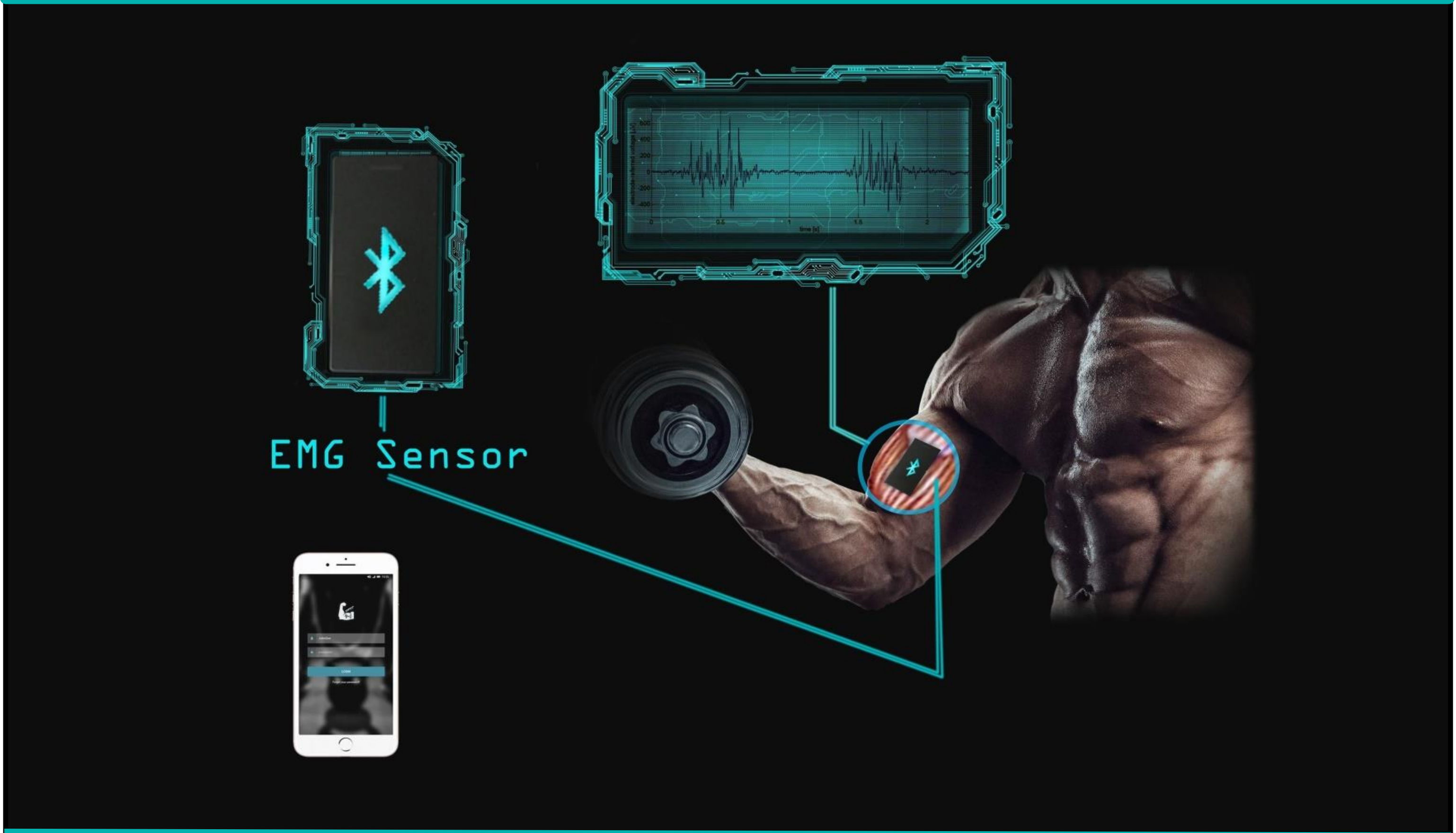
INVESTIGATING THE USE OF EMG BIOFEEDBACK ON EXERCISE SELECTION AND MUSCLE ACTIVATION FOR MOBILE STREGNTH TRAINING APPLICATION



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INVESTIGATING THE USE EMG BIOFEEDBACK ON EXERCISE SELECTION AND MUSCLE ACTIVATION FOR MOBILE STRENGTH TRAINING APPLICATION

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ii. Abstract

This paper examines the effects of an electromyography (EMG) biofeedback on a strength training application and its potential to improve individualisation and exercise selection, using the measure of muscle activity. To examine this, an application was built and tested using a pre-and post-test, randomised single-blind design over a duration of four weeks. The bicep short head muscle was the focus point for this study, therefore, a variety of biceps curl was chosen as the exercise to execute. The participants were divided into two groups: the *EMG group* performed individual selected exercises based on their EMG feedback and the *control group* had to execute all exercises. The overall volume of this study was normalised. The objective of this study was to provide a new approach for predicting the optimal individual strength training exercises for the bicep, using a EMG driven application. The results of the study did not provide any statistically significant improvements using biofeedback versus no feedback. However, the *EMG group* showed a slight increased improvement compared to the *Control group*. The lack of statistically significant results, other observations and indications were discussed.

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1. Introduction

Over the last decades there has been an increase in the amount of people practicing fitness and strength training, and it is anticipated that this number will increase in the future (Kirkegaard, 2007). However, maintaining a good strength training regime can prove to be difficult, since it requires knowledge regarding training intensity, frequency and exercise selection (Schoenfeld, 2010; Tan, 1999). For instance, in order to improve personal weak areas and avoid injuries, the proper exercise program and intensity level has to be selected based on the individuals' capabilities (Schoenfeld, 2010; Tan, 1999). Therefore, it is imperative that new effective ways of providing people with valid information regarding exercise selection and strength training factors are found. Furthermore, maintaining an exercise regime and getting successful results over an extended period, requires a significant level of discipline and motivation.

In this case, it has been proven highly effective having access to a personal trainer, which can improve both persistence and motivation (Jeffery et al., 1998; Kranz et al., 2013). The continuous monitorisation of exercise execution, individualised advice, corrections and motivational feedback, are just some of the roles undertaken by a personal trainer, which can led to successful results (Jeffery et al., 1998; Kranz et al., 2013). However, having a personal trainer can prove costly and intrusive, depending on the extent of the inquired service (Jeffery et al., 1998).

Implementing new technology into fitness and rehabilitation has shown the potential to improve physical health, and increase healthcare awareness with the use of fewer resources (Boulos et al., 2014; Cowan et al., 2012; Kranz et al., 2013; Liu et al., 2011). Furthermore, smartphones are rapidly becoming an essential and a widespread part of modern life in the western world (Fox and Duggan, 2012; Handel, 2011). These smartphones, embedded with powerful sensors, such as accelerometer, digital compass, gyroscope, GPS, microphone and cameras, offer great utility and possibilities for expanding the usage within the domain of fitness (Lane et al., 2010). Already, technological advancements have allowed health applications to utilise this sensorial data for health and fitness feedback, such as heart rate monitors, step counter, exercise trackers, etc. (Kranz et al., 2013). Yet, many of these applications and technologies have deficiencies and limitations, because they are not based on theory, behavioral theories and guidelines from the medical and health industry (Boulos et al., 2014; Cowan et al., 2012). In the field of rehabilitation and strength training, studies have shown that the use of biofeedback technology can significantly improve the health and mobility for people suffering from brain injury, cerebral palsy and stroke (Coleman, 2001; Shusong & Xia, 2010; Yoo et al., 2014). Nonetheless, very few commercial applications have been made for direct strength training purposes.

In this paper the following problem will be addressed:

Can an Electromyography (EMG) driven biofeedback application aid in the individualisation, optimisation and assessment of the strength training exercise effect?

From this problem statement, it is hypothesised that using an EMG fitness application will help to locate the most effective exercises and thereby improve individual exercise effect within strength training. This research will try to verify this hypothesis by focusing on answering the following questions:

- *What is EMG and how is it being used?*
- *What factors are involved in conventional strength training?*
- *Can the use of information from EMG help the user to select the most effective strength training exercises?*
- *How to display the information from the EMG to the user in a useful manner?*

Along with these research questions, an EMG system implying an application and a prototype will be created and tested, in order to verify this hypothesis. The test will be conducted by comparing the effectiveness of EMG selected exercise versus random selected exercises.

2. Literature Review[i]

This is a collaborative study, with the focus of creating an EMG driven mobile application, which can provide effective and motivating biofeedback, for the selection and individualisation of strength training exercises. This paper focuses on the creation and evaluation of an EMG feedback feature for individualisation and exercise selection, on a mobile application, whereas, the adjacent study focuses on developing the application and user interface. However, this paper will also present general information about current strength training applications along with interface designs, since the EMG Feedback feature only functions alongside an application. In this section, information regarding the physiology behind and criteria needed for creating a successful strength training regime and application, as well as a general understanding of EMG alongside its means of use will be presented. Furthermore, a review on what similar applications are being used within the scientific field to improve fitness and health will be presented, along with a small review of the current top nine strength training applications on the android market will be conducted.

This knowledge is then synthesised into an application feature that can provide beneficial information about, which exercises to select for optimal benefit, through the use of EMG feedback. This application feature is then evaluated, along with future design recommendations for the development of a successful strength training application.

2.1. Strength training

Creating a strength training application, which uses EMG feedback to evaluate muscle activity and effectiveness, it is critical to understand the physiology behind strength training, in order to understand the feedback, provided by the EMG. However, since the physiology of strength training is a large area of sports medicine and biology, and larger than it can be addressed for this study, this paper will only provide a basis for understanding the general aspects of strength training, which can provide a basis for the criteria of success. The following paragraphs will focus on the definition of strength training, the physiological mechanisms of strength training, muscle structure and function, the neuromuscular system and factors for strength training programming.

2.1.1 What is strength training

Strength training is defined as the process of breaking and rebuilding muscle tissue. When performing strength training there are two main factors to consider, first the stress inflicted and the chemical change within the muscles. During heavy strength training, the muscles used are exposed to high levels of stress, which slowly breakdown the muscle fibers within the muscle. Furthermore, the chemical environment within the muscle changes through the process of energy stores depletion and lactic acid accumulation, which gives the feeling of fatigue. The body´s reaction to these factors is to adapt, by rebuilding and improving the structure of the fibers, in order to survive and withstand the stress inflicted (Bojsen-Møller et al., 2006; Borch et al., 2006). However, the process of self-repair and improvement does not happen during the execution of strength training, but in the resting period that follows (Bojsen-Møller et al., 2006).

2.1.2 Physiological mechanisms of strength training

The ability to create movement in the human body is reliant on the intricate functional relationship between the skeleton frame and the muscles within the body. When movement is required, a neural signal triggering of muscle contraction creates a force which affects the relevant bones and creates movement in that specific part of the body (Borch et al., 2006). This neural signal is transmitted through the neuromuscular system to the muscle fibers.

2.1.2.1 The Neuromuscular system and muscle structure

As mentioned, the muscle needs a neural signal from the brain to active a contraction within the muscles. This process is handled by the neuromuscular system. The neuromuscular system is built from the muscles themselves and the central nervous system.

When creating simple movement, the brain sends an impulse through the nerves to a giving motor neuron, which then activates the contraction of the muscle fibers. The recruitment speed, in which the motor neuron can activate the synchronisation of the muscle fibers, is what determines the force developed (Bojsen-Møller et al., 2006). At the same time, the brain receives information from the muscles, about the current state of the given muscle and this feedback loop is essential for developing well-coordinated movements. The activation of muscle fibers is depended on the type of movement and the type of fibers needed to complete the movement.

Muscles consist of different types of muscle fibers, such as slow twitch (ST) - and fast twitch (FT) fibers. However, the FT is respectively divided into FT1 and FT2, which is super-fast twitch and fast twitch. The ST muscle fibers are also known as endurance fibers, since they are capable of contracting over a long period of time, whereas the FT fibers are explosive, which makes them ideal for strenuous or explosive sports, such as weight lifting (Bojsen-Møller et al., 2006).

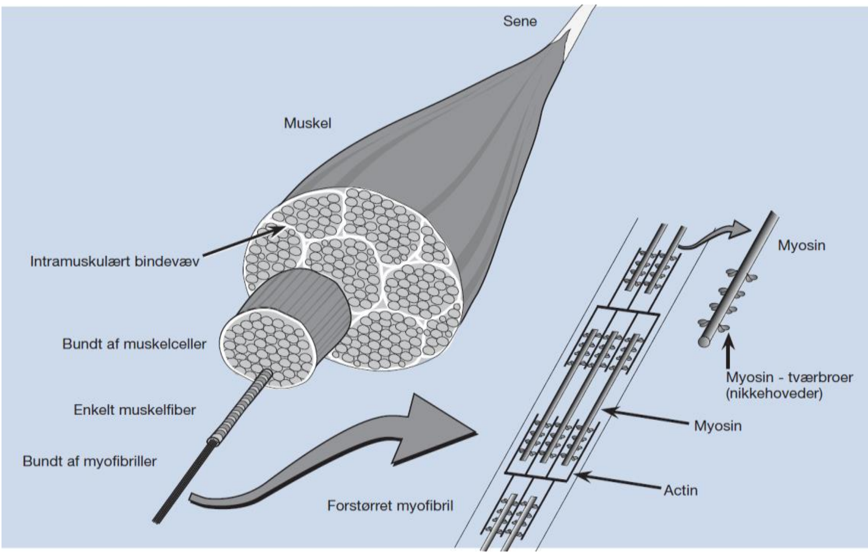

Figure 1 (Danish) - (Bojsen-Møller et al., 2006)

The muscle fibers then consist of bundles of protein threads, also known as myofibrils. The myofibrils, in terms, consist of contractile proteins, actin and myosin, which are the key to muscle contraction (Figure 1). When the muscle fibers receive an activation impulse from the nerve, small molecular "cross bridges" between actin and myosin structures are briefly formed. These small cross-bridges are movable, and when the cross-bridges all tilt in the same direction, it results in a contraction of the muscle and hence the muscle force development (Bojsen-Møller et al., 2006; Borch et al., 2006). When doing a specific strength training exercise, the correct muscle fiber activation and force developed is essential in order to maximize the effect of the training. The muscle contractile force depends on the intensity and frequency of nerve impulses to be sent to the muscle. Thus, the ability to develop large muscle power depends on both neural, muscle structural and biomechanical properties (Bojsen-Møller et al., 2006). The intensity of a nerve impulse, from the motor neurons, and the contractile force is what can be measured by an EMG.

2.1.3 What makes a successful strength training regime

A successful strength training regime is dependent on many variables, such as *intensity, volume, frequency, periodization* and *exercise selection*. When designing a strength training program, *intensity* is one of the crucial variables to maximize strength. It refers to the load or poundage used during an exercise. *Intensity* is described as the percentage of the one repetition maximum load (1RM) lifted (Schoenfeld, 2010; Tan, 1999). As mentioned the body's reaction to a high training intensity is to adapt, by increasing neural activation; greater peak of electromyographic activity in the muscle, which relates to a greater rate of force development (Bojsen-Møller et al., 2006; Borch et al., 2006; Tan, 1999).

Training *volume* is defined as the total capacity performed over a given exercise and is calculated by the repetitions x sets x weight used. As well as *intensity*, *volume* is an important factor when trying to gain strength, since you have to increase volume over time in order to increase muscle fiber activation and size (Bojsen-Møller et al., 2006; Schoenfeld, 2010; Tan, 1999). Also related to *volume* is *frequency*, since the total volume over a week is determined by the number of times you hit certain muscle parts during a week. *Frequency* is therefore defined as the number of time you work out a particular muscle. Here it is recommended that you work out each muscle part at least twice a week (Bojsen-Møller et al., 2006; Tan, 1999).

The concept of *periodisation* builds on the principle that the training year is often divided into different periods of training, with different focus for each period, to achieve improvement. Within each sport, there are large individual differences, as some athletes are planning a relatively short duration (days / weeks) to achieve a peak once or twice a year, while other athletes in a long season is expected to peak every weekend. Strength training athletes often uses the principle of training with high volume and low intensity in the individual exercises, when there is a long time to form the peak, and increases so gradually the intensity and maintains or reduces the amount gradually as the peak approaches. Strength training will be heavily dependent on the other training (technique, endurance, etc.) during the week (Schoenfeld, 2010; Tan, 1999).

Lastly, *exercises selection* has a huge influence on the correct development of a given muscle. However, choosing the correct exercise for the given purpose can be difficult, since individuals are physically different and might respond differently to various exercises. In rehabilitation studies, it has been shown that the use of selective strength training exercises can significantly improve strength and EMG activation in people suffering from patellofemoral pain (Ng, Zhang and Li, 2008). The order of the exercises within each program can be varied. However, it is recommended that you train the large muscle groups so that they are not fatigue by the peripheral muscle groups, thereby determining whether one can lift heavy loads (Schoenfeld, 2010; Tan, 1999).

Taking this information into consideration, it can be assumed that any successful strength training application allows for individual control of these factors. It must provide the user with the ability to, firstly, select exercises based on the needs, track one’s intensity, volume and frequency. Also provide means of periodisation for the user, since this is a fairly complex task, which requires extensive knowledge. Lastly, it must allocate a basis for tracking once performance over time.

2.2. Electromyography

Electromyography (EMG) implies the recording and study of electrical activity within the muscles which is often used in the field of sport science and electro diagnostic medical consultation (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006; Türker & Sözen, 2013; Zwarts & Stegeman, 2003). In sport and exercise science, this technique is often used to determine which muscles are active and contribute during a given exercise on how active a muscle is relative to the activity during a maximum contraction (Lamontagne, 2001; Türker & Sözen, 2013). In other words, EMG provides easy access to the physiological processes, which generates force within the muscles and produce movement. However, since EMG is highly accessible, the chance for misuse and misinterpretations are high (Lamontagne, 2001). It is therefore important to understand the principles behind EMG signal and how it is used.

2.2.1 Source of signal

The electrical signal conducted within the muscle tissue is called muscle unit action potential (MUAP) and can be detected by the electrodes in the muscles or on the surface of the skin. The MUAP is a depolarisation of the motor neuron, which occurs when the central nervous system sends a signal to contract a given muscle. This depolarisation passages along the muscle fibers and produces an electrical wave which can be detected by the recording electrodes (Lamontagne, 2001; Zwarts & Stegeman, 2003). When using a two-electrode EMG system, the MUAP is represented by a triphasic signal, which represents the potential difference between pole A and B (Figure 2).

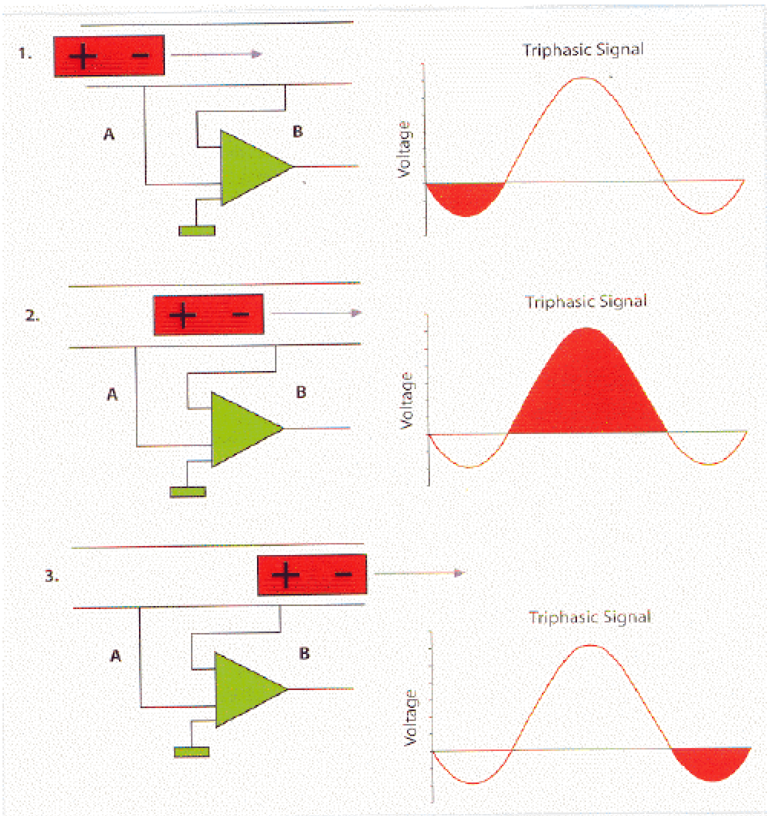

Figure 2 - (Lamontagne, 2001)

The MUAP in these electrodes is limited only to a certain number of fibers adjacent to the electrode. However, it is often thought to accurately represent the collective activity within the entire muscle.

2.2.2 Types of EMG

There are two main methods of measuring the MAUP of the muscles: invasive or noninvasive. The invasive method implies the usage of needles inserted directly into the muscles to record the activity, whereas the noninvasive methods records the MAUP by placing electrodes over the skin surface overlying the muscle of interest, as it is already mentioned in the paragraph above (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006; Türker & Sözen, 2013; Zwarts & Stegeman, 2003). The first method can provide direct and precise recordings of the electrical muscle activity on a particular muscle; however, it is mostly used within the medical field, due to the invasive and unpleasant nature (Lamontagne, 2001; Türker & Sözen, 2013). Surface EMG (sEMG) represents a noninvasive technique for measuring the electrical activity that occurs within a muscle during a contraction and extension phase. sEMG is also known as kinesiological EMG, since it analyses the electrical muscular activity in a bodily movement (Türker & Sözen, 2013). This information allows an understanding of how a muscle works during a movement and exposes the interaction and coordination between different muscles (Lamontagne, 2001; Türker & Sözen, 2013). sEMG has a wide range of applications with in multiple fields, such as medical research, rehabilitation, ergonomics, sports science (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006; Türker & Sözen, 2013; Zwarts & Stegeman, 2003). However, one of the disadvantages of sEMG is that the data can be biased due to external factors, thus raising the question of reliability of this method (Lamontagne, 2001; Türker & Sözen, 2013). Nevertheless, sEMG is the preferred methods use, in sport science studies, when comparing the effectiveness of an exercise (Lamontagne, 2001; Türker & Sözen, 2013) and in rehabilitation exercise (Coleman, 2001; Shusong and Xia, 2010; Yoo et al., 2014), due to its noninvasive nature.

2.2.3 Signal processing and filtering

There are several factors that can influence the quality of the signal detected by the electrodes, of which some can be controlled by the user. Those are i. a. the placement of the electrodes, the distance between the recording electrodes, orientation in regards to muscle fibers and the type of used electrodes (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006). Furthermore, one of the electrical factors that can influence the fidelity and signal, is the noise-to-signal ratio. This factor is the ratio between the amplitude of the EMG signal to the amplitude of the noise signal.

The noise signal is defined as the signal which is not a part of the EMG signal, such as electrical interference (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006). The EMG signal is relatively low, which means that amplification is needed, here usually a differential amplifier is used. The next step is then to filter the noise from the EMG signal; here it has been proven effective to use low pass and high pass filter, to eliminate the low- and high frequencies (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006). In most cases the signal is rectified and averaged to indicate the EMG amplitude, which indicates the MUAP.

2.2.4 EMG recap

To summarise how EMG works, imagining standing, with your ear against a door, outside a room listening to people talking through the door. It would be hard to determine how many people are in the room, but if the entire people yell as loud as they can at the same time, it would provide an idea of the maximum volume of noise, all the people can produce; this is equivalent to the max voluntary contraction in an EMG test. After receiving an idea of the maximum volume, it would be possible to compare the volume of a given number of people talking, relative to the maximum volume, but not who was talking and when. This is the equivalent to EMG amplitude for assessing motor unit recruitment. You can describe the EMG amplitude during a task relative to the maximum, such as 50% of the volume of the maximum condition, as is commonly done. However, surface EMG cannot tell us which motor units and fibers were used, or how many were used at some point during the measurement.

2.3. The use of EMG feedback in fitness and rehabilitation

As previously mentioned, EMG provides an opportunity to understand what happens within the muscle, when doing movements and exercises. It is therefore a valuable tool, which has a wide range of utility and has been proven effective when used for biofeedback applications. EMG is often utilised in sports and exercise studies, to analyse movements or compare the effect of different exercises, on muscle activity, coordination and hypertrophy (Bird, Fletcher and Kock, 2006; Fakuda et al., 2010; Son et al., 2012). Several studies have employed EMG in order to determine the overall effectiveness of the EMG on exercise assessment (Bird, Fletcher and Kock, 2006; Fakuda et al., 2010; Saeterbakken and Fimland, 2012; Son et al., 2012). In a study from

2006, the authors used EMG sensors to determine the MUAP of the different abdominal muscles, in both the concentric and eccentric phase of multiple abdominal exercises. The data collected from the EMG allowed the authors to analyse in what phases, concentric and eccentric, the different muscles were active, and conclude that the crunch exercise had an overall better effect on the activation of the abdominal muscles (Bird, Fletcher and Kock, 2006).

There are, however, some limitations in regards to sEMG when performing analysis of dynamic movements, like strength training. Firstly, any change in the placement of the surface electrodes, can cause imprecise measurements. Furthermore, the speed of the movement and time under tension can be a key factor when comparing two EMG data sets (Stastny et al., 2016).

In the field of rehabilitation, the use of EMG feedback, along with the guidance of a physiotherapist, has proven most effective on the early rehabilitation stages (Coleman, 2001; Lyons et al., 2003; Shusong and Xia, 2010; Yoo et al., 2014). In a study from 2006, investigators compared the effects of an 8-week exercise program with and without EMG biofeedback on the relative activations of the medial and lateral vasti muscle, in subjects with patellofemoral pain syndrome. The investigation revealed that incorporating EMG feedback into a physiotherapy exercise program can have great effect on the muscle activation (Ng, Zhang and Li, 2008).

Furthermore, the use of EMG biofeedback and gamification has indicated a higher level of adherence and motivation in comparison to conventional rehabilitation exercises (Shusong and Xia, 2010; Yoo et al., 2014).

Common for all of these studies is that the use of EMG presents the user, physiotherapist and investigator with valuable information on the muscle activity during exercises, and the information on how to correctly guide or adjust the exercise to ensure the highest amount of MUAP.

2.4. Wearable sensor applications / automatic assessment of physical activity

Conventional methods for measuring and improving exercise execution involve physiotherapists or personal trainers, who observe and correct the person performing the exercise. This method has proven highly effective and motivating for the user (Jeffery et al., 1998; Richard et al., 1997). However, this method has significant deficiencies such as cost, accuracy, opportunity, coverage, and compliance. A physiotherapist or a personal trainer typically splits their attention among several patients at different locations, which means that the patients or clients have to be self-sufficient at some level. Self-reporting is often used to ensure that the patients or clients execute the exercises themselves; however, this is often inaccurate due to forgetfulness, un- and intentional misreporting or lack of knowledge on how to perform the exercises correctly (Chandra, Oakley and Silva, 2012).

Researches have investigated how to improve this, by using wearable sensors to recognize, classify and report activities done, and most studies have proved the effectiveness of wearable sensors on activity recognition (Buttussi, Chittaro and Nadalutti, 2006; Chang, Chen and Canny, 2007, Ermes et al., 2008; Lester, Choundhury and Borriello, 2006). Although, the majority of this research, has been done in controlled environments and with the focus on rehabilitation and in most cases only GPS and accelerometers have been used (Buttussi, Chittaro and Nadalutti, 2006; Boulos et al., 2014; Chen & Pu, 2014; Chang, Chen and Canny, 2007; Lester, Choundhury and Borriello, 2006; Liu et al., 2011).

In regards to the realisation outside the scientific field and towards the commercial market, there are many applications created for the purpose of improving training and health. Since mobile devices are both highly available and are equipped with several sensors that can be used, many developers have created a vast number of fitness and health applications with the purpose of information distribution, exercise library, training logging and tracking tool (Boulos et al., 2014; Chen & Pu, 2014; Liu et al., 2011) The state of the art applications mostly use accelerometer and GPS. However, heart rate monitor and a calorie counter can be depicted as extra options (Boulos et al., 2014; Chen & Pu, 2014; Liu et al., 2011). Furthermore, reviews of these applications have shown that most are not based on behavioural change theories or guidelines and lack the use of biofeedback (Boulos et al., 2014).

Several studies have looked at creating embodied virtual trainer applications, which use all the above-mentioned features to improve health, execution and adherence (Buttussi, Chittaro and Nadalutti, 2006, Kranz et al., 2013). These studies reported that the use of mobile devices and virtual trainers has a big potential, but that more behavioral change theories and sensors must be implemented to improve the effectiveness of these applications. Also, the feedback shown on the mobile device needs to be presented in a useful manner, to ensure correct usage (Buttussi, Chittaro and Nadalutti, 2006, Fox and Duggan, 2012; Handel, 2011; Kranz et al., 2013).

2.5. Current fitness application

Since this paper aims at creating an EMG feedback application, which can provide effective and motivating biofeedback for the selection and individualisation of strength training exercises, a minor heuristic review of nine current strength training applications on the Google play market was done, to provide an overview of features and attributes needed for the development of such an application. The review was done by looking at the functionality and features of these applications, thus classifying them into groups.

Category	Name	Developer	Downloads	Stars
Exercise archive	My Fitness – Strength training	Andrey Tsaregorodtsev	10.000-50.000	4.5
Workout planner	5X5	Stronglifts	500.000-1.000.000	4.9
Training journal	Fitnotes	James Gay	1.000.000 - 5.000.000	4.5
Training journal	Strength Training Planner	Szabolcs Erdelyi	100-500	4.1
Workout planner	Gym Workout Tracker & Trainer	Fitness22	500.000-1.000.000	4.5
Training journal	Fit Journals	Sultan Seidalin	50.000-100.000	4.5
Training journal	WORKIT Gym Log Workout Tracker	WorkIt	50.000-100.000	4.4
Workout planner	30 days Fitness Challenge	Leap Fitness Group	5.000.000 – 10.000.000	4.8
Exercise archive	Female Fitness - Bikini Body	VGFIT LLC	500.000-1.000.000	4.4

Table 1 - Application overview

Four criteria were used to assess of the current strength training applications. The *application usability and effectiveness for strength training* were evaluated based on interaction features (control, appropriate output, ease of use) and customisability, i.e. if the users can modify the application to their specific needs. Also it was assessed whether the application allowed for proper tracking of strength training features mentioned in the literature review, such as intensity, volume, frequency, periodisation and exercise selection. *Instructional features* of the application were examined, i.e. how well the instructions of the exercises were presented on the smartphone. This included the clarity and level of instructions, sufficient level of detail, etc. providing the user with sufficient knowledge about the given exercise. Also the *sensor data usage* was evaluated. In other words, to what extend the application utilised the smartphone sensor capabilities, information recorded (e.g. GPS, accelerometer data etc.) and external sensor output. Lastly, the applications ability to *motivate* was examined. How well the application was suited for generating adherence and long-term motivation, based on variety in the training experience, proper statistical feedback on training progress, to maintain extrinsic motivation.

Through the review, three categories were identified: *training journal, workout planne*r and *exercise archive*. *Training journal* applications core feature is to work as a diary and calendar for the exercises done. Here the users can plot in their training program, exercise by exercise and repetitions, sets and weight, and the application keeps track of the progress through the use of statistics. *Workout planners* are applications, which has pre-programmed workout regime that the users can choose between, based on their needs and desire. The application has the cognitive learning, where it already has pre-programmed weight, repetitions, sets and progress, based on the 1RM value of the user. *Exercise archive* is a class of applications that provides the user with a large, detailed, browsable library of exercises that can be used. The applications have either a visual and written, or video explanation of each exercise with key points on executions and performance.

The review, delivered key insights to the strengths and limitations of the current popular strength training applications. Firstly, even though the Google play market has a large selection of strength training applications, these provide very limited variety. As shown by the classification, there are only three primary classes within the Health and Fitness category on the Google play market. Also, when examine the different applications and categories many deficits were revealed. The *training journal* applications provide limited motivation based on progress feedback. Most applications present feedback in a statistical format, which require detail knowledge of how to use this information. In other words, this means that these applications are not well suited for beginners. However, these applications offer great usability through the use of customisation of exercises and the information presented to an intermediate user with sufficient strength training knowledge. The *workout planners* are very rigid and only allow for small individualisation based on user experience. Furthermore, even though these applications offer a large collection of workouts, they provide only limited advice and information on what workouts are best suited to once level of experience. They do provide great opportunities for progression autonomously. The main deficit of the *exercise archive* applications is that their collection is very limited based in comparison to what else can be found on the web. Furthermore, they also lack details on how to execute the exercises correctly and to what extend the exercises are useful.

Overall the applications provide limited to no suggestions and corrections, in order to maintain adherence and motivation. Also, the applications require physical interaction, meaning that the users have to divert their attention from training, to on logging their performance, in order to get precise tracking of exercises. Additionally, even though most smartphones have a large variety of sensors available (Lane et al., 2010), the majority of applications use very limited sensory feedback.

The main findings of this small review, was that applications like these should build its *foundation* on providing the user with sufficient knowledge on how to structure the *intensity, volume, frequency, periodisation* and *exercise selection* (Bojsen-Møller et al., 2006; Schoenfeld, 2010; Tan, 1999). This could be done by providing examples based on different needs, which can be tailored to each individual. Furthermore, the applications should provide the user with simple *instructional information* and guidance to ensure usability and motivation. Likewise, to assure motivation, the application should provide a data tracking system, which gives the user more information of their progress. Lastly the use of more sensory input should be considered, thus adding additional progress information. Here, the use of external sensors, such as electromyography, could be used based on use for the analysis of movement in sports and rehabilitation (Bird, Fletcher and Koch, 2006; Fukuda et al., 2010; Son et al., 2012; Saeterbakken & Fimland, 2012).

2.6 Application Interface.

As previously mentioned the overall study focuses on creating a mobile strength training application that presents the EMG feedback in a useful way, however this paper focuses on the creation of the EMG feedback feature. Even though the aim of this paper is not on the interface design, it is important to understand the functioning of a well-designed interface in order to present the feedback to the user in a useful manner. However, the field of interface design is a vast area within human-computer interaction and far beyond the scope of this paper, only key aspects of interface design will be presented in the section below.

“The best interface is one that is not noticed, and one that permits the user to focus on the information and task at hand instead of the mechanisms used to present the information and perform the task" (Galitz, 2007, p. 4).

As mentioned in the quote above, the interface of any application has to be made in a way that allows the user to fully exploit their possibilities. Furthermore, the GUI can be used for

“*improving the ‘look and feel’ of a product […] to improve the ease of use of the system […] and […] to increase the usability of a product by reducing the number of errors that users make and by improving their performance*” (Barker & Lamont, 1994).

In other words, the layout and appearance of an interface often decides whether a medium succeeds or fails to convey its content (Borchers et al., 1996). If the interface is overly complex and ineffective, the users will have difficulties doing the task at hand, which in term, can lead the user away from using the interface permanently, due to aggravation, frustration and increased stress (Galitz, 2007). Also, using an interface which displays too much information at the same time, can lead to information overload. This is a state where the user cannot comprehend the amount of information given, which can lead to misinterpretation of the information. Therefore, it is important to limit the amount of information visible at the same time, and gradually guide the user through the different information. Furthermore, the interface should focus on the key aspects needed for the user (Müller et al., 2009; Seto et al., 2012).

2.7 Recap

As mentioned this paper focuses on the development of the EMG feedback application for the strength training mobile application, which can provide effective information about which exercises to select to ensure maximal muscle activation. What can be taken from these theories and studies is that when creating the EMG feedback application, the use of EMG MUAP measurements is needed to compare the muscles activation between exercises. It is also important that the experimental design takes into consideration the strength training factors and to normalise these factors between participants. Lastly, the information provided by the system has to be shown to the user in a valuable manner, though a simple but useful interface.

3. Development

The purpose of this paper is to create a biofeedback based application concept, which determines individualised training regimes. The design procedure of this prototype, its development decisions and the external parties that brought their contribution throughout the process will be discussed in the current section.

3.1. Collaboration

The study conveys into two components: the EMG processing unit that has the purpose to process information proportionally to its recordings, unit that is being focused on as the main partition of this study, while its adjacent part consists in a mobile application interface which conveys the information to a target audience. The purpose of the interface is to find optimal means in conveying the EMG data into a format that is understandable and accessible to fitness enthusiasts. This is a secondary goal in the study that will prove the potential that the use of EMG data has in a strength training application. All of this was possible through collaboration with

Jennifer, an 8th semester Medialogy student, who focused her study on the construction of such an interface. The exchange of information between the two parties lead to the creation of both studies.

To obtain the methodology of testing our hypothesis, several theoretical aspects needed to be understood. Besides academical research, several external parties external parties was involved. Firstly, Sydvestjysk hospital appointed a meeting with an ENG and EMG expert. This provided information towards EMG basics, choosing the proper type of EMG sensors, setting up an EMG system and filtering the recorded EMG data.

While the research provided understanding on strength training, the strength training methodologies were defined alongside Signe, who is an authorised personal trainer at Fitness World Kolding. She provided aid, not only in picking the ideal exercise for the participants, but she also visually assessed the execution quality of the exercises individually.

3.1. Prototype

As stated above, Sydvestjysk hospital scheduled a meeting with and ECG/EMG expert. The encounter resulted in gaining extra knowledge on the functionality principles of EMG already confirming the already conducted theoretical research from a more practical approach (have to help me with more accurate information). Also, the expert guided aided towards the optimal choice in regards EMG electrodes. It was acknowledged that while pin-based returns more precise readings, the non-intrusive nature of the surface EMG electrodes proves ideal for the current study.

Proceeding the choice of electrodes, was the selection of a microprocessor. The go to option was the development board kit from Bitalino named the Bitalino Plugged. Besides the EMG processing unit, the Bitalino Plugged kit offers several auxiliar processing units such as Electrocardiography (ECG), Electrodermal Activity (EDA), Electroencephalography (EEG), Accelerometer (ACC), Light (LUX) and Pushbutton (BTN) alongside a freeware which offered storing and visualisation options of the recorded data.

Despite its wide variety of processing units and its provided software, the Bitalino showed one limitation: the EMG recording presented 1.65 mV limit. This proved inconvenient for this study since previous studies have shown that a human being can produce a voltage of 10 - 30 mV (Bird, Fletcher and Kock, 2006; Fakuda et al., 2010; Saeterbakken and Fimland, 2012; Son et al., 2012), thus making the results futile. Software alternatives were Arduino Studio and Unity 5. However the voltage limitation was due to the hardware construction and not its programing, making it less probable to cancel it using the already mentioned software.

The optimal solution proved to be an Arduino Uno connected to a Grove EMG sensor that processed the information through a Microsoft Excel extension named PLX-DAQ.

3.2 Interface

As mentioned the full extent of the interface development and design choices can be found in the collaboratory report. However, a small overview of key choices is presented below. A user interface has the purpose of conveying the correct information to the target audience (Borchers et al., 1996). This user interface was created under the form of a mobile application, thus providing the accessibility factor (Fox and Duggan, 2012; Handel, 2011). The development of the interface underwent several design choices.

The interface presents a light blue colour palette of the buttons and logo highlighting the man-machine amalgam (respectively muscle activity and EMG tracking) (Haraway, 1991, p. 150) with a dark grey background that delivers an ideal contrast according to the Limbic® Map by Häusel (Häusel, 2014). This design was chosen to represent the link between man and machine, in other word, a cyborg (Haraway, 1991, p. 150; McLuhan, 1994).

Besides its visual representation, a well-designed interface needs a navigational structure. The structure chosen is nonlinear and presents its features in categorised tabs, through which the users need to navigate according to the task at hand (Figure 3).

These features of the interface were physically portrayed through a desktop mock-up version of a mobile application, which only access potential usable features without accessing or recording real data. This version of the interface, along with a real time graph over the sEMG recordings, will be presented throughout the testing sessions, as the participants will have to execute the different exercises. At the end of session the interface will represent the ranking of the performance relative to the exercises (Figure 3).

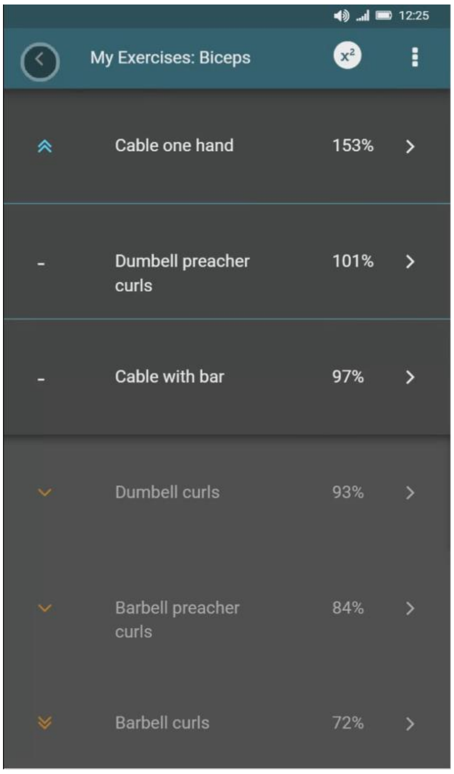

Figure 3 - Interface exercise ranking

4. The Prototype

Since the purpose of this paper is to evaluate the use of an EMG based feedback feature for individualisation and exercise selection, on a mobile application. A physical prototype had to be developed. In this section the more specific information regarding the final prototype can be found.

4.1 Hardware

The hardware use to develop this prototype was the Arduino Uno board along with an Arduino Grove EMG detector kit. The Grove EMG Detector kit consisted of an Arduino shield, which was attached directly onto the Arduino board. Furthermore, two EMG electrodes and a ground electrode were connected to the muscle using sticky pads with conductive gel, and connected to the shield through 3.5mm connector cable. The EMG electrodes were situated at the base of the muscle and at the middle of the muscle. The ground was on a prominent bone thus assuring a ground for the electrical circuit (Figure 4).

Figure 4 - A Grove EMG Detector sensor connected on a forearm

4.2 Software

To make a fully functioning prototype the Arduino based system had to be programed and signal processing had to be implemented. The raw data measured from the electrodes is amplified by the grove EMG detector bridge and then digitised with a sample rate of 300 Hz through the Arduino board. The signal is then filtered using an exponential moving average bandpass filter with cutoff frequency between 5Hz – 25Hz (Potvin and Brown, 2004). The output of the data was done with a 20 ms delay, thus assuring the recording of a considerable amount of values per second. The full programming file can be found in the appendix.

```
EMA_S_high = EMA_a_high * (EMA_S_high + sensorValue - oldSensorValue);
EMA_S_low = (EMA_a_low * EMA_S_high) + ((1 - EMA_a_low)*EMA_S_low);
```

To log the data additional software was used; in this case, the PLX-DAQ software. This cannot be described as stand-alone software, but merely as a Microsoft Excel extension. It reads the data from the code run by the Arduino system and stocks it into a Microsoft Excel file. This provided a simple mean of collecting the data, which can be transformed into plots, thus ensuring a clear visualisation later on.

5. Methods

In order to answer hypothesis presented in the introduction, a proof of concept test was conducted. In this test, each participant underwent two stages; max voluntary isometric contraction (MVIC) test and pre-measurements, and the proof of concept testing. The testing was conducted in collaboration and at Fitness World Kolding.

5.1. Participants

12 participant (four female and eight male) aged between 20 and 45 years, all with prior strength training experience, volunteered for this study. The participants were carefully informed about the design of the study with special information as to possible risks and discomfort that might result. Thereafter, the all the participants were asked to sign a written consent, which can be found in the appendix, before participation in the study. The participants were healthy and habitually physically active. To ensure the quality of the results of this study, the participants were asked not to differ from their weekly strength training routine and only to alter the biceps exercises given in this study. The participants were recruited through advertisements in Fitness World Kolding and on social media.

5.2. Procedure

A pre-and post-test, randomised single-blind design was used in this study. Since this study aimed to prove that biofeedback can improve exercise selection, it was decided that an isolation movement should be used. Biceps curl variations were chosen due to is accessibility to measure and because it is a simple exercise to do movement analysis on (Bojsen-Møller et al., 2006, Delavier, 2010). At the initial assessment, the participants underwent a MVIC pre-test, where Biceps brachii short head EMG values were recorded using an Arduino based surface EMG system, to establish a baseline.

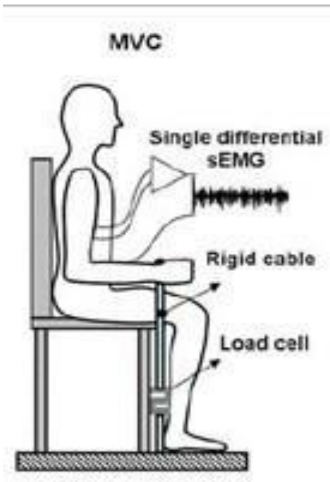

Figure 5 - MVIC pre-test setup

However, before the any testing was done, some different measurements were taken, in order to validate the findings of the study. Firstly the circumference of the biceps was measured, along with the skin fold measurement of the triceps. Furthermore each participant's 8 RM for each exercise was found, to ensure the correct weight lifted during the testing. Six biceps curl variations were chosen based on feedback received from the personal trainer collaborating with this study; *Standing biceps dumbbell curl*, *Standing biceps barbell curl*, *Dumbbell preacher curl*, *Barbell preacher curl*, *Standing cable single arm curl*, *Standing cable barbell curl*.

EMG measurements were then recorded for each exercise, for each participant, to establish an EMG baseline. During this measurement the personal trainer then evaluated the execution of each exercise.

After establishing the baseline of physical measurements and EMG activation for each exercise, the participants were randomly assigned into two groups by the researchers and a personal trainer, namely, *control group* and *EMG group* with five participants in each group. Since the experimental design was a single-blinded design, each participant was unaware that there was another group.

5.3. Assessment

The study lasted four weeks, the *control group* had to execute all six exercises with two set of eight repetitions, whereas, the *EMG group* had to only train three EMG selected exercises for four sets of eight repetitions. The exercises selected for each participant in the *EMG group*, had been chosen based on the highest average normalised MUAP values measured during the baseline testing. Each participant was given standardised instructions and demonstrations of each exercise in the first testing session. A lifting plan along with self-reporting training journal was then given to each participant, to ensure compliance and progression. An example of these can be found in the appendix.

After the four weeks of the experiment, the same procedure as the baseline testing was conducted in order to compare the pre- and post-test data. To analyse and compare the EMG data, the data had to be normalised. Since each participant was compared to themselves, it was chosen to use MVIC average (Fakuda et al., 2010).

5.4. Expected Results

Based on the knowledge synthesised from the literature review, it was expected that *EMG group* was, at the least, equal or more effective than the *Exercise group*. Meaning that, the participants within the *EMG group* would show higher increase in muscle activity through the EMG values, along with increase in 8 RM, biceps circumference and loss in skin fold fat, than the *Exercise group*.

6. Results

In this section, the results from the proof of concept test are presented. Due to unfortunate circumstances, only eight participants, four female and four male, completed the study. The data recorded was checked for *normal distribution* using Shapiro-Wilks normality test while the *homogeneity of variance* was checked using the Levene's variance analysis test. The data was analysed using independent t-test.

Figure 6, shows a representation of the EMG data received from one participant, in the *EMG group*, during Biceps Barbell Curl pre-and post-test.

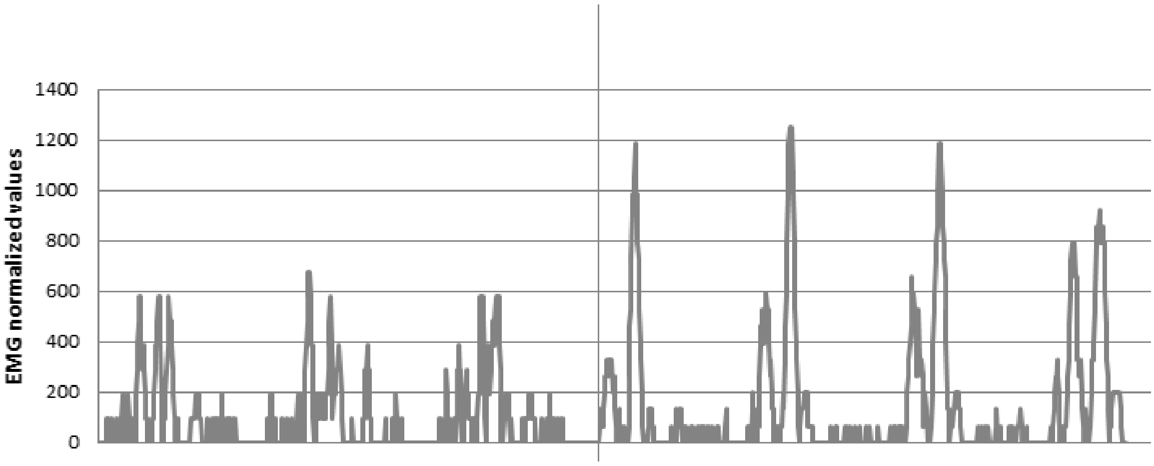

Figure 6 – EMG pre-/post test

6.1. Intra group results

In this subsection, the results of the intra-group analysis are presented. The gathered data is segmented accordingly to the two conditions: *Control* and *EMG*. This was done to show if any significant improvements were found, within the groups.

6.1.1 MVIC

For the MVIC data recorded, an independent-t paired test was performed to investigate the difference between the pre- and post-test. The result of the independent-t test showed no statistically significant improvement within any of the groups. *Control*: p-value 0.16 > 0.05, SD =1.4 and 1.8; *EMG:* p-value 0.07>0.05, SD =3.7 and 4.6.

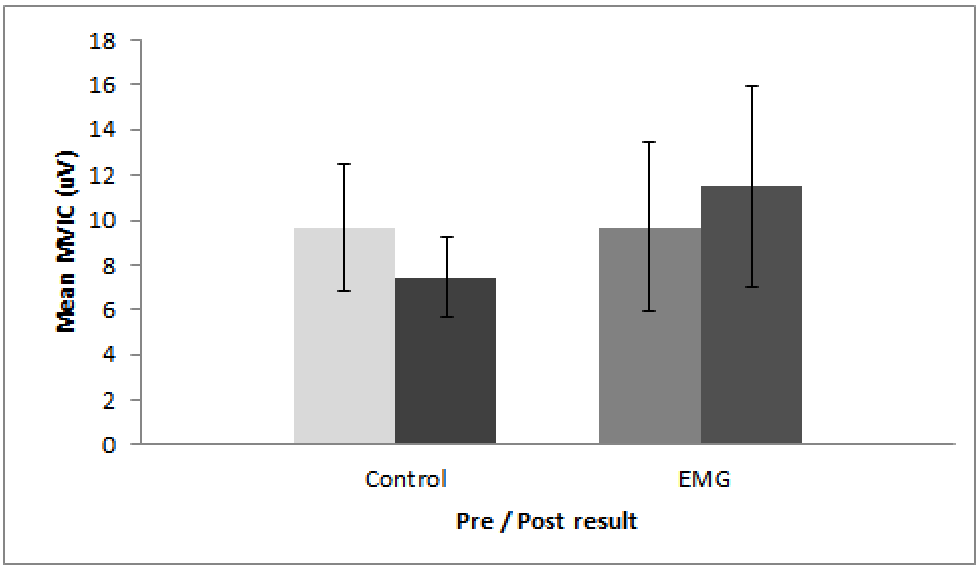

Figure 7 -Mean MVIC pre and post

6.1.2 EMG Average

Same analysis was done for the average EMG data recorded. The result of the independent-t test showed no statistically significant improvement within any of the groups. *Control*: p-value 0.17 > 0.05, SD =49.8 and 48.7; *EMG:* p-value 0.2>0.05, SD =67.8 and 81.7.

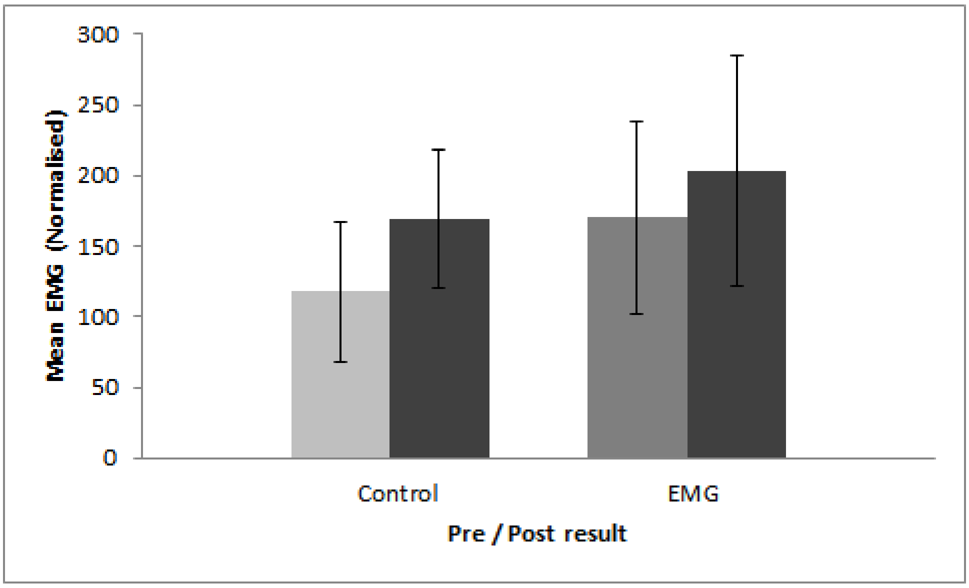

Figure 8 -Mean EMG pre and post

6.1.3 RM strength

Independent-t paired test was performed on the recorded RM data. The result of the independent-t test showed statistically significant improvements within both of the groups. *Control*: p-value 0.02 > 0.05, SD =4 and 6.4; *EMG:* p-value 0.008>0.05, SD =1.6 and 2.49.

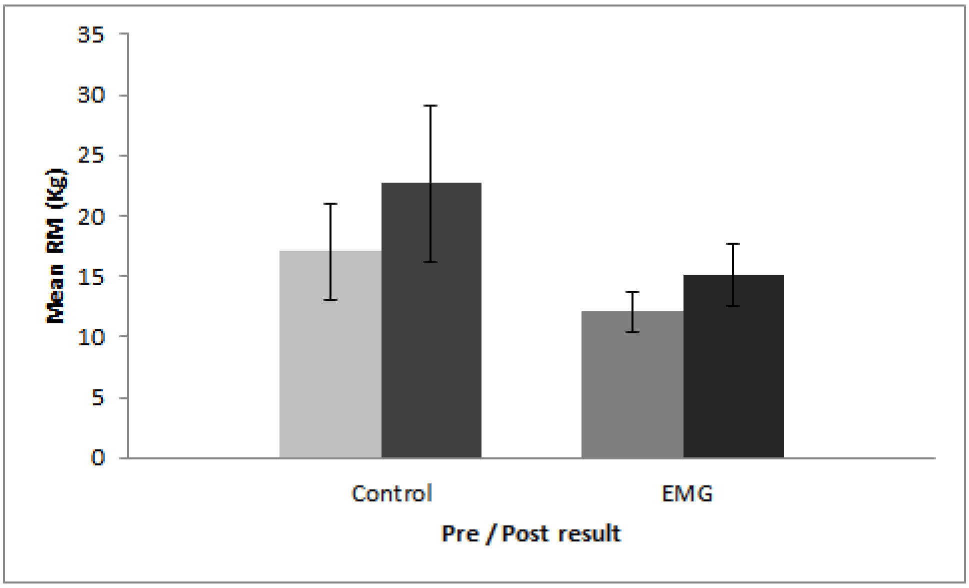

Figure 9 -Mean RM pre and post

6.2. Inter group result

In this subsection, the results of the inter-group analysis are presented. Here the differences between each group were investigated. In other words, if the *EMG* condition performed better than *Control* condition, as expected by the literature review. The RM difference between the groups was not analysed since strength and kilo lifted is dependent on the individual and the exercise.

6.2.1 MVIC

An independent-t unpaired test was performed to investigate the difference pre- and post-test, between the groups. The result of the independent-t test showed no statistically significant improvement between the groups. Pre: p-value 0.99 > 0.05, SD =2.8 and 3.7; Post*:* p-value 0.14>0.05, SD =1.8 and 4.4.

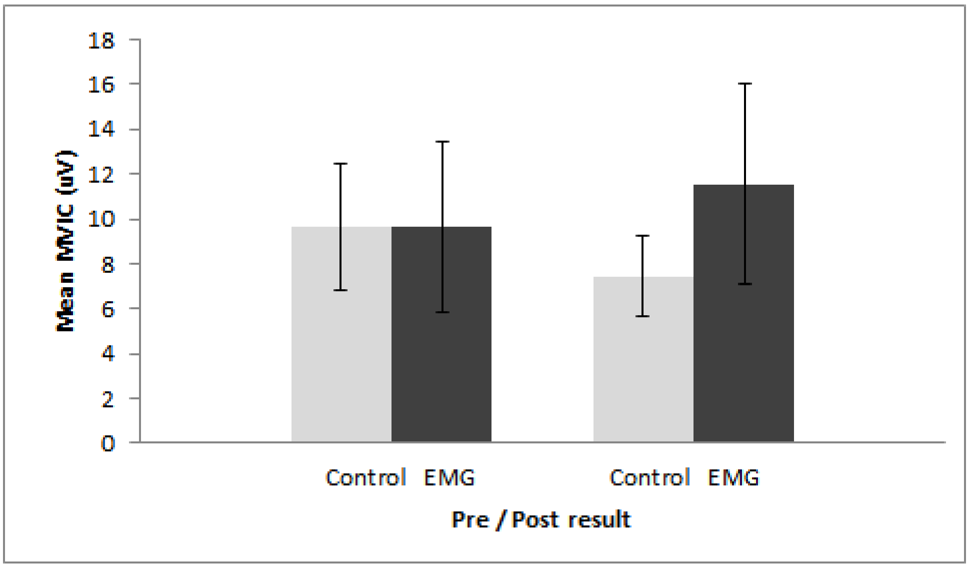

Figure 10 -Mean MVIC pre and post

6.2.2 EMG Average

The EMG data underwent the same procedure. The result of the independent-t unpaired test showed no statistically significant improvement between the groups. Pre: p-value 0.25 > 0.05, SD =49.8 and 67.8; Post*:* p-value 0.49>0.05, SD =48.7 and 81.7.

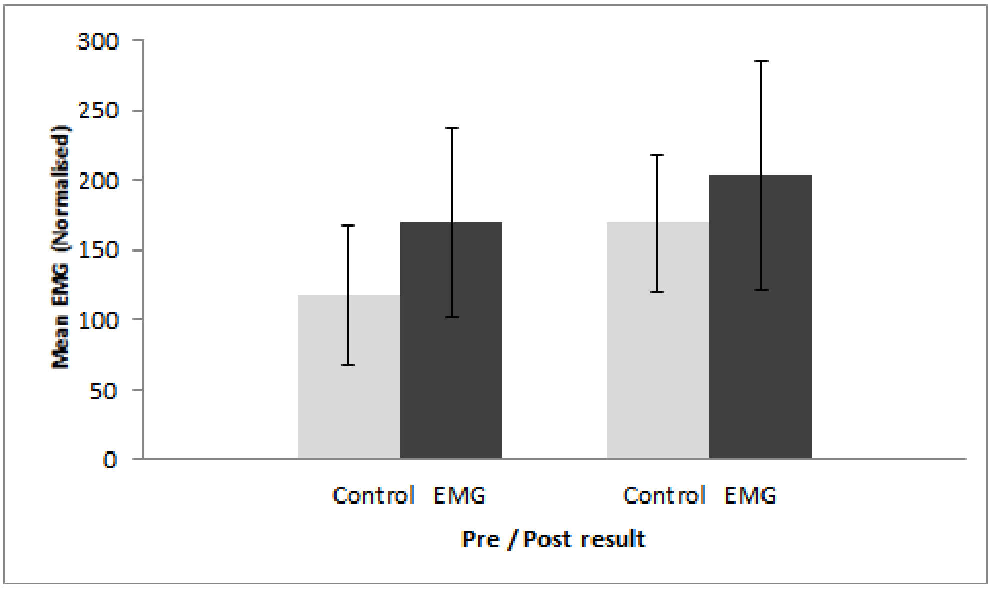

Figure 11 -Mean EMG pre and post

6.3. Overall crosstab result

Analysis of the biceps circumference and skinfold measurement was not analysed, since no visible difference was found. However, one participant did increase the biceps circumference by 1,3 cm. An overview of the different results can be seen in the crosstab below.

Participants	MVIC (µV) Pre / post		EMG MUAP (Normalised) Pre / post		Average 8RM (KG) Pre / post		Biceps (cm) Pre / post		Skinfold (mm) Pre / post	
EMG1	5	7,4	218	238	12,5	16,6	30,5	30,5	28	26
EMG2	13,9	17,4	71	110	11,6	14,3	33,2	34,5	7	6
EMG3	8,62	8,88	209	298	14	17,6	36,9	36,5	19	12
EMG4	11,1	12,47	183	169	10,16	12	28	27,7	12	10
CON1	8,9	8,7	82,5	127,2	22	31	30,5	30,3	28	23
CON2	10,3	5,6	77,9	212,1	14,3	17,5	32,3	32,5	22	24
CON3	6,3	6,2	185,3	211	13,3	17,6	40,7	41,5	28	26
CON4	13,1	9,3	124,6	126,9	18,5	24,5	41,5	41,8	7	8

Table 2 – Pre-/post-test crosstab

7. Discussion

The objective of this study was to provide a new approach for predicting optimal strength training exercises for the bicep, using a sEMG driven application. The results showed that there were no statistically significant differences both within and between the two groups, in both the biceps MUAP and MVIC. However, some statistically significant results were found in the RM intra group differences, where both groups increased significant pre- and post-test. Furthermore, some observations and tendencies were found during the testing, which will be addressed and discussed in the following section.

The lack of statistical significant differences in the MVIC, both within and between groups, will be approached from several perspectives. Firstly, it was observed during the testing sessions that some of the participants did not provide a maximal effort throughout the MVIC measurement. This assumption was justified based on the feedback from the participants, whereas one in particularly expressed slight pain in the wrist and another was not committed into performing at their maximum strength capacity, acknowledging that they were overwhelmed by the weight.

Furthermore, the placement of the sensors could also have resulted in inadequate results (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006). When placing the sensors a certain procedure, obtained from the collaboration with sydvestjysk neurologisk afdeling, was used to ensure the correct placement of the sensors. However, this procedure did not fully establish the same placement between testing sessions, which can ultimately lead to a distorted reading of the adjacent muscle fibers (Lamontagne, 2001; Reaz, Hussain and Mohd-Yasin, 2006). This uncertainty could have been prevented by measuring the distance between the electrodes and the placements related to the elbow joint. Lastly, when performing a MVIC, it is empirical to set the angle of the elbow at 90°, in order to get the correct isometric measurement (Lee & Jo, 2016). However, factor was difficult to control, which evidently could have influenced the measurements. A possibility to ensure this could have been achieved, by immobilising the humerus bone to a support and fixing the length of the rigid cable (Figure 5), in order to achieve a 90° the elbow flexion.

When comparing the within group EMG average results, no statistically significant difference was found between pre- and post-test. Although, as it can be observed in Figure 8, the *control group* improved slightly more than *EMG group.* In this study the outliers of the EMG measurements were not filtered, because it was intended to provide a holistic view on the data obtained in this study. However, had the outliers been removed from the data sets, there would have been found a statistically significant improvement in the *EMG group* pre-and post-test with a p-value of $0.03<0.05$, using a paired independent t-test.

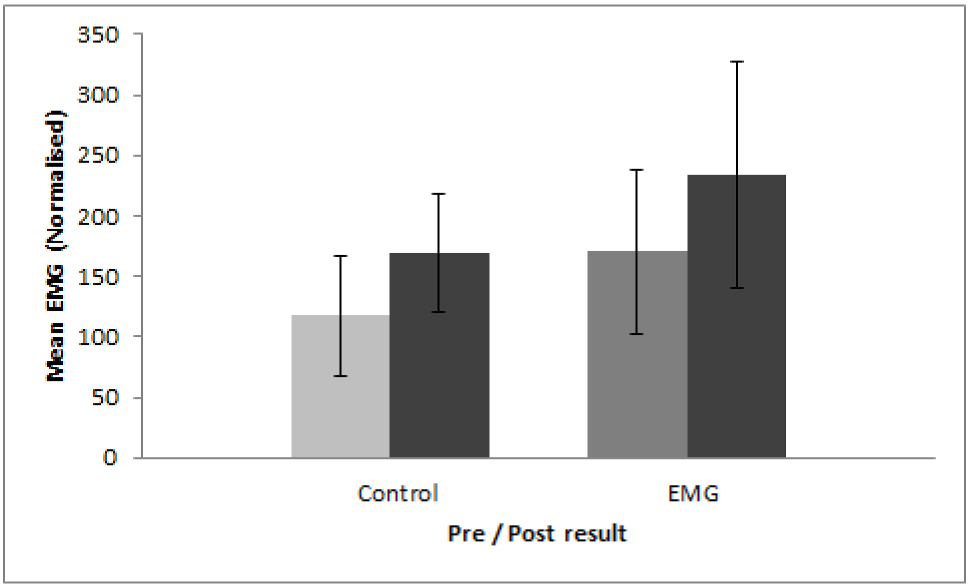

Figure 12 -Mean RM pre and post

This finding proves great potential for the use of EMG feedback, which correlates well to similar studies done with EMG feedback (Ng, Zhang and Li, 2008). Yet, due to the small data sample, this finding cannot be considered conclusive. Although, removing the outliers and comparing the difference between the groups, no statistically significant result was found, with a p-value of 0.26 > 0.05. Some of the factors, which could have lead to the lack of statistically significant results are; *Time under tension (TUT)*, *Duration* of the experiment, *Compliance*. As stated in the literature review *TUT* is one of the key factors for hypertrophy and strength training (Bojsen-Møller et al., 2006; Schoenfeld, 2010; Tan, 1999). In this study, each participant was instructed to use a *TUT* of 2121, meaning two seconds in the concentric phase, one second rest, two second eccentric and one second rest. However, it was observed that some of the participants changed the speed when nearing fatigue or when observing the real time feedback (moving graph) provided by the application interface. This might have influenced the validity of the data collected. Another factor is the duration of the experiment. Here it was intended for the experiment to last between six to eight weeks, based on similar studies (Bird, Fletcher and Kock, 2006; Fakuda et al., 2010; Son et al., 2012) and theory behind muscular and neurological adaptations (Bojsen-Møller et al., 2006; Fleck, 1999). Unfortunately, due to the collaboration agreement with Fitness World Kolding, the late arrival of equipment and the recruiting participants, the duration of the experiment was reduced to four weeks, that still proves to be a time period in which noticeable hypertrophy changes can occur (Bojsen-Møller et al., 2006; Fleck, 1999). Lastly, the level of compliance within the experiment was less than expected. Based on the self-reporting training journals, which each participant logged, not all participants managed to comply with the structure of the experiment. It was intended that each participant would train three times a week, and performing each exercise to their maximum capability, unfortunately this was not the case, due to personal schedule and self-motivation. This observation correlates with the literature on intrinsic motivation and personal trainers, where it was stated that performing self-reporting often results in forgetfulness, un- and intentional misreporting, or lack of knowledge on how to perform the exercises correctly (Chandra, Oakley and Silva, 2012). This factor has a huge influence, since the compliance also relates to the training volume. Specifically, the *control group* was intended to execute six exercise implying two sets each, while the *EMG group* had to execute three exercises with four sets each. Meaning that not performing an exercise, as a member of the *control group*, would result in losing ⅙ of the training volume, while, in the case of the *EMG group* will result into losing a ⅓. In other words, the *EMG group* would lose considerable more training volume, thus getting less physiological adaptations (Bojsen-Møller et al., 2006). To counter this factor, the experimental procedure could have been altered, in order to ensure full compliance, by making the participants meet up at the gym and having a personal trainer present when performing the exercises three times per week. Although, this would have been optimal, it would also have been improbable and costly. Therefore, the self-reporting procedure was chosen, despite its deficits.

Regarding the RM data collected, statistically significant improvements within the groups, in relation to the 8 RM increase over the duration of the experiment, was found. Here both group improved significantly between the pre- and post-test. This was also expected since neural adaptations to strength training occurs swift, thus allowing for an increase in weight lifted. It is however, important to mention that this study refers to strength in two ways; weight lifted (RM) and MUAP. Even though, no statistically significant difference was found in the MUAP (EMG average) and statistically significant result was found in the RM, these cannot be directly correlated, since RM is dependent on the exercise performed and the individual's strength, whereas the MUAP if related to the amount of fibers engaged during contraction (Bojsen-Møller et al., 2006; Schoenfeld, 2010; Tan, 1999). For example, when executing an exercise, the weight lifted differs between using a barbell or two individual dumbbells: using the barbell, one muscle receives an aid from its agonist, while dumbbell exercises imply an isolation of the muscle during the execution. Furthermore, when lifting a dumbbell unilateral, the activation signal is stronger, since it is not divided between muscles (Bojsen-Møller et al., 2006).

The signal processing and analysis used in this study should also be addressed. There are two key steps in the processing stage, which determines the quality of the data recorded: the filtering and the data normalisation. This study utilises the signal processing method adopted by several other studies (Bird, Fletcher and Kock, 2006; Fakuda et al., 2010; Halaki and Ginn, 2012; Son et al., 2012), where the raw EMG signal is filtered using an exponential moving average bandpass filter with two cutoff frequencies, in order to get only the frequencies that are most dominant within the muscle. Here, the two cutoff frequencies chosen, high and low, where based on similar studies (Potvin and Brown, 2004). However, many studies use different cutoff frequencies, which indicate that changing these could have resulted in different findings. The next step was to rectify the signal to only get absolute values, which are optimal for quantifiable analysis (Lamontagne, 2001). The rectified data was then normalised, which might be the point in which improvements could have been made. In order to compare EMG data within and between groups, muscles and day of execution, the data set has to be normalised. Normalisation occurs to even out the playing field between the participants. For example, if one person is by nature stronger that the other, then comparing them directly would be uneven. So the data is normalised, in order to equalise the parameters (Fakuda et al., 2010; Halaki and Ginn, 2012). There are two primary ways of normalising the data sets obtained between groups; Root mean square (RMS) - and MVIC normalisation (Fakuda et al., 2010; Halaki and Ginn, 2012). The RMS method reflects the level of MUAP during contraction, which is considered more stable and less influenced by outliers. It can however, reduce the significance of certain singular data points (Fakuda et al., 2010). The MVIC normalisation, which was used for this study, is a way of normalising the data based on the individual's maximum capability to perform the action. For example, if person A is able to produce

100 μV and person B can only produce 50 μV at MVIC, then the data is normalised by converting it into percentage of this MVIC. In this instance, if person A produces 50 μV and person B produces 25 μV, during a contraction, both produce 50 percentage of their capability, thereby being equal. This method was chosen, since it is frequently used when analysing MUAP amplitude between participants (Halaki and Ginn, 2012). It is also considered highly precise if the correct MVIC value is found, which can prove complex and difficult. Furthermore, the data can then be normalised using MVIC peak or average. Both of these have deficits: the peak normalisation can provide very imprecise analysis, if the wrong data point is determined as the peak, whereas the average does not provide a precise indication of the MVIC (Fakuda et al., 2010; Halaki and Ginn, 2012). However, based on the sensitivity of the equipment used in this study, the MVIC average normalisation was used, which might have caused the loss of certain data points. Using the alternative method, yet not recommended by literature (Fakuda et al., 2010; Halaki and Ginn, 2012), could have delivered more accuracy in data measurements.

Besides the limitations mentioned above specific to the current state of the prototype, a behavioral observation was made, which has to be taken into consideration as an acknowledgement for further testing. The behavioral effect observed was the Hawthorne effect (McCarney, 2007), which can be described as the pressure that individuals feel when executing a task while being observed, influencing their performance, instead performing naturally. This was observed during the test sessions when the participants asked if their performance was satisfactory to the investigator's needs, thereby implying their fear of underperforming.

All the above mentioned circumstances and theory presented provide explanation for the inadequacy of the findings in this study. However, there is another factor which is the key weak point of this study, namely the sample size. In this study only a small sample group was recruited, whereas four participants fail to complete the experiment, meaning that any and all result of this study should not be considered conclusive. Therefore, it is essential that a larger sample group has to be recruited and tested for a longer duration than six weeks, in order to verify the tendencies highlighted in this study.

7.3 Future development

If a continuation of this study had to be made, several aspects have to be considered. Firstly, it is vital that the signal filtering is optimised based on the sensors used for the recordings. The vast literature on EMG usage suggests that the filtered interval is situated between 5 and 500 Hz (Lamontagne, 2001; Potvin and Brown, 2004; Reaz, Hussain and Mohd-Yasin, 2006; Türker & Sözen, 2013; Zwarts & Stegeman, 2003). However, based on the experience of this study, the optimal frequency is highly dependent on the sensors used. A solution for future iterations would be to conduct a randomised control trial of the multiple frequencies, in order to refine the signal to noise ratio. In other words, this solution implies a number of preliminary test sequences performed under different frequency intervals, thus determining the optimal filtering values which can deliver clean recordings. Furthermore, for the intent of creating a commercialised and more appropriate version of this overall prototype, meaning interface and EMG feature, it is advised that the current sEMG-s are replaced with wireless versions (Figure 13). This recommendation is based on field observations and the need for dynamic movement while performing strength training (Bojsen-Møller et al., 2006).

The factor of digitised recording and logging of fitness activity is something that has been around for some time and people have got accustomed to it (Fox and Duggan, 2012; Handel, 2011). Although it was not intended for this study to create a well-designed interface, it is however, crucial to have, in order to present the information, gathered from the EMG feature, to the user. Thus, a mock-up version application was created for this study in order to present the possibilities of such a system with a minimal amount of resources invested. The concept was well received by the target audience and a fully functional application was requested, making this another point to be approached on for future development. Nevertheless, this topic was approached in the adjacent report which ultimately presents in depth theory regarding interface design development and possible modifications to be brought to future versions.

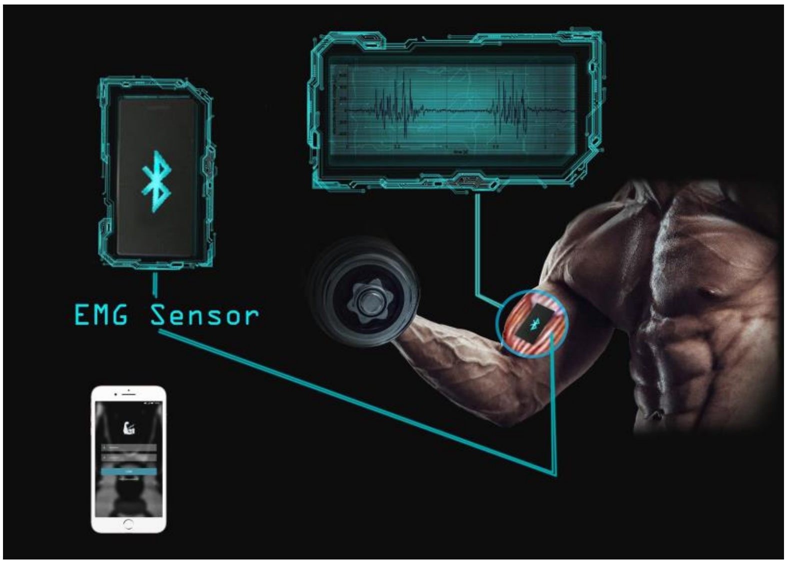

Figure 13 -Future version of EMG feature

8. Conclusion

This paper was a part of a collaboratory study, with the focus of creating an EMG mobile application, which can provide effective and motivating biofeedback, for the selection and individualisation of strength training exercises. The main goal of this paper was the creation and evaluation of an EMG feedback feature for individualisation and exercise selection, on a mobile application, whereas, the adjacent study focused on developing the application and user interface. The presented literature showed a great potential in the use of EMG biofeedback in both sports and rehabilitations (Bird, Fletcher and Kock, 2006; Fakuda et al., 2010; Ng, Zhang and Li, 2008; Son et al., 2012). This was also reflected by the results obtained from this study, with *EMG* selected exercises improving slightly better than the *Control*. However, no statistically significant results were found to support this observation. The general results obtained from this study did not find any statistical significant difference between the groups, which could be due several aspects presented in the discussion above. The lack of statistical significant results, led to the conclusion that more extensive and thorough testing is required, with a larger sample group, in order to get more definitive results.

9. References

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Appendix A

Participation contract

AALBORG UNIVERSITET

Consent to Participate in a Research Study
Aalborg Univerity ● Esbjerg, DK

Title of Study: EMG based individual assesment and strength training optimization

Investigators:

Name: Nicolai Jensen **Dept:** AAUE

Name: Laurentiu Toader **Dept:** AAUE

Name: Jenny Matthiesen **Dept:** AAUE

Introduction

- You are being asked to be in a research study of strength and hypertrophy optimization using biofeedback applications.
- You were selected as a possible participant because you fit the participant profile for this study.
- We ask that you read this form and ask any questions that you may have before agreeing to be in the study.

Purpose of Study

- The purpose of the study is to investigate if the use of EMG biofeedback can help determine which exercises will produced optimal hypertrophy and strength gain in the biceps. All test iterations will be conducted at Fitness World Kolding.
- Ultimately, this research may be published in a journal or as a scientific paper.

Description of the Study Procedures

- If you agree to be in this study, you will be asked to do the following things:
  Each participant will be asked to follow a specific biceps training program over a course of 4 weeks.
  Along this, three test iterations will be made, in the beginning, middle and in the end of the testing period.
  Also, you will be required to fill in a training journal, during the 4 weeks, to track the progress.

Risks/Discomforts of Being in this Study

- The study has the following risks. First, there is a chance of injury, if the exercise is not executed correctly; however this responsibility falls on the participant. Second, there are no further reasonable foreseeable risks. However, there may be unknown risks.

Benefits of Being in the Study

- There are no benefits of participation in this research study, except the possible gain in strength and hypertrophy.

Confidentiality

- The recordings of this study will be kept strictly confidential. Research recordings will be kept in a locked file and all electronic information will be coded and secured using a password protected file. We will not include any information in any report we may publish that would make it possible to identify you.

Right to Refuse or Withdraw

- The decision to participate in this study is entirely up to you. The decision of participation is binding, however, in the event of you being unable to participate further on, this will not have any consequences.

Right to Ask Questions and Report Concerns

- You have the right to ask questions about this research study and to have those questions answered by me before, during or after the research. If you have any further questions about the study, at any time feel free to contact me, Nicolai at rawphysique9@gmail.com. If you like, a summary of the results of the study will be sent to you.
- If you have any problems or concerns that occur as a result of your participation, you can report them to the Nicolai at previous mail listed.

Consent

- Your signature below indicates that you have decided to volunteer as a research participant for this study, and that you have read and understood the information provided above. You will be given a signed and dated copy of this form to keep, along with any other printed materials deemed necessary by the study investigators.

Subject's Name (print): ______________________________

Subject's Signature: ______________________________ Date: ____________________

Investigator's Signature: ______________________________ Date: ____________________

Appendix B

Training Journal

Day:______________________________Date:_______________________ time:________

Training motivation

1- Not motivated

10- Highly motivated

1	2	3	4	5	6	7	8	9	10

Exercise:	Set (EXAMPLE)	Set	Set
Dumbbell curl	12,5 kg x 8 rep		
Barbell curl	14 kg x 8 rep		
Dumbbell preacher curl	10 kg x 8 rep		
Barbell preacher curl	22,5 kg x 8 rep		
Barbell Cable Curl	25 kg x 8 rep		
Dumbbell Cable Curl	10 kg x 8 rep		

Noter til træning, mad osv:

Appendix C

Arduino code

```
int sensorPin = 0;       //pin number to use the ADC
int sensorValue = 0;     //initialization of sensor variable
float EMA_a_low = 0.03;
float EMA_a_high = 0.88; //initialization of EMA alpha
int EMA_S_low = 0;
int EMA_S_high = 0; //initialization of EMA S
int highpass = 0;
int bandpass = 0;
int SensVal = 0;
float oldSensorValue = 0;   //ADDED THIS TO KEEP TRACK OF PREVIOUS SENSOR VALUE

void setup(){
  Serial.begin(12800);              //setup of Serial module, 12800 bits/second

  EMA_S_low = analogRead(sensorPin);     //set EMA S for t=1
  EMA_S_high = analogRead(sensorPin);
}
void loop(){
  sensorValue = analogRead(sensorPin);    //read the sensor value using ADC

  EMA_S_high = EMA_a_high * (EMA_S_high + sensorValue - oldSensorValue);
  EMA_S_low = (EMA_a_low * EMA_S_high) + ((1 - EMA_a_low)*EMA_S_low);

  oldSensorValue = sensorValue; // USED TO SAVE THE OLD SIGNAL VALUE
  bandpass = EMA_S_low;     //WE ALREADY CALCULATE EVERYTHING


  SensVal = abs(bandpass);
  float voltage = (SensVal * (5.0 / 1023.0))*1000;

 // print out the value you read:
  Serial.print("DATA,TIME");
  Serial.print(",");
  Serial.println(voltage);
    delay(05);                     //20ms delay
}
```

Footnotes

[i] Some sections of the literature contain information comparable to previous studies, since this study is an adaptation from previous work. Previous work include: Jensen, N & Toader, L. (2017). Investigating the use of biofeedback on exercise correctness and muscle activity. Unpublished manuscript. Aalborg University, Esbjerg, DK. Jensen, N (2017). State of the art- Individual assessment of strength training on mobile devices. Unpublished manuscript. Aalborg University, Esbjerg, DK.