TRACKING OF STRENGTH TRAINING: VALIDATION OF A MOTION-RECOGNITION ALGORITHM AND A PILOT TOWARDS 1RM, MUSCLE LOADING AND FATIGUE INDEX USING A SMARTWATCH APP

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Ubiquitous wrist-worn devices have become a noteworthy research topic in motion recognition of strength training exercises. This study was designed to develop a watchOS and iOS application and assess its exercise recognition and repetition counting accuracy. As a pilot, a method to estimate the 1 repetition maximum and muscle stress and fatigue was explored. To test the exercise recognition and repetition counting accuracy, a workout consisting of nine sets with five randomly ordered resistance training exercises and repetition amounts was conducted when wearing an Apple watch. Overall mean %error in exercise recognition was 3.5% and 0.92% in repetition counting. In the future this app can also be used for estimation of 1 repetition maximum, muscle stress and fatigue.

KEYWORDS: strength training, sensor, app, training control, training supervision.

INTRODUCTION: To ensure a proper workout intensity, a coach or a workout assistant device is needed to avoid overload and promote sufficient load to allow positive adaptation. Different types of workout assistants for planning, tracking, or recognition have been developed to support the workout process (Pernek, Hummel, & Kokol, April 2013). Although the intensity of endurance activities, such as outdoor running or cycling, can easily be calculated by Global Positioning System data, intensity estimation of stationary workouts, such as weight lifting, is rather complex. There are a number of linear transducers available to track the motion of the barbell (Lorenzetti, Lamparter, & Luthy, 2017). In addition, the exercise type and the number of repetitions are of interest.
Counting the number of repetitions and the internal loading conditions on the muscle during the strength training are important (Schellenberg, Taylor, & Lorenzetti, 2017). Recently, wrist-worn smartwatches have become a noteworthy research topic in motion recognition given that the promising computational power of the smartwatches is superior to previous activity trackers. In addition, their user interface is more enhanced and therefore prone to calculate the internal loading condition in real time (Huber, 2017). These advantages should be used in recognition, tracking, and monitoring of complex strength workout exercises. However, although some investigations on smart watches exist to detect exercises and count repetitions, there is still a lack of research related to fatigue and estimation of strength and internal loading conditions.
Therefore, the first objective of this study was to develop a workout analysis application for an Apple Watch and iPhone using a recognition algorithm developed and provided by FocusMotion. The second objective of this study was to determine the exercise recognition and repetition counting accuracy for the Apple Watch. Furthermore, we aimed to establish the ability to estimate 1 repetition maximum, muscle loading and muscle fatigue.

METHODS: To develop iOS and watchOS applications, Xcode (Apple Inc.), an integrated development environment program for macOS, is required (Apple, 2017). Xcode 8 and Swift 3, which are more resilient to errors than Objective-C, were used to program both the watchOS and iOS applications (Apple, 2014). The accelerometer data of the Apple Watch 2 were analyzed using a machine-learning algorithm developed by FocusMotion (www.focusmotion.io).
To test the exercise recognition and repetition counting accuracy, a workout consisting of nine sets with five randomly ordered resistance training exercises and repetitions was conducted with one Apple Watch mounted on the left wrist. Barbell biceps curl, barbell bench

press, barbell back squat, lateral raise and dumbbell biceps curl with twist were considered as frequently used exercises in the daily strength training process and thus selected for this study. Repetition count was defined as five, ten or 15. In repetition counting, %error was calculated for each data point for further descriptive analysis as follows:

$$\%error = \frac{(X_{measured}\text{-}X_{accepted})}{X_{accepted}} * 100\ [\%],$$

where $X_{measured}$ is the measured amount of repetitions, and $X_{accepted}$ is the true repetition count. Further descriptive statistics were performed using SPSS (version 24: SPSS, Inc., Chicago, IL, USA). In analyzing exercise recognition, measured data were defined as recognized or unrecognized, and occurrence was addressed. Here, %error was then calculated using the true occurrence ($X_{accepted}$) and measured occurrence ($X_{measured}$) as described above. Wilcoxon signed-rank tests were used to identify significant differences between analyzed conditions.

To quantify muscular loading, an approach proposed in bone modeling by Carter et al. (Carter, Fyhrie, & Whalen, 1987) was used to estimate daily loading stimulus on a bone. This formula was adapted to a muscle model, where the applied loading stimulus on a particular muscle during a workout can be calculated by the following formula (1):

(1) (2) (3) (4)

$$S \propto \left[\sum_{j=1}^{k} N_j \sigma_j^m\right]^{\frac{1}{m}} \qquad \sigma = \frac{F}{A} \qquad A = \frac{F_{max}}{250'000\frac{N}{m^2}} \qquad \sigma = \frac{F}{F_{max}} * 250'000\frac{N}{m^2},$$

where k is the number of different daily loadings applied to the muscle, N is the number of repetitions per day for each loading condition, σ is the effective stress for each loading condition and m is a constant weighting of the relative importance of stress magnitude and loading cycles, which is defined as 2.4 (Carter et al., 1987). Given that only acceleration data are recorded by the Apple Watch, stress must be calculated indirectly using a formula (2), where F is the current training load and A the corresponding physiological cross-sectional area of the trained muscle. Narici et al. (Narici, Landoni, & Minetti, 1992) demonstrated that at maximum voluntary contraction, the mean stress value is approximately 250 $\frac{kN}{m^2}$ for the quadriceps muscle group. Applying this assumption, the cross-sectional area can be calculated by the formula (3). Thus, the exerted stress of a particular exercise on a muscle can be estimated by formula (4). Here, F is the applied training load, and F_{max} is the current 1RM. Based on the load-velocity relationship, different formulas to indirectly calculate 1RM were previously proposed (García-Ramos, Pestaña-Melero, Pérez-Castilla, Rojas, & Haff, 2017; González-Badillo & Sánchez-Medina, 2010; Sánchez-Medina, González-Badillo, Pérez, & Pallarés, 2014; Sayers, Schlaeppi, Hitz, & Lorenzetti). Although the application can only calculate V_{mean}, formulas using peak bar velocity (V_{peak}), mean propulsive bar velocity (MPV), and mean concentric bar velocity (MCV) were also included.

RESULTS: For exercise recognition, the overall mean %error was -3.49%. The Series 2 Apple Watch exhibited a mean %error of -2.22%. In addition, the %error of exercise recognition according to different exercises is dependent on the amount of repetitions performed. For the repetition counting, the overall amount of recognized repetition (*Mdn* = 10) did not significantly differ from true values (*Mdn* = 10, T = 264, *p* = 1.000, *r = 0.00*). Overall mean %error in repetition counting was 0.92%. Muscle failure was achieved at a loading stimulus of 60 MN/m^2 at both 60% and 80% 1RM.

DISCUSSION: For exercise recognition, the algorithm achieved a low overall mean %error of 3.49%. Other studies testing a single customer grade sensor mounted on the wrist achieved similar results. Cho et al. (Cho & Lee, 2016) reported a mean exercise recognition accuracy of 97.7% analyzing three strength training exercises with Samsung Galaxy Gear. Guo et al. (Guo, Liu, & Chen, 2016) achieved an exercise recognition accuracy of 93% among 12 exercises. A Myo Armband was investigated by Heli Koskimäki et al. (Koskimäki & Siirtola,

2016) to recognize 30 exercises and achieved a mean exercise recognition accuracy of 55.8% exclusively using the built-in accelerometer.

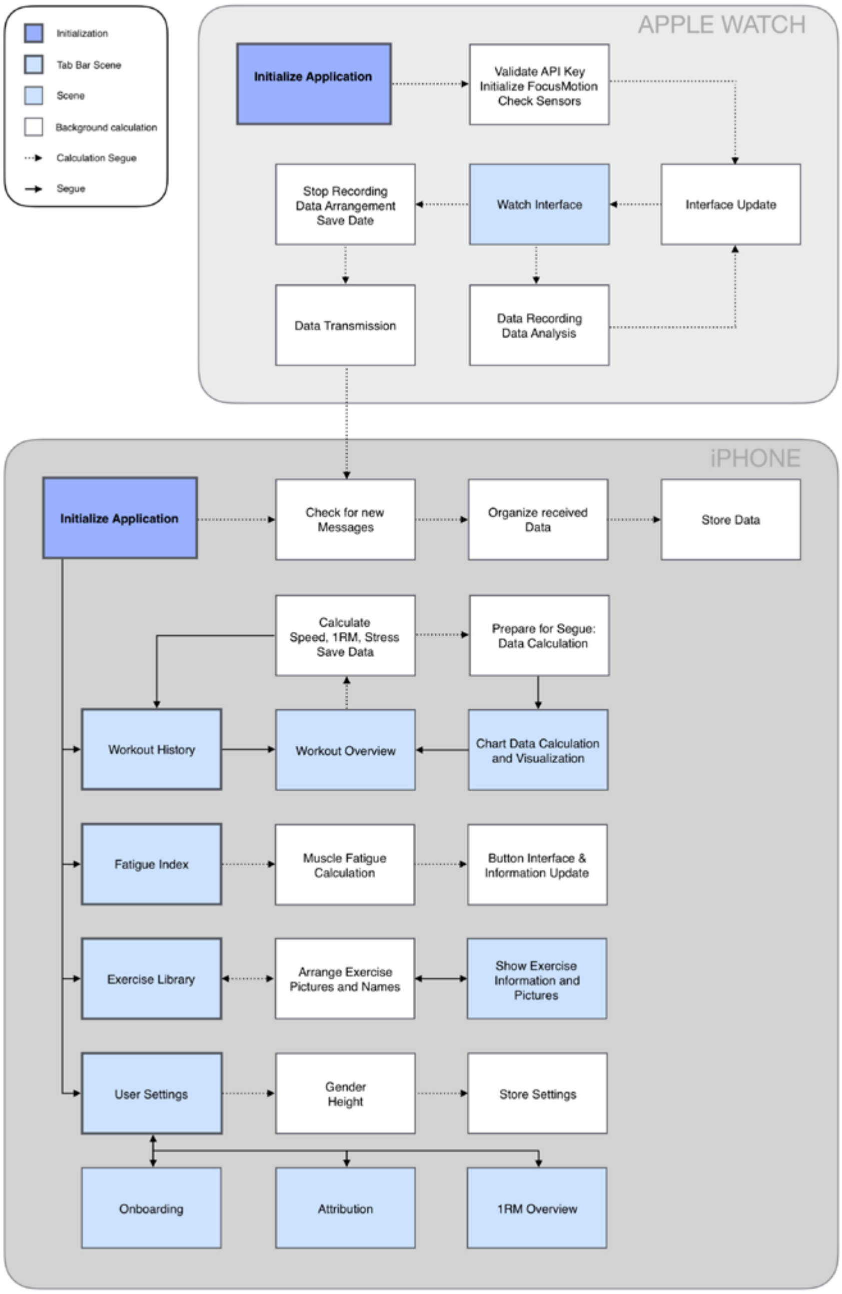

Figure 1: Workflow of the watchOS and iOS application running process presenting all programmed scenes, segues and calculations.

For repetition counting, an extremely low overall mean %error of 0.92% was observed for repetition counting. Similar low repetition miscount rates were achieved by Pernek et al. (Pernek et al., April 2013) (1%) and Shugang et al. (Shugang et al., 2016) (2%).
Although velocity data are indirectly calculated using a fixed weight displacement, both implemented 1RM estimation equations of Sayers et al. (Sayers et al.) provide reliable results for the bench press exercise.
The adapted formula of stress estimation revealed a maximal stress value of approximately $60 * 10^6 \frac{N}{m^2}$ until muscle failure appeared in both 60% and 80% 1RM examinations at the bench press exercise performed by a male strength-trained sports student. This method represents a first step towards muscle fatigue estimation using a formula.

CONCLUSION: The recognition algorithm provided by FocusMotion is fully integrated into watchOS. The designed application exhibited high functionality despite still being in an early development phase and met the Human Interface Guidelines of Apple. The application was accepted by Apple for further beta-testing and distribution using TestFlight. Although accuracy testing was conducted under non-laboratory conditions, the algorithm exhibited high accuracy in exercise recognition among all conditions. Compared with other studies, the overall mean %error in exercise recognition was 3.5%, revealing high accuracy. Even higher accuracy exposed the repetition counting accuracy testing by a mean %error of 0.92%. Considering these results, the implemented algorithm is a precise method to detect exercises and count repetitions with only a smart watch. The implementation of a strength estimation parameter in a watchOS succeeded with promising application in the future.

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