, therefore, fundamental to every basketball player (Figure 1). The main purpose of practicing the jump shot is to establish high-quality and consistent shooting mechanics which can be evaluated by different spatial and temporal parameters such as jump height, body rotation, horizontal drift or release deviation.

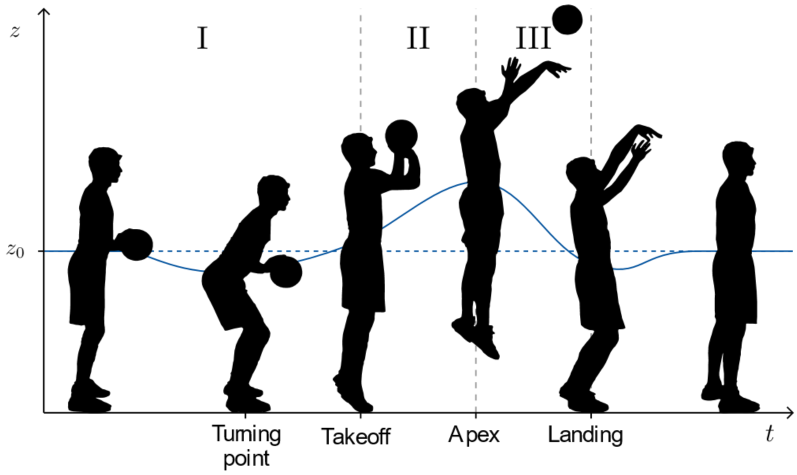

Figure 1: Illustration of proper shooting mechanics. The different phases of a jump shot (I: Preparation, II: Execution, III: Follow-through) are displayed. The blue line indicates the vertical displacement of the center of mass.

METHODS: Ten participants took part in the acquisition of the dataset. They all gave their written informed consent to participate in the measurements. Four IMUs (composed of a triaxial

accelerometer and a triaxial gyroscope) were attached to the foot opposite to the shooting hand, the lower back, the upper back and the shooting hand (Mundt et al. 2018). The sampling frequency of each sensor was about 100 Hz. To synchronize all sensors, the data was upsampled and equally distributed in time to 200 Hz. With this dataset a machine learning algorithm was trained to classify jump shots in unseen data. For this purpose, a convolutional neural network (CNN) was selected since recent research has shown promising performance for the HAR task (Baloch et al. 2019).
Of the ten participants, the data of six right-handed, male basketball players (age: 25.5±1.6 years, height: 188.5±5.3 cm, weight: 83.5±10.2 kg, experience: 9.7±4.9 years) was used for the training of the CNN and the data of the other four was used for the evaluation of the corresponding. The evaluation group covered a wider range than the training group: a female player, a left-handed male player, an unexperienced male individual and a right-handed male player. The training group had to perform 34 different exercises for five repetitions each and the evaluation group had to perform ten shooting exercises for ten repetitions. The measurement protocol of the training group was composed of five jumping actions, two passing actions, three basketball-related actions and 24 jump shooting actions which were performed in a randomized order. After excluding erroneous samples and data augmentation, the dataset for training the CNN consisted of balanced 16360 samples composed of 7770 jump shooting activities (47%) and 8590 non-jump shooting activities (53%). The data samples were augmented by randomly shifting the applied window of 500 frames around the labeled activity. The final model architecture is displayed in Figure 2.

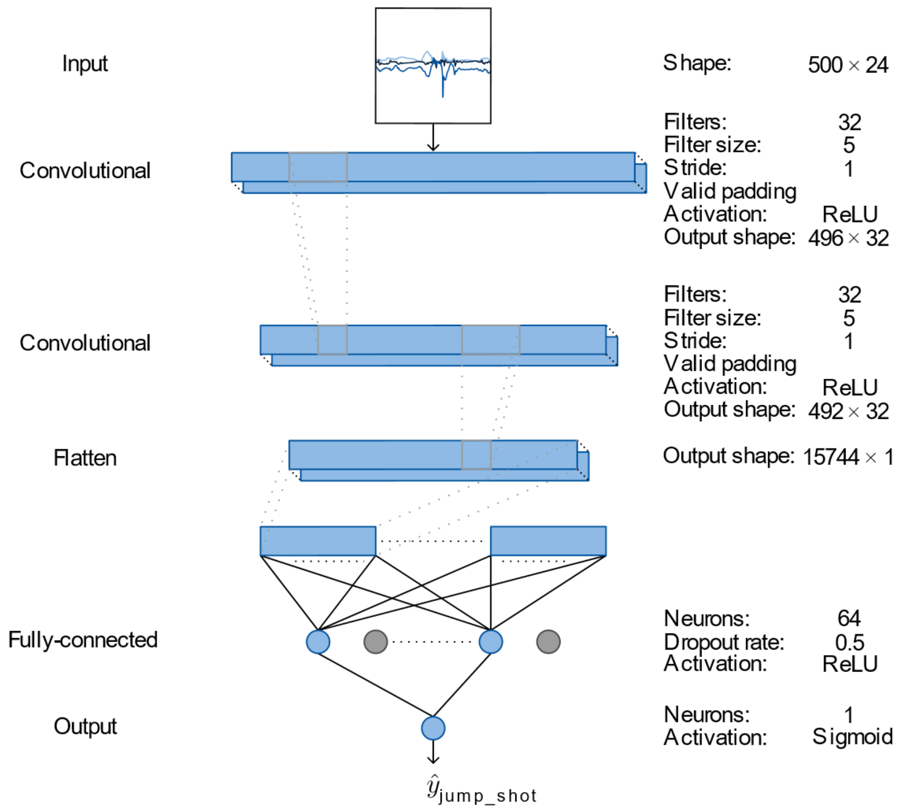

Figure 2: Final model architecture of the convolutional neural network.

Average pooling and max pooling layers were tested during the tuning phase but did not show any significant impact on the recognition performance. For training the network, the raw data was used as input without prior filtering. Furthermore, the Adam optimization algorithm was used with an initial learning rate of 0.001 and a binary cross-entropy was applied to calculate the loss. It was trained for three epochs with a batch size of 16. All parameters were selected based on an exhaustive search of different considerations using a leave-one-subject-out cross-validation. As part of the cross-validation, the combination of different IMU positions as inputs were evaluated to test if it is possible to reduce the number of applied sensors. After optimizing the model architecture and its hyperparameters, 20 models were trained using the data of all six participants of the training group without splitting. These models were evaluated separately with the data of the four left out participants. This was done with the aim to test if the networks would be able of successfully classifying the jump shot in different user groups. In this case, the input did not consist of labeled samples, but the entire measuring series were segmented and then passed to the network (Figure 3). The overlap was set to 0.5 except for the last window which is set accordingly to the length of the series to not lose any data. In the end, the model with the best overall performance was selected for the recognition task.

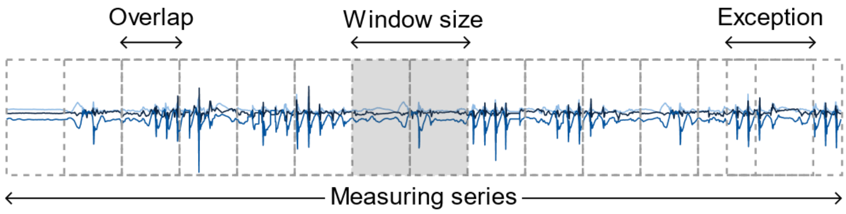

Figure 3: Illustration of the segmentation with an overlap of 0.5 and an exceptional overlap for the last window to cover the entire measuring series.

RESULTS: Figure 4 shows the receiver operating characteristic curve of the leave-one-subject-out cross-validation for the validation set. The curve showed very high skill of the model with a nearly perfect shape of the curve and an area under the curve of 0.995.

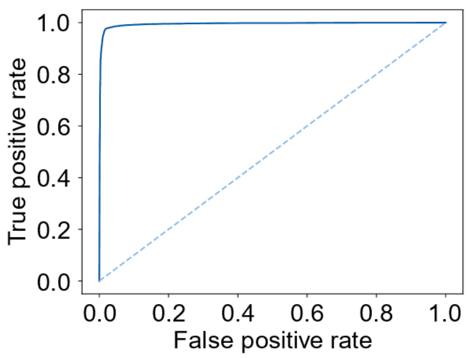

Figure 4: Receiver operating characteristic curve of the leave-one-subject-out cross-validation for the validation set. The area under the curve is 0.995.

Table 1 shows the results of the leave-one-subject-out cross-validation of the validation set for the single IMUs and for different IMU combinations. The recognition performance of all IMUs showed a recall of 0.975 with a precision of 0.980. Nevertheless, the combination of the IMUs on the shooting hand and the upper back were already capable of yielding a performance of 0.973 in recall and 0.977 in precision.

Table 1: Results of the leave-one-subject-out cross-validation for the validation set. The results are presented for the single IMUs as well as different IMU combinations.

IMU	Precision	Recall
Foot	0.875	0.885
Lower back	0.870	0.912
Upper back	0.966	0.932
Shooting hand	0.964	0.964
Hand & upper back	0.977	0.973
Hand & upper back & foot	0.975	0.982
All	0.980	0.975

Table 2 shows the results of the evaluation of the final model. The results showed an inconstant but promising recognition performance for the different user groups. The best results could be achieved for the right-handed male player and the inexperienced male, while the results for the left-handed male player and the female player were worse.

Table 2: Evaluation of the final model with participants representing four different user groups.

Participant	Precision	Recall
Right-handed	0.974	1.000
Female	0.924	0.942
Left-handed	0.932	0.812
Inexperienced	0.990	0.990

DISCUSSION: The aim of this study was to train a convolutional neural network on the classification of jump shots in arbitrary basketball motion sequences. As it is displayed in Figure 4, the outcome of the model was almost independent of the threshold with the predicted probabilities being very accurate. For this reason, the threshold was kept at the default value of 0.5 and was not further adjusted. The results of the leave-one-subject-out cross-validation (Table 1) revealed three facts. First, the designed model yielded a high recognition performance. Second, the model worked user-independently. Third, the small loss in performance when using less than four IMUs indicated that the number of sensors can be reduced. Especially the combination of one sensor placed on the shooting hand and another one placed on the lower back revealed highly accurate results. In sight of practicability, the application of an IMU to the shooting hand might not be favorable, because it might destruct the player. Table 2 shows that the user-independency had some limitations when different user groups were considered. Especially the jump shot of the left-handed player and the female player were more difficult for the model to recognize. However, the performance did not take any loss due to the segmentation process comparing the values of the right-handed male player with the results of the cross-validation. At this point, it is important to note that one participant of each group is not necessarily representative which needs to be considered as a limitation of this study. In future work, the model must be evaluated with more participants of the particular groups to support these preliminary findings. Furthermore, to improve the performance of the network and to obtain more stable results, the dataset for training must be extended. In this regard, different user groups should be considered for training the network and not only right-handed, male basketball players. Nevertheless, the results showed the capability of the model to classify jump shots in different user groups and various shooting forms.

CONCLUSION: Research has shown the great potential for IMU-based applications in the field of sports. In this regard, this study provided an algorithm which is capable of recognizing the basketball jump shot. Using this information, motion analysis can be performed on the particular sequences relevant for the evaluation of jump shot performance. This possibility should be analyzed in future work. In this regard, a promising pilot study has already been conducted. An algorithm was developed that allowed for the analysis of the extracted jump shot motion. Hence, the proposed method can be seen as a first step towards an easy-to-use and user-independent tool that can provide useful information about quality and consistency of the jump shot. This makes it possible to monitor training progress and to enable the individual player to self-evaluate and adapt their shooting mechanics to enhance performance.

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