Designing Smart Training Gloves

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Abstract
Fitness activity trackers have traditionally provided low-level insights on aerobic activity, calorie consumption and heart rate. Recent developments in data science have allowed context-specific activities to be recognised, such as strength training. In this work we specifically look at the quality of performed training exercises: recognizing correct execution and providing actionable feedback to users. We illustrate our approach on three example exercises known as the bicep curl, lateral raise and arnold press. Our results show the opportunity of designing training devices that offer instantaneous feedback by implementing multi-class classification.

Authors Keywords
Machine-learning; classification; exercise; accelerometer.

Introduction
Regular exercise and physical activity yield great health benefits: it can help control weight [1], combat health problems and diseases [2,3], attribute to a better mental well-being [4, 5, 6] and even improve academic performance [7].

While a healthy physical activity can be attained with just 30 minutes of moderate-intensity activity for 5 days a week [1], less than 5% of the adult population actually meet these requirements [9]. A longitudinal study conducted in Portugal[10] suggests that physical activities for all age groups has significantly declined from 2002 to 2010.

Studies in the past have shown that using wearable fitness trackers such as pedometers help motivate people to increase their physical activity [11,12]. However, recent studies suggest that they can also have an adversarial effect [13,14]. If the goals set by the trackers are unrealistic, or if the feedback mechanism is not responsive enough, they can be experienced as demotivating.

A popular way of reaching a healthy lifestyle is strength training [15]: it is shown to enhance cardiovascular health, physical performance and cognitive abilities [16]. For those that are new to strength training, it can be difficult to perform the exercises properly. Usually, proper form is taught by personal trainers or more experienced gym-goers, meaning that those independently trying to improve their physical well-being get demotivated. When training exercises are done improperly, not only do the health benefits quickly disappear, they can cause severe injuries.

Related work

Wearable training trackers have had an immense rise in popularity over the past decades. A well-known device is the FitBit Tracker: a wireless, wearable device that keeps track of personal fitness data. Its functionality is basic: it can track metrics including walking activity, heart rate and sleep patterns to distill insights about the user’s fitness levels.

Apple Watch is a similar player in the field of training wearables. This wrist-worn device is equipped with sensors including a heart rate sensor, inertial sensors and a myriad of other sensors that facilitate tracking of fitness. Apple Watch has hugely innovated in the area of providing users with motivation — the introduction of personalized milestones and challenges actively help users stay active.

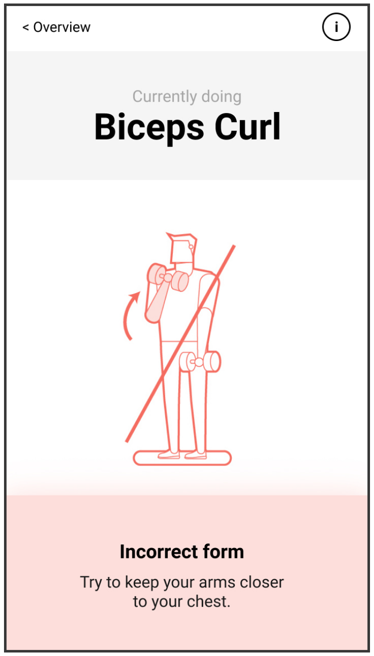
The aforementioned examples are only able to detect basic fitness activity among their users, and generally do not perform well outside of aerobic exercises. With the mainstream rise in prevalence of machine learning, more advanced fitness trackers are being developed. This new generation of devices is able to access and analyze much larger data streams, offering insights past basic statistics on movement and heart activity.

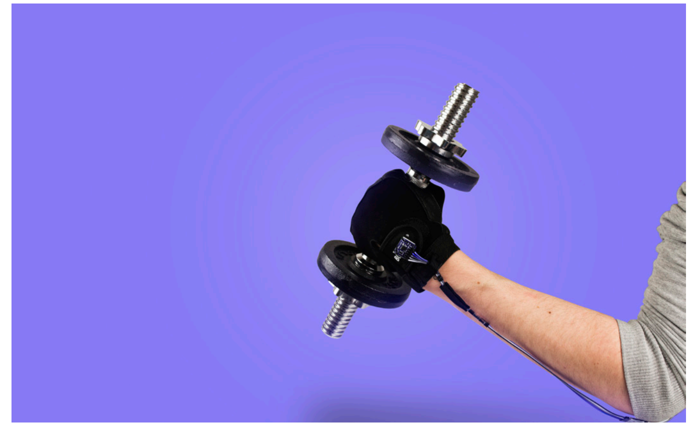
RecoFit[17] is an arm-worn device that automatically tracks repetitive exercises. Equipped with inertial sensors, this wearable is able to identify weight training and calisthenic exercise sets with high precision. They detect gym exercises based on segments of 5 second time intervals. Sensor data from the 3-axis accelerometer and 3-axis gyroscope first are recognised as exercises, then processed to keep track of the training exercises.

Cyclops[18] is a wearable fitness tracker based on computer vision. The single-piece fisheye lens is to be mounted on the user’s chest, where it identifies the user’s limbs and synthesises the body posture. The approach taken in this study is novel: instead of multiple motion sensors and external cameras, only one central camera is needed.

Garcia et al.[19] present a machine learning evaluator of form using the Microsoft Kinect motion sensor, able to offer instantaneous feedback to end-users on elaborate details of training exercises. This work focuses mainly on joint-based exercises such as squats and push-ups.

The outlined examples showcase the possibilities in single-sensor exercise recognition, but are limited in their feedback mechanisms. In order to provide true value to users, a rich feedback system needs to be integrated. This is why we aim to include it in our proposed solution.





Our promise

Based on the previously outlined societal developments it is clear that there is a great opportunity to stimulate more active and healthy lifestyles with a new generation of wearable training devices in combination with machine learning algorithms.

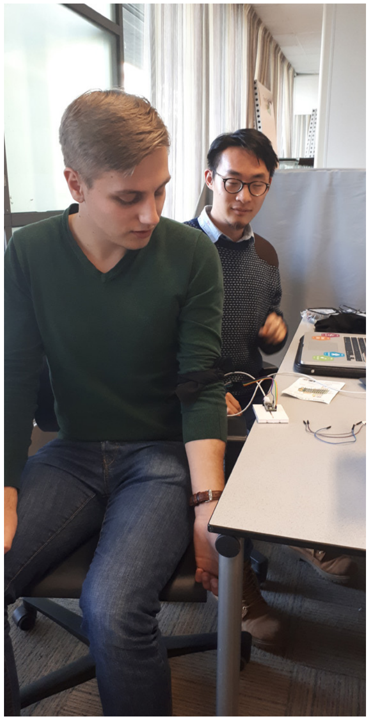
We aim to enhance the quality and efficiency of an active and healthy lifestyle. In order to achieve this goal, a smart and easy-to-use training glove was developed, it assesses people's form when they perform training exercises. During strength training exercises it is of the utmost importance to perform them in good form. If done improperly there is a serious risk for injuries to occur, and a vastly reduced effectiveness of exercises.

Our solution

Our Smart Training Gloves can provide users with assistance without invasive sensors or difficult set-up procedures. The gloves track movements made during training exercises and provide feedback on how to improve your form during weight lifting training. The sensors that are embedded in the gloves make them easy to put on and use. Training with bad form will be a thing of the past.

The decision to attach a sensor to a glove was made after prototyping it on different objects and locations. The glove provided the most portable and stable results. It is most stable because during exercise clothing can move around a lot. The glove however will always be in the same position and orientation. This helps to increase the accuracy.

Three weight training exercises were selected for their diversity and versatility to showcase the possibilities of the product. If exercises are done incorrectly, the system picks up on the specific issue and displays strong visual feedback to improve the user's form. When exercises are done correctly the workout schedule will advance.



Users are always kept up to date with the current exercise, upcoming exercise and the remaining amount of repetitions. This will guide the users to a healthy, productive workout.

Method

This study uses a dataset of acceleration data tagged with exercise classes that was generated by the authors. A triaxial accelerometer located near the back of the hand was integrated in a weightlifting glove, allowing it to capture hand- and arm movements during exercises. The triaxial accelerometer (ADXL355) was connected to a microprocessor (Arduino Uno Rev3), and was positioned to not influence natural movements, allowing a similar range of motion compared to not wearing gloves.

The data required to solve the learning problem was acquired after answering three questions. First, the decision was made as to what data was necessary. Next, the source of this data was determined. Finally, a decision was made on how much data was needed so that the model would be accurately trained.

What data is necessary?

The goal of the algorithm is to determine if- and what movements are being performed. To capture these movements in the form of data, accelerations in the X-, Y-, and Z dimensions were analysed to evaluate three dimensional movements. The movements concerned are strength training exercises which can be done with sufficient- and insufficient form. Therefore, all recorded exercises were labelled.

The training exercises were clustered into three groups: Biceps Curl, Lateral Raise and Arnold Press. In each of these groups, two variations were performed: the exercise with good- and with bad form.

Source of the data

The weightlifting glove with the triaxial accelerometer was used to gather the data for the machine learning model. While the prototype was worn, a guided sequence of training exercises were performed. For each exercise, 30 repetitions were performed in good form, followed by 30 repetitions in bad form.

Because of the sudden change in acceleration seen at the start of an exercise, a threshold value could be set that started the sampling of data. After it starts, a fixed time interval of 1800 milliseconds takes place in which acceleration data is recorded. The dataset was created by the researchers because an online dataset was not readily available for implementation. The scale of the project and the algorithm used allowed for self-generated data.

Amount of data necessary

An insight gained from the previous project was that the assumption that five to ten recordings of each training exercise were sufficient for reliable accuracy was false. While the in-sample accuracy was sufficient, a smaller dataset lead to an overfitted model which did performed poorly with new data. Another factor in this was the fact that all training data was generated by one person, which results in a dataset that might be great a great fit for the individual that supplied the data, but unusable for others.

Correspondingly, the amount of recordings per exercise class was increased from 10 to 60 ± 1, resulting in a total data set of 361 samples. Additionally, the data set was made more representative by including samples recorded by different participants.

Problem formulation

The objective of the smart glove system is to provide its users with better insights on their performance when doing fitness exercises. The system needs to provide positive feedback when exercises are being performed correctly, and constructive feedback if an exercise is performed incorrectly.

Essentially: the problem that needs to be solved is the real-time multi-class classification of training exercises performed by users. The system's output is driven by the order in which classes are being detected.

Feature extraction

The aim of feature extraction is to use the initial measured data to create values for classification. Data acquired in this project consists of raw movements captured by an accelerometer. The accelerometer captured data from three different axes each consisting of 180 data points with 10 milliseconds in between each data point. For each axis, the raw data was processed into four features: the arithmetic mean, the minimum value, the maximum value and the standard deviation.

The data was not cleaned nor were outliers removed. This was not necessary since the data was self-generated and did not have any outliers that were not part of the movement. Feature preprocessing was also not used because all data came from the same sensor and each axis had the same minimum and maximum values on a linear scale. For this reason, data centering, scaling or whitening was not required.

Learning algorithm classification

Multiple machine learning algorithms were evaluated to determine the one best suited to this project. The k-Nearest Neighbour algorithm was evaluated which lead to the conclusion that it would not be ideal. The algorithm is prone to overfitting and the fact that it has updatable data has no use in this project. Artificial neural networks (ANN) were also evaluated. Because they allow analyzing and classifying raw data, an ANN would be able to see time-associated patterns. This would make it the most accurate option. However, training an ANN to provide accurate classification requires a lot of data. Estimates for this project came down to at least 6000 samples. This wouldn't be feasible given the scope and time constraints that the project has.

The Support Vector Machine is the algorithm that was chosen. It provides great accuracy, both in-sample as out-of-sample. It also does not require as much data to be reliable compared to an ANN. Less than 500 training samples seemed to be enough for our implementation. Experimentation with the Radial Basis Function was done but impacted the accuracy negatively. As the gamma parameter increased slightly above 0, the accuracy dropped rapidly. This indicates that a linear support vector would be best for classification.

Classification

In this project, a linear support vector machine was used to solve the multi-class classification problem. The library used was the LIBSVM library by C.-C. Chang and C.-J. Lin. This algorithm was used to facilitate supervised learning.

For the scope of this project, three different exercises were specified as the main classes in the model, the exercises being A: Biceps Curl, B: Lateral Raise and C: Arnold Press. Within these main classes, a distinction was

C-value	Accuracy
100000	96.72
10000	98.25
5000	97.60
2000	96.94
1000	98.47
500	98.03
300	97.60
200	97.82
140	96.72
120	96.72
100	96.94
90	97.38
80	97.38
70	97.38
64	97.38
60	97.60
50	96.72
40	97.82
30	96.51
20	**98.03**
10	97.38

made between good- and bad form. For example, B0 meant that the Lateral Raise exercise was done with good form, while B1 meant that the exercise was done with bad form.

The input for the algorithm was the labelled training data gathered by the researchers who did exercises with the physical prototype. For each of the exercise classes—A, B and C—a minimum of two sub-states were recorded—good and bad. Since strength training exercises can be done wrong in numerous ways, the algorithm needs to be able to detect the correct error and provide the user with feedback that is specific to the error.

The result of training the LIBSVM algorithm with the self-generated training data was a classification model, able to make knowledgeable predictions on exercises performed by users. This linear kernel had a total of six classes.

Parameter tuning

A K-Fold Cross Validation was implemented to generate a more robust training model by splitting the data in random samples. In this case, the K-number was set at 5 partitions. This number was kept low as the pool of data points for the training set was small. A higher K-number would yield a low number of sample combinations, limiting the number of truly different iterations.

C value

In the SVM the goal is to search for a hyperplane with the largest minimum margin and a hyperplane that correctly separates as many data points as possible. The C-value is a parameter that decides the balance between these two values.

The Smart Glove uses a C-value set at 20. This value resulted in the highest accuracy while still being as small as possible to prevent overfitting. These accuracy results were gathered using in-sample data.

Evaluation

Both in-sample and out-of-sample data were logged in a confusion matrix and classified as true positive and false positive. In-sample tests resulted in a 98.03% accuracy score. This was based on 361 training samples. Out-of-sample testing with 120 samples resulted in a 100% accuracy score.

The precision, recall and F1-scores were created by using data from a confusion matrix.

	Precision	Recall	F1-score
In-sample	97.231%	97.235%	97.233%
Out-of-sample	100%	100%	100%

The high out-of-sample scores can be explained by the samples consisting of movements that are over-exaggerated and perhaps unrealistic. The out-of-sample data was recorded by the researchers who knew what kind of movements were expected from the algorithm. Doing these, no movements that could be in between classes were tested.

Discussion

This project shows the possibility of integrating machine learning in products designed for qualitative feedback. The benefits of self learning systems became apparent, especially in a societal context, and this was also voiced by peers. The use of a GUI and focussing on the product side was also well received.

However, there are still some drawbacks that need to be taken into account. The amount of exercises for the developed prototype is fairly low, and increasing this with different states might make the model less reliable. These problems could be addressed by changing the feature extraction process. Another drawback is the fixed window of time where the movements are being recorded. Empirical evidence suggests that accurately detecting the start and the end of exercises is difficult, which is why a fixed interval of 1800ms was used. This fixed interval had the unfortunate result of slower movements to not be captured fully, thus skewing the arithmetic mean.

Using a complex sensor that is better suited to recognizing movements could also improve the product. A sensor like the Microsoft Kinect would be able to capture different movements with all body parts, not just the hands.
Feature extraction could also have been handled in a more systematic way. The chosen features consisted of the mean, minimum value, maximum value and the standard deviation of the raw data. However it would have been better if the raw data could be used to extract time-associated patterns from. This would allow to not only know what happened, but also when it happened. Implementing this could improve accuracy drastically.

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