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Monitoring changes in physical activity data during strength training of people with myotonic dystrophy type 1

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Abstract

Myotonic dytrophy type 1 (DM1) is an incurable neuromuscular disease and muscle weakness is a prominent symptom. Research has shown that strength training can be an interesting solution to help with this symptom. Therefore an assistive technology aiming at supervising strength training at home for people with DM1 has been developed and tested in the home of 10 patients for 10 weeks. As many change point detection (CPD) techniques have been used for monitoring change in activity data in the past, no one applied these techniques to physical activities of people with DM1 disease. Hence, physical activity data have been collected during the 10-week experiment and state-of-the-art CPD algorithm has been used to analyze changes in physical activity during the strength training program at home. The results prove that many challenges need to be addressed in this context and could act as a guideline for future works.

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Keywords: Activity recognition ; change point detection ; wearable device ; health monitoring ; assistive technology ; myotonic dystrophy type I

1. Introduction

Myotonic dytrophy type 1 (DM1) is an incurable neuromuscular disease with the highest prevalence in the Saguenay-Lac-Saint-Jean region of Quebec, Canada [2]. Muscle weakness is a cardinal symptom of this disease and has shown to be declining between 25-53% over a 9-year period for DM1 affected patients [6]. Since no curative treatment exists for this disease, strength training seems to be an interesting solution to counter this effect. Furthermore, it has been shown as safe [8] and as leading to maximum force gain when supervised [13]. Supervising a training

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program in a controlled environment such a clinic or a physical training center is not an easy task. Indeed, many stakes (transportation, availability, costs) prevent the application of such programs in a controlled environment. Actually, home-based strength training for this population seems to be an interesting way to tackle these barriers. In fact, it has been highlighted that a strategy involving research or rehabilitation team help to gain maximum adherence to training programs for DM1 patients [1]. Hence, a technological solution aimed at supervising home training programs of DM1 patients has been developed by our team and has been installed in the home of 10 persons affected by the DM1 disease while they followed a 10-week training program. A previous study related to this project [9] evaluates the clinical benefits of a such home program while assessing standardized clinical tests. Another one [3] presents the assistive technology that supervises the training sessions while motivating the patients through the 10-week program. This assistive technology, with the help of a wristband with an integrated inertial movement unit (IMU), allowed the gathering of a lot of information such as the activities performed each day (walking, running, sit to stand, stand to sit) by each participant. Thus, this paper will focus on analyzing the gathered data to monitor changes in their physical conditions by applying change point detection (CPD) methods. These methods can be useful to detect changes in physical activity between the beginning and the end of the program and can also be used to evaluate the impact of health events (events that affect the health of an individual and therefore can affect his daily routine). To the best of our knowledge, no study applied CPD techniques to monitor changes occurring during a training program followed by DM1 patients.

This paper is organized as follows. Section 2 reviews the literature about CPD methods and their application to physical activity data. Section 3 details the data collection process. Moreover, it explains how the device works, how the data was collected and how these data was processed afterwards. Section 4 presents the CPD methods used and how they have been used. Finally, Section 5 is devoted to the presentation and the discussion of the results obtained. Section 6 concludes this paper.

2. Related works

Change Point Detection (CPD) techniques are largely studied in the literature. In fact, CPD techniques can be divided into two categories: supervised methods and unsupervised methods. Supervised methods tend to need a relatively large amount of labeled data for training. Hence, this makes them inapplicable for this study as the amount of available data is limited, so this paper focuses on unsupervised methods. In the past decades, many unsupervised CPD techniques have been investigated. In this work, we uncover those that were used in a context that is similar to the one of this study.

Some studies applied CPD techniques on smart homes data to evaluate changes in daily routine and to detect health events. For example, Dawadi et al. [5] collected data from 18 smart homes for a period of two years where elderly people lived. The algorithm PCAR was applied to model the daily routines of these peoples and to track their behavioral changes. In the meantime, standardized cognitive and physical evaluations has been made twice a year for each of these residents. Hence, it was possible to validate the correlation between the changes in the daily routine detected by the algorithms and the changes detected by the standardized tests. The results shown that a correlation exists for some of the residents and that it is possible to detect changes in the daily routine with PCAR.

Smart home data has also been used in pair with CPD techniques to detect health events. Sprint et al. [11] unfolded case studies where health event occurred for 3 elderly persons living in a smart home. The first person followed a radiotherapy treatment after lung cancer diagnostic. This event triggered differences in the daily routine that was recognized by most of the CPD algorithms. Notably, the activities such as *sleeping* and *going outside* was the most disturbed by this event. Another person has been diagnosed with insomnia during the data collection. CPD algorithms detected changes mostly with the *going outside* activity as well as *sleeping*. Finally, the third person fell in her home. However, the changes that occurred in her daily routine were not significant enough to be detected by CPD techniques.

Other studies applied CPD techniques to physical activity data. A research team used wrist-worn device to track physical activity during a 10-week program [12]. Eleven participants worn their wristband during the first week to establish a baseline. Next, an individual program for each participant has been established toward personal health goals (e.g. increasing steps per day). This program was carried out over the next 8 weeks and participants did a self-assessment each week to assess whether they were achieving their goals. Each participant wore the wristband during the ninth week to assess the effect of the program. Thus, changes observed by CPD techniques between the baseline and the last week has been compared to auto evaluation reports. The results show significant changes for 5 out of the 11 participants as well as some discrepancies between auto-evaluation reports and change scores.

Wrist-worn device has also been used to monitor changes in activity data of 15 patients in inpatient rehabilitation [10]. The goal of the study was to evaluate changes in physical activity data such as the number of steps, heart rate or rest periods during the rehabilitation program. The results have shown many changes during the rehabilitation process for most of the participants. In fact, the changes scores are highly variable and the greater changes from the beginning of the experiment are mostly reported at the end of the therapy.

While physical activity data has been used for change point detection, CPD techniques have not been applied to patients with DM1 following a strength training program yet. Hence, in this paper, our goal is to apply recent CPD algorithms in this context.

3. Data collection

The technology developed as part of the Acti-DM1 project is aimed to assist people with DM1 to perform their strength training program at home. These devices can record physical activity data and they were used for data collection.

3.1. Technology

The assistive technology consists of two devices: a wristband with an IMU and a Raspberry PI 3 as the main computation unit. The wristband is a custom device developed in our previous work [4] that uses the data of the integrated IMU to automatically recognize activities such as running, walking, sit to stand, stand to sit and rest. The main computation unit is composed of a Raspberry Pi 3b+. It receives the data sent by the wristband, provides guidance during a training session while recognizing training sequences and back up the data each day to a distant location when an internet connection is available.

In the regular mode, the wristband sends the recognized activities to the main unit in real time (one per second). When the wristband gets out of range (ex.: outside of the home), it gets disconnected from the main unit and the offline mode is then activated. While in the offline mode, recognized activities are stored in the wristband internal memory. As the available memory is low, no temporal information is stored: only the count of each recognized activity is kept. When the wristband reconnects to the main unit, these counters are sent back to the main unit and the regular mode is then re-activated. For more specific details about the technology, the reader can refer to our previous work [3].

3.2. Process

Ten participants followed the strength training program with help of the technology to achieve their training program at home. Moreover, a personalized strength training program designed by a physiotherapist during the 10-week experiment has been assigned to each participant. Besides, they were assessed with standardized clinical tests before and after the 10-week training program to assess their physical condition [9]. Also, these participants had to wear their wristband every day except at night to recharge the battery. Phone calls were made every week to ensure safety and to make sure everything was working properly. Finally, this experiment has been approved by the Ethics Review Board of the CIUSSS-SLSJ (*Centre Intégré Universitaire de Santé et de Services Sociaux du Saguenay-Lac-St-Jean*, Saguenay, Québec, Canada), with file number 2020-7.

Unfortunately, five participants in the technological group left the experiment before the end or had to be excluded. One participant had to leave because of changes in family responsibilities, one had to leave after the death of family member, one dropped out because of surgery, one was not able to pursue after the first week due to internet coverage limitation, and a problem encountered with the SD card of the Raspberry Pi 3 did not allow the data of one participant to be recovered.

3.3. Data

At the end of the experiment, five participants completed the experiment for at least 8 weeks. Thus, the data of 5 participants was available for behavioral change detection. After some data cleaning (deletion of duplicates), this information were available: events that occurred (e.g. the connection/disconnection between the wristband and the main unit, the end of a training session), the activities recognized when the wristband was offline, the immobile indicator that was reported each second (more details below) and, finally, the activity recognized at each second when the wristband was connected to the main unit.

Following the cleaning process, a feature extraction program has been implemented to build a new dataset aimed at the CPD techniques. The program splits a day into n equally sized periods (in this paper, $n = 24$). For each period in a day, the features are computed from the sequential cleaned data appearing in the period's time frame. In the final stage, 4 features were extracted: *wear_seconds*, *low_activity_seconds*, *moderate_activity_seconds* and *missing_seconds*.

- *wear_seconds* is a feature that represents the number of seconds in the period where the wristband was worn. This feature is calculated from the immobile indicator. This indicator is generated by the wristband with the help of the IMU. When a tiny movement is detected, the moving indicator is set to true. If the wristband is completely still (e.g. on a table), no movement is detected by the IMU and thus the indicator is set to false.
- *low_activity_seconds* contains the number of seconds in the period where an activity that implies a low physical effort is recognized. This feature is the addition of the number of seconds the activities *stand to sit* and *sit to stand* were recognized by the wristband. Obviously, it also takes into account the activities recognized when the wristband was offline.
- Similarly, *moderate_activity_seconds* contains the number of seconds in the period where an activity that implies a moderate physical effort is recognized. This feature is the addition of the number of seconds the activities *running* and *walking* were recognized by the wristband.
- Finally, the wristband normally reports the recognized activity each second. However, some factor can prevent this. For example, if the battery goes completely discharged, the wristband will not report its status anymore. Hence, the data of the period will be missing. Another example can be linked to connections and disconnections of the wristband from the main unit. When the link between the main unit and the wristband is lost, some delay is necessary for the wristband to figure it out and start the offline mode. Because of this delay, some data get lost during the process and are categorized into feature *missing_seconds*.

4. Change point detection techniques

CPD techniques processed the extracted features to track change in physical activity data collected during the 10-week experiment. The techniques used in this paper were selected by some criteria. First, the collected data were noisy and the participation varied from one participant to another. Hence, we selected algorithms which their efficiency was already proven for physical activity data in a similar context. Second, a relatively short amount of unlabeled data was available. Consequently, supervised method as well as methods that need a lot of data labelled or not were discarded. Finally, our search was limited to only recent algorithms. As a result, two algorithms were identified for our purpose: sw-PCAR [12] and RulSIF [14].

4.1. sw-PCAR

Permutation-based Change Detection in Activity Routine (PCAR) [5] is an algorithm that models the daily routine using activity curves. The activity curves then allow the detection of changes in the daily routine. However, this method needs a relatively large amount of data to detect changes efficiently. Thus, PCAR has been adapted to allow the processing of smaller windows of data. The adapted algorithm is called sw-PCAR (small window-PCAR) and has been applied to physical activity data [10, 11, 12].

This algorithm breaks a day within the selected windows into n intervals. Each interval contains a probability distribution representing the probability of occurrence of each activity. Then, the days within a window W_i of data are averaged to give an aggregated window $\hat{W}_i$ of size one day which contains a n-sized probability distribution. The symmetric Kullback-Leibler (KL) divergence distance between the probability distributions of two aggregated windows is then used to produce a change score CS between these two windows of data. A significance-testing method is integrated to this algorithm. However, the significance testing of sw-PCAR was not used. In fact, the available data needed a more case-specific method to evaluate if a change seemed significant or not.

4.2. RulSIF

Relative unconstrained Least-Squares Importance Fitting (RuLSIF) is a method that quantify the amount of change between two time series samples by comparing their underlying probability distributions [14]. In fact, this method directly estimates the density ratio of the underlying distributions without estimating their probability distribution first. These kinds of methods are called direct density ration estimation. This one uses the Pearson divergence dissimilarity measure to estimate the ratios. Then, we use the results of this dissimilarity measure as change score CS. Moreover, this method has also been used for detecting changes in physical activity data [12, 11].

A great advantage of RulSIF is the fact that it can be also applied to multidimensional data. Hence, it is possible to compare windows which had been pre-processed differently. In this paper, we tested RulSIF with three modes: vector, matrices and features-matrices.

To use RulSIF in the vector mode, the two windows to compare are processed in the same way as sw-PCAR: each window of data are averaged to produce two aggregated windows of size one day. Thus, the two windows are now represented as two vectors that contains the data of n intervals of the day. The matrix mode compares the windows of data without aggregating them. This way, two matrices of size (number of days $\times$ n) are used for the change score calculation. Finally, the features-matrix mode creates a vector for each feature as in the vector mode, but groups these vectors into one matrix that is used for the comparison of the two windows of data.

4.3. Windows selection

Each algorithm takes two windows of data and produces a change score that quantifies the amount of changes between them. A window of data is a period of length w days which contains the features extracted from the dataset and each day within a window is split into n intervals. For these experiments, the length of a window of data (w) is set to 7 and the number of intervals in a day (n) is set to 24.

Only the complete weeks of each participant has been retained for comparison. As a result, the 10th week has been eliminated as it was incomplete for all the participants. So, each complete week becomes a window of data of length 7. Then, the baseline (week 1) is automatically compared with all the others to produce $m - 1$ change scores where m is the number of complete weeks. Figure 2-b is a good example of this: the week one is the baseline and eight change scores has been calculated by each CPD techniques. In fact, most of the analysis has been made with the first window as a baseline, even if the baseline can be any windows.

5. Results and discussion

As mentioned earlier, we were able to analyze changes in activity data for people who participated in the experiment for at least 8 weeks. This section first quantifies the global participation and evaluates the stability of the participant's routines. Then, a participant who has two health events during the data collection is presented as a case study. Finally, the limitations and challenges of this study are discussed.

5.1. Participation

For this section, we will only focus on the data collected from the five participants that completed the 10-week experiment. Table 1 shows statistics about the data collection participation of these five participants. The collected weeks column is the number of weeks that were collected during the experiment. The valid days are the number of days where the technological setup was operational. For example, if the wristband was not operational during some days because of a dead battery, the number of valid days is lower. The wearing rate is calculated from the valid days which contains at least four hours of wearing time. Finally, the average time worn column is the average wearing time of valid days.

First, the wristband of participant 1 broke during the data collection and was repaired two weeks later. Hence, these two weeks were categorized as invalid. Furthermore, we can see that the participation rate varies a lot from one participant to another. For example, the wearing rate of participant 1 is 84% and has an average of 7.14 hours of wearing time per day while the participant 5 has a wearing rate of 41% and an average wearing time of 3.65h. Finally, the global wearing rate of the five participants is 68% and the global average time worn per day is equal to 5 hours.

Table 1. Data collection participation

Participant number	Collected weeks	Valid days	Valid days (%)	Wearing rate (%)	Average time worn (h)
1	9	45	71	84	7,14
2	9	39	62	85	5,09
3	9	60	95	72	4,55
4	9	57	90	60	4,57
5	8	46	82	41	3,65

5.2. Day-to-day stability

Detecting changes in the daily routine can be a good way to track behavior changes during the experiment. Each participant had to wear their wristband each day to allow the collection of data while performing daily activities. However, day-to-day instabilities are observed for most of the participants. These instabilities could potentially affect the sensitivity of CPD algorithms. Therefore, to evaluate such instabilities, the following method has been applied. For each feature of each participant, scores are generated by averaging combined change scores of each week. The combined change score of a week is calculated by evaluating the change score between this week and all the others with the help of sw-PCAR. This gives $n - 1$ change scores that are averaged. The greater the scores are, the highest is the instability. Figure 1 shows instability scores generated for each participants.

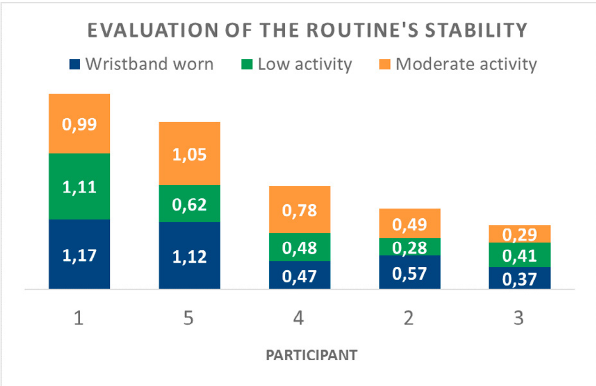

Fig. 1. Evaluation of the routine's stability

The routine's stability varies a lot from one participant to another and is relatively high for most of the participants. For instance, while participant 3 has the more stable routine, participant 1 has a relatively unstable routine. Moreover, it is important to keep in mind that day-to-day instabilities can be greatly affected by different levels of participation during the experiment. However, it is also possible that a part of these instabilities are due to changes in the physical condition during the 10-week experiment. In fact, Sprint et al. [10] showed results that have a high variability for people following an inpatient rehabilitation program in a previous study and suggested that it could have been caused by changes in their physical conditions. Still, for the current study, the data available does not show enough evidence to support this theory.

5.3. Case study - participant 4

Participant 4 is a good candidate for a case study as its data are representative of the study and its the only one where health events were reported during the data collection. Two events were reported: gastroenteritis was reported in week 4 (event 1) and influenza was reported in week 9 (event 2). Hence, its data is analyzed as a case study.

Figure 2-a presents the feature data recorded during the experiment for each day with markers that show where the two events occurred. With this figure, it is possible to see that the wristband was not worn during the days following

these two events. Furthermore, the day-to-day variability seems to be relatively high. However, he is still a good candidate for CPD analysis.

Figure 2-b shows the change scores generated by sw-PCAR and the three modes of RulSIF. These comparisons have been made with the week one as the baseline. Also, the change scores of all features of one week has been averaged to allow the display of only one score by week for each algorithm.

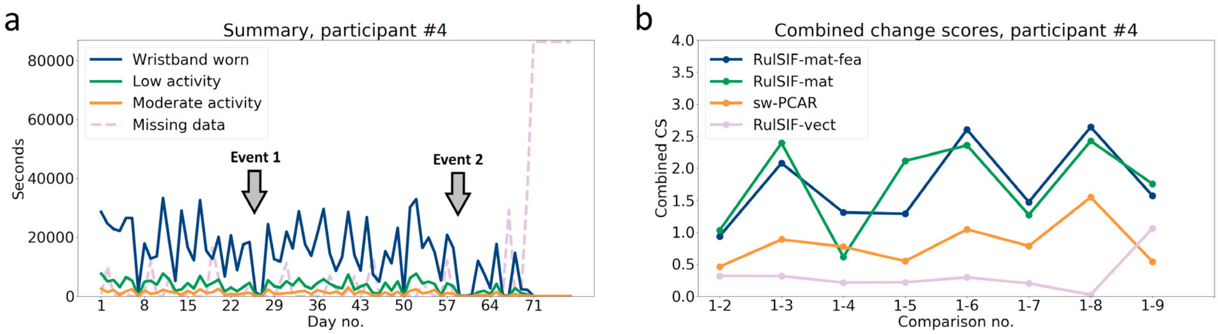

Fig. 2. (a) summary of features data; (b) combined change scores of each method.

The change scores seem to be greatly affected by instabilities in the routine. In fact, participant 4 is one of the three participants whose routine is the more unstable (see Figure 1). Still, some change scores peaks can be observed. For example, it is possible to detect a peak in weeks 3, 6 and 8. Nevertheless, no peak is observed for the two weeks where health event has been reported (weeks 4 and 9).

To help determine if there is a change observed for weeks 4 and 9, a comparison with the average was made by first calculating the average change scores of the nine weeks and, then, subtracting the change scores of weeks 4 and 9 from this average. This process gives the differences from the averaged change score for these weeks. These results are shown in Table 2.

Table 2. Participant 4: differences from average of weeks 4 and 9

Algorithm	CS average	CS week 4	CS week 9
sw-PCAR	0,82	-0,05	-0,28
RulSIF-vect	0,33	-0,12	0,73*
RulSIF-mat	1,74	-1,13	0,01*
RulSIF-mat-fea	1,74	-0,43	-0,17

The change scores generated by all algorithms ran for week 4 are smaller than the average. Furthermore, in week 9, only RulSIF-vect generates a change score significantly greater than the average. Consequently, we can conclude that none of the health event triggered a significant change in the routine.

Obviously, as mentioned before, this participant did not wear his wristband the days that followed the health event. Also, its routine is relatively unstable. Therefore, the sensibility of the CPD algorithms used was significantly affected.

5.4. Discussions

This study has some limitations. The dropout rate was higher than expected. Also, the participation was relatively inconsistent for most participants. As seen in Table 1, three participants out of five had a wearing rate of less than 80%. Moreover, the daily routine of some of the participants was relatively unstable and noisy. Therefore, these factors made the analysis of behavioral change more complex and alternative ways of using the results provided by the CPD techniques have been used.

In addition, analyzing physical activities of people with DM1 unfold some challenges that need to be taken into consideration. First, this population tends to be less active [7]. As a result, it could be more difficult to perceive the effects of a health event over the time series of physical data. Also, people with DM1 are more at risk of developing a health event that could disturb the data collection. For instance, a study revealed that they are more at risk of falling, developing cardiac problems and developing sleep apnea [7]. Thus, one of the participants had to dropout the data collection due to cardiac problems that led to surgery.

Despite the challenges encountered in this study, we were able to use the state-of-the-art CPD methods to track changes over activity data of 5 peoples while analyzing the effects of two health events that occurred for one participant presented as a case study. As changes in physical conditions induced by the training program are deemed low [9], no significant changes have been detected by the CPD techniques tested in this study. However, we have quantified the stability of each participant's routine which revealed interesting information regarding their day-to-day instabilities in performing mobility related activities.

6. Conclusions and future works

In this study, we monitored the physical activity of 10 participants with DM1 over a period of 10 weeks while they were following a strength training program. Then, we analyzed the data collected and applied state-of-the-art CPD techniques to monitor changes in physical activity during the experiment. We had to overcome many challenges as the data suffered from inconsistencies due to factors like a relatively high dropout rate, challenging participation rate and moderate day-to-day instabilities. We managed to overcome these challenges and presented an interesting case study where health events were observed. Moreover, it is the first study to monitor and analysis changes in physical activities of people with DM1 while they were performing a strength training program at home. As a result, it could act as a guideline for future similar work because it unfolds many challenges that need to be taken into consideration while working in this context.

As future works, we want to apply the knowledge acquired from this study to experiments with more persons for a longer duration. To do so, improving our custom-made wristband to make it even more sturdy and reliable could be a great avenue.

References

[1] Aldehag, A., Jonsson, H., Lindblad, J., Kottorp, A., Ansved, T., Kierkegaard, M., 2013. Effects of hand-training in persons with myotonic dystrophy type 1–a randomised controlled cross-over pilot study. Disability and rehabilitation 35, 1798–1807.

[2] Bouchard, G., Roy, R., Declos, M., Mathieu, J., Kouladjian, K., 1989. Origin and diffusion of the myotonic dystrophy gene in the Saguenay region (Quebec). The Canadian journal of neurological sciences. Le journal canadien des sciences neurologiques 16, 119–122.

[3] Chapron, K., Lapointe, P., Lessard, I., Darmstadt-Belanger, H., Bouchard, K., Gagnon, C., Lavoie, M., Duchesne, E., Gaboury, S., 2021. Acti-DM1: Monitoring the Activity Level of People with Myotonic Dystrophy Type 1 Through Activity and Exercise Recognition. IEEE Access 9, 49960–49973.

[4] Chapron, K., Plantevin, V., Thullier, F., Bouchard, K., Duchesne, E., Gaboury, S., 2018. A more efficient transportable and scalable system for real-time activities and exercises recognition. Sensors (Switzerland) 18.

[5] Dawadi, P.N., Cook, D.J., Schmitter-Edgecombe, M., 2016. Modeling Patterns of Activities using Activity Curves. Pervasive and mobile computing 28, 51–68.

[6] Gagnon, C., Petitclerc, É., Kierkegaard, M., Mathieu, J., Duchesne, É., Hébert, L.J., 2018. A 9-year follow-up study of quantitative muscle strength changes in myotonic dystrophy type 1. Journal of neurology 265, 1698–1705.

[7] Johnson, N.E., 2019. Myotonic Muscular Dystrophies. Continuum (Minneapolis, Minn.) 25, 1682–1695.

[8] van der Kooi, E.L., Lindeman, E., Riphagen, I.I., 2002. Strength training and aerobic exercise training for muscle disease, in: Cochrane Database of Systematic Reviews. John Wiley & Sons, Ltd, Chichester, UK.

[9] Lessard, I., Gaboury, S., Gagnon, C., Bouchard, K., Chapron, K., Lavoie, M., Lapointe, P., Duchesne, E., 2021. Effects and Acceptability of an Individualized Home-Based 10-Week Training Program in Adults with Myotonic Dystrophy Type 1. Journal of neuromuscular diseases 8, 137–149.

[10] Sprint, G., Cook, D., Weeks, D., Dahmen, J., La Fleur, A., 2017. Analyzing Sensor-Based Time Series Data to Track Changes in Physical Activity during Inpatient Rehabilitation. Sensors (Basel, Switzerland) 17.

[11] Sprint, G., Cook, D.J., Fritz, R., Schmitter-Edgecombe, M., 2016a. Using Smart Homes to Detect and Analyze Health Events. Computer 49, 29–37.

[12] Sprint, G., Cook, D.J., Schmitter-Edgecombe, M., 2016b. Unsupervised detection and analysis of changes in everyday physical activity data. Journal of Biomedical Informatics 63, 54–65.

[13] Tollback, A., Eriksson, S., Wredenberg, A., Jenner, G., Vargas, R., Borg, K., Ansved, T., 1999. Effects of high resistance training in patients with myotonic dystrophy. Scandinavian journal of rehabilitation medicine 31, 9–16.

[14] Yamada, M., Suzuki, T., Kanamori, T., Hachiya, H., Sugiyama, M., 2013. Relative Density-Ratio Estimation for Robust Distribution Comparison. Neural computation 25, 1324–1370.