Development of a wearable free-weight exercise assistant

Ochoa, G.J.

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Master Thesis

Development of a Wearable Free-Weight Exercise Assistant

by G.J. Ochoa Lopez

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Abstract

In this work, the effectiveness of a system that uses sinusoidal motion models based on acceleration and orientation data to assess the quality of individual free-weight exercise repetitions was explored. Two inertial measurement units, one on each wrist, were worn by participants while performing correct and incorrect repetitions based on five common mistakes. Data were analyzed and relevant signals per exercise were selected. Based on readings from correct repetitions, the sinusoidal motion models were developed. The models were then coupled into three different systems that were evaluated based on the accuracy of counting repetitions and on the predicted quality of the repetition. The results depend on the system being evaluated, on the number and type of selected signals, and on the exercise carried out. Acceleration and orientation signals, when used together, yield an acceptable performance. For exercises without rotations, the sole use of acceleration data produces unsatisfactory results. Further work needs to be done before such a system can be used as a training tool with the purpose of improving exercising technique and help prevent injuries.

Chapter 1

Introduction

Physical activity is fundamental in order to achieve and maintain an adequate state of health. It has been proven that it also contributes to the primary and secondary prevention of chronic diseases [24], aiding in the forestallment and treatment of cancer, osteoporosis, cardiovascular diseases, obesity, and diabetes [19]. These conditions account for approximately a trillion dollars in healthcare costs in the United States alone and are becoming the paramount cause of morbidity and mortality in the Western nations [11].

An increasing number of wearable computing systems aimed at monitoring physical activity has entered the market in recent years. Brands such as Fitbit [2], Nike [7], and Jawbone [5] have established themselves as the activity-monitoring solutions for walking and running. Garmin and Polar, on the other hand, offer a more diverse set of systems aimed at professional users in areas such as cycling, swimming, and climbing. All these solutions make use of sensors such as accelerometers, gyroscopes, microphones, and GPS systems to adequately track users' activities.

The aforementioned wearable systems are a tool for attacking physical inactivity, the single most important cause of chronic diseases [11]. However, manufacturers have focused solely on developing devices aimed at cardio activities. Resistance training has not received much attention even though studies show that it complements cardio to achieve a complete exercise program [8]. Current resistance-training tracking applications lack the capabilities to detect which type of exercise is being carried out, to automatically count the number of repetitions, and to give feedback on the quality of these repetitions. At the moment, tracking is based on manual input applications such as Jefit [6], Fitocracy [3], and Gorilla Workout [4]. Even though gamification techniques are used to engage users, the manual input becomes tedious and could potentially decrease motivation for regular usage and training.

Within the resistance-training domain, the free-weight exercise area is of particular interest. This subdomain involves the use of dumbbells and barbells, and more than 90 percent of the resistance-training injuries are caused by incorrect free-weight exercising [14]. Nonetheless, studies highlight how safe and beneficial these exercises are when proper feedback on the technique and execution is available [13]. Qualified fitness instructors are often the source of this feedback and they are usually available at gyms and sports centers. People, for a variety of reasons including gym membership costs, lack of time, and comfort, often prefer to exercise at home and are thus unable to receive feedback on their exercising technique.

It has been shown that it is possible to successfully recognize what type of exercises are being carried out and to count the number of repetitions of these exercises using data from acceleration and orientation sensors [12]. The next step in developing a complete free-weight exercise assistant is to provide feedback on the quality of the repetitions. By providing the feedback to the user a complete training solution can be achieved, which can then be used for tracking progress and to help improve the exercising technique and thus help reduce injuries.

In this work, a wearable sensor was selected and data from wrist-worn accelerometers and gyroscopes were obtained from ten different subjects performing five different free-weight exercises. The subjects were asked to perform correct repetitions and then to perform incorrect repetitions based on five common mistakes. The data were used to develop an understanding of how quality could be measured. Once this understanding was achieved, a sinusoidal motion model-based system was built around signal attributes of correct repetitions for each person. The system's input consists of acceleration and orientation signals of a series of repetitions. This system is able to provide output feedback on the quality of the input repetitions. A performance evaluation was then carried out on the feedback output. The steps in this scheme are depicted in Figure 1-1.

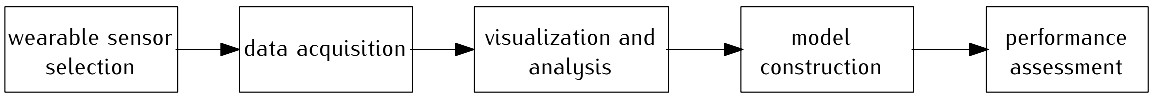


Figure 1-1: Scheme followed during the development of the system

In brief, the objectives during the development of this wearable system will be the following:

1. Analyze acceleration and orientation measurements to understand which signals are more appropriate to be used by the system for each type of exercise. It is to be determined whether all the signals are necessary to perform a quality assessment on individual repetitions.

2. Given the peculiar characteristics of the error types analyzed, the acceleration and orientation readings' performance at detecting these mistakes should differ.

3. Based on the previous point, the combination of the different signals should provide means for a better judgement on the quality of an individual repetition.

This report has the objective of documenting the progress in the development of such a system. Chapter 2 analyzes previous similar works and offers a comparison between these and the current system, presenting at the same time the novel contributions achieved. In Chapter 3 the procedure that led to the sensor selection is discussed. Wearable sensors have specific requirements and each of the options that were contemplated offered different tradeoffs. The data acquisition steps are also presented in this chapter. An analysis based on the visualization of the data is conducted in Chapter 4. The term *quality* is formally defined and the procedure that led to the selection of the relevant signals is presented. The model design and implementation, as well as the different types of testing systems used and their differences are covered in Chapter 5. Chapter 6 discusses the outcome of these experiments, while Chapter 7 presents concluding remarks and suggestions for future research.

Chapter 2

Related work

Different research related to resistance training has been done in the past. A literature study was carried out in order to understand previous approaches and, whenever possible, build upon them.

Fitlinxx [1] offers a solution that is able to monitor machine weight-lifting exercises. This system gives the user feedback on how fast or slow the repetition is being carried out. Its mechanism, hooked to the machine's weight-lifting transmission system, captures the exercise signal and is then able to detect repetitions. The main disadvantage of this system is that it has to be mounted on a specific machine, limiting its versatility and is therefore not able to monitor free-weight exercises.

The Personal Wellness Coach system [9] monitors aerobic and anaerobic exercises using data from accelerometers and a heart-rate monitor. Their system counts repetitions of anaerobic exercises using a single peak acceleration footprint per repetition. Because of this, the system is able to count repetitions for a wide variety of repetitions from different exercises.

In [15], Melzi et al. developed a wearable wireless sensor network to supervise resistance training exercises. Their system uses two sensors, one on the elbow and one on the wrist, using only accelerometers to obtain information on the exercises being carried out. Their approach uses a personal computer to display the movements being carried out by a virtual assistant. The synchronization between this virtual assistant and the user allows the system to calculate uniformity and regularity of the movement but decreases portability. Feedback on the exercise speed, uniformity, regularity, and execution is provided. Suggestions on how to correct errors is also provided.

The approach in [16] proved that exercise recognition can be achieved in a user independent, multi-activity environment using only an arm holster-worn smartphone as a sensor. For the first part of their experiment only acceleration data was used with good results. When the gyroscope measurements were introduced and combined with the acceleration data, the results outperformed the acceleration-only tests by a modest amount. Nevertheless, their results indicate that the addition of a gyroscope is beneficial for fitness activity recognition systems.

An algorithm based on dynamic time warping was introduced in [17] that allows an acceleration stream to be processed in real time using a smartphone. This technique makes it possible to calculate the number and the duration of individual repetitions. Duration is one of the metrics that can be used to provide feedback to the user. An interesting part of this work is that their solution is able to monitor resistance training using exercise machines, free weights, and resistance bands. In order to monitor exercise using machines, the smartphone is placed on the stack of weights.

In [12], Chang et al. developed and compared a Naïve Bayes Classifier and a Hidden Markov Model to count repetitions and distinguish between different free-weight exercises. Data was obtained from an accelerometer mounted into a workout glove and an accelerometer on the user's waist. Even though their approach was successful, in this work it was decided to use wrist-worn sensors. The reason for this was that a wrist-worn device could be converted easier into an ankle-worn device for leg resistance training and used as part of a future study.

In [22] and [23] a model-based system was developed using a body motion tracking approach. This approach, successful nonetheless, requires a Microsoft Kinect or a similar sensor. These type of sensors have additional requirements such as minimum space needs and are also not very portable.

A system used for COPD rehabilitation was developed by Spina et al. in [21]. This system uses orientation data to model rehabilitation exercises using a smartphones' built-in sensors. Our system builds on this approach by including acceleration signals and the ability to assess two limbs simultaneously.

The previously discussed systems have all contributed to the field of recognition and tracking in resistance training exercises. Some of these papers use accelerometers and gyroscopes [16], others use only accelerometers and possibly other non-gyro sensors [9], [15], [17], [22], and [23]. Feedback to the user is also given in [9], [15], [22], and [23]. The aim of this project is to build upon these approaches by using both accelerometers and gyroscopes and to extend the feedback provided based on the quality of the repetition and on five different common mistakes.

The novel contribution of this project is a pioneer study on the effectiveness of model-based methods using accelerometer and orientation data with the purpose of detecting free weight mistakes in order to help the user improve the exercising technique and aid in injury prevention.

Chapter 3

Sensor Selection and Data Acquisition

A specific set of requirements needs to be met by a sensor in order to be useful for a wearable application. Once the sensor is deemed as appropriate, the data acquisition phase can begin. This chapter explains in detail the procedure that led to the selection of the used sensor and the data acquisition method, as well as other related aspects. Figure 3-1 shows in green the sections of the scheme that will be covered in this chapter.

Figure 3-1: Steps covered in Chapter 3

3.1 Sensor selection

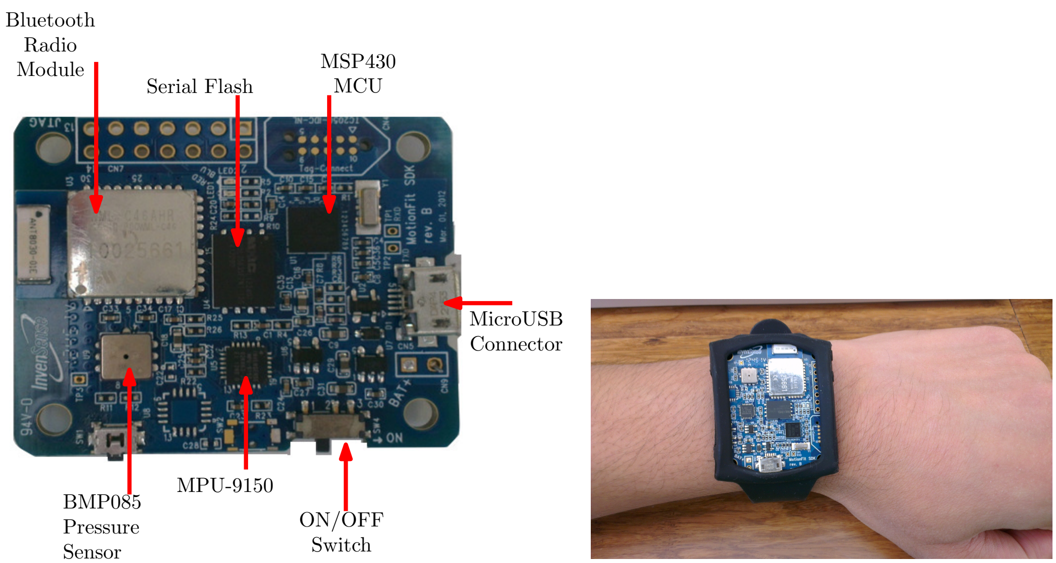
When building a wearable sensing system it is necessary to have an understanding of the precise movements that will be carried out. In this case, each of the different free-weight exercises has a distinctive motion in the 3D coordinate system. There are also a number of desired characteristics a wearable sensor should have. They should be small and lightweight in order to be as unobtrusive as possible and to allow movements and activities to be unrestrained. However they should be able to sense different relevant physical quantities. In this case, they should fit comfortably on the users' wrists. Ideally they should be within an affordable price range, looking ahead to a possible application. With these requirements three different sensing elements were considered for this system.

The first alternative studied was the use of a smartwatch. An off-the-shelf smartwatch has a series of advantages. The first one is the unobtrusiveness offered, which would allow a user to perform movements without many additional restrictions. The second advantage would be robustness. Most of these smartwatches are water and sweat resistant. The long battery life and the Bluetooth connection are also convenient. There are two big disadvantages though: cost and lack of orientation sensors. A price tag in the $150-$350USD range for a single device is not very appealing. More importantly, the smartwatches available only have accelerometers. Smartwatches with gyroscopes that would allow for orientation monitoring are either not commercially available or there is no support offered for developers by the vendors.

A second alternative that has been seen before in [16], [17], and [21] is using the smartphone as both a sensing and a processing device. Smartphones offer higher processing power than smartwatches, an excellent battery life, and contain not only accelerometers but gyroscopes as well that could be used to monitor the orientation of the exercises carried out. A disadvantage of this approach is that it is uncommon for a person to own two smartphones in order to wear them simultaneously to keep track of the arms' movements. Additionally, smartphones are bulkier and might restrict motion.

The third option consists of using an inertial measurement unit (IMU) such as the MPU-9150 by Invensense. An IMU contains an accelerometer, a gyroscope, and a magnetometer and is thus able to monitor the acceleration and orientation of the movements carried out. The IMU would then send the data to a smartphone for processing. An IMU is significantly smaller than a smartphone, being less obtrusive. They are also cheaper than a smartwatch, making it feasible to monitor the movements of both arms with one unit per arm. For these reasons, an IMU was chosen for this project.

Figure 3-2a shows the MotionFit SDK, which was chosen for this project. The SDK is optimized for wearable applications and includes a Bluetooth radio for wireless communication and a lithium battery. An additional benefit is that the size of the SDK fits commercially available wrist straps for music players, as shown in Figure 3-2b.



(a) Hardware diagram (b) SDK within wrist strap

Figure 3-2: MotionFit SDK

3.2 Communication implementation

An overview of the communication can be seen in Figure 3-3. The two MPU-9150 units connect via Bluetooth to the smartphone. The packets are then received and processed by CRNTC+ [10], a toolbox for prototyping applications for sensing systems.

A meticulous investigation was carried out with the final goal of understanding the communication details of the IMU. The first step was to understand the packets' format. This was possible by studying the code from a Python appli-

Figure 3-3: Communication overview

cation found on the manufacturer's web site[1]. A dollar sign in the first byte indicates a valid data packet. There are three types of packets: debug packets, quaternion packets, and data packets. It is possible to distinguish them by analyzing the contents of the second byte. A "1" indicates a debug packet, a "2" indicates a quaternion packet, and a "3" indicates a data packet. For the purpose of this project only data packets are relevant.

Seven different types of data packets exist. Of these, only the acceleration and quaternion packets are used. Acceleration packets are identified by a "0" in the third byte, while quaternion packets contain a "4". Acceleration data is included in the next twelve bytes, where each of the three dimensions requires four bytes. Quaternion packets, on the other hand, require sixteen bytes. All packets consist of 23 bytes. The remaining bytes are used in debug packets or with other data packets which are not used in this study and therefore their contents will not be detailed. Figures 3-4 and 3-5 show a graphical representation of acceleration and quaternion packets.

After understanding the packet format it was possible to start porting the Python application to Java, the language used by CRNTC+. A simple Android example application, Bluetooth Chat[2], served as a first attempt to verify the functionality. This application was used to detect and correct minor errors and it also served as a model for implementing the MotionFit SDK module within CRNTC+.

A workaround for connectivity with more than one MotionFit SDK was de-

[1]http://www.invensense.com/developers/downloads

[2]http://developer.android.com/tools/samples/

vised, since they all share the same universally unique identifier (UUID) and Bluetooth in Android searches for devices and connects via UUIDs. This workaround consists of noting individual media access control (MAC) addresses. In Android it is possible to iterate over a list of paired devices, and when a UUID match is found, that device can be polled for its MAC address. If the MAC address matches, then it is possible to connect to this device. There is one minor disadvantage that arises from this implementation: the IMUs have to be paired manually before connecting. This prevents the smartphone from automatically discovering new IMUs.

<table>
<tr><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td><td>20</td><td>21</td><td>22</td></tr>
<tr><td>$</td><td>3</td><td>0</td><td colspan="3">x</td><td colspan="3">y</td><td colspan="3">z</td><td colspan="11">...</td></tr>
</table>

Figure 3-4: Data packet containing acceleration values

<table>
<tr><td>0</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td><td>8</td><td>9</td><td>10</td><td>11</td><td>12</td><td>13</td><td>14</td><td>15</td><td>16</td><td>17</td><td>18</td><td>19</td><td>20</td><td>21</td><td>22</td></tr>
<tr><td>$</td><td>3</td><td>4</td><td colspan="3">q_1</td><td colspan="3">q_2</td><td colspan="3">q_3</td><td colspan="3">q_4</td><td colspan="8">...</td></tr>
</table>

Figure 3-5: Data packet containing quaternion values

3.3 Selected free-weight exercises and mistakes

A set of common, representative free-weight exercises was selected in order to be used for the recording of the data set. Table 3.1 shows these exercises, the muscle group they exercise, and the respective posture.

	Exercise	**Muscle group**	**Posture**
1	Lying Fly	Chest	Lying
2	Palms-In Shoulder Press	Shoulder	Standing
3	Shoulder Press	Shoulder	Standing
4	Lateral Raise	Deltoid	Standing
5	Biceps Curl	Biceps	Standing

Table 3.1: Exercises used for the recording of the data set

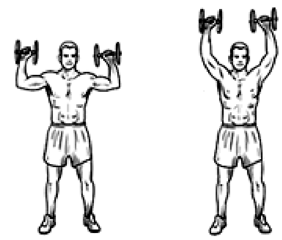
These exercises will be carried out correctly by the volunteers and are shown in Figure 3-6[3] . Additionally, five common exercise mistakes will be replicated to obtain their data. These common mistakes were obtained from [18] and [20], and confirmed by personnel from the Student Sport Centre Eindhoven. They include:

1. Rushing repetitions, which raises blood pressure, increases risk for joint injury and compromises results
2. Incorrect range of motion due to over stretching, which damages the joints
3. Incorrect range of motion due to under stretching, minimizing exercise benefits
4. Not keeping dumbbells leveled on exercises with symmetric movements
5. Bouncing and using momentum or gravity instead of a smoothly controlled motion

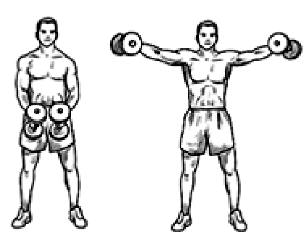
[3] Images taken from *www.dumbbell-exercises.com*

(a) Lying fly

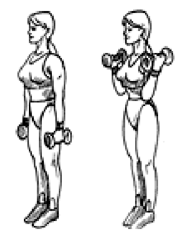
(b) Palms-In Shoulder Press



(c) Shoulder Press



(d) Lateral Raise



(e) Biceps Curl

Figure 3-6: Exercises used for the recording of the data set

3.4 Data acquisition

Ten participants were chosen for this experiment, with five female and five male subjects. The mean age is 26.8 years and the corrected sample standard deviation is 2.89 years. The recordings took place in the Student Sport Centre Eindhoven. While the participants were performing the exercise script, the data was being labeled by an observer. The participants wore the wrist straps housing the IMUs in both wrists. Special care was taken to ensure that the IMU placement within the wrist strap was always constant.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10
Gender	F	M	F	M	F	F	F	M	F	M
Repetitions	223	243	230	256	249	244	248	271	241	224

The complete details of the process can be seen in the Data Recording Plan in Appendix A.

Chapter 4

Data analysis

Once the data has been recorded it is possible to visualize it. An analysis was carried out in order to have a better understanding of which signals better represent each exercise and are thus better at determining a repetition's quality. Figure 4-1 shows the scheme's sections that will be covered in this chapter. First, the results of the recordings will be presented for selected exercises and mistakes. The definition of *quality* will also be formalized in this chapter. Then the signals that contribute the most in the quality assessment for each exercise will be presented.

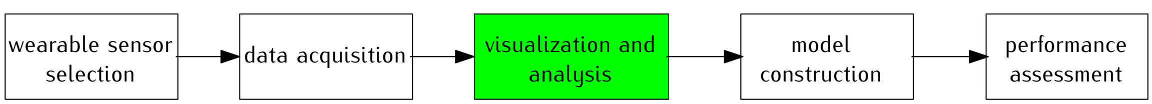


Figure 4-1: Steps covered in Chapter 4

4.1 Data visualization

As it was previously mentioned, each exercise and each mistake have a unique acceleration and orientation signature. The IMU made it possible to monitor acceleration values A_x, A_y, and A_z and to obtain quaternions which were then converted to Euler angles E_x, E_y, and E_z for easier interpretation. Figure 4-2 shows the axes relative to the SDK. Blue represents the x axis, green represents y, and z can be seen in red.

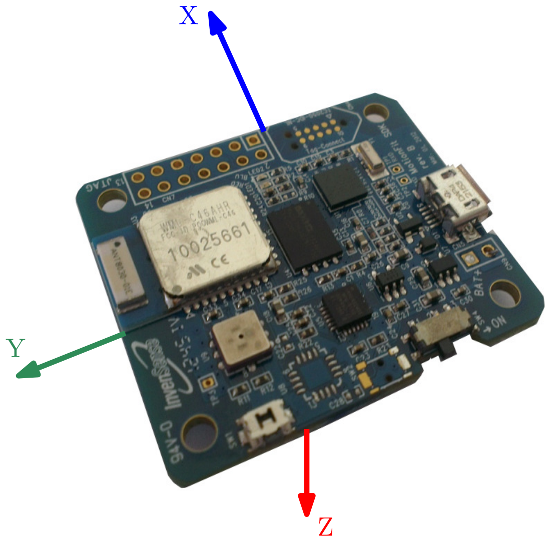
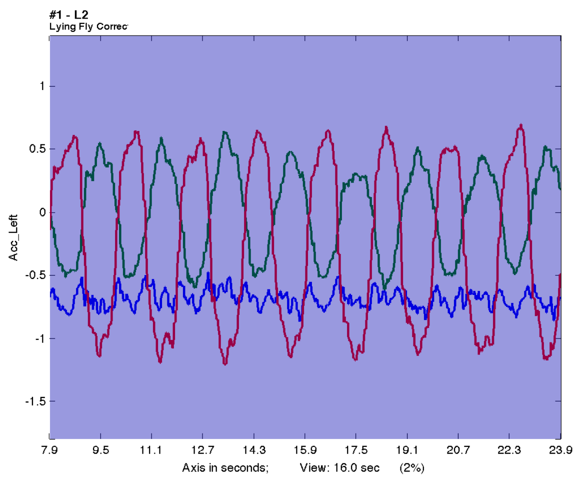


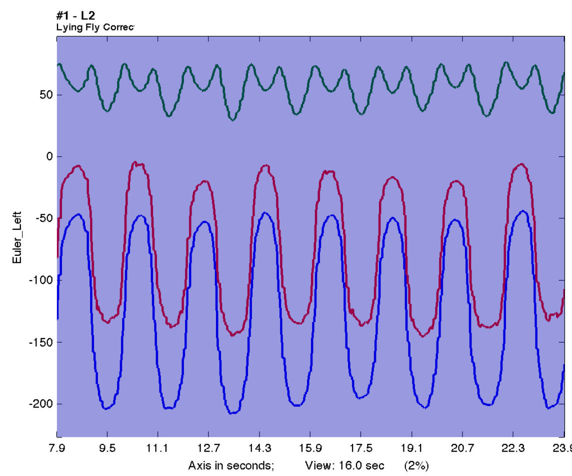
Figure 4-2: The axes: x in blue, y in green, z in red

Figure 4-3 shows the acceleration and orientation data graphs from the left hand for the lying fly and palms-in shoulder press exercises in their correct form. The graphs show eight repetitions of the lying fly and ten repetitions of the palms-in shoulder press. This data was taken from a 33-year-old female participant. Note that since the exercises shown are symmetric for both hands, the data from the right hand has a similar yet non-identical shape.

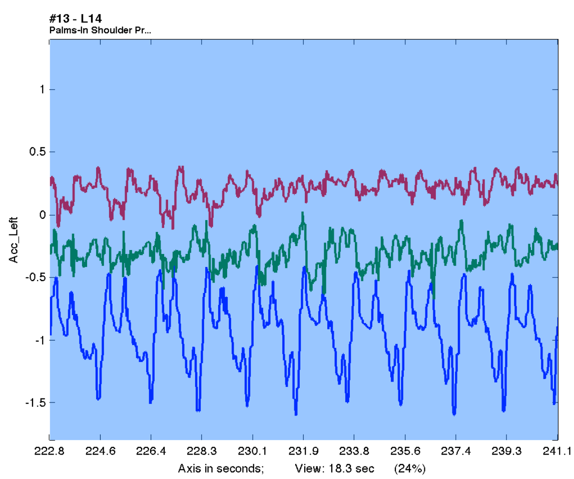
From the graphs it can be clearly seen that the movements are periodic and that the values for the different axes vary between exercises. A simple, intuitive visual inspection reveals individual traits that can be used to distinguish between the different exercises. For example, the acceleration in z for the palms-in shoulder press (Figure 4-3c) appears very noisy and is constrained between a small range of values. On the other hand, the lying fly's acceleration in z (Figure 4-3a) has more variation and shows a more smooth and periodic form. Additionally, the y and z acceleration values of the lying fly (Figure 4-3a) and of the palms-in shoulder press (Figure 4-3c) show a negative correlation. The mean value of each axis also differs per exercise. Perhaps this is better illustrated now with the Euler angle graphs. Since the palms-in shoulder press presents almost no rotation, the values depicted in Figure 4-3d do not vary a lot. The angles in Figure 4-3b change much more due to the nature of the movement required to perform lying fly repetitions. Similar comparisons can be carried out with the other exercises. These differences and similarities were used by the authors in [12] in order to automatically detect which exercise was being carried out. The remaining graphs for the complete set of correct exercises for this participant can be seen in Appendix B.



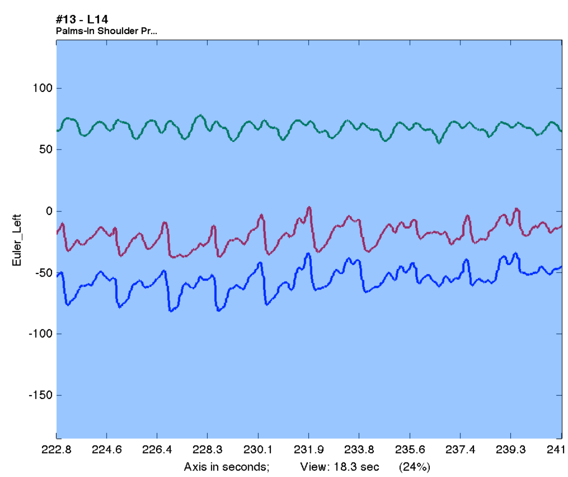
(a) Acceleration for lying fly



(b) Euler angles for lying fly



(c) Acceleration for palms-in shoulder press



(d) Euler angles for palms-in shoulder press

Figure 4-3: Correct lying fly and palms-in shoulder press. The x axis is shown in blue, y in green, and z in red.

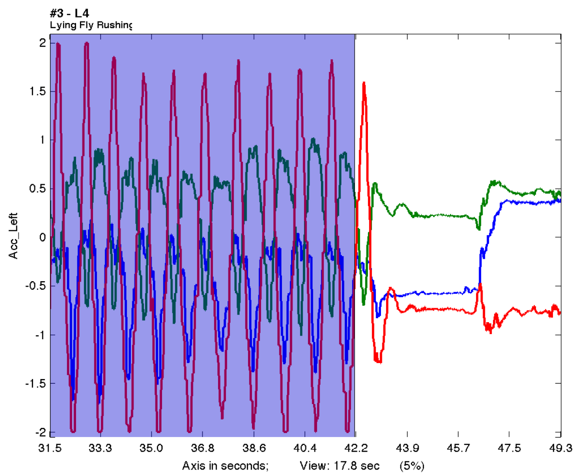
A similar analysis was carried out between the correct version of the exercises and the different mistakes. This analysis allowed to identify the characteristics that differentiate between correct and incorrect repetitions. Figure 4-4 shows two of the common mistakes while performing the lying fly. Comparing them to Figure 4-3a and Figure 4-3b, it is evident that there is a difference in the magnitude for the rushing repetitions case in the acceleration values. Since repetitions were carried out faster in the same range of motion, an acceleration of higher magnitude took place. This is evident in all of the three axes. Moreover, the period of each repetition is much shorter. Over stretching shows a slightly less notorious difference in the acceleration graph; the peak magnitudes are slightly higher. Figure 4-4d reveals a much more pronounced difference in the orientation readings. Considerable magnitude changes can be seen in the values of all three axes due to an excessive range of motion. Similar analyses were carried out for the remaining errors and for the remaining exercises, revealing analogous results. Refer to Appendix C for the remaining common mistake-graphs for the lying fly.

A particular type of mistake occurs due to the individual's laterality. Normally one hand or leg is stronger than the other. This becomes evident when performing symmetric exercises, such as the ones performed in this study. The strong hand carries out the exercise more smoothly and in the complete range of motion. The weak hand, after a number of repetitions, starts struggling and the range of motion decreases. The corresponding graphs can be found in Appendix D.

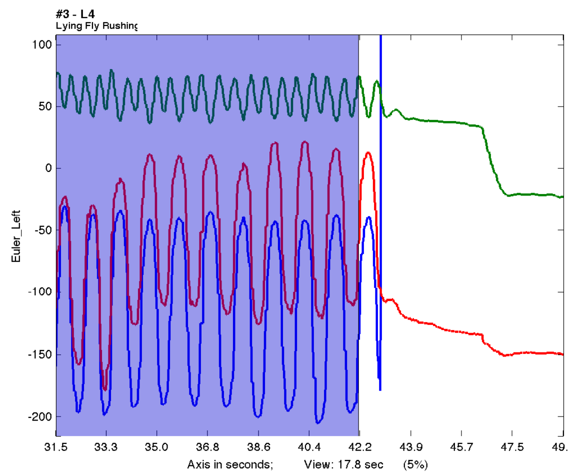
4.2 Defining quality

Before tackling more technical issues, the definition of quality needs to be formalized. Previous works in activity recognition have analyzed topics from a qualitative point of view, but there is still no common understanding as to what characterizes the quality of an activity, in this case, the execution of a repetition.

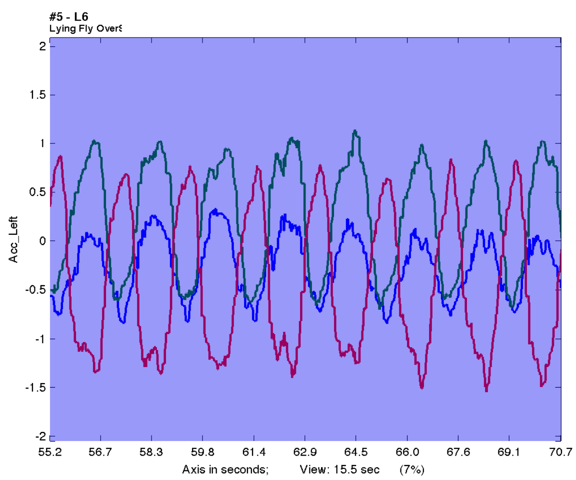
One of the main contributions listed in [23] is precisely a formalization of the term *quality* in the activity recognition context. After analyzing a series of definitions for the term they found that a shared trait is that "one starts with a product specification and a quality inspector measures the adherence of the final product to this specification." The definition makes it obvious that to measure quality, a standard to measure against is required. If a specification of how an



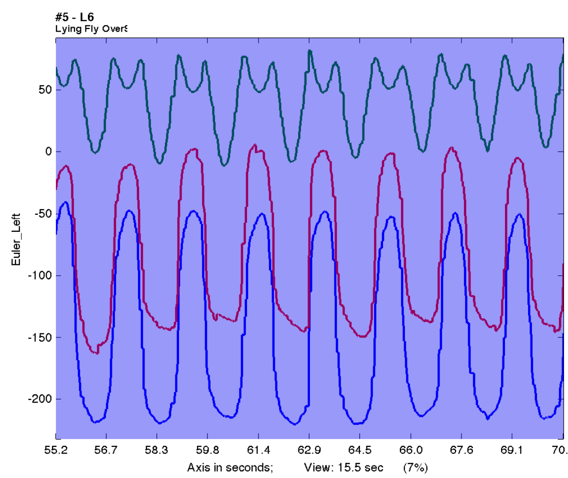
(a) Acceleration for rushing lying fly



(b) Euler angles for rushing lying fly



(c) Acceleration for over stretching lying fly



(d) Euler angles for over stretching lying fly

Figure 4-4: Incorrect lying fly. The x axis is shown in blue, y in green, and z in red.

activity has to be performed can be obtained, then it is possible to measure the quality of a repetition by comparing its execution against this specification.

The formal definition of quality is then defined as *the adherence of the execution of an activity to its specification*. One of the benefits of this specification is that if there are multiple ways of performing an activity, as long as a specification is available, quality can be measured. This definition was developed by Velloso et al. and was deemed as appropriate for this assignment, thus being selected.

4.3 Signal selection

The exercises selected for this study make use of both arms simultaneously. Acceleration and orientation data was gathered from each arm, totaling six signals per arm.

Recall that a model-based approach is being followed. A model, in essence, is an abstraction or approximation that should fit the problem at hand. Determining the right level of abstraction that makes a good model was one of the key issues faced during the development of this system, particularly because predictability and complexity are normally conflicting.

Due to the nature of the movements carried out, some of the signals might not be as significant as others when determining the quality of a repetition. By analyzing the movements of each exercise it was possible to select the signals that contribute to determining the quality of a repetition. Consequently, trivial signals were also identified and their use in the model was prevented, simplifying the approach greatly. A summary of this analysis is presented next for each exercise. Review Figure 3-6 and Figure 4-2 to recall the exercises and the axes orientations.

4.3.1 Lying fly

The main motion of the lying fly occurs in the z axes. There is no movement in the x direction and, depending on the lying fly variation, there might or might not be movement in the y direction. As for the angles, the main changes occur in the x and z axes.

4.3.2 Palms-in shoulder press

The movement for this exercise is mainly in the x axis. The y and z axes present minimal movement. There are slight rotations around the three axes, since the sensor mostly moves in one axis. In this case, because of the position of the arms, the x axis is in the up-down direction.

4.3.3 Shoulder press

This exercise is similar to the palms-in shoulder press, but with the palms now facing the front. The movement is only up-down, again in the x axis. Again, slight movements are present in the y and z axes. Minimal orientation changes take place in all three axes.

4.3.4 Lateral raise

Motion in this exercise is mostly limited to the z axis. Nonetheless, it can be seen from the data that the acceleration signature of the x axis is less noisy. When the arms are lowered, gravity causes a value of one in the x axis, and as the arms are raised, the value changes smoothly. The main angle change takes place around the y axis. Less significant changes also occur on the x and z axes.

4.3.5 Biceps curl

The acceleration signature depends on the particular type of biceps curl being carried out. It was observed, however, that the values of the x axes fluctuate smoothly between $[-1, 1]$. This happens because the up and down positions of the exercise flip the sensors in the x axis, causing a positive and a negative measurement of gravity. The main rotation occurs around the y axis.

This analysis was done with the ten participants, confirming that the signals selected were always descriptive and that the majority of the signals can be omitted. In some cases, only one signal out of the six is considered representative. These signals are presented in Table 4.1. Acceleration signals are labeled with an A and orientation signals are labeled with an E. The respective axis is indicated as a subscript.

	Exercise	**Signals**
1	Lying Fly	A_z, E_x, E_z
2	Palms-In Shoulder Press	A_x
3	Shoulder Press	A_x
4	Lateral Raise	A_x, E_y
5	Biceps Curl	A_x, E_y

Table 4.1: Signals selected for each exercise

Chapter 5

Model design and implementation

Having an understanding of the data makes it possible to design a better model. The model needs to be generic enough to suit different exercises but at the same time it needs to have an acceptable performance. Once it has been designed, it has to be implemented and coupled to the system in order to test it and verify its effectiveness. Figure 5-1 shows the scheme's sections covered in this chapter.

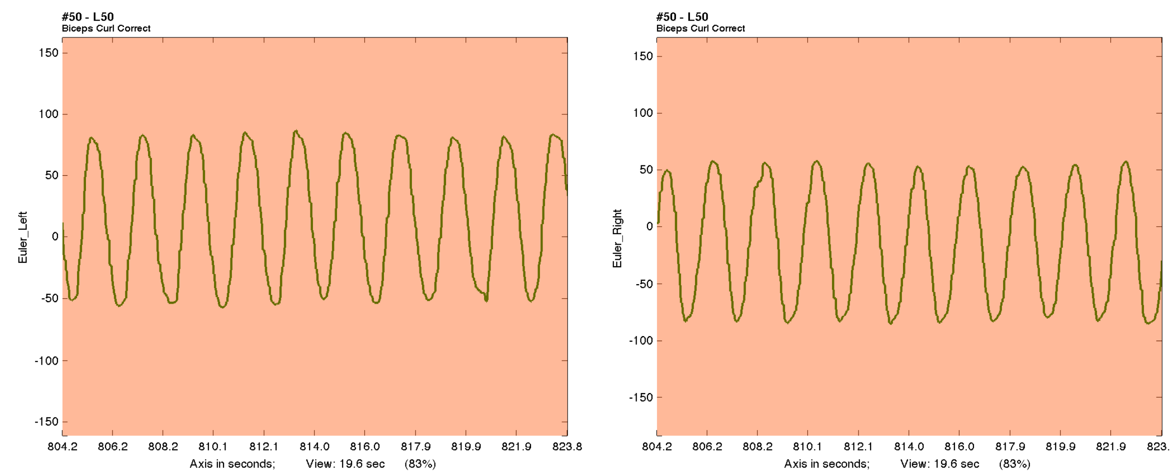
Figure 5-1: Steps covered in Chapter 5

5.1 Design

Formalizing a correct repetition from a particular exercise provides a means to assess the quality of other repetitions from that same exercise. By observing in which ways and how much a different repetition coincides or differs it is possible to deem it as appropriate or unsuitable.

The signals from Table 4.1 all follow a repetitive, sinusoidal-like behavior. Therefore a sinusoidal motion model, based on the one implemented by Spina et al. in [21], was selected. A model will be created for each arm due to the differences of movements between arms.

To predict the quality of a repetition a model based on the data of a single signal will be used. The E_y signal from a series of correct biceps curl repetitions will be used as an example. Figure 5-2 shows this signal for both arms. At a first glance it can be seen that it takes approximately 2 seconds to perform a repetition. Its peak values are around 75 degrees for the left arm and around 50 degrees for the right arm. The minimum values, on the other hand, are around -50 degrees for the left arm and -75 for the right arm. The crossover point for the left arm is around 20 and for the right arm it is located around -20. Additionally, there is some synchronization between both signals. Note that these are just estimations obtained from a quick glance.



(a) Left arm

(b) Right arm

Figure 5-2: E_y signal to be modelled

The precise values of these parameters will be computed from the series of correct repetitions. The standard deviations of some of these parameters will also be computed. Table 5.1 shows the notation that will be used from now on, the values of these parameters for this particular example, and the corresponding units. The symbols and values for the standard deviations of each parameter are shown in parentheses.

	Symbol	Description	Value	Units
1	$T(\sigma_T)$	Period of the signal	198.7 ($\pm$4.9)	samples
2	$\epsilon_L^+(\sigma_{\epsilon_L^+})$	Mean peak for the left signal	83.3 ($\pm$1.8)	degrees
3	$\epsilon_R^+(\sigma_{\epsilon_R^+})$	Mean peak for the right signal	54.3 ($\pm$2.6)	degrees
4	$\epsilon_L^-(\sigma_{\epsilon_L^-})$	Mean valley for the left signal	-53.7 ($\pm$2.1)	degrees
5	$\epsilon_R^-(\sigma_{\epsilon_R^-})$	Mean valley for the right signal	-83.6 ($\pm$1.5)	degrees
6	α_L	Mean crossover for the left signal	14.8	degrees
7	α_R	Mean crossover for the right signal	-14.6	degrees
8	$\Delta(\sigma_\Delta)$	Synchronization value	94.2 ($\pm$48.1)	degrees

Table 5.1: Symbolic notation, description, sample values, and units of the model parameters

These parameters define the standard of a correct repetition according to our model. Note that the data from the sensors was sampled at 50Hz, but in MATLAB, after importing the sensor data, it was up sampled to 100Hz. By extracting these same parameters from a different repetition and comparing them to the standard, an assessment on the quality can be given. Note that the synchronization value is obtained by subtracting the signals.

5.2 Implementation

A script was developed in MATLAB in order to obtain the precise numerical values of the model. The input values are a series of correct repetitions and the number of these repetitions. The corresponding parameter values are then computed and returned as output.

In order to calculate T and σ_T, the position of each individual peak is registered. The distance between neighboring peaks is calculated and averaged, obtaining an estimate for the period. The standard deviation is calculated from these distances as well.

To obtain ϵ_L^+, ϵ_R^+, ϵ_L^-, ϵ_R^-, and their corresponding standard deviations, a number of peaks and valleys equal to the number of repetitions was found. Since at the moment raw data is being used, it might be the case that multiple peaks are found within a single repetition. To have the correct peaks, a minimum distance parameter can be introduced depending on the speed at which the user is training.

Once the mean peaks and valleys have been obtained it is possible to determine α_L and α_R. These values are selected as the middle point between the mean peaks and the mean valleys for each hand and are the ones that determine the start and end of a repetition.

Table 5.1 shows the values obtained from using the series of repetitions on signal E_y as an input to this script. A new repetition R can then be compared to the model's values in order to verify if it is correct or if it is incurring in the rushing repetitions, over stretching, under stretching, not leveled, or bouncing mistakes. Table 5.2 defines the criteria that determines the feedback of repetition R.

	Feedback	**Condition**
1	correct	$R_T > T - x_1\sigma_T$ $R_{\epsilon^+_{L/R}} \in [\epsilon^+_{L/R} - x_2\sigma_{\epsilon^+_{L/R}}, \epsilon^+_{L/R} + x_3\sigma_{\epsilon^+_{L/R}}]$ $R_{\epsilon^-_{L/R}} \in [\epsilon^-_{L/R} - x_4\sigma_{\epsilon^-_{L/R}}, \epsilon^-_{L/R} + x_5\sigma_{\epsilon^-_{L/R}}]$ $R_\Delta \in [\Delta - x_6\sigma_\Delta, \Delta + x_7\sigma_\Delta]$
2	rushing reps.	$R_T < T - x_8\sigma_T$
3	over stretching	$R_{\epsilon^+_{L/R}} \in [\epsilon^+_{L/R} + x_9\sigma_{\epsilon^+_{L/R}}, \epsilon^+_{L/R} + x_{10}\sigma_{\epsilon^+_{L/R}}]$ $R_{\epsilon^-_{L/R}} \in [\epsilon^-_{L/R} - x_{11}\sigma_{\epsilon^-_{L/R}}, \epsilon^-_{L/R} - x_{12}\sigma_{\epsilon^-_{L/R}}]$
4	under stretching	$R_{\epsilon^+_{L/R}} < \epsilon^+_{L/R} - x_{13}\sigma_{\epsilon^+_{L/R}}$ $R_{\epsilon^-_{L/R}} > \epsilon^-_{L/R} + x_{14}\sigma_{\epsilon^+_{L/R}}$
5	not leveled	$R_\Delta \notin [\Delta - x_{15}\sigma_\Delta, \Delta + x_{16}\sigma_\Delta]$
6	bouncing	$R_{\epsilon^+_{L/R}} > \epsilon^+_{L/R} + x_{17}\sigma_{\epsilon^+_{L/R}}$ $R_{\epsilon^-_{L/R}} < \epsilon^-_{L/R} - x_{18}\sigma_{\epsilon^+_{L/R}}$

Table 5.2: Feedback criteria

The x_1 to x_{18} variables were adjusted empirically to obtain the best results according to the labeling of the mistakes. They are fixed for every exercise type and participant independent, but can vary between different signals. Once these values are determined they are assumed to be fixed.

A series of different experiments were carried out after the model of a correct repetition was obtained. These experiments are explained next.

5.3 Single signal input using raw data

The first attempt at predicting the quality of a repetition consisted of using only the raw data of a single signal. The raw data of a series of correct repetitions was used to build the model and the raw data of different repetitions was then used as input. The new input signals were segmented into individual repetitions using α_L and α_R. After segmentation, the parameters listed in Table 5.1 were extracted for each repetition and then a quality assessment was given based on these values and on the relationships listed in Table 5.2. Figure 5-3 shows an overview of the system. The raw input signal on the left is compared to the model in order to assess the quality of the repetitions and present it as the output. The output is an array of binary values where each element indicates whether or not one of the mistakes was detected. This model was built using raw data.

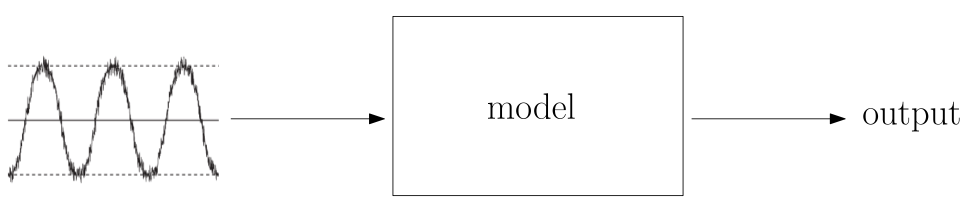


Figure 5-3: Diagram of the single signal input system using raw data

Tradeoffs are present when it comes to using raw data. On one hand, battery-consuming and computationally-expensive filtering computations are avoided. This is critical when dealing with resource-constrained systems such as the smart-phone used. On the other hand, the noise in the data can influence negatively the output of the system.

5.4 Single signal input using filtered data

The second attempt consisted again of using only a single signal, but this time using a moving average filter to smoothen the data. The model was now created from the smoothened data of correct repetitions. The same procedure was followed for the segmentation, parameter computation, and quality assessment parts. An overview of the system is shown in Figure 5-4. The filtered input signal on the left is compared to the model in order to assess the quality of the repetitions and present it as the output. This model was built using filtered data.

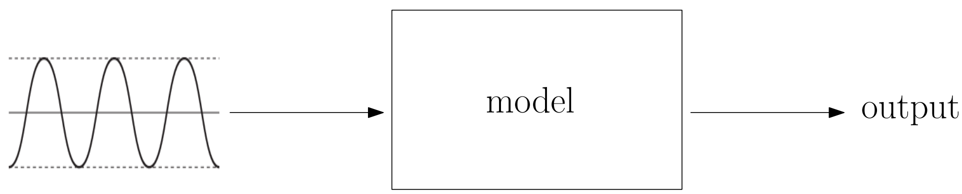


Figure 5-4: Diagram of the single signal input system using filtered data

A moving average filter is one of the simplest filters available but it is optimal when it comes to reducing random noise.

5.5 Multiple voting signals

From the data analysis carried out in Chapter 4 it appears that some signals are better suited to predict particular errors. For example, acceleration signals appear to be better at detecting bouncing mistakes, while orientation signals are better at determining over and under stretching. To obtain the best performance out of the system, a voting algorithm over the different signals can be used. Figure 5-5 illustrates this concept.

Table 4.1 listed the signals deemed relevant per exercise. Notice that the palms-in shoulder press and the shoulder press only had one signal. In this case the outcome will be selected by this single signal. When it comes to the lateral raise and the biceps curl, the output will be determined differently. The relationship between the different errors and the signals will be studied in order to determine which signal is more accurate at detecting a certain error. The signal with a higher accuracy will have a higher weight in the outcome. A similar approach was used for the lying fly, but this time with all three signals. Notice that this approach can be extended to n voting signals.

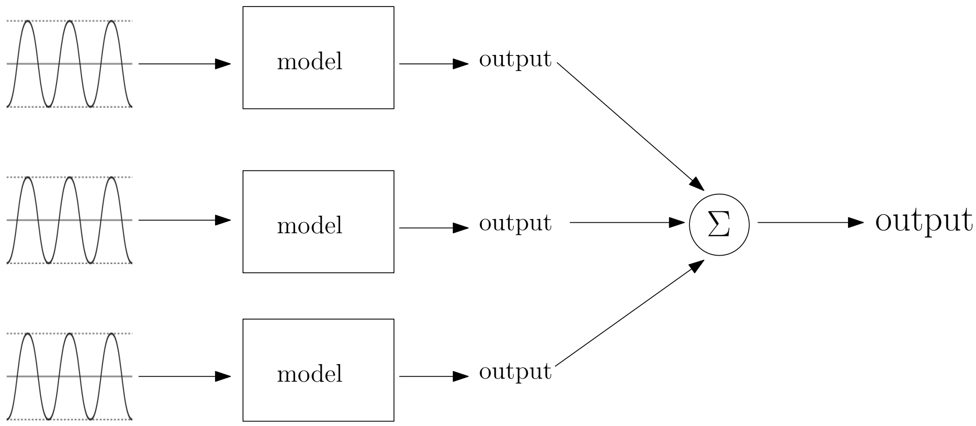


Figure 5-5: Diagram of the multiple voting signals system

Chapter 6

Performance assessment

After obtaining a standard and defining the different testing systems a series of repetitions were used for evaluation purposes. First the performance metrics used are explained and then the three different systems are evaluated and the results are analyzed in-depth. Figure 6-1 shows the section covered in this chapter relative to the entire scheme.

Figure 6-1: Steps covered in Chapter 6

6.1 Performance metrics

Two metrics will be used to measure the performance of the systems: prediction accuracy and the accuracy in counting the number of repetitions. These metrics are explained next.

6.1.1 Prediction accuracy

The data set used was recorded in such a way that only one mistake was carried out at a time. Correctly determining whether this mistake was made or not is one of the metrics that will be used to measure performance. It will be measured as the percentage of correctly detected mistakes out of the total repetitions incurring on this mistake. Prediction accuracy varies depending on the signals and exercises carried out, as well as between participants.

In a realistic scenario it would be possible for an instance of a repetition to have more than one mistake. For example, an individual can incur into over stretching and under stretching when performing a lateral raise repetition. The individual can exceed the movement in such a way that the arms, in the upper motion, go above the horizontal. On the way down, the arms can stop at some intermediate point. Additionally it is possible that one arm incurs in one mistake and the other arm incurs in a different one. If indeed more than one mistake is detected, then further studies need to be carried out to determine how to better inform the users about these mistakes.

6.1.2 Accuracy in counting repetitions

Due to noise and the movements carried out by the participants it is possible that the number of repetitions carried out and the number of repetitions detected by the system are not the same.

If the correct number of repetitions is denoted as r_c and the number of repetitions counted by the system as r_s, then the system's error is given by $e = r_c - r_s$.

False repetitions occur when the crossover values (α_L and α_R) are crossed more than three times in a repetition. False repetitions have an impact on prediction accuracy. If a false repetition is detected, the system will most likely treat it as a rushing repetition only, but other errors are also possible.

It is also possible that a repetition or series of repetitions is not detected, leading to $r_s < r_c$. This occurs when the α_L and α_R values are not crossed due to a change in the movement or orientation.

Maximizing the accuracy in counting repetitions is therefore necessary not only to keep correct records but also to provide adequate feedback.

6.2 Single signal input using raw data

The prediction accuracy results for the first system are shown in Figure 6-2. The number of graphs per exercise varies depending on the signals selected on Table 4.1. The results are shown for each of the ten participants. Mistake 1 in the mistake axis represents "Rushing Repetitions", 2 represents "Over stretching", 3 represents "Under stretching", 4 represents "Not Level", and 5 stands for "Bouncing".

The first thing that is noticeable is the difference in performance between participants. This is because the system's output is highly dependent on the repetitions that were used to build the model. Some participants had very low quality data in certain exercises. Figure 6-2c shows an example of this in participant seven, which had an accuracy of zero for all the mistake categories.

Another important point is the low accuracy for the not level category. A first approach to this mistake was to calculate the standard deviation of the signals for both arms and, based on this, detect whether or not the arms were leveled. This approach worked only when the signals were in phase, which is not always the case. This approach was thus dismissed. The current approach focuses on the peaks and valleys of the signals. If the signal of one arm is within an acceptable range while the other is not, then the repetition is categorized as not leveled. This approach is still not very effective since some peaks and valleys cannot be detected when the arm is below or above certain thresholds.

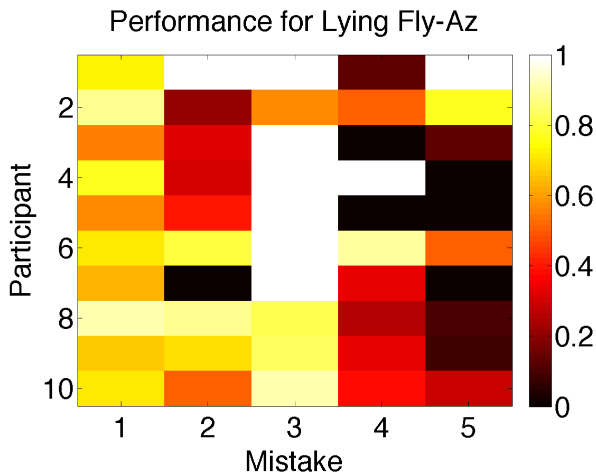
The results for the lying fly can be seen in Figure 6-2a through 6-2c. For the rushing repetitions case, an interesting aspect is why E_x is so much better at detecting rushing repetitions compared to E_z, which is even below A_z. As it was mentioned previously, orientation signals are smoother than acceleration signals. From these three signals, E_x was the smoothest one, thus giving the best results. A_z was not as smooth as E_z but the hill-climbing algorithm used to detect peaks performed better with that signal. The reason of this is that E_z presented, on occasions, several peaks and valleys per repetition of similar magnitude, negatively affecting the hill-climbing algorithm.

Over stretching is complicated to detect in the lying fly. There is so much someone can over stretch doing this movements. Under stretching, on the other hand, is simpler for all the exercises. For this reason, it is the case that under stretching is detected easier. Since a smaller range has to be covered when under stretching, a smaller acceleration also takes place. For this reason A_z also performs well when recognizing under stretching.

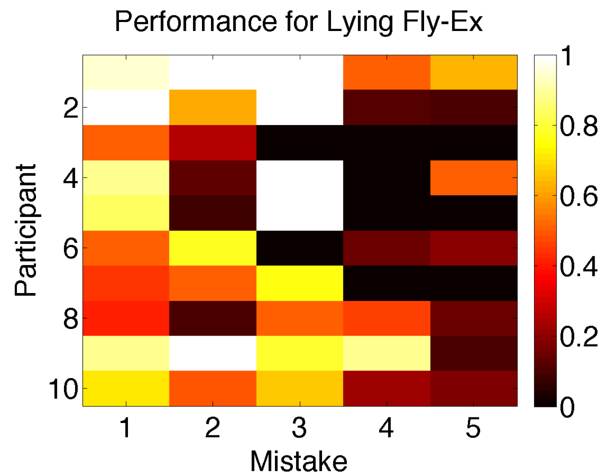
Since the range of motion for bouncing is the same as the range of motion for correct repetitions, orientation angles should remain constant and therefore they are not good at detecting bouncing mistakes. A_z also performs poorly. The reason from this can be inferred from the data. Some participants rotated slightly their wrists when descending, which changed the acceleration readings. Participant 1, a fitness instructor, performed the movement adequately and this is in turn reflected in Figure 6-2a. Even though the exercises were carried out under supervision, small changes in position while doing a free fall are hard to detect.

Figures 6-2f and 6-2g show that the detection for the lateral raise errors is high for both signals. The reasons for this is that it is very easy to both over stretch and under stretch while performing repetitions of this exercise, making the detection of these mistakes a simple task. Signal A_x is good at detecting rushing repetitions, under stretching, and bouncing. It performs well for over stretching. Signal E_y, on the other hand, is good at detecting rushing repetitions, over stretching, and under stretching. It performs poorly for bouncing, since ideally the rotation for a correct repetition and bouncing should be the same.

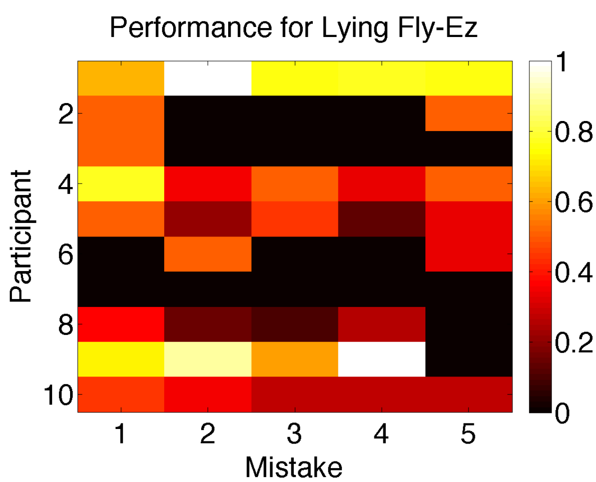
Biceps curl is an interesting exercise in the sense that it is easy to under stretch but it is hard to over stretch, as is the case for the lying fly. This causes a better detection of under stretching than for the over stretching case in both the acceleration and orientation signatures. Figure 6-2h shows that the acceleration signal A_x outperforms E_y greatly at detecting the bouncing error type. As mentioned previously, orientation angles should not change during bouncing. However, due to inertia during the free fall, it might be the case that there is a slight change.



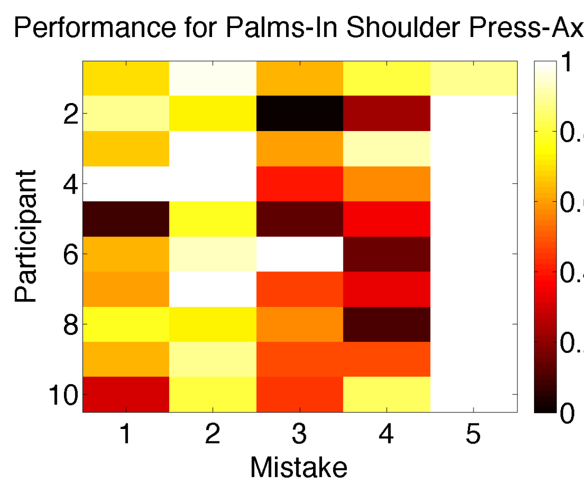
(a) Lying fly using Az



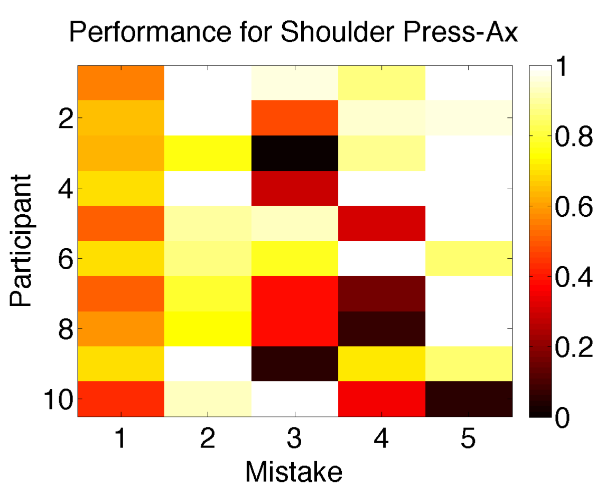
(b) Lying fly using Ex



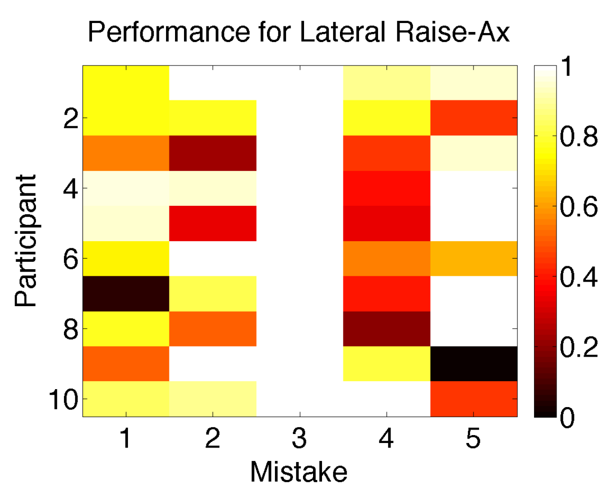
(c) Lying fly using Ez



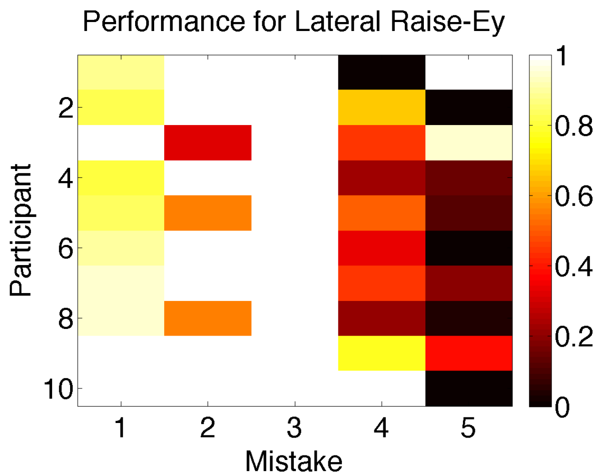
(d) Palms-in shoulder press using Ax



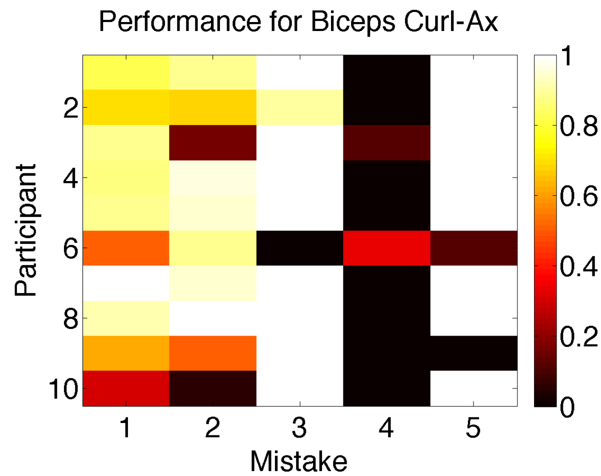
(e) Shoulder press using Ax



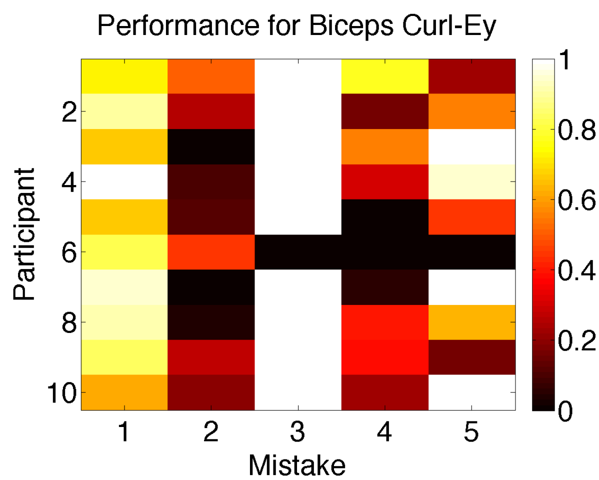
(f) Lateral raise using Ax



(g) Lateral raise using Ey



(h) Biceps curl using Ax



(i) Biceps curl using Ey

Figure 6-2: Prediction accuracy for single signal input model using raw data

Table 6.1 shows the results for the accuracy in counting repetitions for each participant for selected signals. "Ex1" stands for "Exercise 1", which is the lying fly. "Ex2" is the palms-in shoulder press, "Ex3" stands for shoulder press, "Ex4" stands for lying fly, and "Ex5" stands for biceps curl.

From the data it is possible to see that the palms-in shoulder press and the shoulder press exercises represent a problem. The number of repetitions the system counts is more than double the number of repetitions carried out for most of the participants. The remaining exercises have a much lower error because their data is smoother, making repetition count simpler.

	Ex1-Ex			Ex2-Ax			Ex3-Ax			Ex4-Ax			Ex5-Ey			Total		
	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e
1	43	40	3	44	100	-56	45	116	-71	43	43	0	48	45	3	223	344	-121
2	46	44	2	45	107	-62	51	106	-55	48	46	2	53	52	1	243	355	-112
3	46	11	35	49	53	-4	45	106	-61	45	47	-2	45	45	0	230	262	-32
4	46	29	17	54	119	-65	51	83	-32	52	48	4	53	49	4	256	328	-72
5	44	25	19	58	134	-76	50	94	-44	49	45	4	48	44	4	249	342	-93
6	49	22	27	50	47	3	51	80	-29	46	44	2	48	37	11	244	230	14
7	44	12	32	49	105	-56	51	94	-43	51	50	1	53	49	4	248	310	-62
8	53	47	6	53	108	-55	56	103	-47	52	52	0	57	54	3	271	364	-93
9	49	44	5	49	99	-51	51	50	1	46	47	-1	46	45	1	241	285	-45
10	46	30	16	43	125	-82	46	64	-18	45	44	1	44	44	0	224	307	-83

Table 6.1: Accuracy in counting repetitions for single input raw data. r_c stands for the correct number of repetitions carried out, r_s for the number of repetitions the system detected, and e for the error.

Figure 6-3 shows the series of correct palms-in shoulder press repetitions for one participant. It can be seen that there are two peaks per repetition, both of which have a similar magnitude. Additionally, the crossover value for this signal is $-.92$. This value is crossed at least two times per repetition, explaining the amount of repetitions detected for the palms-in shoulder press and the shoulder press, since the system believes there are at least two repetitions for every repetition.

Since the repetition error is extremely high for the palms-in shoulder press and the shoulder press, the prediction accuracy results for these exercises are not reliable. A filtering strategy needs to be used.

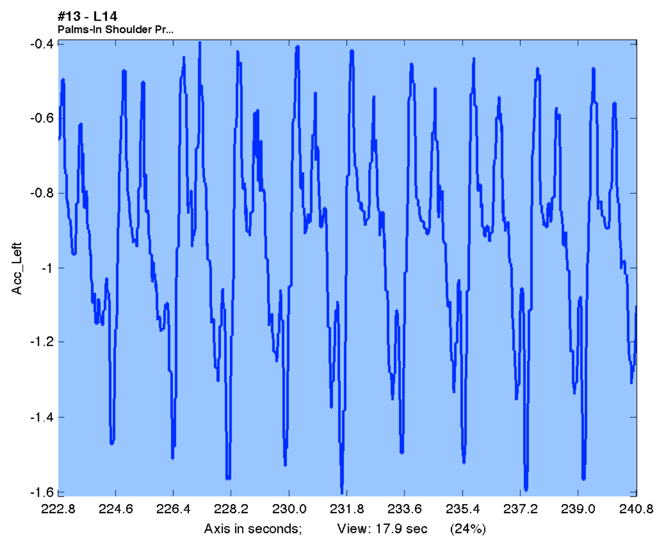


Figure 6-3: A_x signal for palms-in shoulder press correct repetitions

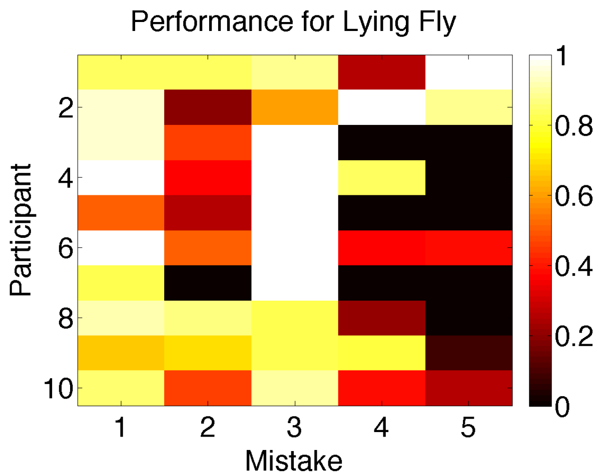
6.3 Single signal input using filtered data

The prediction accuracy results for the system that uses filtered data are shown in Figure 6-4. The results are similar, yet the differences are worth discussing.

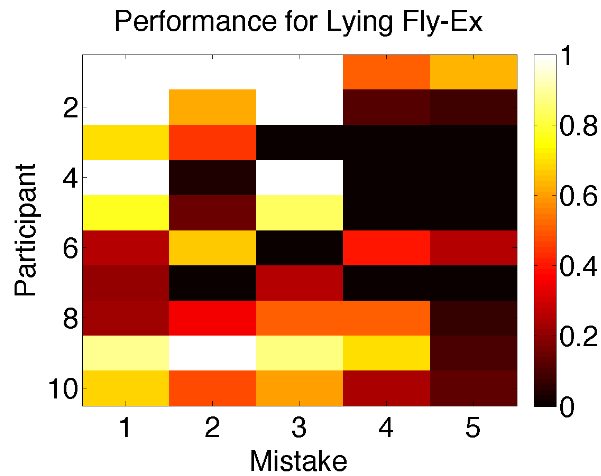
There is, in most cases, a general increase in accuracy detection for all signals and all error categories. This is the result of the filtering, which helps the hill-climbing algorithm detect peaks better. There was also a slight increase in the bouncing error detection for lying fly and for lateral raise using their respective acceleration signals.

In general, the moving average smoothing filter improved more the performance when an acceleration signal was used. Orientation data, which is smoother than acceleration data even when raw, was not greatly affected.

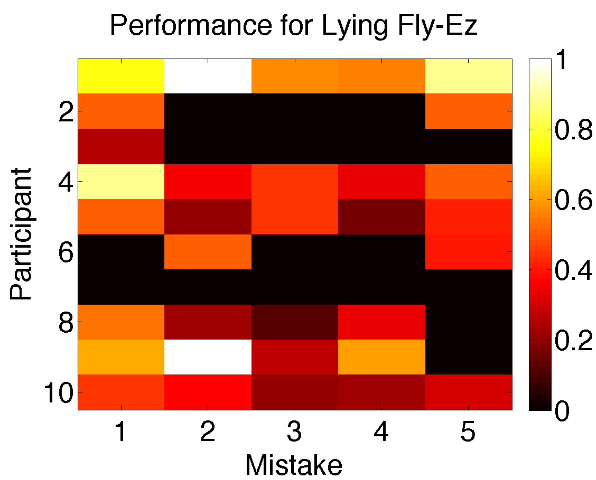
The benefits of filtering are better reflected by the results shown in Table 6.2. There is an improvement for most signals in most exercises, producing a smaller total error. The results from the palms-in shoulder press and shoulder press are still very unreliable, so a stronger moving average filter will be used just for study purposes. There was a trivial improvement for the shoulder press but in general, due to the characteristics of the data which cannot be smoothed completely using a simple moving average filter, the accuracy is poor.



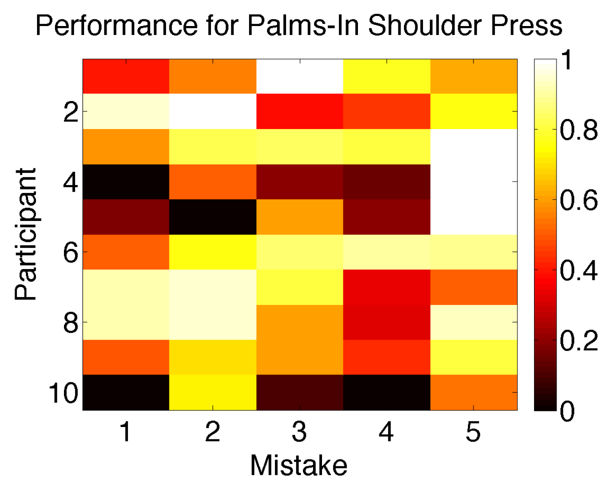
(a) Lying fly using Az



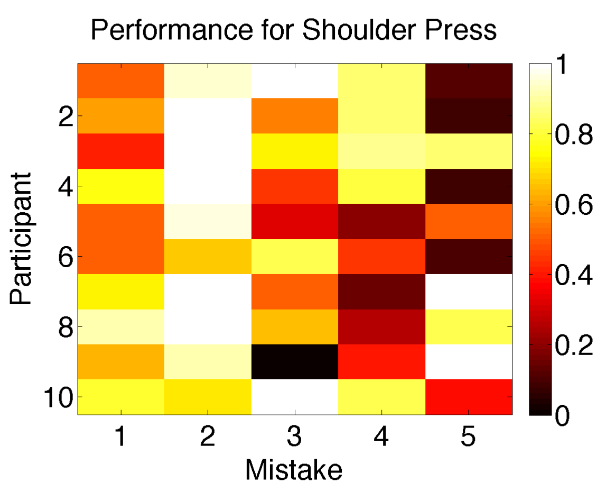
(b) Lying fly using Ex



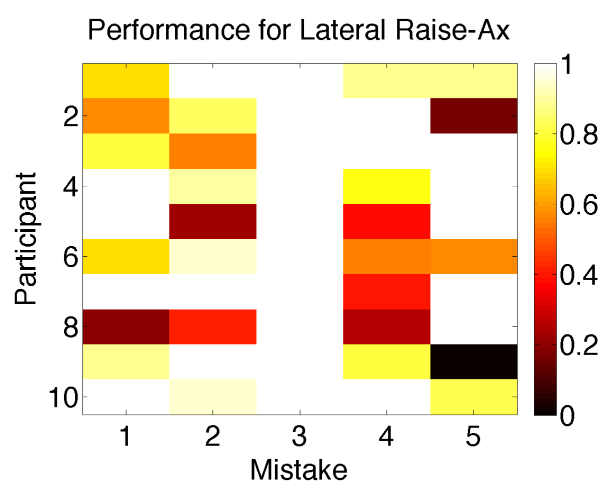
(c) Lying fly using Ez



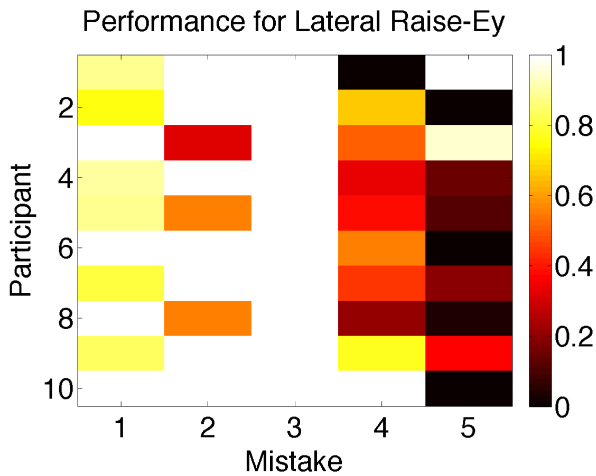
(d) Palms-in shoulder press using Ax



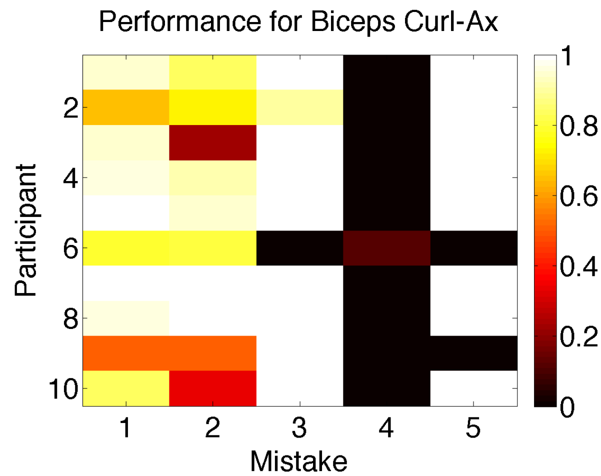
(e) Shoulder press using Ax



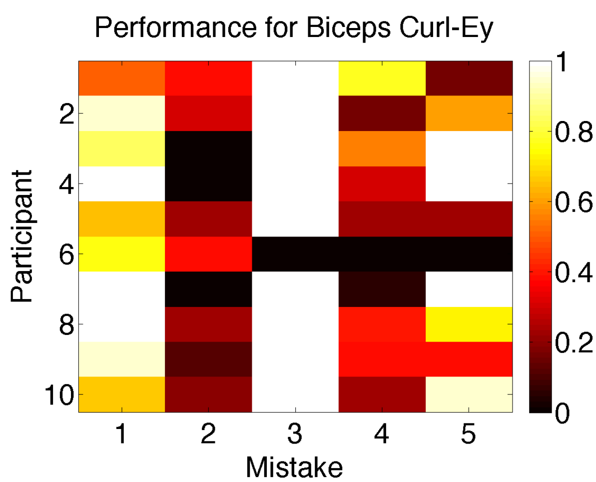
(f) Lateral raise using Ax



(g) Lateral raise using Ey



(h) Biceps curl using Ax



(i) Biceps curl using Ey

Figure 6-4: Prediction accuracy for single signal input model using filtered data

	Ex1-Ex			Ex2-Ax			Ex3-Ax			Ex4-Ax			Ex5-Ey			Total		
	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e
1	43	42	1	44	104	-60	45	106	-61	43	43	0	48	44	4	223	339	-116
2	46	47	-1	45	97	-52	51	110	-59	48	47	1	53	52	1	243	353	-110
3	46	14	32	49	52	-3	45	67	-22	45	47	-2	45	46	-1	230	226	4
4	46	38	8	54	110	-56	51	67	-16	52	48	4	53	51	2	256	314	-58
5	44	36	8	58	115	-57	50	72	-22	49	45	4	48	46	2	249	314	-65
6	49	32	17	50	44	6	51	71	-20	46	45	1	48	38	10	244	230	14
7	44	10	34	49	99	-50	51	81	-30	51	47	4	53	50	3	248	287	-39
8	53	48	5	53	97	-44	56	105	-49	52	51	1	57	58	-1	271	359	-88
9	49	46	3	49	91	-43	51	52	-1	46	45	1	46	44	2	241	278	-38
10	46	34	11	43	107	-64	46	62	-16	45	44	1	44	44	0	224	291	-68

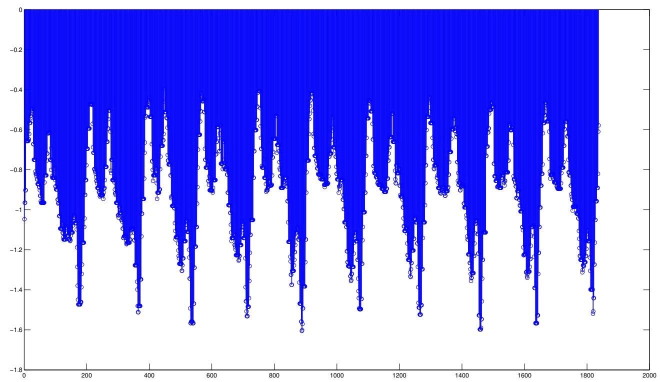
Table 6.2: Accuracy in counting repetitions for single input filtered data. r_c stands for the correct number of repetitions carried out, r_s for the number of repetitions the system detected, and e for the error.

6.3.1 Aggressive filtering

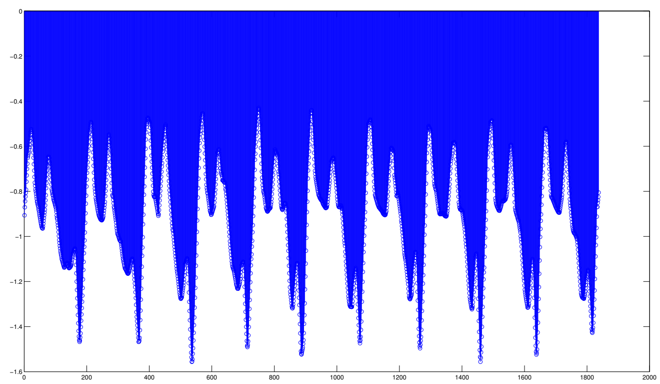
By using a more aggressive filter better results could be obtained. The selected span of the filter was five samples. Even though improvements were seen for prediction accuracy, these improvements were not enough to better the accuracy in counting repetitions for palms-in and shoulder press exercises. For this reason, a test was carried out with a span of forty samples. A comparison between the raw data, a five sample filter, and a forty sample filter can be seen in Figure 6-5.

The results shown in Figures 6-4d and 6-4e represent the results after the forty sample span. Table 6.3 lists the accuracy in counting repetitions. Notice that the error represents for most cases less than ten percent of the total repetitions.

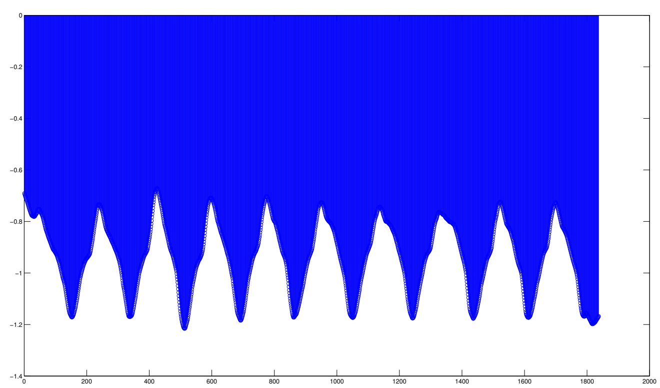
This test is useful to highlight two things. First, it shows that filtering is not everything. There can be low performance if the model data is poor. Second there is a tradeoff between the accuracy in the number of repetitions and the computational requirements to perform a filter over forty samples. This tradeoff



(a) Raw data



(b) Moving average, 5 sample span



(c) Moving average, 40 sample span

Figure 6-5: Comparison between raw data and different spans for the moving average filtered data is something that should be further analyzed once the application is ported.

	Ex2-Ax			**Ex3-Ax**			**Total**		
	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e
1	44	43	1	45	41	4	89	84	5
2	45	49	-4	51	56	-5	96	105	-9
3	49	45	4	45	43	2	94	88	6
4	54	36	18	51	56	-5	105	92	13
5	58	67	-9	50	48	2	108	115	-7
6	50	41	9	51	31	20	101	72	29
7	49	43	6	51	50	1	100	93	7
8	53	55	-2	56	60	-4	109	115	-6
9	49	46	2	51	50	1	100	96	3
10	43	40	3	46	52	-6	89	92	-3

Table 6.3: Accuracy in counting repetitions for single input filtered data with 40 sample span. r_c stands for the correct number of repetitions carried out, r_s for the number of repetitions the system detected, and e for the error.

6.4 Multiple voting signals

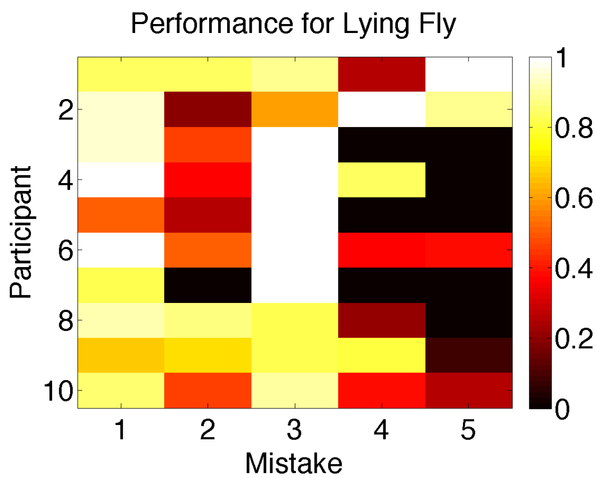
The results for the prediction accuracy for the multiple signal voting system can be seen in Figure 6-6.

The multiple voting signals scheme provides the highest error detection from all the systems, since it combines the strengths of the different signals to provide one output. The disadvantage is that all the different signals need to be processed. This processing, however, could be parallelized amongst the different cores available in smartphone processors.

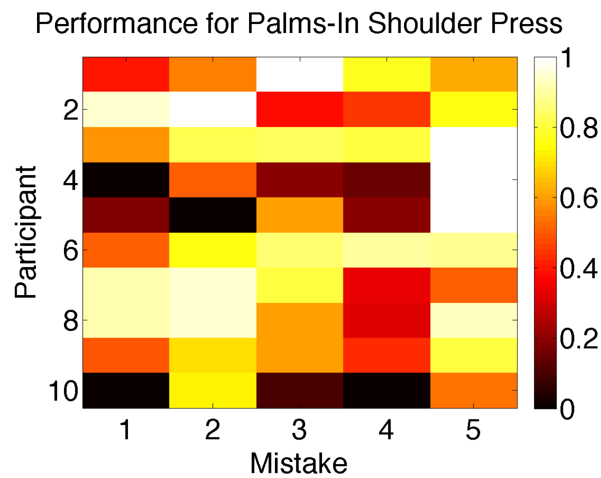
The accuracy in counting repetitions is presented in Table 6.3. Again, it was based on the signal that performed better, and thus the results are the same as those for the filtered data. These results are also the ones that had the minimum error.

	Ex1			Ex2			Ex3			Ex4			Ex5			Total		
	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e	r_c	r_s	e
1	43	42	1	44	43	1	45	41	4	43	43	0	48	44	4	223	213	10
2	46	47	-1	45	49	-4	51	56	-5	48	47	1	53	52	1	243	251	-8
3	46	14	32	49	45	4	45	43	2	45	47	-2	45	46	-1	230	195	35
4	46	38	8	54	36	18	51	56	-5	52	48	4	53	51	2	256	229	27
5	44	36	8	58	67	-9	50	48	2	49	45	4	48	46	2	249	242	7
6	49	32	17	50	41	9	51	31	20	46	45	1	48	38	10	244	187	57
7	44	10	34	49	43	6	51	50	1	51	47	4	53	50	3	248	200	48
8	53	48	5	53	55	-2	56	60	-4	52	51	1	57	58	-1	271	272	-1
9	49	46	3	49	46	2	51	50	1	46	45	1	46	44	2	241	231	9
10	46	34	11	43	40	3	46	52	-6	45	44	1	44	44	0	224	214	9

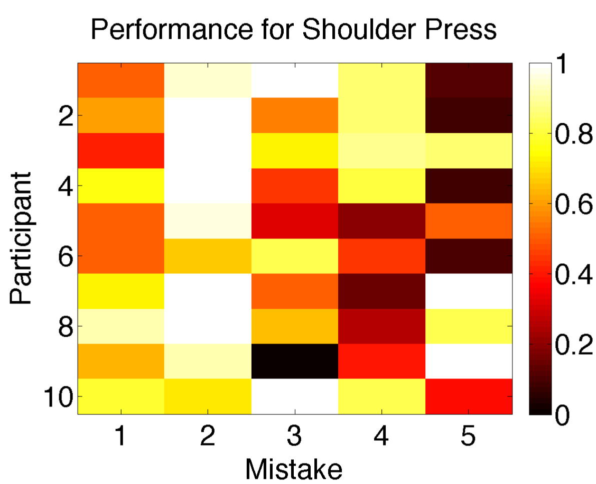
Table 6.4: Accuracy in counting repetitions for multiple single input using filtered data. r_c stands for the correct number of repetitions carried out, r_s for the number of repetitions the system detected, and e for the error.



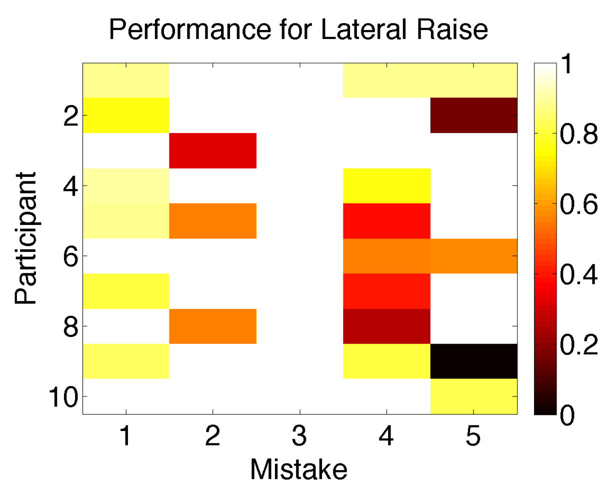
(a) Lying fly



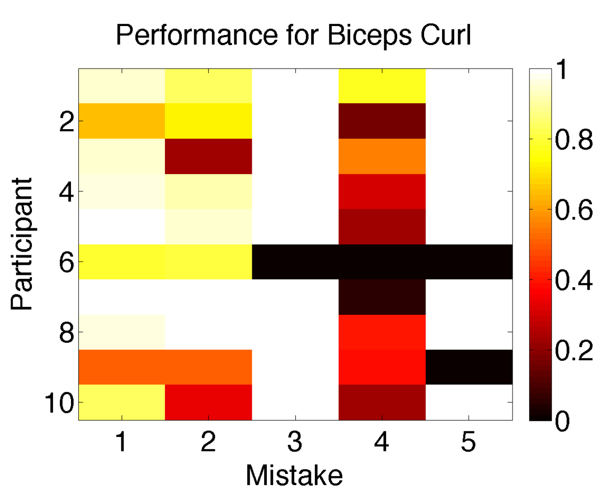
(b) Palms-in shoulder press



(c) Shoulder press



(d) Lateral raise



(e) Biceps curl

Figure 6-6: Prediction accuracy for multiple signal model using filtered data

Chapter 7

Conclusion and future work

This work researched the possible use of a sinusoidal model to assess the quality of free-weight exercise repetitions. Acceleration and orientation data from volunteers were recorded while performing five different exercises. Repetitions were carried out according to the correct specifications and incurring in five different common mistakes. Differences could be observed between the graphs of the correct and incorrect repetitions. These differences were explored further through a quantitative analysis and exploited in order to assess the quality of individual repetitions. By building a model of a correct repetition from a particular exercise type it was possible to compare new repetitions to the standard. It was also observed that not all signals were relevant in order to determine quality. These signals could then be left out, reducing the system's complexity. Based on a series of criteria, the new repetitions are labeled as correct or as incurring on one of the different error types analyzed.

Three different systems were developed using the models for the correct repetition. The first one used raw data from a single signal to both build the model and assess new repetitions. The second one used filtered data again from a single signal. The third model used a voting algorithm from the signals deemed relevant of each exercise in order to produce the output. The different tradeoffs and performances of the different systems were analyzed.

The study shows that model-based methods using accelerometer and orientation data can be used to detect certain free weight mistakes. The extent of the effectiveness depends in general on the movements and rotations required per exercise, on the participants fitness level, and on the number of signals used as input to the system. It was discovered that not all signals are necessary to perform a quality assessment on individual repetitions.

Carrying out the three different system experiments allowed to confirm that the acceleration signals differ from the orientation signals in the performance they have at detecting each of the types of mistakes. Acceleration was discovered to be particularly effective to detect bouncing, while orientation readings are very effective at detecting over and under stretching. These signals were then combined in order to leverage their individual performances on a system that outperforms single-signal systems.

Even though the results were not entirely satisfactory, the study helped in understanding the limitations of the approach and of the different types of signals involved. It can be concluded that further research needs to be carried out, but the results in the exercises that involved rotations are favorable towards the use of a sinusoidal model to detect mistakes and help prevent injuries.

7.1 Future work

A series of recommendations for future work are offered in order to improve the system's performance. Alternative research lines are also presented that derive from findings discovered during the development of this study.

In order for a fitness assistant such as this one to reach the market and be successful, a study on how to better deliver feedback to the user needs to be carried out. Should feedback be given after each repetition or after a series of repetitions? How should feedback be given in case multiple mistakes are detected? Different alternatives such as sound beeps, spoken feedback, and bursts from a vibration motor exist to notify the user and they should all be considered. The timing of the feedback with respect to the repetition is something that should also be taken into account.

Alternative methods for accuracy in counting repetitions and prediction accuracy exist. One of these approaches could be the use of a different filtering algorithm in order to improve data smoothness. Dynamic time warping or a different model construction technique could yield better results. These approaches will offer different tradeoffs which in turn might be worth studying further.

It was discovered that volunteers that exercised regularly produced smoother data than volunteers that engaged in little or no physical activity. Their data also resembled more a perfect sinusoidal, leading to better results for physically active users since a sinusoidal motion model was used. The differences result from less trembling caused by muscle tiredness and from a better muscle control in more physically-fit users. An interesting question that raised from this discovery is whether or not these differences could be used to estimate users' fitness levels and to track their progress.

Appendix A

Data recording plan

Technische Universiteit
Eindhoven
University of Technology

Data Recording Plan

by
Gerardo Ochoa

Date: November 3, 2013

Supervisors: Dr. O. Amft
F. Wahl

Contents

1 Introduction

On-body motion sensors are becoming more ubiquitous and thus offer an excellent opportunity to gather measurements by monitoring daily activities without becoming obtrusive. Multiple sensors such as accelerometers, gyroscopes, GPS receivers, and microphones placed in different locations are frequently used to ensure proper coverage due to the diverse range of activities carried out by people throughout the day. A common architecture in this type of scenarios is to interconnect the sensors to a central hub for data collection, usually a smartphone. The reasons for this are the increasing processing power, the wireless connectivity offered, and the Internet access smartphones provide.

Exercise and fitness related activities will be the main focus of this project, particularly those that involve dumbbells and weights. These exercises, a complement to cardio activities, pose a danger to users when done incorrectly. A study [2] was carried out on the epidemiology of weight-training related injures. One of its findings is that sprains, fractures, dislocations, and strains are amongst the most common injuries. An adequate technique and professional supervision have been found to be among the most important strategies in the prevention of injuries [1].

For the development of this project measurements will be carried out using 9-DOF inertial measurement units (IMUs). Measurements from participants performing a set of predefined exercises will be obtained and used in developing an understanding of the differences between correct and incorrect repetitions. The objective is to develop a system that will help to improve the technique and thus aid in injury prevention.

When obtaining data for a study, it is of vital importance to detail the procedure in such a way that measurements can be easily replicated. This document describes how the recordings of the data-set used took place. The remaining part of this document is organized as follows: Section 2 presents the details on the IMU used. In Section 3 a a thorough explanation of the sensor placement, participant information, and activities carried out is presented. Section 4 shows the precise order in which the script was carried out and Section 5 summarizes the document and presents some conclusions.

2 Inertial Measurement Unit

The measurements will be obtained by using Invensense's MotionFit SDK, depicted in Figure 1. Data from the accelerometers and gyroscopes will be sampled at 50 Hz. Magnetometer data will not be used. Recordings will be carried out from participants that will wear two wrist straps, one on each wrist. The wrist straps will house a MotionFit SDK. The acceleration values obtained consist of the acceleration in each of the axes x, y, and z. The gyroscopes' output is given in quaternion representation, consisting of the four values x, y, z, and w.

The SDK contains an MPU-9150, a 9-axis single-chip tracking device optimized for wearable sensor applications. The SDK includes a Bluetooth Radio Module for wireless communication and a rechargeable battery. Data from the SDKs is sent via Bluetooth to a smartphone.

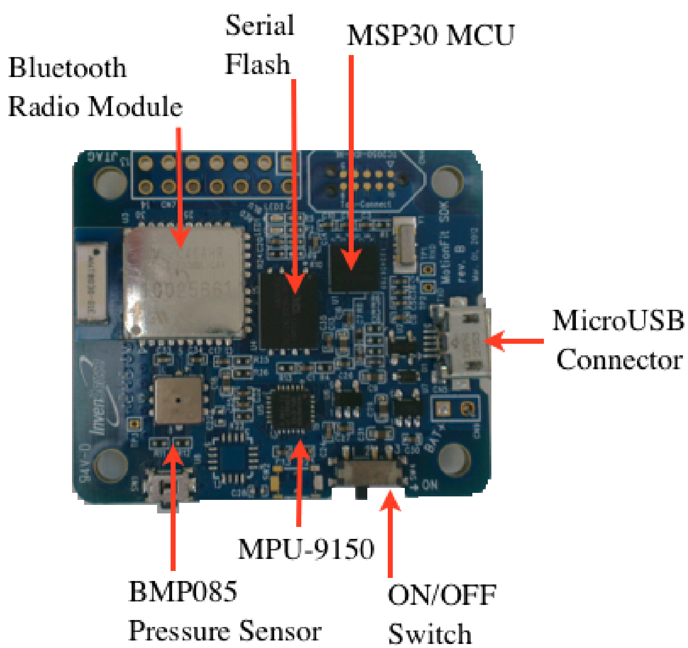


Figure 1: MotionFit SDK

3 Recording Details

3.1 Sensor Placement

As mentioned before, each participant will be wearing two wrist straps, one on each wrist. The placement of the sensors affects the values in the recordings. For this set of recordings, the SDKs were placed within the wrist straps as shown in Figure 2. When the wrist strap is placed on a flat surface, the circuit board components should be facing up. The ON/OFF switch should be on the left opening for easy access and the Bluetooth Radio Module should be in the steel buckle side.

Figure 2: Sensor placement within wrist strap

Once the SDK is properly housed, participants should put the wrist straps on as they would with a watch. The circuit board should be in the outer part of the wrist. Figure 3 shows a proper placement. The perspective of the image is as seen by the volunteer. The microUSB connector should be facing the volunteer's body. The wrist straps should be comfortable to the user, yet tight in order to prevent displacements.

3.2 Participant selection

Ten participants were chosen for this experiment, with five female and five male subjects. The mean age is 26.8 years and the corrected sample standard deviation is 2.89 years. Table 1 shows in detail the information for the different subjects recorded.

Sex	F	F	F	F	F	M	M	M	M	M
Age	24	24	26	27	33	24	26	26	28	30

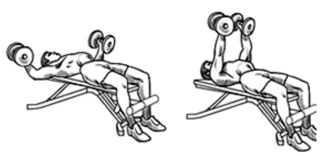
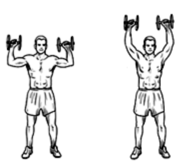
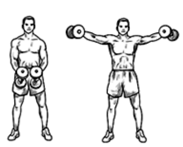
Table 1: Gender and age of volunteers

(a) Left wrist (b) Right wrist

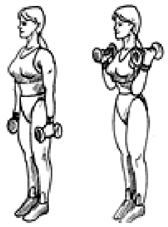
Figure 3: Appropriate placement on wrists

3.3 Activities

This section presents the exercises[1] that will be recorded, being carried out by the volunteers. Note that these exercises require the hands to be synchronized during every repetition. The reason for this will be explained in the next section.

1.  Lying Fly
2.  Palms-In Shoulder Press
3.  Shoulder Press
4.  Lateral Raise

[1]Images taken from *www.dumbbell-exercises.com*

5.  Biceps Curl

3.4 Common mistakes

In addition, exercises will also be carried out but this time done incorrectly. In order to prevent injuries, the weights used will be minimal (1 kilogram) and participants will be supervised. Warming up is mandatory before carrying out these exercises. The common exercise mistakes were obtained from [3], [5], and from coaches at the Student Sport Centre Eindhoven. The common mistakes include:

1. Rushing repetitions: doing weight-lifting repetitions too fast raises your blood pressure and increases the risk for joint injury, while at the same time comprising results
2. Incorrect range of motion due to over stretching/under stretching
3. Not keeping dumbbells leveled
4. Bouncing dumbbells or using gravity to descend instead of the desired smoothly controlled motion

In the previous section it was mentioned that all the exercises required the hands to be synchronized during every repetition. This was done on purpose to test for the mistake of not keeping the dumbbells leveled. Not keeping dumbbells leveled occurs naturally since one arm is always stronger than the other one, depending on the laterality of each individual.

3.5 Ground truth determination

The exercises will be executed under the supervision of a researcher who will perform labeling tasks for each activity on the recording script (see Section 4). Each label consists of two pieces of information:

1. Time stamp
2. Exercise description

The ACTLog tool [4] will be used in this process.

4 Recording script

The complete script is as shown:

1. Lying Fly
   1.1. 10x correct
   1.2. 10x rushing repetitions
   1.3. 10x over stretching
   1.4. 10x under stretching
   1.5. 10x not leveled
   1.6. 10x bouncing
2. Palms-In Shoulder Press
   2.1. 10x correct
   2.2. 10x rushing repetitions
   2.3. 10x over stretching
   2.4. 10x under stretching
   2.5. 10x not leveled
   2.6. 10x bouncing
3. Shoulder Press
   3.1. 10x correct
   3.2. 10x rushing repetitions
   3.3. 10x over stretching
   3.4. 10x under stretching
   3.5. 10x not leveled
   3.6. 10x bouncing
4. Lateral Raise
   4.1. 10x correct
   4.2. 10x rushing repetitions
   4.3. 10x over stretching
   4.4. 10x under stretching

4.5. 10x not leveled

4.6. 10x bouncing

5. Biceps Curl

   5.1. 10x correct

   5.2. 10x rushing repetitions

   5.3. 10x over stretching

   5.4. 10x under stretching

   5.5. 10x not leveled

   5.6. 10x bouncing

It is estimated that the participant will take one hour to perform the script, including a brief informative introductory talk, warm up, and short resting breaks. The battery lifetime has been verified for both the MPU-9150 (slightly above 2 hours) and for the HTC One X smartphone that will be used for the recordings.

5 Concluding remarks

The analysis behind the data recording procedure and other related aspects has been illustrated. The methodology followed has been broken down and a list of activities to be measured has been presented. The hardware used in obtaining these measurements was detailed. The script followed has also been included to act as a guide for future reference. In essence, the document contains the information necessary to replicate the measurements.

From the gathered data, analyses will be carried out in order to:

1. Visualize the acceleration and orientation characteristics of each exercise in order to develop an understanding of correct and incorrect exercises.
2. Develop a model to distinguish between correct and incorrect repetitions.

With this elements it will be possible to start the construction of a wearable system that will aid in improving the free-weight exercise technique of individuals in order to prevent injuries.

References

[1] Faigenbaum, A. D., and Myer, G. D. Resistance training among young athletes: safety, efficacy and injury prevention effects. *Br J Sports Med 44*, 1 (Jan 2010), 56–63.

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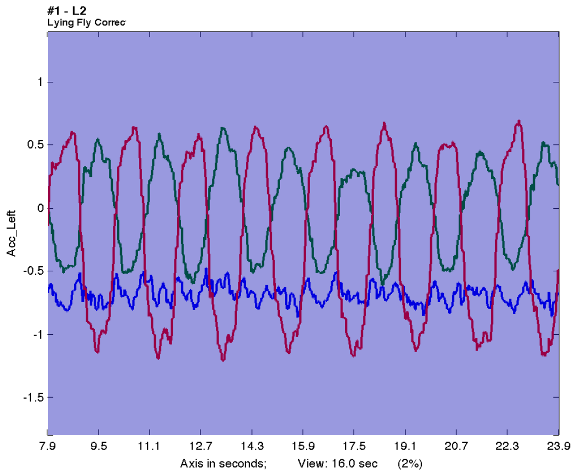
[3] Peterson, J. Take ten: Take-and-save: 10 common mistakes made while strength training. *American College of Sports Medicine's Health and Fitness Journal 9* (2005), 44.

[4] Roberts, F. Documentation for the actlog project. *ACTLab* (2011).

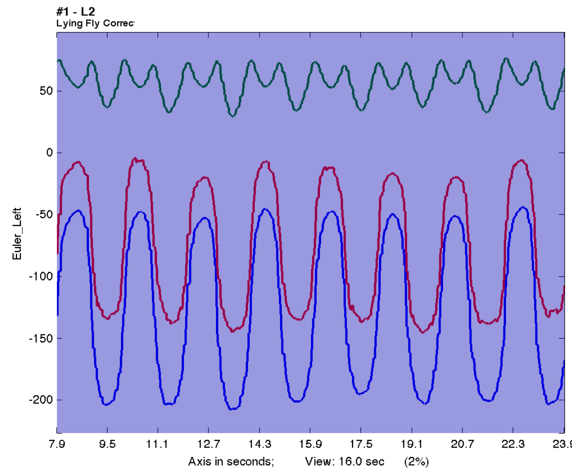
[5] Skarnulis, L. Don't let exercise errors stand in your way.

Appendix B

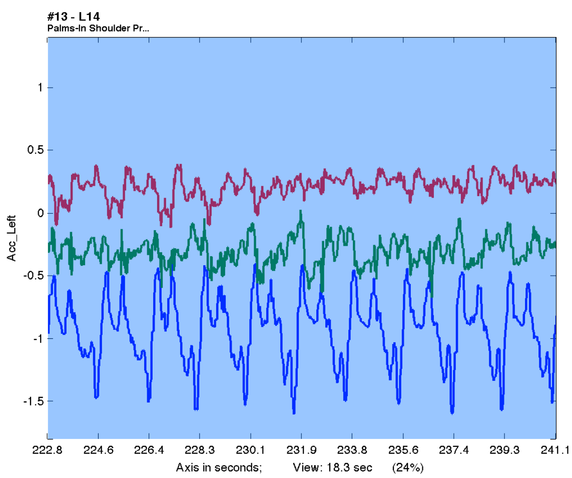
Acceleration and orientation graphs for correct exercises



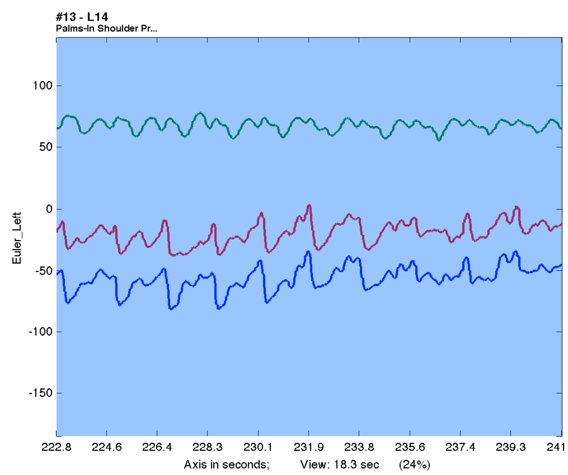
(a) Acceleration for lying fly



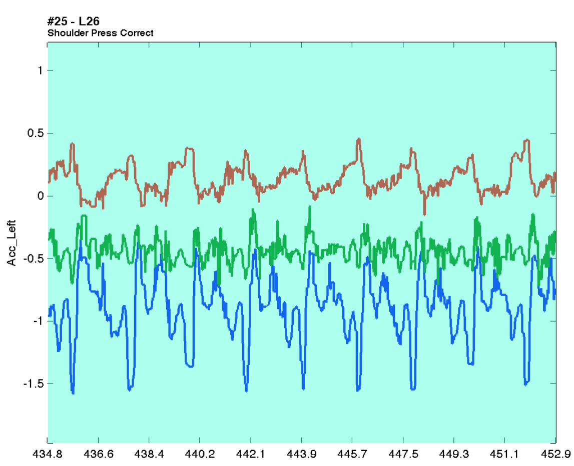
(b) Euler angles for lying fly



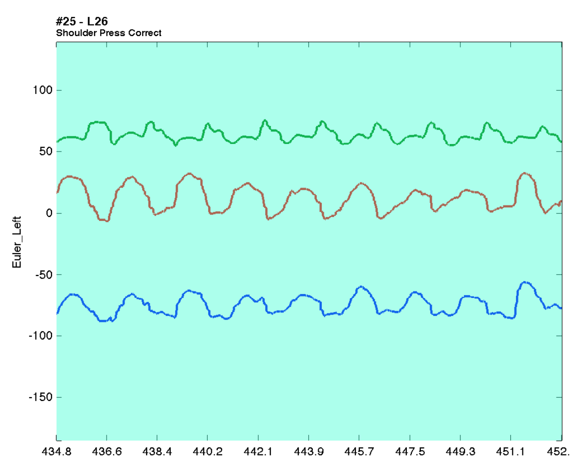
(c) Acceleration for palms-in shoulder press



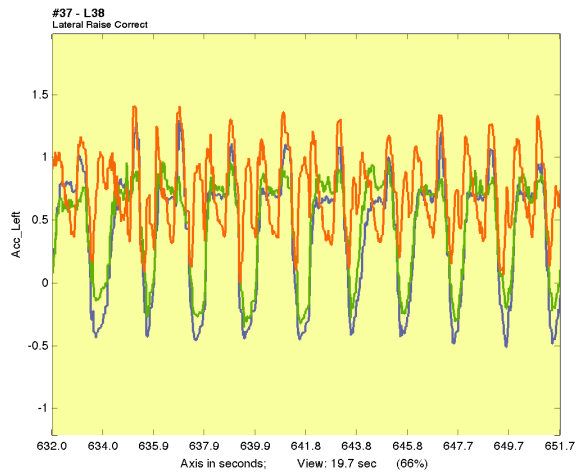
(d) Euler angles for palms-in shoulder press



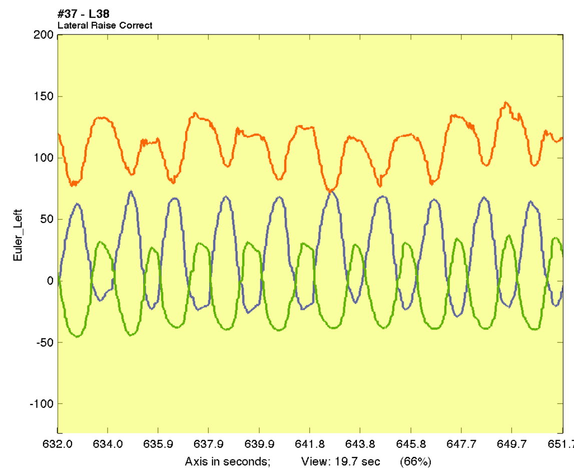
(e) Acceleration for shoulder press



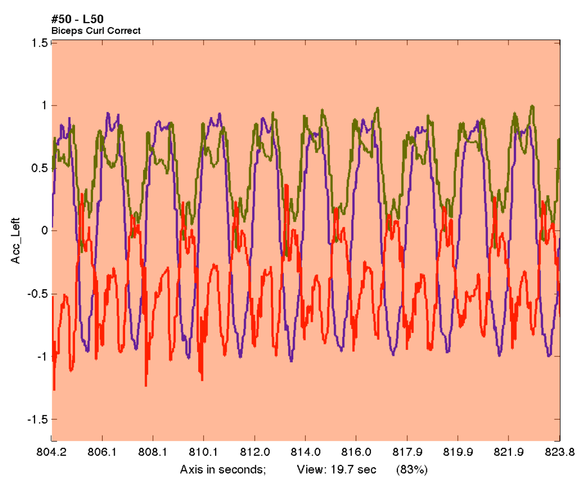
(f) Euler angles for shoulder press



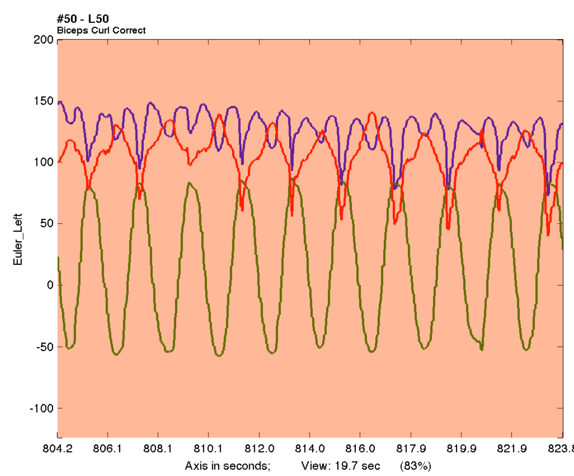
(g) Acceleration for lateral raise



(h) Euler angles for lateral raise



(i) Acceleration for biceps curl

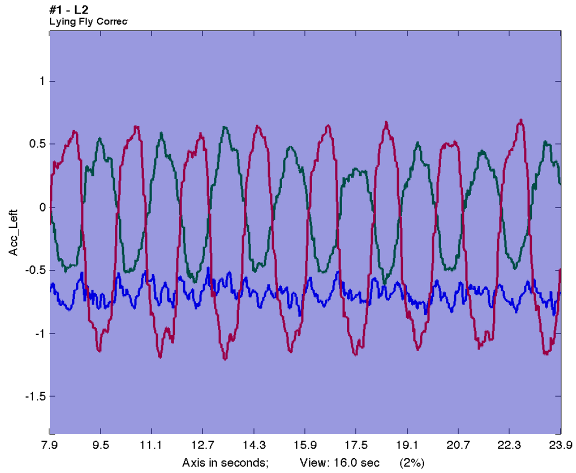


(j) Euler angles for biceps curl

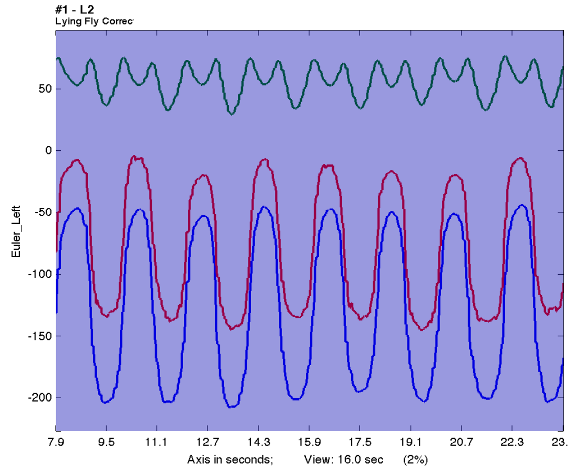
Figure B-1: Acceleration and orientation graphs for the correct exercises, left hand only. The x axis is shown in blue, y in green, and z in red.

Appendix C

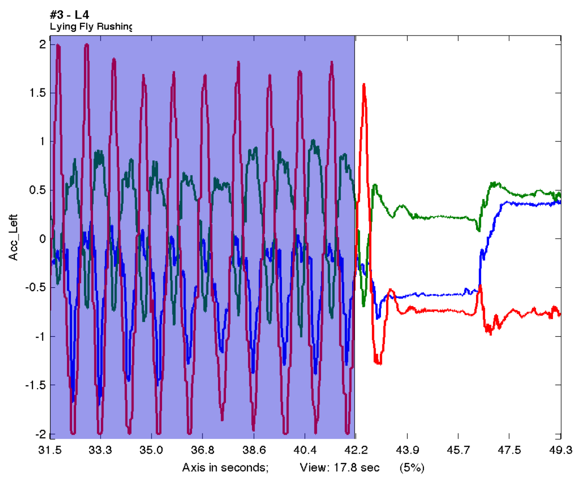
Acceleration and orientation graphs for correct and incorrect lying fly



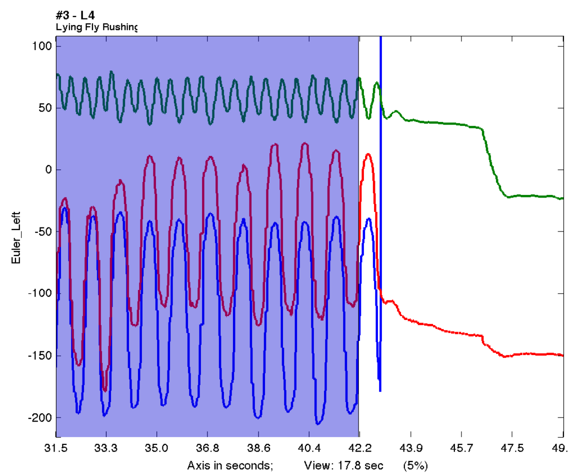
(a) Acceleration for correct lying fly



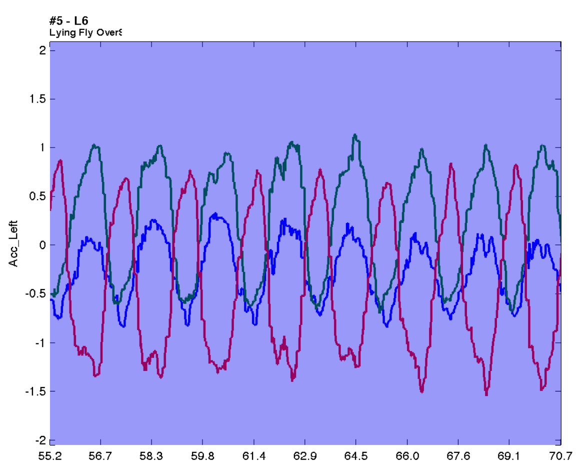
(b) Euler angles for correct lying fly



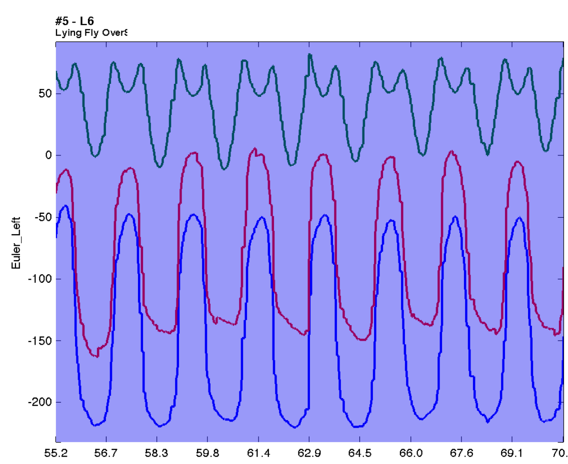
(c) Acceleration for rushing lying fly



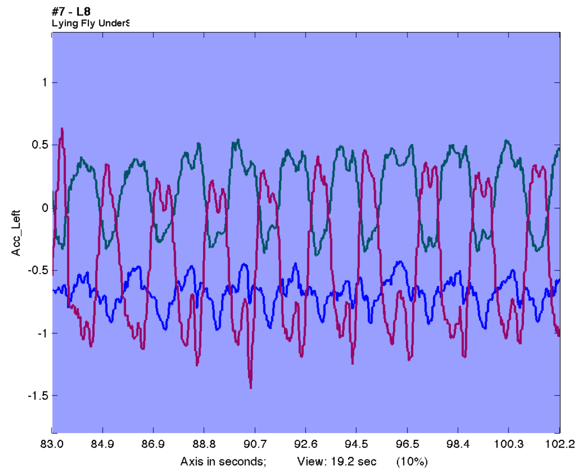
(d) Euler angles for rushing lying fly



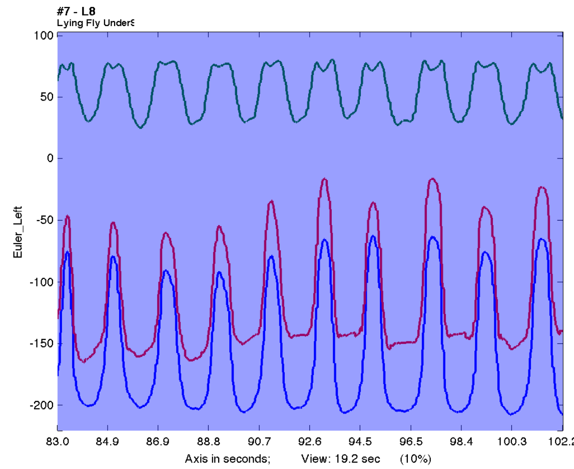
(e) Acceleration for over stretching lying fly



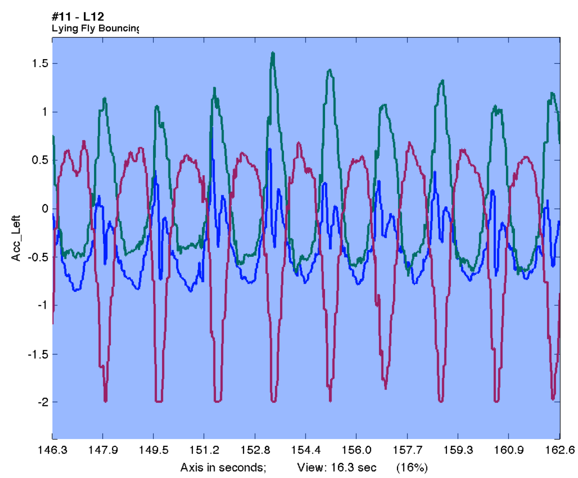
(f) Euler angles for over stretching lying fly



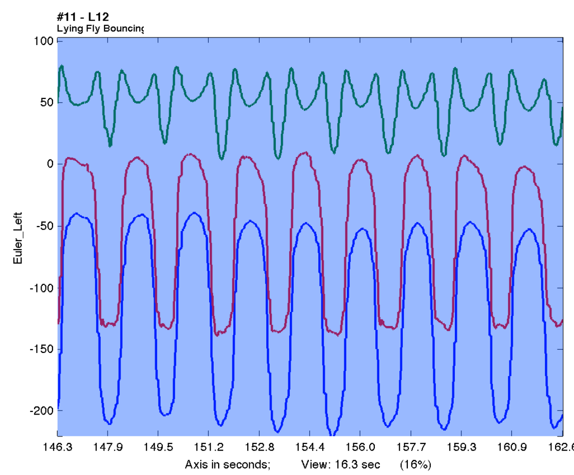
(g) Acceleration for under stretching lying fly



(h) Euler angles for under stretching lying fly



(i) Acceleration for bouncing lying fly

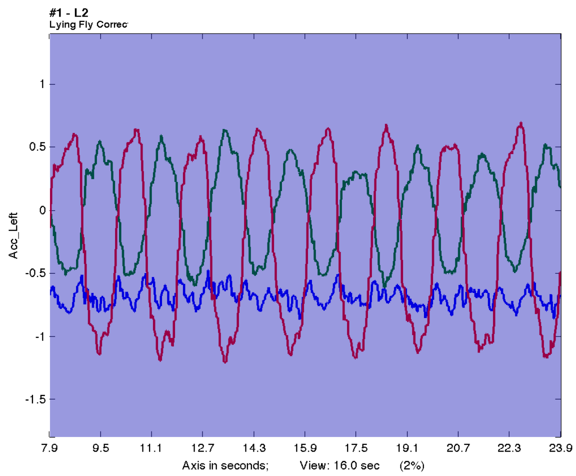


(j) Euler angles for bouncing lying fly

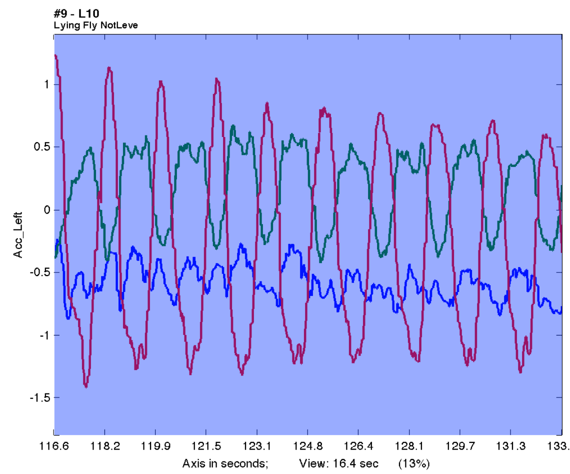
Figure C-1: Acceleration and orientation graphs for the correct and incorrect versions of lying fly, left hand only. The x axis is shown in blue, y in green, and z in red.

Appendix D

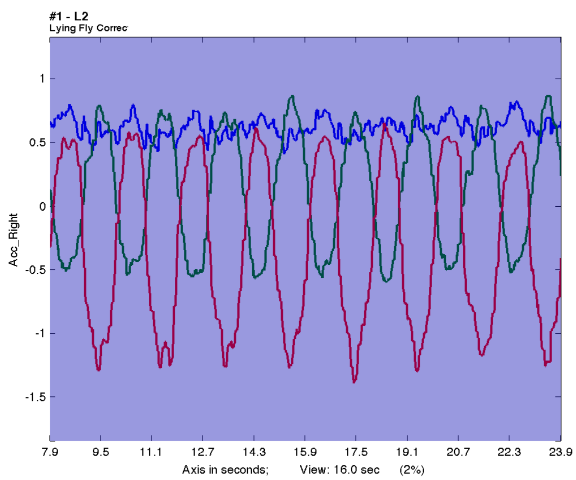
Acceleration and orientation graphs for not-leveled lying fly



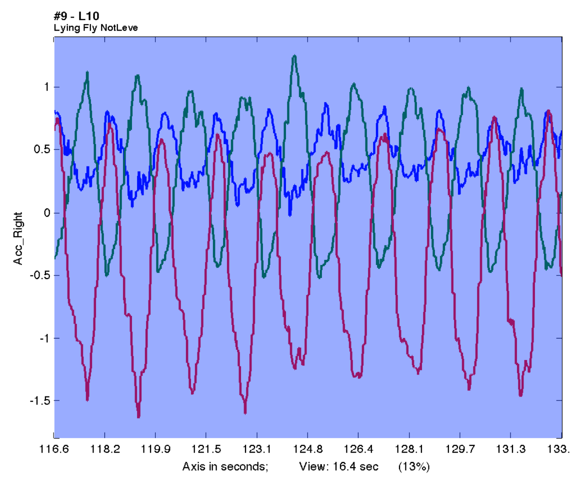
(a) Acceleration for correct lying fly, left hand



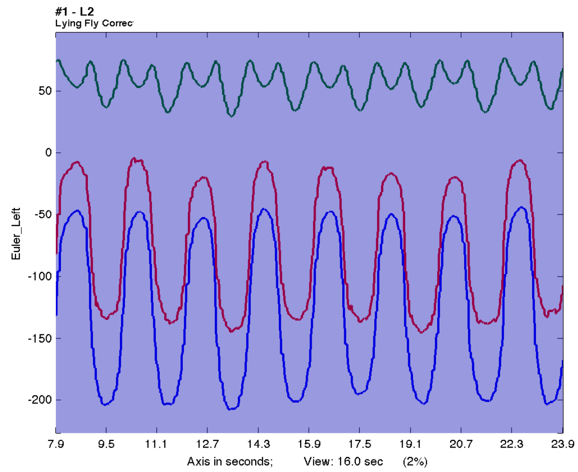
(b) Acceleration for not-leveled lying fly, left hand



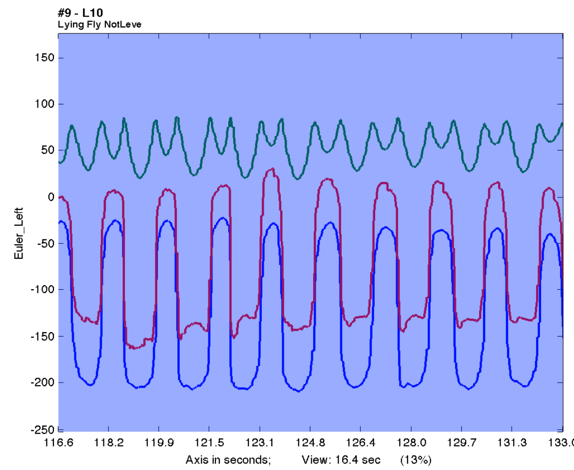
(c) Acceleration for correct lying fly, right hand



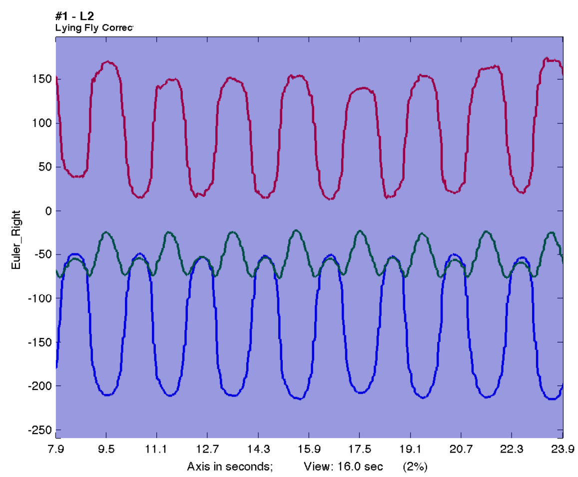
(d) Acceleration for not-leveled lying fly, right hand



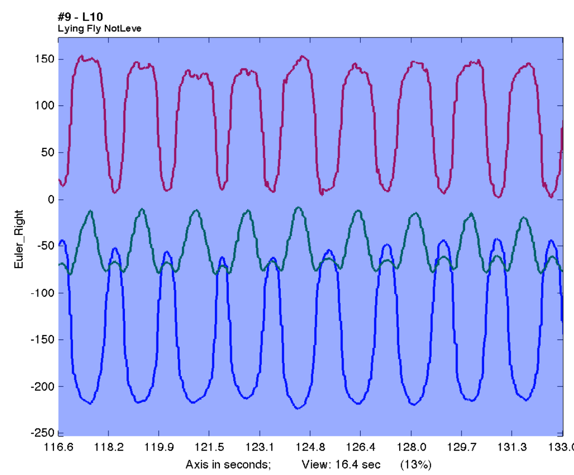
(e) Euler angles for correct lying fly, left hand



(f) Euler angles for not-leveled lying fly, left hand



(g) Euler angles for correct lying fly, right hand



(h) Euler angles for not-leveled lying fly, right hand

Figure D-1: Acceleration and orientation graphs for the correct and not-leveled versions of lying fly for both hands. Note that the y-axis scale might be different for each picture. The x axis is shown in blue, y in green, and z in red.

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