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6 authors, including:

Claudio Crema
Università degli Studi di Brescia

Alessandro Depari
Università degli Studi di Brescia

Alessandra Flammini
Università degli Studi di Brescia

Emiliano Sisinni
Università degli Studi di Brescia

IMU-based Solution for Automatic Detection and Classification of Exercises in the Fitness Scenario

C. Crema, A. Depari, A. Flammini, E. Sisinni
Dept. of Information Engineering
University of Brescia
Brescia, Italy
{claudio.crema, alessandro.depari, alessandra.flammini, emiliano.sisinni}@unibs.it

T. Haslwanter, S. Salzmann
Dept. of Medical Engineering,
University of Applied Sciences Upper Austria
Linz, Austria
{thomas.haslwanter, stefan.salzmann}@fh-linz.at

***Abstract*— Causal relationship between physical activity and prevention of several diseases has been known for some time. Recently, attempts to quantify dose-response relationship between physical activity and health show that automatic tracking and quantification of the exercise efforts not only help in motivating people but improve health conditions as well. However, no commercial devices are available for weight training and calisthenics. This work tries to overcome this limit, exploiting machine learning technique (particularly Linear Discriminant Analysis, LDA) for analyzing data coming from wearable inertial measurement units, (IMUs) and classifying/counting such exercises. Computational requirements are compatible with embedded implementation and reported results confirm the feasibility of the proposed approach, offering an average accuracy in the detection of exercises on the order of 85%.**

Keywords*— *machine learning, data classification, IMU, wearables, mHealth.

I. Introduction and Motivation

Physical activity increases the wellness of an individual. This simple fact, which is instinctively recognized as true by every person who has practiced sport, is supported by a large amount of studies [1]. Recently, the focus has moved to quantify the dose-response relationship between physical activity and health. Results show that 150 minutes of moderate-intensity aerobic activity per week (or 75 minutes of vigorous-intensity aerobic activity) are associated with a 20-30% reduction in the risk of several diseases [2]. Regarding weight training, research shows that adults can benefit from performing activities that maintain or increase muscular strength and endurance for a minimum of two days each week; it is recommended that 8-10 exercises are performed on two or more nonconsecutive days using the major muscle groups [3]. The positive relationship between physical activity and mental health has been investigated as well [4] [5].

Despite several guidelines, promoted by governmental institutions [3], physical activity is not sufficiently carried out [6]. A survey in EU countries showed that only 31% of respondents reported sufficient physical activity [7]. One of the crucial points is related to elderly people, since they would benefit more from physical activity, but they often believe to be too old or too frail to practice it. Besides, exercise is rarely viewed as a necessary prescription medicine, and the elderly often perceive the symptoms associated with exercise (like sweating and muscle soreness) as a negative thing [8].

However, further studies have shown that one of the most efficient ways to get patients motivated is an automatic tracking and quantification of the exercise efforts. For instance, Bravata et al. [9] showed that the use of a pedometer (i.e., step counter) is associated with significant increase in physical activity, (about 2000 steps or about 2 km of walking per day).This work found that setting a step goal and the use of a step diary may be key motivational factors for increasing physical activity and improving health condition.

The industry of electronics has already recognized this opportunity; several tracking devices as well as Apps for smartphones are available on the market. However, this landscape of devices misses two major categories of fitness activities: weight training and calisthenics (strength-training exercises that do not necessarily involve weights, such as sit-ups, pushups, etc). Therefore, a device able to track and automatically analyze this kind of exercises, for example checking for correctness of execution and counting the number of repetitions, could have a big impact on the market, for sport and for physiotherapy applications. The proposed paper explores the possibility of using machine learning techniques, and in particular Linear Discriminant Analysis (LDA), applied to data coming from wearable Inertial Measurement Units (IMUs) for strength-training exercise recognition. Preliminary experimental results of an LDA architecture trained with data coming from a single 6-axis wrist-worn IMU have confirmed the feasibility of automatic classification of weight exercises.

The paper is structured as follows: in the next section an overview of related studies is reported. In section III a resume of some machine learning techniques is provided. Section IV details the proposed approach, and experimental results are discussed

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in section V. Finally some conclusions are drawn.

II. State of Art and Related Studies

In this section, an overview of studies about automatic data discrimination applied to sport science is presented, followed by a discussion of commercially available devices.

A. Automatic classification for sport science

Powerful, low-cost embedded mobile systems have become more and more important in the field of rehabilitation and sports science. Small and lightweight wearables allow to collect data about patients/athletes in a realistic environment for further analysis and classification.

As an example, a smart shoe equipped with an IMU and a classification system able to discriminate between different surfaces (grass, street and trail) and inclinations (uphill, flat and downhill) with a mean classification rate of 85.3 % and 81.2 %, respectively is presented in [10]. The same research group presented in [11] a multi-nodal sensor system (based on accelerometers and gyroscopes) for the classification of treadmill and bicycle exercises. Features extracted from these data are classified by means of a Support Vector Machine (SVM) with a linear classifier. The classifier has an accuracy of 98% when detecting the type of activity (treadmill vs bicycle), but it drops to 61% when it determines the intensity of the bicycle exercise.

Muehlbauer et al. [12] present a work for the automatic identification of exercises that divides the problem into 3 stages: (1) segmenting exercise periods from non-exercise, (2) recognizing which exercise is being performed, and (3) counting repetitions. Accelerometers and, when available, gyroscopes data are recorded by means of a smartphone, worn at the upper part of the arm; autocorrelation features are extracted from them and later classified with a SVM. This work achieves 85% segmentation accuracy and 94% recognition accuracy using subject-independent training.

In [13], authors implement the RecoFit algorithm, an improved version of the algorithm proposed in [12]. The algorithm is based on a SVM classifier that works on autocorrelation features extracted from data recorded by 3-axial accelerometer and gyroscope, recorded by a wearable device worn by the user at his wrist. Recofit introduces dimensionality reduction to allow orientation-invariant analysis. Cross-validation results have been obtained using data of 114 participants, achieving accuracy of 95% and 98% in segmentation and recognition respectively, with an accuracy in counting repetitions 93%.

In myHealthAssistant [14] two accelerometers are used to identify the activity performed by the user; auxiliary sensors are employed to recognize gym exercises, by means of a Bayesian classifier trained on the mean and variance of each accelerometer axis. A smartphone is used as a data aggregator. An accuracy of 92% is achieved for a set of 13 exercises with subject-specific training.

B. Commercial devices

In the last years, several tools for supporting athletes have been proposed on the market. Most of them are smartphone Apps to be coupled with wearable devices to use while performing physical activities. One of the best known is the Runtastic App (www.runtastic.com), available for most smartphones. Recently, a few devices tailored for muscle-strengthen exercises have appeared on the market. Typically, such systems are able to recognize the type of activity performed (steps done, active and sedentary time, stairs walked…) and to estimate the user's heart rate. Just to mention some, consider Jabra Sport Coach (www.jabra.com), TomTom Spark Cardio (www.tomtom.com), Fitbit Charge (www.fitbit.com), and Gymwatch (web.gymwatch.com). Beast (www.thisisbeast.com) adds the possibility of estimating the athlete's strength, whereas a more complete device, able to identify the type of exercise as well, is Atlas Wristband (www.atlaswearables.com).

All the aforementioned solutions take advantage of one or more wearable IMUs to acquire information about the user's movements and a local or remote processing unit for data elaboration and activity/exercise detection. Data visualization/storing and user interactions are usually offered by means of display or coupled smartphone, running a specific user App. It has to be highlighted that such commercial devices cannot be considered references for the present paper due to different capabilities and/or unknown performance.

III. Machine learning techniques

Several methods for data reduction and discrimination have been proposed in the last decades [15]; a brief description of the most used is presented below.

Principal Component Analysis (PCA) is a statistical unsupervised approach, used to project features from a high-dimensional space to a new low-dimensional one, defined by orthogonal principal components (PCs), while retaining the majority of the information held in the original data. The goal of PCA is to maximize the variance between data without considering class separation. High dimensional data can pose problems for machine learning, as predictive models based on such data could lead to overfitting; furthermore, many of the attributes may be redundant or highly correlated, which can also lead to a degradation of prediction accuracy.

Euclidean Distance to centroids (EDC) is a very intuitive supervised classification method. The mean of each class is calculated (the so-called centroids) over all samples; no other information apart from this is used. This method assumes that the distribution of samples around the centroid is symmetrical and similar for each class. The Euclidean distance for each sample to be classified is then calculated, and it is assigned to the class with the lowest distance.

Linear Discriminant Analysis (LDA) method is similar to EDC, but it takes into account the so-called covariance matrix of the different classes; by doing this, the distance between a test sample and a given class centroid is weighted according to the overall variance of each class. This method is valid only if the classes have similar variance-covariance matrices; otherwise, the covariance matrix will be inaccurate.

Quadratic Discriminant analysis (QDA) is similar to LDA, with the difference that QDA does not assume that the classes have similar variance-covariance matrices, making it more suitable than LDA when the classes have very different variance structures. The boundary produced by QDA is quadratic, which may consist of two separate sections of boundary lines, making this method more flexible in some specific situations.

Support Vector Machine (SVM) method can create a complex decision boundary between classes. The classification rule is determined by only a small number of training sets, called Support Vectors, which lie near to the decision boundary. Hard margin SVMs assume that two classes are perfectly separable, and aim to find the optimal boundary that separates them, with the maximum possible margin. Soft margin SVMs tolerate a degree of misclassification and are designed to balance the classification error with the complexity of the model.

IV. The Proposed Approach

The basic idea of the proposed solution is shown in Fig. 1. One or more wearable IMUs take care of acquiring the user's movements while performing exercises and communicate, for example through the broadly-used Bluetooth connection [16], with a processing unit for data evaluation. Following the recent trends in personal systems for medical and sport/fitness support, the latter could be implemented with a smart device, such as a smartphone, tablet and even a smartwatch. Indeed, the term mHealth was coined to address the use of smart devices for supporting healthcare [17], [18]. Interesting to notice, it is possible to exploit the embedded accelerometers of such smart devices as the IMU for data acquisition, thus simplifying the system architecture. Following such a paradigm, it is evident that data elaboration implemented by the processing unit should have a complexity compatible with the computational resources available in the employed smart device. Despite the use of cloud-based architecture could overcome this limit, it has not been considered here since we wanted our solution to be able to operate even without an Internet connection.

Fig. 1. System architecture: the wearable IMU device is connected to a smart device by means of a Bluetooth connection.

The proposed algorithm is based on the work presented by Morris et al. [13], where a combination of PCA and SVM method to classify data is employed. In this work, data classification is performed by combining PCA and supervised LDA; LDA has been chosen instead of SVM because it is mathematically simpler, thus less demanding in terms of computational time and resources. PCA and LDA must be first trained by using a large set of training data, acquired when the users are performing well-known exercises. In our work, the machine training is carried out by using data of all subjects but one; then, this excluded data-set is classified with the trained machine, and the performance evaluated. This procedure is called leave-one-out, a common technique for data cross-validation. Such a process is usually a one-time operation and it is complex, long-lasting and requires a considerable amount of computational resources; for those reasons, usually it is performed by an ancillary PC.

More specifically, the proposed system adopts a single wrist-worn wearable IMU and it is trained to detect whether a user is performing a specific group of target exercises (segmentation), to classify which exercise is being performed (classification) as well as the number of repetitions of that exercise being performed by the user (exercise counting).

In the following subsections, details concerning the adopted IMU and the processing algorithm are given.

A. The employed IMU device

The IMU used in this work is a commercial device, called x-IMU, manufactured by x-IO technologies (http://x-io.co.uk). The device is relatively small (57x38x21 mm, 49 g with plastic housing and battery), and can be easily worn at the wrist by means of a Velcro band. The small size and weight as well as the application modality assure a minimal if any interference with the normal execution of the workout. It incorporates several sensors: a tri-axial accelerometer with a resolution of 12 bit, a tri-axial gyroscope (temperature compensated) with a resolution of 16 bit, a tri-axial magnetometer with a resolution of 12 bit, all of them factory calibrated and sampled with a tunable sampling frequency, up to 512 Hz. It is equipped with a Bluetooth module, and it has an internal micro SD card for data storage. During the performed experimental tests, data were stored on the SD card and offline transferred to the processing PC. To assure that all data from different users and sessions are consistent the x-IMU was always worn on the right wrist and with a fixed orientation (visible in Fig. 2):

- when stretching the arm forward, the x-axis points in walking direction;
- the y-axis points to left side;
- the z-axis points upwards and indicates gravity.

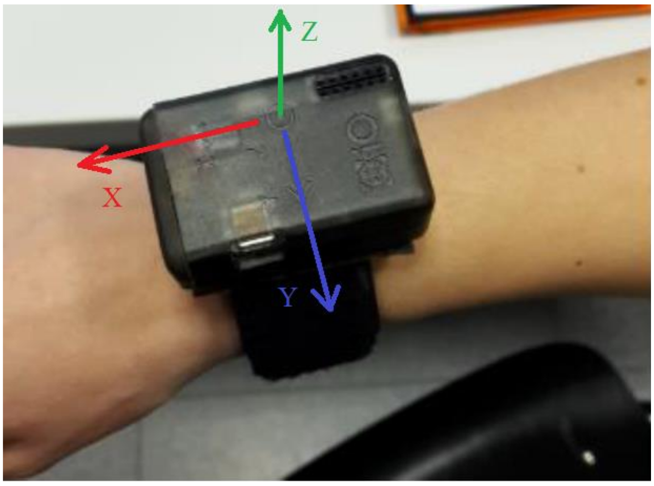

Fig. 2. The x-IMU device worn on a wrist.

B. The Detection and Classification Algorithm

Both LDA and PCA are linear transformation methods. PCA projects the entire dataset onto a different feature (sub)space, and LDA tries to determine a suitable feature (sub)space in order to distinguish between patterns that belong to different classes. As a result, the PCA reduces the number of initial features on which the LDA will have to work on, thus lowering the computational load of the classification.

At the current stage, the algorithm is written and tested in MATLAB, since embedded implementation is beyond the scope of this paper. Such an algorithm uses data from accelerometer and gyroscope; magnetometer data are not employed for this analysis. The segmentation (the block scheme of which is shown in Fig. 3), classification and counting stages are discussed hereinafter.

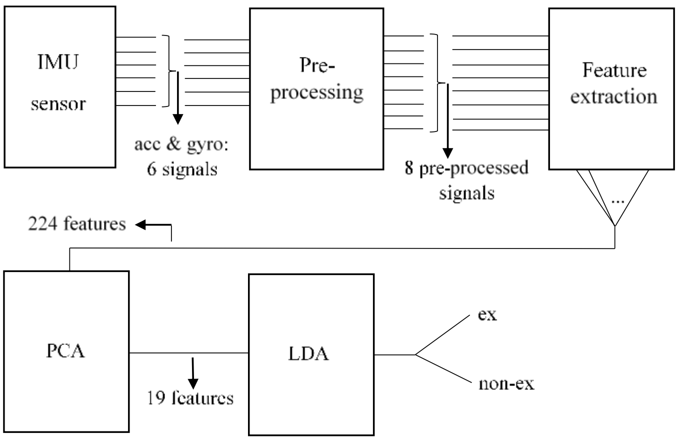

Fig. 3. Block scheme of the Segmenter stage. The Classifier follows a similar approach.

Segmentation stage

The Segmenter is essentially a binary state machine that can distinguish exercise (*ex*, from now on) from non-exercise (*non-ex* from now on). An example of raw accelerometer and gyroscope data can be seen in Fig. 4.

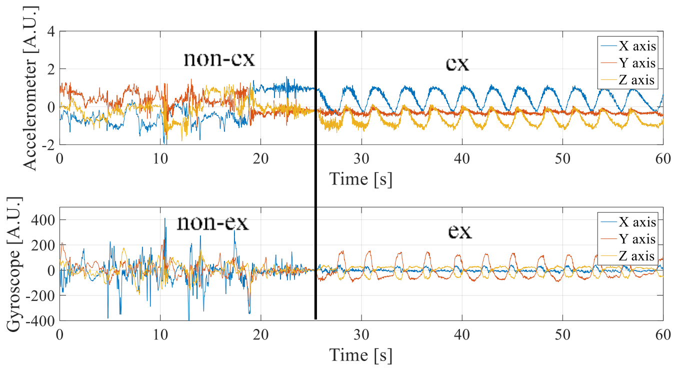

Fig. 4. Raw accelerometer (upper part) and gyroscope (lower part) data; in the left part, data relative to non-ex, in the right part data relative to ex.

The good functioning of the Segmenter is essential, because subsequent stages do not operate during *non-ex* periods, and affects the overall system performance.

The first step of the Segmenter is the preprocessing: accelerometer and gyroscope data are smoothed with a low-pass filter, then windowed into 5 s windows sliding at 200 ms (i.e., each window shares 4.8 s of data with the previous one). For each window, 8 one-dimensional signals are computed: *aX*, the x-axis accelerometer signal; *aXmag*, the acceleration magnitude; *aPC1*, the projection of the three accelerometers signals onto its first PC; *aYZPC1* the projection of the y and z accelerometer signals onto the first. The aforementioned signals are calculated for the gyroscope data as well (*gX*, *gXmag*, *gPC1*, *gYZPC1*).

Subsequently, autocorrelation and statistical features are computed for each signal. In particular, the number of autocorrelation peaks (including prominent and weak), the autocorrelation maximum, and the height of the first autocorrelation peak after a zero-crossing are extracted. The statistical features are the following: RMS (faster motion is more likely to correspond to *ex* than *non-ex*), power bands (10 bands spaced linearly from 0.1-25 Hz, 10 features), mean, standard deviation and variance (3 features), and integrated RMS. After this, to improve the precision of the Segmenter, the RMS, mean, standard deviation and variance are computed for every first half and second half of each window. A total of 28 features for each pre-processed signal are obtained, leading to 8*28 = 224 features for each observation window. Interesting to note, during the supervised labeling, the *ex* and *non-ex* phases have to last more than 75% of the observation window (as indicated in Fig. 5).

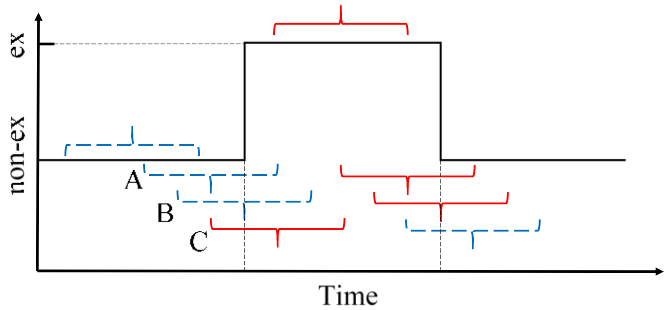

Fig. 5. Dashed windows are marked as non-ex, while the solid line are for ex. Window A and B are marked as non-ex; window C is marked as ex. A similar situation appears when changing from ex to non-ex.

Before the LDA procedure, the number of features is reduced by means of the PCA. The optimal number of the PCs is a parameter that is empirically determined; a tradeoff among computational complexity and system performance led to the choice of the first 19 PCs. The last step of the Segmenter is the aggregator, which tries to detect and filter out “glitches” in *ex* and *non-ex* classification using a time threshold.

Classification Stage

After the Segmenter processing, *ex* windows are marked according to a set of possible exercises by the Classifier. Processing is the same as for the Segmenter: for every 5 s window, the three derived signals *aX*, *aYZPC1*, *gPC1* are reused. For each signal, 20 features are calculated: five autocorrelation bins, RMS, ten power bands, mean, standard deviation, kurtosis, and interquartile range. Once again, features are reduced by a PCA to (this time) 20, then used by the actual LDA classifier. The last step of the Classifier is the majority voter logic, the aim of which is to univocally assign the exercise type to each observation window.

Counting stage

The Counter assumes that the segmentation and classification stages have been already performed. Another PCA is carried out: the three accelerometer signals are projected along the PC and the expected repetition period, estimated with the lag of the autocorrelation maximum, is used to reject PC peaks that do not correspond to actual repetitions (too close or too far).

V. EXPERIMENTAL RESULTS

Test data have been collected from a group of 7 volunteer, 5 males and 2 females, aged 22-37, from amateur to expert in weightlifting. They performed a circuit of nine exercises (squats, deadlifts, rowing, bench press, shoulder press, biceps curls, french press, lateral raise, and lateral raise bent forward) while wearing the x-IMU (Fig. 6). The volunteers kept a diary where they annotated the timing of the exercises, in order to help the labeling phase, as well as every unusual fact during the training. An important thing is that, between two sets of exercises, the subjects had to act as normal as possible, to create a dataset with the highest possible data variability.

Fig. 6. One volunteer performing an exercise while wearing the x-IMU.

The number of correctly and wrongly detected/classified events lead to the computation of true positives/negatives, *TN*, and *TP*, and of false positives/negatives, *FN* and *FP*, from which precision, accuracy and recall are evaluated [19]. A pictorial description for the Segmenter is visible in Fig. 7.

The single stages (Segmenter, Classifier and Counter) have been analyzed separately. The following results are obtained by using a single-user dataset, since, as previously mentioned, a leave-one-out logic has been adopted for the machine training. Validation results related to the Segmenter are shown in TABLE I. The dataset has been grouped into exercises, to have a better evaluation of the capability of the Segmenter of distinguishing *ex* from *non-ex*. The last row measures the three statistical parameters on the complete dataset.

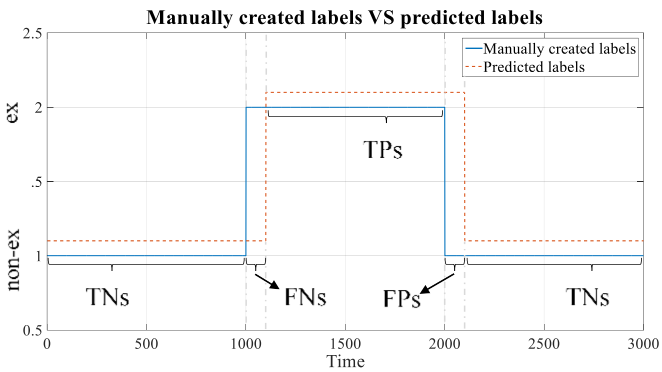

Fig. 7. Results of the Segmenter applied to an experimental dataset (dashed line) overlayed to original labels (solid line).

TABLE I PERFORMANCE OF THE SEGMENTER STAGE.

Exercise	*Precision [%]*	*Recall [%]*	*Accuracy [%]*
#1 (Squats)	90.03	100	98.16
#2 (Deadlifts)	93.29	99.09	98.79
#3 (Rowing)	87.50	100	98.13
#4 (Bench Press)	75.28	100	96.32
#5 (Shoulder Press)	57.55	99.29	91.15
#6 (Biceps Curls)	98.38	94.06	98.68
#7 (French Press)	96.26	95.71	98.39
#8 (Lateral Raise)	100	81.46	96.37
#9 (Lateral Raise, bent forward)	80.04	93.52	92.79
TOTAL	**74.49**	**95.51**	**94.36**

It is clear that the precision of the Segmenter is worse than recall and accuracy. This means that a high number of *FP*s are produced by the Segmenter, thus a significant amount of *non-ex* windows are recognized as *ex*. This is due to the fact that subjects perform stretching between different sets of exercises, and the repetitive nature of such an activity leads the Segmenter to consider the related data as an exercise. This problem could be solved by considering stretching as another class of exercises. Conversely, the overall accuracy of the Segmenter is good, reaching values higher than 90%.

To evaluate the Classifier performance, it is necessary to compare the manually create labels, related to specific exercises, with the predicted ones. The workouts are labeled as increasing numbers, going from 1 to the number of exercises, i.e., 9. It should be noticed that the Classifier is processed only on data predicted as *ex* by the Segmenter, thus reducing the dataset on which evaluating the Classifier performance. Moreover, that fact implies that performance evaluation is related only to the Classifier and not to the sequence Segmenter+Classifier. The confusion matrix related to the Classifier is reported in TABLE II. The same dataset used to evaluate Segmenter's performance has been used, once again grouping the data into exercises; for the sake of readability, exercise name has been replaced by a numerical label, as in TABLE I. Results show that the Classifier performance presents a great variability, going from 100% precision for #6 and 100% recall for #1 and #7 to 36% recall for #8. This could be due to the combination of the non-correctness of execution performed by some subjects, and the relatively small number of examined workouts. In order for the Classifier to work in a proper way, analyzed data should present the largest "statistical variance" possible. Interesting to notice, the exercise with the lowest recall (i.e., #8) is the "lateral raise"; the Classifier labels most of the windows as "lateral raise, bent forward" (i.e., #9), very similar to #8. Hence, the low recall could be due to the incapacity of distinguishing between those exercises with very similar execution.

TABLE II CONFUSION MATRIX RELATED TO CLASSIFIER STAGE

		Predicted Class								
	Exercise	***#1***	***#2***	***#3***	***#4***	***#5***	***#6***	***#7***	***#8***	***#9***
Actual Class	***#1***	**659**	0	0	0	0	0	0	0	0
	#2	0	**636**	23	0	0	0	0	0	0
	#3	0	158	**318**	0	0	0	0	0	0
	#4	2	0	0	**392**	142	0	0	0	0
	#5	32	0	0	38	**494**	0	0	0	0
	#6	0	0	0	0	0	**380**	7	0	0
	#7	0	0	0	0	0	0	**350**	0	0
	#8	0	0	0	0	0	0	0	**118**	209
	#9	0	0	0	0	0	0	0	17	**368**

Finally, to evaluate the performance of the Counter, it is sufficient to compare the number of actual repetitions with the number of predicted repetitions. Preliminary tests show that the Counter achieves performance that goes from 100% accuracy, to a 30% error in the worst case. It should be highlighted that the Counter algorithm is still in a preliminary phase and the counting algorithm is quite simple and prone to errors; thus these results can be anyway considered promising.

CONCLUSIONS

In this work, an IMU-based system for the detection of exercises in the fitness scenario has been proposed. The presented architecture adopts machine learning techniques to process data from a wearable device hosting a 6-axis IMU and provides indication related to the class of performed exercises and number of repetitions. The system has been trained and validated by using a set of exercises of weightlifting performed by several volunteers with different skill. Experimental results agree with the recent research work in similar fields, reaching an average accuracy in the exercise detection around 85%. Algorithm optimization to improve exercise-counting performance and to reduce computational effort and thus allowing a possible embedded implementation is currently under investigation.

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