Classification of Basic Footwork in Fencing Using Accelerometer

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Abstract— **Analysis and recognition of motion patterns from data acquired by body-worn inertial sensors is an emerging technology in sports. In this paper we propose an effective method for recognition of fencing footwork using a single body-worn accelerometer. We present a challenging dataset consisting of six actions, which were performed by ten persons and repeated ten times by each of them. We propose a segment-based SVM for time-series classification together with a set of informative features. We demonstrate that the method is competitive with 1-NN DTW in terms of classification accuracy. The proposed method achieves classification accuracy slightly better than 70% on the fencing footwork dataset.**

Keywords— Activity recognition, sport sciences, time series, signal processing, fencing

I. Introduction

The use of technology in sport is rapidly increasing and biomechanical analysis in most sports is routine at the elite level these days. Sports biomechanics allows detailed analysis of sports movements to allow better sports performance and/or less injury risk [1]. Since the very beginning of sports, training methodology has been improved in order to achieve better results in shorter time [2]. Each sports discipline developed a set of exercises aimed at perfecting particular skills. Recent advances in technology allow enhancing the training process, in particular by providing tools for analysis of performed actions.

One of the major aims of sports data analysis is to provide assistance for training. Object or motion tracking is one of the most frequently used techniques in sports analysis. It has been used in visual tracking of balls, players, referees, etc. [3]. As demonstrated in [4], video recording of an action may provide valuable feedback for the athlete. RGB videos are used for tracking players in team sports [4] as well as in motion analysis of particular action [5]. Motion-capture systems are employed frequently in applications requiring more precise measurements [6, 20].

Numerous studies have demonstrated that inertial measurement units (IMUs) have considerable potential in sports performance analysis [7]. The advantage of such sensors is that they can be easy installed. They provide high accuracy measurements with relatively low cost. The usefulness of inertial sensors for sports analysis has been shown in several papers [8]. In [20] an inertial device consisting an accelerometer and a gyroscope has been employed for monitoring of athletics sprint performance. The experimental results demonstrated the IMU device has the ability to determine the sprint start. However, because the sprint start is a highly explosive movement, the 50th Hz sampling rate of the utilized IMU has proved to be insufficient for precise determination of the sprinter's start. In human action recognition the reconstruction of joints position is often not necessary since the acceleration itself can provide relevant information. For instance, in [9] a single accelerometer is utilized for classification of sports activities.

While a considerable research has been done in the area of golf [10], other sports seem to receive less attention. In particular, in the area of fencing very limited research has been done until now. Analysis of biomechanics and performance of lunge is provided in [11], [12], whereas in [13] a motion capture system has been utilized in classification of movements of the sword arm.

In this work we propose a single accelerometer-based method for classification of basic footwork in fencing. Having on regard that all actions in fencing are strictly associated with footwork we claim that it is an important step towards creating a full system for analysis of both technique and tactics. We perform analysis of acceleration data by extracting a set of informative features. The classification of motion data is performed using Support Vector Machine (SVM) and Dynamic Time Warping (DTW). Our experimental results indicate that a single accelerometer may be a valuable tool in analysis of footwork in fencing, providing quantitative evidence of its significance for dynamical motion analysis.

II. Method Framework

A. Footwork in fencing

Fencing position is standing sideways, with sword arm directed towards the opponent, see Fig. 1 (left). We can distinguish the front leg and the back leg (also called lunging leg). The most basic footwork includes steps and lunges.

Fig. 1 Fencing position (left) and fencing lunge (right)

step forward is performed by moving the front leg forwards and then moving the back leg and thus returning to the basic position. A step backward is similar, but initiated by the back leg. A lunge is performed by lifting the front leg and then making a dynamic push-off with the back leg. Once the lunge is finished fencer stands with the front leg bend about 90 degrees in the knee joint and back leg straight, see Fig. 1 (right). Return to the fencing position is usually done by bending the knee of the back leg and moving the front leg backwards. Typical footwork of a fencer includes moving forward and backward in order to keep proper distance to the opponent and performing a lunge during an offensive action.

Lunges can vary in speed, acceleration and length. According to prof. Czajkowski, one of the inventors of modern theory of fencing, there are four basic types of lunges [14]:

- rapid - fastest possible lunge, with relatively short distance, intended to surprise the opponent,
- with increasing speed - started slowly and finished quickly, intended for feint attacks,
- with waiting - with a short pause after lifting the front leg, intended to wait for the opponent to react and perform a counter-action
- jumping-sliding - longest possible lunge, using maximum leg force fencer actually jumps forward, sliding the back leg on the floor.

Automatic recognition of such actions is challenging due to strong similarity between some of them. For instance, lunge with increasing speed may be similar to lunge with waiting or jumping-sliding lunge. It is worth noting that even fencing experts can have difficulties in visual distinguishing among some actions, particularly when they are performed not fully correctly, which is often the case. Thus, our work differs significantly from the work carried out in the area on wearable-device based action recognition in that we classify similar motion patterns, whereas in typical approaches to action recognition meaningfully different activities like walking, jogging, sitting, standing, lying etc., are typically classified [15].

B. Database

The aim of this work is to classify 6 basic footwork movements, as described in previous section, namely: step forward, step backward and four types of lunges (rapid, with increasing speed, with waiting, jumping-sliding). Since there are no publicly available databases with such data, we recorded a dataset consisting of synchronized inertial and RGB-D data. The data was gathered due to courtesy of Aramis Fencing School, one of the biggest fencing institutions in Poland. We recorded 10 fencers, with various fencing experience - from intermediate to professional level.

The recordings were conducted in the following manner. Each person was asked to attach an inertial sensor to his/her knee and then to perform specific actions on a command. Each action was repeated 10 times. Every action was saved as a separate data sample. We used an x-IMU sensor, which provides 9 axes inertial data (accelerometer, gyroscope, magnetometer) with frequency of 256 Hz, and a custom made recording software, which saves the data in Matlab format in order to facilitate further processing. Together with the inertial data we recorded the video as well. In this work we focus on the accelerometer measurements. The motivation of such an approach is our desire to construct a low-cost system, which could provide support for both the fencing coaches as well as the fencers.

III. PROPOSED METHOD

A. Data Features

A range of different approaches has been developed so far to obtain features from accelerometer data. The features can be derived from the time-varying signal, through frequency analysis or wavelet analysis that allows deriving the so-called time-frequency features [15].

In order to analyze the motion data we calculated a number of different features, which were used to discriminate between six classes of the footwork. In a preprocessing step, we performed spline interpolation in order to ensure equal length of each sample. Having on regard that each action takes about two seconds and the frequency of recording is 256 Hz, we interpolated each data sample to 512 data points.

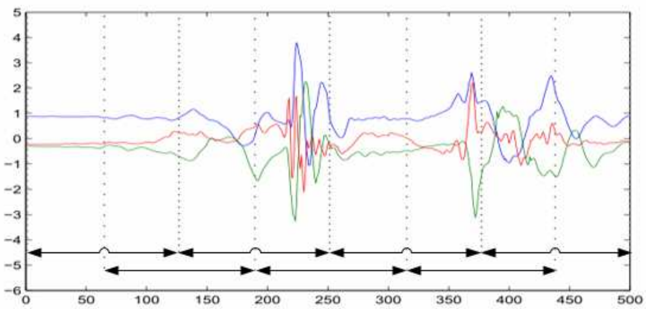

Fig. 2 Data sample (acc x,y,z in time) divided into 7 overlapping windows

Given samples with normalized length we divided the data sample into equi-sized segments with 50% overlap, see Fig. 2. Owing to dividing the window into equal-length segments and then extracting the features of data samples that fall within each segment we obtained a possibility to model how the actions are being done with relationship to time. In the next section we will demonstrate the efficiency of segment-based method via extensive experiments based on features extracted both in the whole-sequences and subsequences. In the experiments we examined different segment sizes (32, 64, 128, 256). Since the best results were achieved using segments of size 128 we decided to employ such a segment size in the experimental evaluation of the algorithm. The signal in each segment has been filtered with a highpass filter with stopband frequency at 0.4 and passband frequency at 0.8. In each window a number of features has been computed. The final set of features was selected based on manual and automatic feature selection. We considered three types of features:

- Time-domain features. Using the filtered signal, the difference between the original and the filtered signal and the first derivative of the filtered signal, in the segments we computed the following features: mean value for each axis, root mean square (RMS) value for each axis, mean value of magnitude, RMS of magnitude. This resulted in total of 24 features per segment.

- Frequency-domain features. We performed short-time Fourier transform in each window, for the filtered signal, difference between the original and the filtered signal and the first derivative of the filtered signal, then we computed RMS and mean values of magnitudes for each axis. This resulted in total of 18 features per segment.
- Wavelet features. Using the Daubechies 3 wavelet mother, we computed multilevel wavelet decomposition coefficients for both the original and the filtered signal. Then, for each axis, we computed sum of normalized absolute differences of coefficients for the original and the filtered signal. By using sums for the levels 3,4,5,6, we obtained 12 features per segment.

The experimental results demonstrated that the time-domain features provide the most efficient recognition. Therefore, results presented in this work include only the time-domain features. It is worth noting, that for comparison we also conducted experiments with gyroscope data using all of the abovementioned features. However, the results were not significantly better in comparison to the results obtained on the basis of the accelerometer.

B. Classification

The classification of the footwork has been achieved using Dynamic Time Warping (DTW) and Support Vector Machine (SVM). Dynamic time warping is a well-known technique to find optimal alignment between two given time-series [16]. The time-dependent sequences are warped in a nonlinear fashion to match each other using Dynamic Programming. These sequences may be discrete signals (time-series) or feature sequences sampled at equidistant points in time. Various modifications of DTW have been proposed to speed up the computations as well as to better manipulate the possible routes of the paths. It has been successfully applied in several domains including speech recognition and aligning biometric data, such as gait [17]. The disadvantage of DTW is heavy computational burden required to obtain the optimal time alignment path. A DTW introduced in [16] approximates a time series by dividing it into equal-length segments and calculating the mean value of the data points that fall within each segment. The alignments of the modified DTW are very similar to those produced by classic DTW, whereas the speedup is one to three orders of magnitude, with no significant loss of accuracy for classification tasks.

In this work we consider DTW-feat, a modification of DTW which compares series of features, computed in time windows, rather than raw signals. The features are not limited to mean value, but may include any of the features discussed in the previous subsection. Both DTW and DTW-feat employ 1-Nearest-Neighbour (1-NN) for final step of classification.

SVM is primarily a classification algorithm that performs classification tasks by constructing hyperplanes in a multidimensional space to separate data examples of different class labels [18]. The data separation is achieved by the hyperplane that has the largest distance to the nearest training-data point of any class. In general, the larger the margin the lower the generalization error of the classifier. However, the use of standard SVM can lead to poorly fit models if any examples are mislabeled or extremely unusual. To account for this, the idea of a soft margin SVM has been introduced to permit some examples to be placed on the wrong side of the margin. The C parameter trades off misclassification of training examples against simplicity of the decision surface, that is the ability to generalize the classifier to unseen data. It controls the tradeoff between the overfitting (the model is too complex and it fits the data as well as the noise) and underfitting (the model is not complex enough to fit the data). If the values of C are not properly tuned the SVM can have poor predictive accuracy.

In addition to performing linear classification the SVM can efficiently carry out a non-linear classification using the kernel trick, which implicitly allows mapping the data into high-dimensional feature spaces. The most commonly used kernel is RBF (Radial Basis Function). For the RBF kernel, the γ parameter controls the width of the radial basis function. When gamma is too small, the model can be too constrained and cannot capture the complexity of the data. Although basic SVM is a binary classifier, it can be easily extended for more classes by training multiple one-vs-all binary classifiers. In this work we employ a multi-class SVM classifier with both linear and RBF kernels.

IV. Experiments And Results

We have used our dataset to evaluate the proposed method for accelerometer-based classification of basic footwork in fencing. In this section we present and discuss results computed with different classifiers - DTW, DTW-feat, linear SVM and SVM-RBF. All experiments were conducted in two modes: for each performer separately (Person Dependent - PD) and for the whole dataset (Person Independent - PI) using five-fold cross-validation and leave-one-out, respectively.

A. DTW classification

We have implemented DTW classifier for the proposed classification task. With regard to local path restrictions we evaluated typical approaches. We found that a path in 3 directions in the distance matrix to directly adjacent data points with the lowest local distance is the most versatile and thus it was employed in the evaluation of DTW classification accuracy on fencing footwork dataset. The DTW classifier was used directly with the accelerometer signal normalized to zero mean and unit variance.

The experimental results are shown in Table I. As we can observe, the classification accuracy of actions of particular person (PD) is much better on average to classification accuracy, which has been obtained on the whole fencing footwork dataset (PI). This means that DTW does not generalize well among the actions performed by different performers. As we can notice in the discussed table, the accuracy of DTW-feat, which has been determined on features computed on segments of size equal to 16, is only slightly worse. It is worth noting, that processing time required for the DTW-feat classifier is considerably lower than for the basic DTW classifier.

TABLE I. ACCURACY [%] OF DTW ON FENCING FOOTWORK DATASET (PD - PERSON DEPENDENT, PI - PERSON INDEPENDENT)

	DTW	*DTW-feat*
PD	98,18	96,51
PI	56,75	56,15

Table II shows the confusion matrix which has been obtained by DTW for the PD case. The meaning of the acronyms used in the table is as follows: IS - incremental speed lunge, JS - jumping- sliding lunge, R - rapid lunge, W/W - lunge with waiting, SF - step forward, SB - step backward. Sample videos illustrating the considered actions can be downloaded from: http://home.agh.edu.pl/~fmal/spa/. As we can notice, we obtained perfect classification accuracy for step forward and step backward actions, i.e. the actions that differ significantly among themselves, as well as differ with the remaining actions. The results were obtained with five-fold cross-validation.

TABLE II. CONFUSION MATRIX (%), DTW CLASSIFIER, PERSON DEPENDENT (PD)

	R	*IS*	*W/W*	*JS*	*SF*	*SB*
R	**99,1**	-	0,9	-	-	-
IS	1,8	**97,3**	0,9	-	-	-
W/W	0,9	4,4	**94,7**	-	-	-
JS	-	1,8	-	**98,2**	-	-
SF	-	-	-	-	**100**	-
SB	-	-	-	-	-	**100**

B. SVM classification

The classification accuracy obtained by linear SVM is shown in Table III. As we can notice, the classification accuracy that has been obtained for each performer is slightly worse in comparison to classification accuracy obtained by DTW. The classification accuracy obtained by the SVMs on the whole dataset is far better in comparison to accuracy obtained by the DTW. The classification accuracy on this challenging dataset that was obtained by SVMs with the proposed set of features is very promising. The results were achieved using linear SVM with C set to 1 and SVM-RBF with $C = 100$ and $\gamma = 0.01$.

TABLE III. ACCURACY [%] OF SVM-LINEAR ON FENCING FOOTWORK DATASET (PD - PERSON DEPENDENT, PI - PERSON INDEPENDENT)

	SVM linear	*SVM-RBF*
PD	93,88	94,21
PI	70,71	70,71

Table IV shows the confusion matrix which has been obtained by linear SVM on the fencing footwork dataset. As we can notice very good classification accuracy has been obtained for step forward (SF) and step backward (SB). The classification accuracies are slightly worse in comparison to DTW accuracies obtained for the performers and then averaged over persons. The smallest accuracy has been obtained for incremental speed lunge (IS) action. As we already mentioned, this action is not easily distinguishable from the rapid lunge (R), lunge with waiting (W/W) and jumping-sliding lunge (JS) actions, and even fencing experts sometimes have troubles with the correct classification of these actions.

By comparing the results presented in tables I-II and III-IV one can conclude that the SVMs built on the proposed set of features have better generalization capability in comparison to DTW. Moreover, the SVM-based classifiers have far smaller computational requirements. In time series classification, the combination of 1-Nearest-Neighbor classifier with the DTW has been proven exceptionally hard to beat [19]. However, as the experimental results demonstrated, the SVM built on properly selected and normalized features can be competitive with DTW both in terms of accuracy and processing speed. Proper modeling of motion patterns with relationship to time is the most important issue in obtaining high classification accuracy. In this work we achieved this by extracting the informative features on several overlapping segments. The resulting segment-based SVM for time-series showed better classification accuracy and generalization performance over single DTW on the challenging fencing footwork dataset. Despite their simplicity, segment-level-based representation of motion patterns and the resulting segment-based SVM are powerful.

TABLE IV. CONFUSION MATRIX (%), SVM LINEAR CLASSIFIER, PERSON INDEPENDENT (PI)

	R	*IS*	*W/W*	*JS*	*SF*	*SB*
R	**75**	7,4	-	17,6	-	-
IS	17,1	**46**	9	27,9	-	-
W/W	-	19,2	**59,7**	21,1	-	-
JS	15,6	23,8	10,1	**50,5**	-	-
SF	0,9	0,9	-	-	**98,2**	-
SB	1,9	-	-	-	1,8	**96,3**

Table V illustrates confusion matrices for PD and PI, which were obtained by the linear SVM. The symbol *L* stands for lunge and it represents actions denoted by *R*, *IS*, *W/W* and *JS*. As we can observe, in the case of different actions, i.e. a scenario that is typically considered in work devoted to accelerometer-based activity recognition, the proposed method achieves promising results. For instance, UCI HAR Dataset contains data for walking, walking upstairs, walking downstairs, sitting, standing, laying, which were recorded at a constant rate of 50 Hz by a smartphone (Samsung Galaxy S II). It is worth noting that our dataset was recorded at 256 Hz, and this in turn allowed us examine several advanced digital signal processing techniques.

TABLE V. CONFUSION MATRIX, SINGLE CLASS FOR ALL LUNGE (L) ACTIONS, ACC FEATURES, SVM CLASSIFIER, PD (LEFT), PI (RIGHT)

	L	***SF***	***SB***
L	**1**	-	-
SF	-	**0,99**	0,01
SB	-	-	**1**

L	***SF***	***SB***
1	-	-
0,02	**0,98**	-
0,04	-	**0,96**

The results presented above were obtained on the features, which were selected from a larger pool of features and gave the best results. We considered several feature set, which were chosen both manually as well as using AdaBoost. The feature pool included features described in Section III A. For instance, for the wavelet features we obtained accuracy for the PD and PI cases equal to 92,07% and 69,35%, respectively, cf. results in Table III.

The data processing has been done in MATLAB. The classification has been realized using WEKA. We utilized own implementation of DTW as well as AdaBoost for feature selection.

V. CONCLUSIONS

In this work we proposed an effective method for recognition of fencing footwork using a single body-worn accelerometer. We recorded a challenging dataset and as far as we know, this is the first dataset for fencing footwork recognition. Moreover, this dataset differs from other accelerometer-based activity recognition databases as it contains highly dynamic and similar actions. We proposed a segment-based SVM for time-series classification together with a set of informative features. We demonstrated experimentally that the proposed method is competitive with 1-NN DTW in terms of classification accuracy, which is state-of-the-art method for time-series classification. The proposed method demonstrated its effectiveness by achieving the classification accuracy slightly better than 70% on the fencing footwork dataset consisting of six actions, done by ten performers and repeated ten times. Regarding the complexity of the actions the results that were achieved in this work are very promising. As future work we will investigate new spatio-temporal features. Another direction that will be explored is developing mechanisms for DTW to provide better generalization among different realizations of the same action.

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