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## Fine Classification of Complex Motion Pattern in Fencing

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### Abstract

The subject of this study was fencing and the object was to classify the fundamental motions of fencers by creating a library of movements. Based on this library, thus, the recognition of motions during a real fencing match can be made. Kinematic data were acquired by a motion capture system (Vicon). The automated algorithm that recognized motions is based on three steps: a Principal Component Analysis for data dimension reduction, an innovative wavelet-based analysis of signals and a feature extraction method. The algorithm was tested on high level fencing athletes and it was found to be robust with a 12% of misclassification rate. It gave a description of how athletes move and showed that in real match athletes do not execute fundamental motions but they mix different techniques in order to surprise the opponent.

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Keywords: fencing, motion capture, classification, recognition, wavelet analysis, PCA, feature extraction

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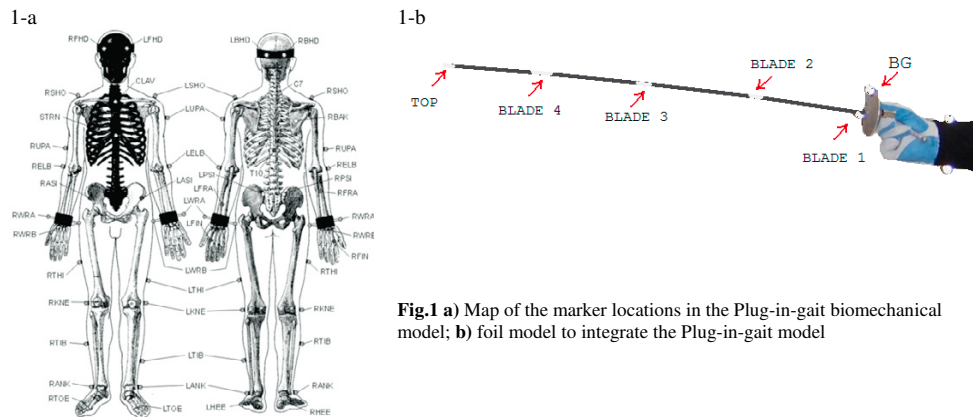
### 1. Introduction

Athletes are usually subjected to hard practice to improve their performances. To minimize errors during movements, they have to follow personalized training programmes and the final outcomes depend on the knowledge of the movements from a biomechanical point of view. In the case of simple periodic motions, e.g., gait and cycling, scientific literature suggests many standard methods to analyze them. By contrast, if we have a complex motion characterized by a high variability, standard methods might be inefficient because the differences among movements are very subtle.

The subject of this work is the fencing and in particular the foil speciality. Fencing is a combat sport and the key to winning is surprising the opponent with rapid and variable motions. Thus, the peculiarity of sports like this or similar ones, is that, when environment conditions change (e.g. during matches or during training), motion characteristics change as well; therefore, it is interesting to compare different situations. In order to achieve an automatic comparison of movements, a method that recognizes motions during a real match is required. The purpose of this work was to develop a tool of algorithms that are able to classify and recognize fundamental motions of attack and defense in fencing. The algorithms have to be robust for changes in motion velocity and for variations of motion patterns so that athletes can be studied during competition.

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**Fig.1 a)** Map of the marker locations in the Plug-in-gait biomechanical model; **b)** foil model to integrate the Plug-in-gait model

## 2. Methods

Data were acquired by a Vicon system (612 Oxford Metrics Ltd., Oxford, UK), composed by nine IR cameras, with resolution of 0.8 Megapixel and a frame rate of 200 Hz. Through the dedicated software Workstation, 3D trajectories were reconstructed in a virtual environment.

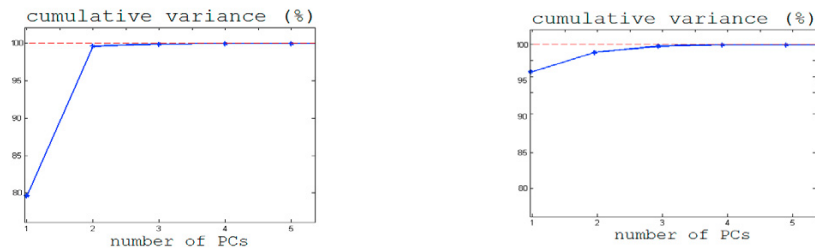
The biomechanical model used was the “Plug-in-gait”: this is the default model employed in Vicon software, it is a full body model, suitable for every type of motion, and utilises markers spread all over the body (Fig. 1). This default model was modified to include the foil: since the foil is not a rigid segment (i.e. it has an elastic behaviour), it was necessary to use more than three markers to follow the entire object in the virtual environment. We chose to divide the foil into five equal segments and the foil base (named bellguard) was equipped with another marker placed corresponding to the thumb position, in order to create an orthogonal reference for the weapon (Fig. 2). The Polygon software uses the modified biomechanical model to compute joint angles.

The acquisition protocol consisted of five repetitions for each movement. The protocol also involved data capture of motions with and without moving legs and with different velocities. Subjects were asked to execute movements in the most precise way possible. Since high-level athletes were involved in this study, it is assumed that captured motions were perfectly executed.

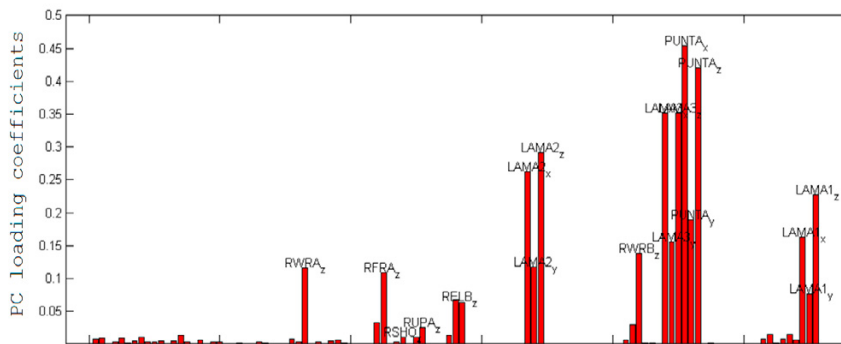
The total amount of suitable data was huge (around 150 cinematic variables), with many variables not of interest for the purpose of classifying different motions. Data consisted of all the x, y and z coordinates time series for each marker, and the joint angles computed by the Vicon software. Therefore, reduction of dimensionality was achieved by using both Principal Component Analysis (PCA) technique [1] and empirical considerations.

For first, it was noticed that the reliability and the repeatability of joint angle variables were not verified. Actually angles are affected by a high noise due to the artefacts related to soft tissue and induced by the fencing clothes that are necessary to guarantee the safety of athletes during the contest. These artefacts mostly affect angles data than coordinates data because angles are more sensitive to them [2-5].

Empirical observations were that the more meaningful variables during the motion of the upper part of the body are those related to the arm that holds the foil, whereas during the motion of the lower part of the body are those related to both legs. These considerations fitted well with the results from the Principale Component Analysis (PCA) [6]. It has been seen that the real dimension of the data set was lower than the original one since the first two PCs explained more than 95% of the total variability (Fig. 2). In addition, considering loading values of PCA, the variables related to the armed arm were the most correlated with the first PC for upper limbs motions (Fig. 3). For lower limbs motions, loading values related to lower part of the body were not higher for the first PC than for the rest: this might be because the motion of legs is transmitted to the rest of the body and, thus, the trajectories are highly correlated.



**Fig. 2** Cumulative percentage of total variance for two different motions: a parry in first position (left), and an attack with leg motion (right).



**Fig. 3** Loadings of the first PC for a parry in first position. The coefficients represent the contribution that original variables give to the the first PC. Only the original variables that have a weight above 0.1 are labeled.

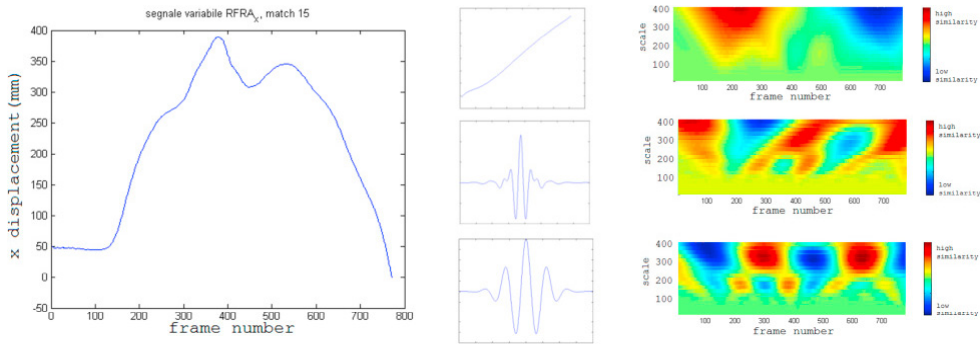
In conclusion, due to the reliability considerations about joint angles, the empirical observations and the PCA results, only the coordinate variables of the armed arm and the lower limbs were studied so that the data set was reduced.

C3D files produced from Vicon software were pre-processed in Matlab™. The pre-processing consisted of extracting the useful sequences and normalizing them in amplitude and time. We named these sequences *Primitive functions*; each represents a characteristic pattern for a variable in a specific motion. This library was the basis for the motion pattern recognition.

The recognition process involved two main steps: identification of motion in time, by using a Continuous Wavelet Transform (CWT) based on *Fencing-Oriented Mother Wavelet* (FOMW), and a subtle distinction by using a clustering method.

The main results of this work was the introduction of a new set of primitive wavelet, based on the knowledge of the fundamental motions of attack and defense in fencing. Therefore, *Fencing-oriented mother wavelets* are ad hoc wavelets [7] that take their patterns from the shapes of the *primitive functions* in the library. Actually the initial hypothesis was that Wavelet Transforms (WT) of the match signals (i.e. acquired during the contest) using the FOMWs show a peak in correspondence of the time index  $t$  and the scale  $s$  at which the motion is executed during the match.

The use of CWT instead of a simple covariance function was because motions can be executed with different velocities, and CWT permitted to identify the correlation between the analyzed *match signal* and *primitive functions*, since the scale factor stretches and shrinks the *primitive functions* [3]. With the term *match signal* we indicate an entire acquisition in which athletes move without constraints during the contest.

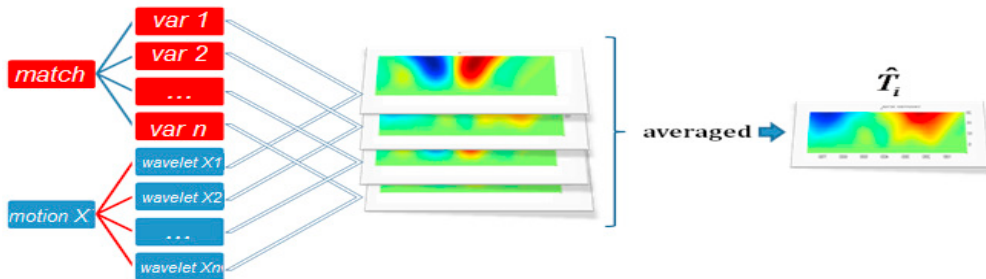


**Fig. 4** In the left column there is the signal to be analyzed. In the center are three different mother wavelet (fencing-oriented mother wavelet, Meyer and Morlet). In the right are the three respective wavelet transforms.

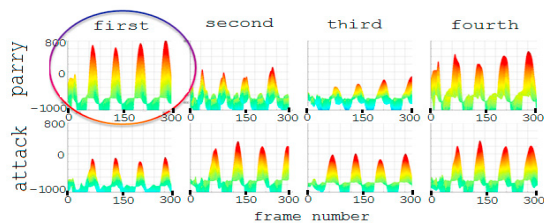
The *pat2cwav* function of Matlab was used. Through this function we obtained the *fencing-oriented mother wavelet* library from the *primitive functions* library. *pat2cwav* allowed choice the desired pattern (the *primitive function* in this case), the fitting method (polynomial fitting was the type selected in this work), the degree of the polynomial curve and the regularity of the curve (7<sup>th</sup> degree and continuous curve). The output was a function that respects the constraints of a wavelet function so it has finite energy, it respects the admissibility criterion and its Fourier transform is real and vanishes for negative frequencies [8].

The advantages of using ad hoc wavelet instead of normal ones are shown in Fig. 4. In the left column is the *match signal* function (in particular, the variable  $RFRA_x$ , that is the x coordinate of the Right FoReArm marker), in the center column are the FOMW related to that specific variable and two other classical types of mother wavelet (Meyer and Morlet), finally the right column shows the relative WTs. The purpose of this demonstration is to highlight the index time  $t$  (in this context we use the number of frames as a time index) at which the motion is actually executed during the match: in the case of the reported example,  $t$  was equal to 200 (that is 1s, because the rate of acquisition was 200 frame per second). Among the three surface graphs, the best recognition can be seen in the first graph where an evident peak is found around  $t=200$ , whereas the other two graphs do not show clearly this unambiguous recognition. We considered the peaks of these surfaces graphs because WT coefficients can be interpreted as a similarity index.

For each fundamental fencing motion we had a group of FOMW, each of them corresponding to one of the selected meaningful variables. The recognition algorithm proceeded with the WT computation (Fig. 5) so that, for each motion, a number of WT equal to the number of the selected variables were computed. This procedure may



**Fig. 5** It represents the flow of work: from every acquired match time series,  $n$  meaningful variables are extracted. Each *var i* is then transformed with its relative *wavelet Xi* for a specific motion. The  $n$  wavelet transforms are averaged to produce the coefficient matrix  $\hat{T}_i$ .



**Fig. 6** In the eight images, the graph represents the coefficient matrix  $\hat{T}_i$  for each fundamental motion of the upper part of the body (e.g. parry in first position, second, etc). The x-axis represents time (expressed as frames number), the y-axis represents the magnitude of coefficients.

seem redundant because all the computed WTs bring the same information: however, it was useful maintaining all the WTs because some non ideal or corrupted graph patterns present in the match variables could produce errors in the recognition. These possible errors were absorbed with the average operation among all the WTs. The  $\hat{T}_i$  matrix was made of the means of the corresponding points on the WTs, that is, the point at the row  $i$  and the column  $j$  corresponds to the average of the values of the corresponding position, taken from all the WTs. Thus, it is no longer a WT but a simple matrix of coefficients. Then, all the  $\hat{T}_i$  matrices – one for each basilar motion  $X_i$  – are compared, and the highest  $\hat{T}_i$  matrix is considered to be the right response (Fig. 6).

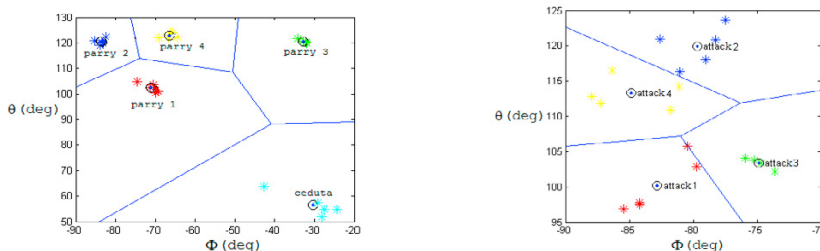
With this method we can identify the motion in time, however some errors are made in distinguishing the different typologies especially with very similar movements.

Therefore, some motion features (Fig. 7), such as angles of meaningful body segments (different from those computed by Vicon models) and relative distances between joints, were extracted from the identified sequence of the unknown match; they were represented as point in two space and compared with clusters created from training acquisitions.

These clusters were spread out as shown in Voronoi diagrams [9-10] (Fig. 8), so we can understand the nature of motion by observing which cluster centroid was the nearest to the specific point.



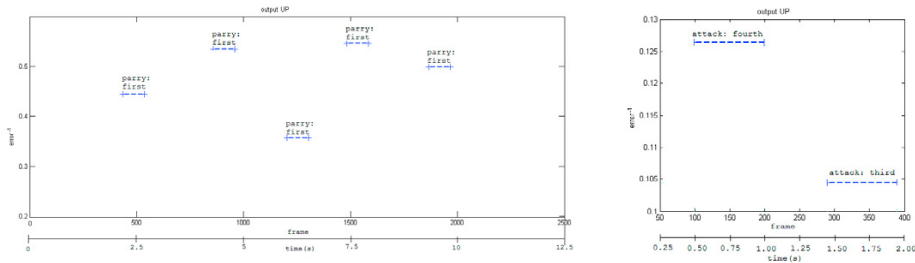
**Fig. 7** A fencer with the analyzed, meaningful segments represented (left); the figure illustrates the absolute angles computed from the selected segments (right)



**Fig 8** The graphs illustrate the observation extracted from matches (coloured star-marks), represented in the two-dimensional feature space. The straight blu lines are the borders of Voronoi regions

### 3. Results

The algorithm was tested on acquisitions captured from high level fencing athletes. Acquisitions were of two different types: constrained and free. In the former, athletes acted following precise commands, in the latter they moved freely, as if they were really fighting in a match. The output was given as a graph (Fig.9): in the x-axis there is the time index in which the motion is revealed; in the y-axis there is a measure of accuracy, that is the inverse of distance between the point and the centroid in the feature space. In the first type of acquisitions recognition was correct for the majority of cases, with a rate of misclassification of 12% out of 50 trials, while in the second type (similar to real competitions) the situation was more complex; athletes did not execute only the fundamental movements but the varied attacks and defense motions in order to surprise the opponent, therefore the outputs of the program could not give a precise classification but it described a similarity between the analyzed motion and the fundamental movements. Thus, this means that our method is robust to variations of motion and context.



**Fig 9** This is the way in which the algorithm gives the outputs: when the motion is recognized in time a dotted line is drawn. The name of motion is upon the line. On the left there is the outcome of a constrained acquisition. On the right there is an example of free acquisition.

### Conclusion

This study presented a new method to automatically classify and recognize complex motions in fencing. The recognition employed the use of a new family of wavelet functions, the FOMW (Fencing Oriented Mother Wavelet), and a classification based on extraction of significant physic features. Patterns of FOMW were created from kinematic variables acquired with a motion capture system and reduced in number by a PC Analysis. The algorithm was tested on 50 constrained trials executed with different velocities and it was found to be robust with a 12% of misclassification rate. The algorithm applied to free trials gave a description of how athletes move and showed that in real match athletes do not execute fundamental motions but they mix different techniques in order to surprise the opponent.

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