Utilizing Gyroscope Data for Classifying Types of Fencer Movements in an Assistive Coaching System

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***Abstract*—Assistive coaching systems are actively being integrated into various sports. They enable a better understanding of aspects of one's physical form and techniques that require improvement, leading to enhanced sports performance and reduced injury risk. This paper investigates the informativeness of gyroscope data in the development of a component of such a system, specifically the module for classifying types of movement in sports fencing. It is shown that data obtained from the gyroscope are sufficiently informative to classify atomic movements. During the experimental study, gyroscope signals from four professional fencers were recorded for six characteristic fencing movements. Based on the gathered data, a regression model was trained, capable of classifying types of movements for both right-handed and left-handed athletes.**

***Index Terms*—sports analysis, fencing, inertial measurement units, gyroscope, activity recognition**

I. Introduction

Methods of motion analysis and assessment of an athlete's functional state are actively being implemented in training and competitive practice [1]–[6], which allows for understanding an athlete's individual response to physical load and consciously adjusting the training plan and planning recovery periods [7], [8]. Understanding an athlete's current physical state during a match or competition allows for more accurate tactic selection and decision-making regarding substitutions in team sports [9].

In team sports, for instance in football, test load is represented by protocols of short submaximal exercises [10]. Load during a match is assessed based on the distance covered and distribution of speeds at different intervals, using video analysis [11] or athlete tracking systems [12]. Wearable devices recording heart rate are used to assess functional state [8], [13].

Such comprehensive assistive systems are not mobile and typically come with a high cost, which is not a problem in sports like football, American football, hockey, basketball, but can be a barrier for use in individual sports with less active funding.

In individual sports such as tennis, fencing, it's important to understand not only functional readiness [14]–[16] and current fatigue, but also to assess technique and quantitative movement parameters: developed speed, sharpness, reaction time. It is also important to monitor the dynamics of these parameters, for example, changes in movement parameters with progressive fatigue.

Functional readiness and fatigue assessment systems in individual sports, like in team sports, are based on heart rate measurement [17]–[19].

For analyzing the load and technique in individual sports during training, video registration-based systems can be convenient. However, the use of such systems in a competitive process can be challenging, as there is usually no opportunity to position a video registration and image analysis system on the competition site [20]–[25].

In addition to video analysis systems, wearable MEMS sensors (accelerometer and gyroscope) are used. Their undeniable advantages are small size and the possibility of individual use on the competition site where a video registration system cannot be placed. The temporal resolution of such systems is higher than that of video image data unless costly high-speed shooting is used, allowing for more accurate analysis of temporal and speed parameters of movements. However, it is important to consider the disadvantages of such systems - their use must be allowed by the competition regulations, as some sports have strict requirements for equipment.

In individual sports, motion recognition is not the ultimate goal [26]. The goal is to evaluate the quantitative and qualitative parameters of movement. However, for this, it is first necessary to break down complex movements into atomic ones and assess their parameters. For example, in the work [27], an assistive system for fencing is described, allowing for the classification of movements, distinguishing different types of strikes, and then evaluating the quality of these strikes based on temporal and speed characteristics. The use of such systems can improve the technique of exercise performance, which not only improves sports results but also reduces the risk of injury [28]. The use of such systems can be useful not only for professionals but also for amateurs, helping them better understand aspects of their physical form and techniques requiring improvement.

Tennis and fencing have a lot in common in terms of technique and movement coordination requirements. Both sports require high precision of movements, reaction speed, and good coordination. Therefore, the development of intelligent monitoring systems, similar to those used in tennis [27], is relevant for fencing as well.

Modern assistive coaching systems in fencing and other individual sports requiring high technique and coordination include a module for classifying movements and quantitatively assessing them (Fig.1). It's also necessary to evaluate an athlete's fatigue level to monitor changes in technique as fatigue sets in.

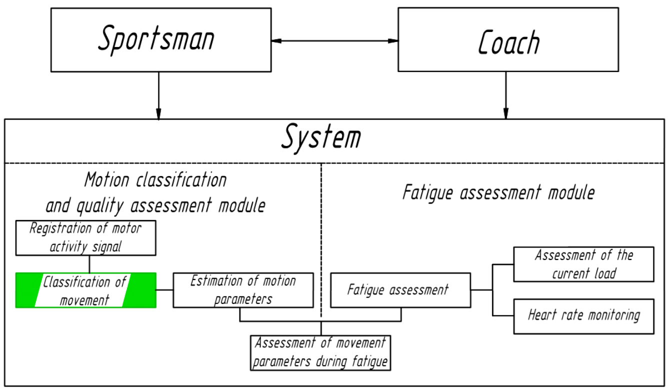

Fig. 1. Block diagram of the system.

Movement classification is a key feature of assistive coaching systems, automating the assessment of movement techniques. Research [29] focuses on classifying movement using temporal patterns. In work [30], authors developed the OpenPose system for real-time 2D human pose estimation. Authors [31] present an analysis of complex fencing movements, providing accurate technique classification. In study [32], authors introduced a new approach to automating fencing movement classification. Researchers used 2D pose data and classified actions using a skeleton-oriented approach. Their developed system, FenceNet, achieved 85.4% accuracy.

Evaluating movements and techniques is crucial in many sports. Authors explore kinematic characteristics of lunges and flash attacks in fencing [33]. Methods for action segmentation and detection using temporal convolutional networks applicable in sports were developed [34]. Authors describe recognizing action dynamics in fencing [35].

Athletes experience daily physical loads far exceeding the average person's, making the assessment of athletes' functional state a current issue. In work [36], methods for classifying activity using data from wearable sensors were developed. Another study examines monitoring training loads to understand athlete fatigue [37]. Authors [38] proposed a system for fencing training support with functional state monitoring.

This paper focuses solely on analyzing the classification of fencing athletes' movements using a gyroscope.

The study's aim is to evaluate the effectiveness and informativeness of gyroscopic data in the context of accuracy and detail in recognizing specific movements. This approach allows for deeper exploration of the potential of gyroscopic signals in movement classification and detailed analysis, which has practical significance in improving fencers' techniques.

II. Materials and Methods

A. *Biomechanics of Fencing Movements*

Fencers move laterally in a straight line, approaching or distancing from their opponent. In the basic stance, knees are slightly bent, and the armed hand is directed towards the opponent. The technique of side movement differentiates between the front and back leg. Basic leg movements include steps and lunges. A forward step starts with the front leg, followed by the back leg, ending in the basic position. A backward step is similar but starts with the back leg. A lunge dynamically shortens the distance to the opponent during an offensive action. It's performed by slightly lifting the front leg, then pushing off with the back leg. A lunge usually ends with the front knee bent, pushing back with the front leg, and returning to the basic position.

Thus, for movement classification, it's reasonable to use 4 sensors located on the legs, torso, and the hand holding the épée. This work specifically examines épée fencing.

Typical movements in fencing include:

- Hand thrust (Fig. 2A)
- Hand closure
- Step thrust (Fig. 2B)
- Step closure
- Lunge thrust (Fig. 2C)
- Lunge closure

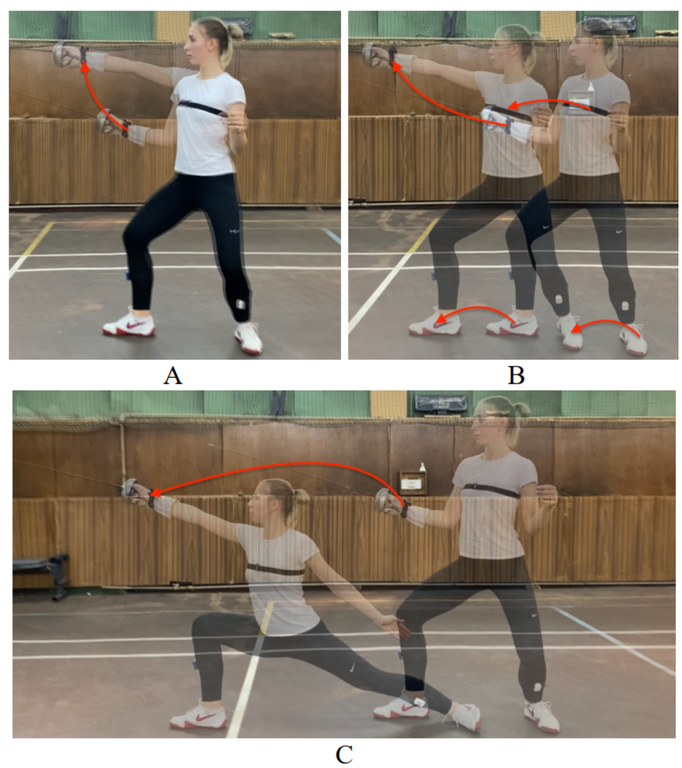

Fig. 2. Biomechanics of fencing movements.

In practice, the list of training movements and combat movements is broader and also includes: flash attacks, squats, defenses, and others. Movements can also be combined, interrupted, or changed after their initiation in response to the opponent's actions.

In the considered movements, a direct forward movement – thrust, and a reverse movement – closure can be distinguished.

III. Data Collection and Evaluation

A. Experimental Research

The experimental study involved four fencers aged between 17 and 20 years (Table I). All of them had been professionally engaged in sports fencing for 4 to 8 years, training 4–5 times a week. Three of the athletes held the title of Candidate for Master of Sports in Russia in fencing and had participated in national and international competitions. Three athletes were right-handed and one was left-handed; this feature was taken into account in the development of algorithms and software.

TABLE I
Basic Data about the Fencing Volunteers

	Fencer 1	**Fencer 2**	**Fencer 3**	**Fencer 4**
Age	20	18	17	20
Leading hand	Right	Right	Left	Right
Experience	6-7 yrs	7-8 yrs	4-5 yrs	6-7 yrs

The "Kolibri" research system by Neurotech was used for data recording. This system consists of four wireless sensors, each providing synchronous EMG recording along with accelerometer and gyroscope data.

The EMG recording function was not used in this study. The three-axis accelerometer data and gyroscope data on the angle of rotation around three axes were recorded. Based on the study's goal, processing and classification were carried out based on gyroscope data. The sampling frequency for the gyroscope's angle of rotation in the "Kolibri" system was 125 Hz. Data from the four sensors were transmitted to a base station via radio channel, then via USB interface. The software supplied with the system enables exporting accelerometer and gyroscope data to a CSV file for further processing.

The "Kolibri" system sensors were attached to the athlete at points significant for the described movements: on the wrist of the leading hand (right for right-handers), on the torso in the area of the thoracic spine, and on the shins of both legs (Fig. 3). For the legs, sensors were distinguished between the front and back leg, typical for a fencing stance. The difference in fencing stance for right-handers and left-handers was considered (Fig. 4).

For each of the 6 movements considered, 70 repetitions were recorded, 10 for the first volunteer and 20 for volunteers 2, 3, and 4.

B. Data Preprocessing and Classification Method

Data processing was carried out using the Python programming language. Gyroscope signal preprocessing consisted of two stages: automated separation into individual movements, parameter extraction.

Fig. 3. Sensor placement and axis orientation.

A threshold algorithm was used to divide the recorded signals into separate intervals containing individual movements (Fig. 5). Thresholds were empirically determined. At this stage, the goal was not to implement an algorithm for isolating atomic movements during a real fencing match, but to automate the data processing during the study.

In the second stage, a set of parameters was calculated for each separate interval with an individual movement.

During the execution of each movement, recordings were made from 4 sensors. Each sensor recorded the change in the angle of rotation around three axes. Thus, each movement corresponded to 12 signals. For each of these, a set of 8 statistical parameters was calculated:

- Duration of the movement in counts
- Average value over the interval
- Standard deviation
- Minimum and maximum value over the interval
- Median value
- 25th and 75th percentile

Consequently, each movement was characterized by 96 parameters, which were used for training and testing the statistical learning model.

For the method of statistical learning to classify the type of movement, the logistic regression method from the sklearn library was used.

The division of the collected data set into test and training samples was randomized, and the ratio of the training sample to the test sample was 2 to 1.

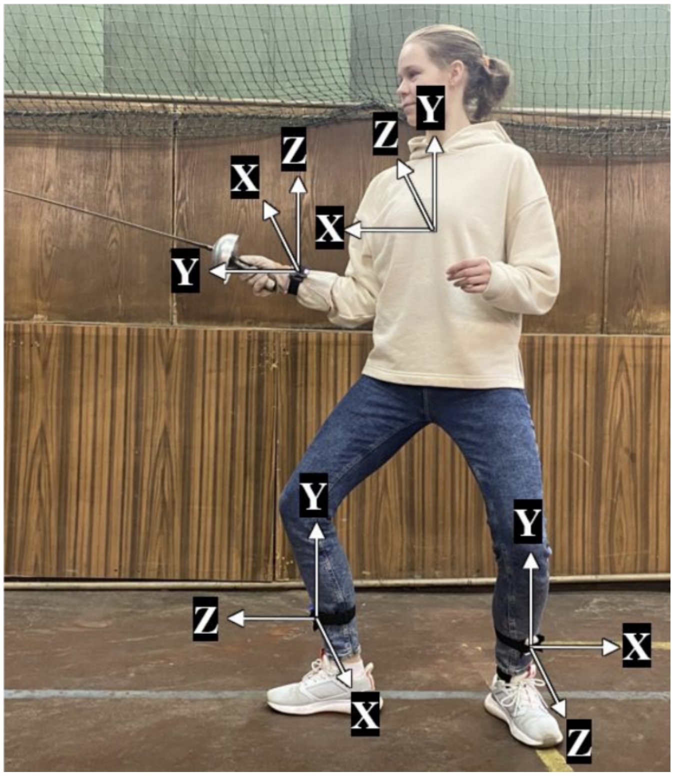

Fig. 4. Sensor placement and axis orientation.

IV. Result and Discussion

The exploration of the used parameter space showed that for direct and reverse movements, most parameters have very similar values. An illustrative example is shown in the figure 6.

This is because the chosen parameters do not reflect the direction of rotation, therefore giving comparable values for direct and reverse movements.

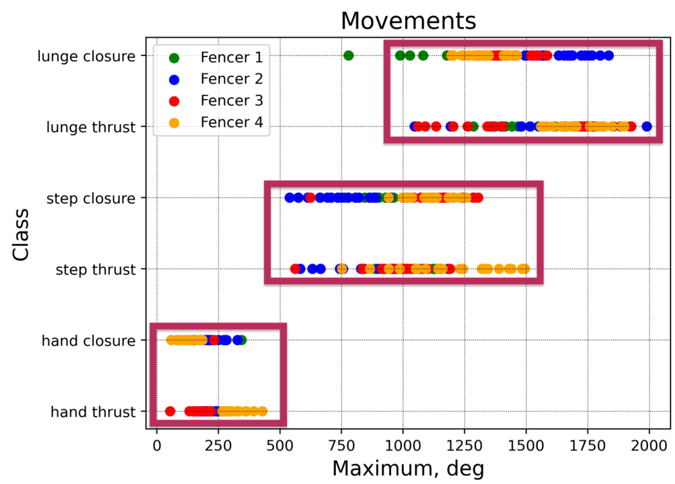

Fig. 6. Movement parameter distribution for direct and reverse movements.

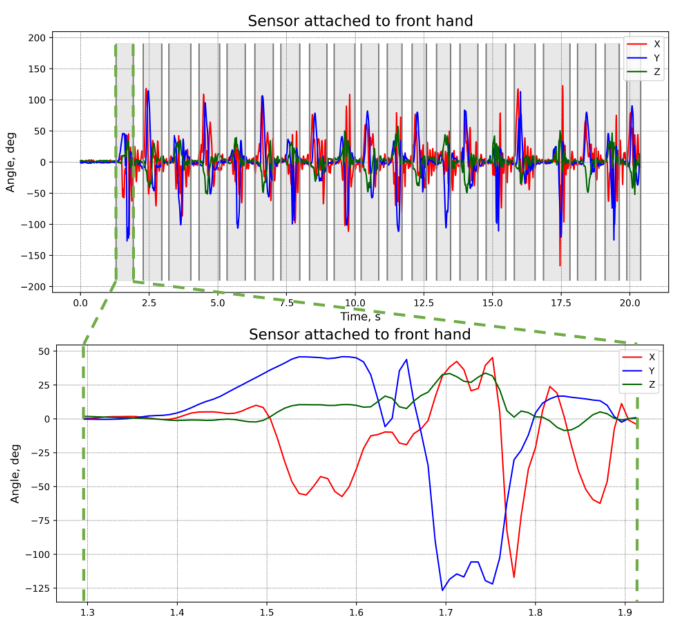

Fig. 5. Signal separation into individual movements.

The results of the classification algorithm on the training and test samples are shown in the figure 7. Results for the training sample are highlighted in red, with numerical values in parentheses, and for the test sample in green, with numerical values without parentheses.

Sensitivity for different movements varied from 0.7 to 0.96. Overall, for all types of movements, accuracy was 0.84 (Table II).

TABLE II
Classification Report

	Precision	Recall	F1-score	Support
Hand thrust	0.9583	0.9200	0.9388	25
Hand closure	0.8182	0.7500	0.7826	24
Step thrust	0.9000	0.8182	0.8571	22
Step closure	0.9048	0.8636	0.8837	22
Lunge thrust	0.6957	0.8000	0.7442	20
Lunge closure	0.8000	0.9091	0.8511	22
Accuracy			0.8444	135
Macro avg	0.8462	0.8435	0.8429	135
Weighted avg	0.8505	0.8444	0.8456	135

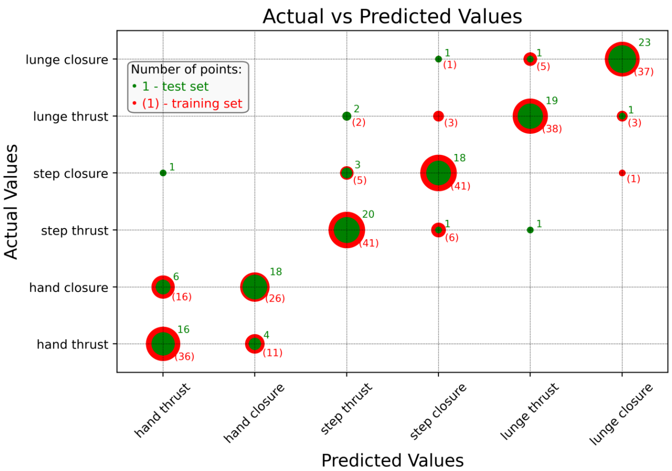

Fig. 7. Classification algorithm results on training and test samples for right-handers and left-handers.

The presented results included all 4 volunteers, including the volunteer with the left leading hand. To assess the impact of adding a left-hander to the training and test sample, a comparison was made with the results of training a similar logistic regression model.

The results of the classification algorithm for right-handed fencers on the training and test samples are shown in the figure 8.

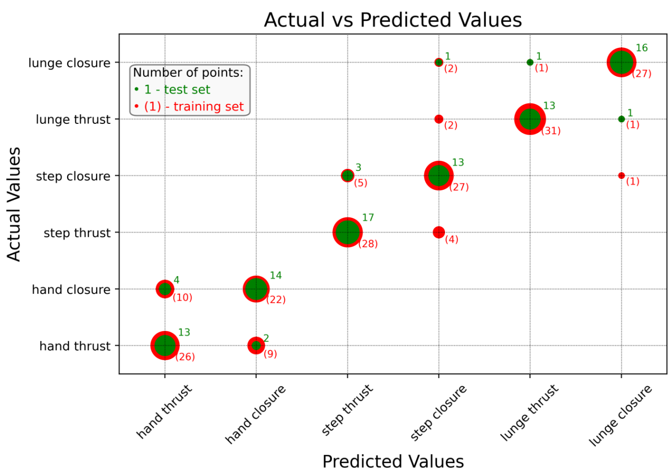

Fig. 8. Classification algorithm results on training and test samples for right-handers only.

Thus, the developed algorithm can be used for both right-handers and left-handers. However, expanding the data set with measurements from fencers with the left leading hand is also necessary.

Adding accelerometer signals to the presented data set will allow more distinct separation of direct and reverse movements.

V. Conclusion

The presented study shows that the data obtained from the gyroscope are sufficiently informative to classify atomic movements based on them. For the presented six movements, sensitivity was 0.76–0.94 respectively when training and using data from right-handers, and for data representing both right-handers and left-handers, it was 0.7 – 0.96 respectively.

Thus, the developed classification algorithm is inclusive, allowing it to work with both right-handers and left-handers without additional adaptation and tuning.

Therefore, combining gyroscope and accelerometer data potentially allows expanding the range of classifiable movements and improving the accuracy and specificity of their classification.

Also, when assessing the technique of a performed movement, supplementing accelerometer data with gyroscope data will provide additional information about rotational movements.

TABLE III
Classification Report Only for Right-Handers

	Precision	**Recall**	**F1-score**	**Support**
Hand thrust	0.9412	0.8889	0.9143	18
Hand closure	0.8750	0.7778	0.8235	18
Step thrust	0.9286	0.8125	0.8667	16
Step closure	0.9286	0.9286	0.9286	14
Lunge thrust	0.7647	0.8667	0.8125	15
Lunge closure	0.8500	1.0000	0.9189	17
Accuracy			0.8776	98
Macro avg	0.8813	0.8791	0.8774	98
Weighted avg	0.8823	0.8776	0.8771	98

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