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Exercise assessment in trampoline sport by automated jump classification

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Abstract

The results of the presented work show that machine learning (ML) can be used to support correct training logging in order to improve technical performance in trampoline gymnastics. They indicate considerable potential for expanding mobile applications in a sport with complex movement requirements.

Keywords: trampoline sport, machine learning, tool, training support

Introduction

Trampoline competitions consist of different routines with ten elements in each routine. A set drill and a voluntary drill are conducted in the qualifying rounds, while a voluntary drill is conducted in the finals. The first exercise in the preliminary round (set) contains ten predetermined skills. In competitions, the judges' job is to score a particular routine and establish an overall score for that routine based on the Overall Difficulty Rating (DD), Overall Skill Execution (E), Time of Flight (ToF) measurement and the newly added Measurement of horizontal displacement (HD; cf. Regulations of the International Gymnastics Federation, FIG, 2021). Time of flight and horizontal displacement are automatically recorded by a measuring system, whereas several judges evaluate the execution of the exercise. The difficulty of each element is calculated by a referee on the basis of the amount of twist and somersault rotation.

At present, there is no known reliable method for the automated detection and recognition of the various gymnastic elements for determining the difficulty of an exercise in trampoline gymnastics. And the use of machine learning methods for the detection of complex jump movements, such as those occurring in trampoline gymnastics, has been insufficiently explored up to now (Helten et al. 2011, Woltmann et al. 2022).

The aim of the presented tool is to use sensor-based data and the machine learning approach to make it utilisable for technical training and to automate the detection of the jumps within an exercise and, in the long term, for competitions.

In the remainder of this work, we present three scenarios in which our tool is used and give illustrative examples on how they improve everyday work of athletes and trainers. Furthermore, we discuss the possibility to use our tool for automatic difficulty determination in competitions.

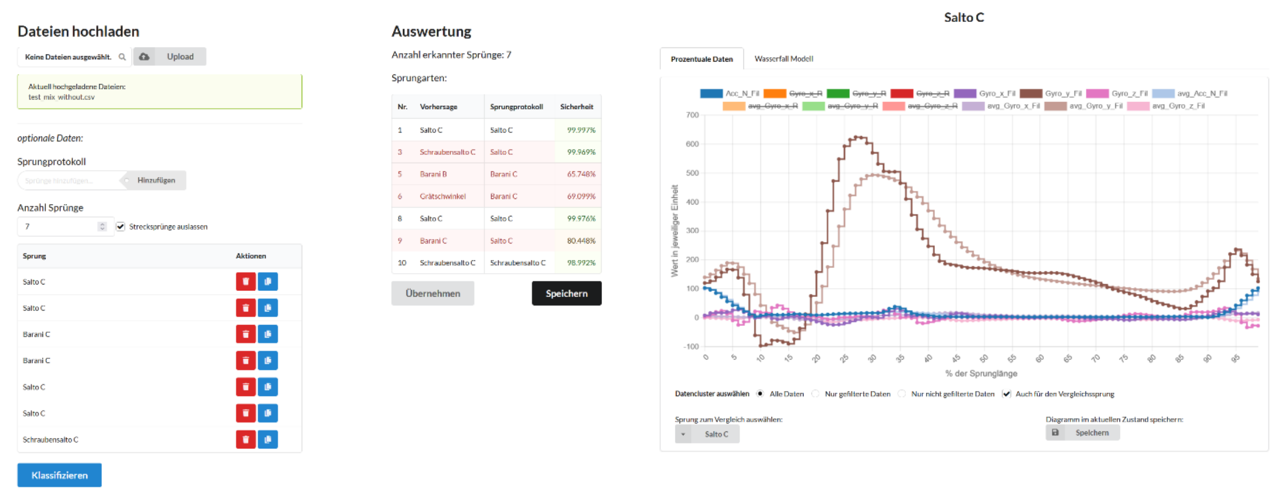
Methods

In order to improve the assessment of exercises in trampoline sport, we present a tool that is able to give athletes the opportunity to analyse their jumps based on sensor data. The data is obtained by equipping the athletes with a single gyroscopic sensor on their back. For the assessment, the user interface of the tool provides three scenarios. Every scenario individually covers one major aspect of the self-assessment process by displaying the most important information for that particular analysis. The three scenarios are: (1) the jump protocol diary with automated jump classification, (2) the jump analysis with the visualization of the sensor data, and (3) the scientific analysis providing further information about the model used for automatic jump classification. In the following, we describe each of the three scenarios and their implementation in the tool. In general, the tool and its scenarios are presented to athlete and trainer as a website.

Firstly, we present the jump protocol scenario pictured in (Fig. 1a). Here, the athletes can upload the measurements from the gyroscopic sensor and the exercise protocol, which contains all jumps of the current exercise. After the upload, the jumps are automatically classified using a neural network (NN), which analyses the sensor data as presented in previous work (Woltmann et al., 2022). In our case, jump classification means the automated labelling of a jump in respect to one of the 148 jump types as defined by the FIG. In addition to the jump type, the NN returns a confidence score (0-100%) for each jump. This score tells the athlete, how certain the classification is.

The second scenario, as illustrated in (Fig. 1b), shows the quantitative analyses of a single jump from the jump protocol. For this, the tool plots all measurement channels as line plots. With the dynamic selection of plotted channels, athlete and trainer can do a detailed analysis for all aspects of the jump. Additionally, the plot shows an average representation of all measurements of the recognized jump type. This allows for a quality assessment on how close the jump was to either the previous jumps or an ideal execution of the jump.

Lastly, the third scenario contains a scientific analysis of the behaviour of the NN for each classified jump. NNs are black boxes by nature meaning a direct interpretation of their inner workings is not possible. Therefore, we use feature importance that calculates the direct impact of each measured channel on the classification decision. For our scenario, we use Shapley Additive Explanation (SHAP) values, as they are known to perform very well with NNs (Lundberg et al., 2017). The SHAP values are visualised as an ordered bar chart where each gyroscopic measurement channel receives a SHAP value showing its quantitative influence on the final jump classification. This leads to the opportunity for discussing the expressiveness of certain channels for a jump type. The third scenario is targeted towards a scientific user and not primarily towards the athlete.



(a) (b)

Fig. 1 (a) The jump protocol screen (scenario 1); (b) The quantitative analysis screen (scenario 2).

Results

Given the three scenarios we described in the previous section, we now illustrate their advantages in the everyday work of athletes and trainers. Our tool can help to prevent and correct common mistakes in protocoling the daily training and adapt training routines.

The automated jump classification for the jump protocol from the first scenario can help in two ways. First, if the athlete has noted the incorrect jump in the protocol, the model would predict the correct jump type with a high confidence score. This indicates a high probability that the jump is incorrect in the jump protocol and may be corrected. Second, if the athlete executes a jump incorrectly, the model would predict the same jump type as in the protocol but with a low confidence score. Therefore, the jump is correct in the jump protocol but the sensor data is not consistent with previous executions of the same jump. In conclusion, the execution of the jump must have been sub-optimal.

The quantitative analysis of the second scenario provides a more detailed view for the error analysis. Sticking to the example of the incorrect jump execution, the quantitative analysis can help to find the erroneous part of the jump. The athlete can go through all plotted measurements to find anomalies, compare their measurements to the average representative of that particular jump type, and search for deviations from an ideal jump.

The scientific analysis in the third scenario helps to get a deeper understanding of the use of Machine Learning in the field of automated athlete data analysis, i.e., trampoline jump classification. SHAP values improve the understanding of the decision making of NNs making them more transparent. In our case, the analysis is used to identify expressive measurement channels for jump types. For example, previous work has shown that the NN correctly identifies the rotation around the athlete's y-axis as the most expressive part for a back tucked somersault (Woltmann et al., 2022). Additionally, this can again be used for error analysis. If a jump is classified wrongly or with a low confidence score, the SHAP values show what channel (and therefore which movement) led to the incorrect classification. From this, athletes can include this information in their next training by actively modifying the particular movement.

Discussion

This study shows that ML methods can be used to detect jumps using sensor data. However, the application of mobile sensors in combination with prediction models for jump detection has been insufficiently studied so far. The approach proposed herein shows considerable potential for expanding mobile applications in sports with complex movement requirements.

In addition to the automated logging of the training data and the quality assessment of various jumps, the automated determination of the difficulty of jumps according to international evaluation rules is a special challenge. The approach presented here shows perspectives for supporting the difficulty judges and enables a phase-specific assessment of individual jumps by using the first scenario in a real-time environment.

For example, currently there is a problem regarding the recognition of combinations of double somersaults and double twists. Here, the exact distinction between “Full in Full out” (one twist in the first somersault, one twist in the second somersault - 822) and “Half in rudy out Fliffis” (half twist in the first somersault, one and a half twists in the second somersault - 813) seems to be possible in the future by using automated jump classification based on sensor data. Finally, this approach seems to be promising for other technical-compositional sports that also calculate the difficulty of elements based on twists, somersaults and twist rotations, such as gymnastics, diving, and rhythmic gymnastics.

Conflict of interest We declare no conflicts of interest.

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