



Research Paper

## A Systematic Review of Fencing Technologies to Assist Smart Sports Athletes

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**Abstract:** Sports have also been touched by the quick changes that modern technologies have brought about in our societies and way of life. With more than 150 member federations, modern fencing is a well-known Olympic sport that first gained popularity as a competitive activity in Europe [1]. Datamining research are being successfully carried out in several sectors to estimate multiple parameters. The information business and society at large have become interested in data mining techniques because of the abundance of data and the pressing need to transform it into knowledge that is valuable. In sports (fencing, for example), where there has been a slight growth in recent years, the effective use of data is still developing. As a result, many sports organizations have started to realize that the data they have extracted contains a wealth of untapped knowledge. For that reason, a thorough analysis of fencing data mining is presented in this article. Beyond inspiring the scientific community to investigate this topic, which is both topical and fascinating, our findings also contribute to a deeper understanding of the sports (fence) datamining potentials.

**Keywords:** Data Mining, Fencing Technology, Machine Learning, Motion Technology

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### I. Introduction:

In the contemporary era, fencing has participated in every Olympic Games, with 36 medals to be won in 12 individual and team competitions. A modified version of fencing is a component of Modern Pentathlon tournaments. Fencing is an open-skilled combat sport where contestants fight in an indirect conflict with their weapons, without any physical contact allowed between them. Men and women fight with the three competing weapons: épée, saber, and foil. Each weapon has its own set of rules. Fencing equipment, masks, gloves, and plastrons are necessary for safety [2]. Because of its asymmetrical form, this sport demands a high degree of coordination, explosive strength, speed, and precision.

The lunge attack is the most typical type of assault. There are also the flèche and those that come from in-stance counterattacks. Learning how to lunge is one of the most important aspects of fencing. Lunge begins with an explosive anterior leg extension and ends with a sword arm extension that threatens the touch zone. The control mechanism behind lunge performance has mostly been described and studied using kinematics and muscle action aspects. The fencer's reaction to his opponent's maneuvers also has a big impact on how well he performs [3]. Because the kinetics and kinematics of the lunge have not yet been quantitatively characterized, technology aids in the study of fencing biomechanics. Sports performance analysis evaluates an athlete's physical condition, technical proficiency, and long-term training results. It's crucial to understand how fencers perform in practice and during a match since it could help them become more strong and coordinated, which may help them avoid injuries, but more significantly, it could help them respond to their opponent's moves faster.

Coaches create a customized training plan for each student to improve skills and technique, and they may track their progress with a range of tools [4].

Analyzing fencers' performance in a practice or competition could be beneficial for both qualitative and quantitative research. Motion-capturing data can be used by fencing professionals to evaluate fencers' attack skills on a qualitative level and by mentors to identify areas in which fencers need to develop. These kinds of findings suggest that the volume and quality of the available data may contribute to the development of new fencing paradigms. Finding the right technology to gather data thus becomes essential; instrumentation is

equally as important as understanding how to do tests. To stay up with the exponential growth of the wearable industry, a reliable scientific examination of these devices is required. Gaining the trust of users, stakeholders, and legislators is essential to the success of a wearable technology. Wearable device makers, athletes, coaches, team management, insurance companies, and other stakeholders can use these recommendations to help evaluate wearable sensor technologies and/or choose appropriate items [5]. Wearable technology such as accelerometers, surface electromyography (sEMG), and inertial systems—which can be used to quantify athletic activity—can provide a quantitative description of motion. The most popular usage for motion capture systems is the assessment of fencing maneuvers. Because multiple sensors can be combined into a single sensor to provide a more comprehensive assessment of a player's development, wearable technology is becoming more and more in demand in the field of sports science. Therefore, our goal was to identify, evaluate, and characterize the various technologies that are available for fence analysis.

## II. Components and Strategies:

**2.1 Search Strategy:** A comprehensive search was carried out starting with the oldest record in PubMed, Scopus, IEEEExplore, ACM Digital Library, Science Direct, Semantic Scholar and Academia. The formulation of research questions is typically followed by the determination of inclusion, exclusion, and quality criteria [6]. As a result, the study's criteria are established in Table 1.

	Criteria
<b>Inclusion</b>	Research in English articles, conference proceedings, or methodology papers that are pertinent to sports data mining methodologies.
<b>Exclusion</b>	Studies that fall short of meeting the standards of excellence studies conducted outside of the workplace Prior to 2010, studies published in languages other than English were published.
<b>Quality</b>	Research with comprehensive findings. Research with varying recommendations or outcomes

**Table 1:** Inclusion, exclusion, and quality criteria.

Choosing the right modifications to include in the research, which is utilized to control the selection criteria in a subset of primary studies, is one aspect of this procedure that may come up [7, 8]. Thus, every paper retrieved will be examined based on the Title, Abstract, Keywords, Proposed Mechanism, Results, and Conclusion in order to guarantee the caliber of this review. Additionally, the following electronic databases were searched for publications for this article.

- (i) PubMed: <https://pubmed.ncbi.nlm.nih.gov/>
- (ii) Scopus: <http://scopus.com/>
- (iii) IEEEExplore: <https://ieeexplore.ieee.org/Xplore/home.jsp>
- (iv) ACM Digital Library: <https://dl.acm.org/>
- (v) Science Direct: <https://www.sciencedirect.com/>
- (vi) Semantic Scholar: <https://www.semanticscholar.org/>
- (vii) Academia: <https://www.academia.edu/>

Finally, Boolean recovery was chosen as the search strategy for these datasets. In essence, it partitions a search space based on consultation criteria, identifying a portion of the documents in a collection [9]. The string ("sports" OR "sport" OR "sports science") AND ("data mining" OR "mining" OR "computational intelligence" OR "machine learning" OR "deep learning" OR "artificial intelligence") is the key in this instance.

**2.2 Eligibility Criteria:** Research that used wearables or motion capture technology to measure fencers' performance during practice or competitions were taken into consideration. Any equipment worn by fencers during practice or competition is referred to as "wearable devices," including but not limited to GPS, accelerometers, inertial motion units (IMUs), sEMG, and other gadgets. Motion capture systems include things like cameras, markers, and Kinect; wearable technology includes things like GPS, IMU, accelerometers, sEMG, and other gadgets that fencers wear for practice or competition. For both male and female fencers, there were no limitations on the country, age, or level of competition. Every type of competition and practice was included in the analysis (whether global or localized). Any physiological and/or biomechanical data collected by wearable technology, including but not restricted to distance measures, velocity/speed, acceleration, deceleration, and muscle activity, was included in the study. Studies that examined footwork, biomechanics, or data mining through the use of machine learning or data mining were also included. English-language journal articles were the only ones that could be included in full. The research did not include scoping or systematic reviews. The search results were separately compared to the eligibility conditions by two researchers (SA and MM). Conversations were used to settle disagreements.

2.3 *Data Retrieval:* The following information was retrieved: the study's year of publication, its type (longitudinal, cross-sectional), its purpose, its sex, its competitive level (élite, novice), its number of participants, its design (experimental, pilot, observational), its clinical scales, and its instrumentation. Furthermore, information was gathered regarding the design of the lab, the company, the model, the dimensions (bi-, tri-), the muscles, the important performance indicators, the presence of external stimuli, and the use of machine learning (ML) or artificial intelligence (AI) algorithms.

2.4 *Analyzing Data:* The Mixed Methods Appraisal Tool (MMAT) has been found to be a useful resource for the Risk of Bias Assessment in evaluating the caliber of the included studies [10]. For the assessment stage of systematic mixed studies reviews—that is, reviews containing studies using mixed methodologies, quantitative, and qualitative approaches—the MMAT is a crucial appraisal tool. It enables the methodological quality of five types of studies to be evaluated: mixed methods studies, non-randomized studies, randomized controlled trials, qualitative research, and quantitative descriptive studies. For the current systematic review, we determined that the "quantitative descriptive" category best reflected the included research (Table 2).

Study Design Category	Qualitative Standards for Methodology	Response YES= ✓, NO= X, UNABLE= U
Screening inquiries (of all kinds)	S1. Are the research questions well-defined?	
	S2. Can the study questions be answered using the data that has been gathered?	
Descriptive Statistics	4.1 Does the sample plan make sense in light of the study question?	
	4.2 Does the study question make sense in relation to the sample plan?	
	4.3 Are these the right measurements?	
	4.4 Is there little chance of nonresponse bias?	
	4.5 Is the research issue adequately addressed by the statistical analysis?	

**Table 2.** Mixed Methods Appraisal Tool (MMAT), 2018 version

Only four distinct organizations were able to obtain kinematic data from fencers using wearable sensors and/or markerless technologies. Malawski assessed fencing gestures for a functional task using a Kinect and two IMUs. Both the wrist and the chest were fitted with IMUs [11]. Using Kinect and a data mining technique, Mawgoud and colleagues gathered data on fencing lunges in order to train a neural network (MLP), give fencers movement attributes, and improve the MLP over time [12,57]. O'Reilly and associates used 5 IMUS on the back, both thighs, and the shanks to assess the accuracy of a lunge [13].

Qualitative Standards for Methods	Qualitative Standards for Methodology						
	S1	S2	4.1	4.2	4.3	4.4	4.5
Said et al. [14]	✓	✓	✓	X	✓	✓	U
Klauck et al. [15]	✓	X	✓	X	✓	✓	U
Zhang et al. [16]	✓	X	✓	X	✓	✓	U
Williams et al. [17]	✓	X	✓	X	✓	✓	✓
Gholipour et al. [18]	✓	✓	✓	✓	✓	✓	✓
Mantovani et al. [19]	✓	✓	U	U	✓	X	X
SuchaNwski et al. [20]	✓	U	X	X	U	✓	X
Morris et al. [21]	✓	X	X	X	✓	✓	X
Bottoms et al. [22]	✓	✓	✓	✓	✓	✓	✓
Gutierrez-Davila et al. [23]	✓	✓	✓	✓	✓	✓	✓
Borysiuk et al. [24]	✓	✓	✓	X	✓	U	✓
Sinclair et al. [25]	✓	✓	✓	U	✓	✓	✓
Borysiuk et al. [26]	✓	✓	U	U	X	U	X

Moorea et al. [27]	✓	✗	✗	✗	✗	U	✗
Kim et al. [28]	✓	✓	✓	✓	✓	✓	✓

**Table 3:** Using MMAT version 2018, an analysis of the quality of the studies included in the systematic review was conducted.

### III. Study Techniques Using Intelligent Data:

This part aims to introduce the researchers' intelligent data analysis techniques utilized in the field of smart fencing training. In the domain of SST, a novel taxonomy of intelligent methods is proposed, following the recent practice of intelligent method taxonomies proposals on other highly domain specific fields, such as intrusion detection [29], very large-scale integrated circuits and systems [30], program binaries [31], and diabetes management [32]. The suggested taxonomy may be expanded as the domain develops and grows in the future. It is based on the techniques that have been found and are presently being employed in the domain. Our taxonomy is divided into primary groups (certain algorithms, like artificial neural networks, can be classified under more than one classification). Since most studies that reported using artificial neural networks also utilized other machine learning techniques (such as decision trees in the same study), we classified artificial neural networks in the machine learning group in our instance. From these studies, the following algorithms were found to be used:

#### 3.1 Strategies for Computational Intelligence [33]:

- Differential Evolution (DE) is an algorithm used in evolution [34].
- Algorithms for Swarm Intelligence: Particle Swarm Optimization (PSO) [36] and Bat Algorithm (BA) [37].
- Fuzzy systems [38].
- Simulated annealing [39].

#### 3.2 Data Mining:

- Traditional techniques for data mining, such as Apriori [40,55].
- Machine Learning: Traditional machine learning techniques, such as K-Nearest Neighbors [45, 54], Gradient Boosting (GB) [44], Random Forests (RF) [43], Adaptive Boosting [42], Decision Trees (DT) [41], (k-NN), k-means clustering [31], artificial neural networks [47] (ANN), Support Vector Machine (SVM) [46,53], and hierarchical clustering [48].

#### 3.3 Deep learning [49,56]:

- Recurrent Neural Networks (RNN) [50], Long Short-Term Memory (LSTM) [51], Convolutional Neural Networks [52] (CNN).

### IV. Review Limitations

It is important to consider the limitations when interpreting the review's findings. The search was limited to four databases, but in order to locate more relevant publications, hand searches and reference lists were added. The search terms and inclusion criteria used in this review also limit the findings, since using different terms and criteria might have included a different number of publications. However, the search terms and criteria were based on comparable reviews that were previously published. Limiting the included papers to those published in English led to a language bias in the selection process. The standardized tool that was used to create the quality assessment checklist was not previously referenced in reviews that were similar in kind.

### V. Conclusions

Currently, the most used motion technology for fence analysis is optoelectronic systems. The majority of research concentrated on the biomechanical characteristics of fencing during elite-level lunge execution. However, the requirement for well-defined performance bands makes it difficult to compare studies. Furthermore, more wearables ought to be used by non-elite athletes to create training plans that are both efficient and less likely to result in injury. Wearable technology is a useful tool that coaches and sports scientists can use to understand performance and modify training plans and game strategy as needed. It is important for scientists and engineers to continue developing wearables that provide detailed information about the health, safety, and overall performance of players. Advances in ICT and video processing methods have made traditional biomechanical data gathering suites easier to transport and set up in field environments. Furthermore, state-of-the-art modeling and analysis methods have been applied to a variety of sports-related problems. These software applications commonly make use of data mining and artificial intelligence (AI). Effective data presentation and visualization can improve athletes' and coaches' cognitive comprehension of complex data outputs.

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