Data-driven modelling of fatigue in pelvic floor muscles when performing Kegel exercises

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Abstract— **This paper studies how to describe, using a piecewise linear dynamical model, the short-term effects of fatigue and recovery on the strength of pelvic floor muscles. Specifically, we first adapt a known model that describes short-term fatigue in skeletal muscles to the specific problem of describing fatigue in pelvic floor muscles when performing Kegel exercises, and then propose a strategy to learn the modelŠs parameters from field data.**

In details, we estimate the model parameters using a least squares approach starting from measurement data that has been obtained from three healthy women using a dedicated vaginal pressure sensor array and a connected mobile app which gamifies the Kegel exercising experience.

We show that describing the pelvic floor muscles behaviour in terms of short-term fatigue and recovery factors plus learning the associated parameters from data from healthy women leads to the possibility of precisely forecasting how much pressure the players will exert while playing the game.

By cross-learning and cross-testing individual models from the three volunteers we also discover that the models need to be individualized: indeed, the numerical results indicate that, generically, using data from one player to model another leads to potentially drastically lower forecasting capabilities.

I. Introduction

The Pelvic Floor Muscles (PFM) support several inner organs such as the bladder, the intestines and, in females, the uterus. Several factors can contribute to damaged or weak PFM, including pregnancy, childbirth, or injuries. These lead in many cases to urinary incontinence, which is estimated to affect about 1 in 3 women [1], and even pelvic floor prolapses. These conditions are moreover frequently accentuated after the menopause.

To strengthen the PFM, and hence alleviate or even cure the issues above, women are often encouraged to perform activities known as Kegel exercises. These consist of repeated contractions and relaxations, and are known to be effective in strengthening the muscles. Women tend thus to be encouraged to perform Kegel exercising in order to prevent or treat the problem [2]. Instructions on how to do these exercises are distributed by health practitioners as verbal instructions, brochures or videos. However, approximately 30% of the women do the exercises incorrectly [3], possibly due to the nature of the location of the muscles and the inability to recognize if the pelvic floor muscles are being activated, or the surrounding pelvic, abdominal or hip muscles. Moreover, to be effective, Kegel exercises must be repeated over long periods of time.

Unfortunately, however, they tend to be experienced as tiring or boring, so that many women either neglect them or do not exercise sufficiently. Several reasons exist for this perception: firstly, women usually do not receive any feedback on whether their exercises are performed correctly, and the effect of successful training might only be recognizable by the women after prolonged training. Secondly, women tend to perform Kegel exercises alone due to several factors, including social taboos associated with female sexual health. This contrasts with other sports, where the social aspect of exercising with others is often a significant motivation to do the sport, and the common sports being well accepted in society.

The authors of this study believe that a new innovative approach can help to alleviate this issue: instead of performing boring Kegel exercises in private without feedback and possibly harming their PFM due to wrong exercises, women should be offered to play a game app, which uses real time data from a vaginal pressure sensor. This option provides immediate biofeedback about the correctness of the exercises, midterm increase in fitness due to training effects and motivating women through appropriately chosen game design. Since gamified treatment strategies, including game mechanisms such as rewarding- and sanctioning systems, compels the user to remain invested in the task at hand, [4]. Gamification is expected to also encourage and motivate women to do regular Kegel exercising and thus enjoy the long-term benefits of a well-conditioned pelvic floor musculature. Furthermore, gamifying the exercises, is not only expected to make Kegel exercising fun and engaging, but also to increase awareness and destigmatize female health. A social network of comparing high scores etc. might be added to obtain positive effects due to social interactions. This is in line with positive evidence that *mHealth* based interventions (i.e., medicine supported by mobile devices) improve health outcomes [5], [6]. Indeed, mobile technology and social media have emerged as effective and inexpensive tools to remotely track and manage people's behaviour, allow personalization of care delivery, and to encourage people to take responsibility for their health and well-being.

We have thus developed a prototype app as described above (see more details on the game and the vaginal pressure sensor in Section II). However, it became apparent that using the collected pressure measurements to model the fatiguing of the muscles during exercises, and the increase in fitness over longer periods of playing the game, is not only beneficial for research purposes (as suitable models do not exist for PFM), but should be used to adapt the game difficulty to the players current fitness and fatigue status to ensure engaging and fair game dynamics.

This paper is hence a first step in this direction, where *we seek to model fatigue in PFM while playing a game controlled by performing Kegel exercises.*

Muscle models: Modelling the dynamical behaviour of PFMs is reminiscent of associating muscular stimulation levels with the corresponding pressure (or force) outputs, a general problem for which researchers have developed many different generic models of different complexities. These include *physiologically based models* (that relate stimuli and corresponding forces as interactions of the fibers at a microscopic level, [7]), *Hill-type models* (that relate stimulation levels and corresponding forces through mechanically-inspired concepts including mass-spring-damper systems as well as a contractile element and parallel elastic element [8])[1], and *black-box models* (that relate input-output relations starting from numerical evidence). The last type is especially interesting if detailed physiological data (such as electromyography levels or thickness and length of specific muscle fibers) is unavailable.

Literature on black-box methods for modelling muscular dynamics can be categorized depending on which estimation tool is used for learning from the datasets. The most common strategies in this case use *Hammerstein-Wiener* or *Nonlinear autoregressive exogenous (NARX)* models, including Neural network (NN) and fuzzy models. Since physiological models of muscular dynamics are typically nonlinear, thus nonlinear identification approaches tend to provide better results than linear ones.

PFM models: Some PFM models can be found in the literature. Considering the effects of dilation using a vaginal dilator of adjustable seize, data-driven dynamical models of female response to the vaginal dilation were derived in [10]. The work used time-series of pelvic floor pressure collected from healthy patients during ad-hoc medical trials to investigate which type of dynamical model can most accurately describe the recorded data as a response to the physical dilation input. This was extended in [11] by also considering psychological input signals. Models of the behaviour of the pelvic floor muscles in connection with childbirth are summarized in [12].

Fatigue models: Several models focusing on fatiguing muscles can be found in the literature [13]–[15]. The authors in [13] presented a model capturing muscle activation, fatigue, and recovery where the behaviour of muscles is described as a group of motor units activated by voluntary effort. Assuming that the brain effort is constant, it models the biophysical mechanisms of voluntary drive, fatigue effect, and recovery in stimulating, limiting, and modulating the force output from muscles. The model in [14] considers fatigue, but also increased fitness due to training using simple, first order dynamics and defining the overall performance as the difference between fitness and fatigue. The model also captures the effects of decreased fitness if the muscles are not further trained.

Several models of the behaviour of the pelvic floor muscles in connection with childbirth are summarized in [12].

Contributions: To the best of our knowledge, there exists no publicly available literature proposing control-oriented models of the fatigue dynamics in PFM. This paper starts to close this gap by focusing on PFM dynamics – more precisely, describing fatigue as a result of performing Kegel exercises. In this paper we consider muscle strength measurements from three healthy women performing Kegel exercises. A known model for muscle fatigue, derived in [13], is adapted and extended to describe the observed measurements. Most importantly, in contrast to [13], we allow for non-constant brain stimuli. In addition, we are interested in the dynamics of fatiguing and recovering muscles. It can be shown that the model is indeed suitable to describe the observed dynamics and suitable model parameters can be derived. The results are a step towards better understanding how Kegel exercises influence the muscle fatigue.

Organization of the manuscript: The paper continues with the description of the sensor and the gamified app in Section II. Section III discusses the modelling problem starting with the known linear model described in [13], and then proposes subsequent adaptations to allow for parameter estimation using the measurement data. Results for learning the muscle model using the experimental data of three healthy volunteers are given in Section IV, before closing the paper with concluding remarks in Section V.

II. Experimental setup

A. The FemFit pressure sensor

To gain detailed insights into PFM dynamics, a novel intra-vaginal pressure sensor array has been developed by the Auckland Bioengineering Institute, University of Auckland (NZ). The sensor array (known as the FemFit, see Figure 1) consists of eight evenly spaced pressure sensors, connected to a flexible printed circuit board (PCB) and encapsulated in a soft medical grade silicone. The PCB is attached to a telemeter encased in plastic which sits outside the body and transmits the pressure signal via Bluetooth communications. The FemFit is 80 mm long, 24 mm at its widest point and 4 mm thick, allowing the device to be flexible and able to conform to the vaginal anatomy. The sensor array enables the simultaneous measurement of the pressure profile along the length of the vaginal duct. Thus, the sensors at the most distal end of the vaginal canal (sensors 7 and 8) will measure abdominal pressure, while sensors 3 to 6 are most likely to measure the pressures developed by the pelvic floor muscles. The FemFit is thus able to provide feedback whether the Kegel exercises are being performed correctly (e.g., contracting the PFM and not the abdominal muscles) or not.

B. Kegeland application

The game is an android mobile application featuring a female character in a fictive world. While playing, the

[1] Several extensions of the Hill-type models exist. For instance, the study in [9] developed a modelling framework to evaluate modifications to Hill-type muscle models when they contract in cyclic loops that are typical of locomotor muscle function. The authors combined a damped harmonic oscillator in series with a Hill-type muscle actuator that consists of a contractile element and parallel elastic element.

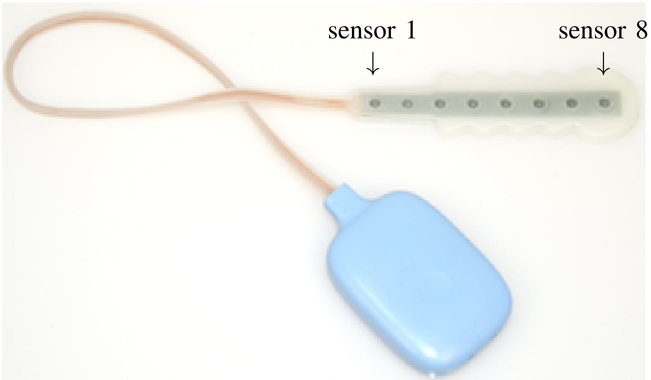

Fig. 1. Photo of a FemFit pressure sensor. The device consists in 8 pressure sensors within a soft medical grade silicon enclosing (in gray), connected to a Bluetooth communication module (in light blue) through a dedicated flexible wiring.

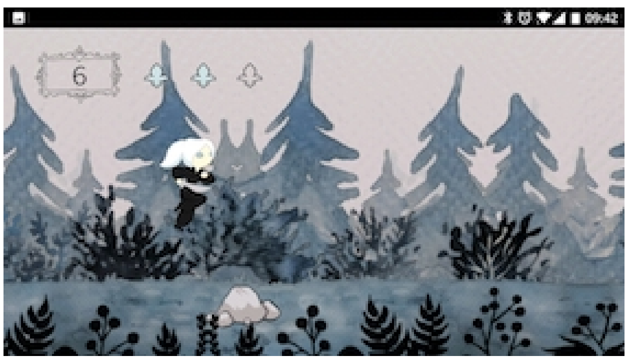

Fig. 2. In-game screenshot from an exercising session.

application collects measurement data from the FemFit via Bluetooth. The user wears the FemFit and uses the pressure sensor as a game controller. By contracting the PFMs, the user sets off a jumping action (of the female character) to avoid incoming obstacles (stones). See screenshot in Figure 2. Before each gaming session, the user can set her personal, maximum contraction pressure through a calibration routine. This information is then used to set the threshold pressure, which the measured pressure is required to exceed to actuate a jumping action in the game. Note that the effect of fatiguing muscles, or other aspects of the derived model, are not yet used in the app. Hence, the threshold does not automatically adapt as the player fatigues; rather, the player must recalibrate as she notices that it becomes increasingly hard or impossible to jump after having played a few sessions. Each course (i.e., game session) nominally contains 10 obstacles, and lasts about 72 seconds. The in-game rewarding system awards one point for each avoided obstacle; when not succeeding in jumping an obstacle will imply the loss of one health point. The system allows for maximum 3 mistakes per course, so that at the fourth the game session terminates earlier than planned. The aim of the exercises is thus to avoid obstacles. The most relevant parameters of each exercise are therefore the required length and frequency of the jumping actions, combined with the number of jumping actions required from the user to finish one course.

C. Collected data

During each gaming session we record the pressure time series from the 8 pressure sensors with a sampling rate of 50 samples per second. The vector of pressure measurements is denoted $p(k) = \left[p_1(k), p_2(k), \ldots, p_8(k)\right]^{\mathrm{T}}$ where the entries of $p(k)$ refer to the individual pressure sensor measurements. Note that $p_1(k)$ and $p_8(k)$ correspond to the first and last sensor in the array. These sensors respectively capture the pressure at the introitus and the abdominal pressure, respectively. Figures 8 and 9 at the end of the manuscript show typical measurement data collected during different gaming sessions.

III. The modelling problem

In this work, we aim to model the fatigue of PFMs due to performing Kegel exercises. Since the model should be applicable to analysis and design methods from the field of systems engineering and control theory, we aim to use dynamical models, consisting of differential equations.

A. Model for constant brain stimuli

As a starting point, we consider the continuous-time model in [13] defined by the following quantities:

- $m_{\mathrm{a}}(t)$:= number of motor units that are in an *active state* at time t, and that are activated by a voluntary drive;
- $m_{\mathrm{f}}(t)$:= number of motor units that are in a *fatigued state* at time t;
- $m_{\mathrm{r}}(t)$:= number of motor units that are in a *resting state* at time t;
- $u(t)$:= muscular activation signal, sometimes referred to as the "brain stimulus" or "brain force";
- M := total number of motor units present in the muscles, assumed to be constant over time, i.e., $m_{\mathrm{a}}(t) + m_{\mathrm{f}}(t) + m_{\mathrm{r}}(t) = M$ for all t.

The model proposed in [13] is

$$\dot{m}_{\mathrm{f}}(t) = -\theta_{\mathrm{f}\mapsto\mathrm{a}} m_{\mathrm{f}}(t) + \theta_{\mathrm{a}\mapsto\mathrm{f}} m_{\mathrm{a}}(t), \tag{1}$$

$$\dot{m}_{\mathrm{a}}(t) = -\theta_{\mathrm{a}\mapsto\mathrm{f}} m_{\mathrm{a}}(t) + \theta_{\mathrm{f}\mapsto\mathrm{a}} m_{\mathrm{f}}(t) + u(t) m_{\mathrm{r}}(t), \tag{2}$$

$$m_{\mathrm{r}}(t) = M - m_{\mathrm{a}}(t) - m_{\mathrm{f}}(t) \tag{3}$$

and is based on two parameters, $\theta_{\mathrm{f}\mapsto\mathrm{a}}$ and $\theta_{\mathrm{a}\mapsto\mathrm{f}}$, to which we can assign the intuitive and respective meaning of recovering and fatiguing factors, since

- $\theta_{\mathrm{f}\mapsto\mathrm{a}} > 0$ describes the recovery of fatigued motor units back into an active state;
- $\theta_{\mathrm{a}\mapsto\mathrm{f}} > 0$ captures the intuition that active motor units fatigue.

Further, the input term $u(t) m_{\mathrm{r}}(t)$ captures the fact that the brain stimulus $u(t)$ activates the resting motor units so that they become active.

Note that the model does not include any driving force or dynamics for muscles to get back into a resting state after having been activated. Indeed, even if no brain stimuli are applied after some time, i.e., $u(t) = 0$ for $t > T$, the number of motor units in the activated and fatigued states will not converge to zero if $u(t) > 0$ for some $t \leq T$. Since in our framework women only activate their muscles when intending to jump over an obstacle in the game, the model of [13] must hence be adapted.

B. Model adaptation

The adaptation needs to allow motor units to transition from active state to resting state when no brain stimuli are applied (i.e., in our case whenever a woman playing the game is not asked to virtually jump over an obstacle). In other words, this means that when $u = 0$ (no stimuli) then the m_{a} should decay to zero, comprising a form of "self-inactivating" component. To model this we add the term $-(1-u)\,\theta_{\mathrm{a}\mapsto\mathrm{r}} m_{\mathrm{a}}$ to (2) where the parameter $\theta_{\mathrm{a}\mapsto\mathrm{r}}$ describes how fast active muscles transition to resting state in case no brain force is applied. Similar to the parameter $\theta_{\mathrm{a}\mapsto\mathrm{r}}$, we further introduce the parameter $\theta_{\mathrm{r}\mapsto\mathrm{a}}$ to parameterise how fast resting motor units can be activated.

Then, the adapted dynamic equation for m_{a} reads

$$\begin{aligned} \dot{m}_{\mathrm{a}}(t) = &- \theta_{\mathrm{a}\mapsto\mathrm{f}} m_{\mathrm{a}}(t) + \theta_{\mathrm{f}\mapsto\mathrm{a}} m_{\mathrm{f}}(t) + u(t)\theta_{\mathrm{r}\mapsto\mathrm{a}} m_{\mathrm{r}}(t) \\ &- \big(1-u(t)\big)\theta_{\mathrm{a}\mapsto\mathrm{r}} m_{\mathrm{a}}(t). \end{aligned} \tag{4}$$

Note that, apart from the added parameter $\theta_{\mathrm{r}\mapsto\mathrm{a}}$, the dynamics remain unchanged for $u(t) = 1$ and for $u(t) = 0$ the amount of activated motor units decreases by $\theta_{\mathrm{a}\mapsto\mathrm{r}} m_{\mathrm{a}}$ without a corresponding term in (1). Hence, the motor units transition into resting state, which acts as a sink when $u(t) = 0$.

C. Discrete time model

To enable estimating the model from measured data using standard discrete-time approaches, we then perform a first-order forward Euler discretization of the dynamics (1), (4) and (3), and obtain the piecewise-linear system

$$\begin{cases} m_{\mathrm{f}}(k+1) = & \phi_{\mathrm{f}\mapsto\mathrm{a}} m_{\mathrm{f}}(k) + (1-\phi_{\mathrm{a}\mapsto\mathrm{f}})\, m_{\mathrm{a}}(k) \\ m_{\mathrm{a}}(k+1) = & \phi_{\mathrm{a}\mapsto\mathrm{f}} m_{\mathrm{a}}(k) + (1-\phi_{\mathrm{f}\mapsto\mathrm{a}})\, m_{\mathrm{f}}(k) \\ & + u(k)\phi_{\mathrm{r}\mapsto\mathrm{a}} m_{\mathrm{r}}(k) - \big(1-u(k)\big)\phi_{\mathrm{a}\mapsto\mathrm{r}} m_{\mathrm{a}}(k) \\ m_{\mathrm{r}}(k) = & M - m_{\mathrm{a}}(k) - m_{\mathrm{f}}(k) \end{cases} \tag{5}$$

where T is the length of the discretization period, and where the piecewise-linearity is induced by the fact that in our assumptions $u(k) \in \{0, 1\}$, and the continuous and discrete-time parameters are connected by the relations

$$\begin{aligned} &\phi_{\mathrm{f}\mapsto\mathrm{a}} := 1 - \theta_{\mathrm{f}\mapsto\mathrm{a}} T, \quad \phi_{\mathrm{a}\mapsto\mathrm{f}} := 1 - \theta_{\mathrm{a}\mapsto\mathrm{f}} T, \\ &\phi_{\mathrm{a}\mapsto\mathrm{r}} := \theta_{\mathrm{a}\mapsto\mathrm{r}} T, \quad \phi_{\mathrm{r}\mapsto\mathrm{a}} := \theta_{\mathrm{r}\mapsto\mathrm{a}} T\ . \end{aligned}$$

D. Estimation problem

Note that due to the known design of the game, $u(k)$ is a known input signal[2]. Further, m_{a} is indirectly measured through the pressure sensors such that we set $m_{\mathrm{a}}(t)$ to be our pressure measurements.[3] In contrast, measurements of the motor units in fatigued and in resting state, as well as the total number of motor units M, cannot be extracted from our data.

The learning problem is then defined as "estimate M, $\phi_{\mathrm{a}\mapsto\mathrm{f}}$, $\phi_{\mathrm{f}\mapsto\mathrm{a}}$, $\phi_{\mathrm{a}\mapsto\mathrm{r}}$, $\phi_{\mathrm{r}\mapsto\mathrm{a}}$, $m_{\mathrm{f}}(k)$ and $m_{\mathrm{r}}(k)$ starting from measurements of $m_{\mathrm{a}}(k)$ and $u(k)$". To make this problem numerically tractable we assume$m_{\mathrm{a}}(0) = m_{\mathrm{f}}(0) = 0$. This implies the possibility of writing the dynamics of m_{a} as a function of only $u(k)$ and the unknown parameters. In other words, recursively expanding $m_{\mathrm{f}}(k+1) = \phi_{\mathrm{f}\mapsto\mathrm{a}} m_{\mathrm{f}}(k) + (1-\phi_{\mathrm{a}\mapsto\mathrm{f}})\, m_{\mathrm{a}}(k)$, leads to $m_{\mathrm{f}}(k) = \sum_{\tau=0}^{k-1} \phi_{\mathrm{f}\mapsto\mathrm{a}}^{k-1-\tau} (1-\phi_{\mathrm{a}\mapsto\mathrm{f}})\, m_{\mathrm{a}}(\tau)$, and using the definition of $m_{\mathrm{r}}(k)$ we can write

$$\begin{aligned} & m_{\mathrm{a}}(k+1) = \\ & \Big(\phi_{\mathrm{a}\mapsto\mathrm{f}} - \phi_{\mathrm{a}\mapsto\mathrm{r}} - (\phi_{\mathrm{r}\mapsto\mathrm{a}} - \phi_{\mathrm{a}\mapsto\mathrm{r}})\, u(k)\Big) m_{\mathrm{a}}(k) \\ & \quad + \Big(1 - \phi_{\mathrm{f}\mapsto\mathrm{a}} - \phi_{\mathrm{r}\mapsto\mathrm{a}} u(k)\Big)\,(1-\phi_{\mathrm{a}\mapsto\mathrm{f}}) \\ & \quad \times \left(\sum_{\tau=0}^{k-1} \phi_{\mathrm{f}\mapsto\mathrm{a}}^{k-1-\tau} m_{\mathrm{a}}(\tau)\right) + \phi_{\mathrm{r}\mapsto\mathrm{a}} M u(k). \end{aligned} \tag{6}$$

It is then possible to use (6) to define a (nonlinear) Least Squares (LS) estimator of $\phi_{\mathrm{f}\mapsto\mathrm{a}}$, $\phi_{\mathrm{a}\mapsto\mathrm{f}}$, $\phi_{\mathrm{a}\mapsto\mathrm{r}}$, $\phi_{\mathrm{r}\mapsto\mathrm{a}}$ and M starting from the knowledge of m_{a} and u. Once the estimates $\widehat{\phi}_{\mathrm{f}\mapsto\mathrm{a}}$, $\widehat{\phi}_{\mathrm{a}\mapsto\mathrm{f}}$, $\widehat{\phi}_{\mathrm{a}\mapsto\mathrm{r}}$, $\widehat{\phi}_{\mathrm{r}\mapsto\mathrm{a}}$ and $\widehat{M}$ have been constructed, it is then again possible to reconstruct an estimate $\widehat{m}_{\mathrm{f}}$ and $\widehat{m}_{\mathrm{r}}$ of m_{f} and m_{r} by leveraging the dynamics in (5).

E. Data preprocessing

In order to prepare for parameter estimation, i.e., training model (5), the measurement data as described in Section II-C need to be pre-processed. As a first step, the average $\bar{p}(k)$ of the array of pressure measurements $p(k)$ is obtained. As a by-product, the averaging also acts as a noise filter.

Note that not all of the absolute pressure measurements are of importance for training the fatigue model. Rather, the *increase* in pressure compared to the base value is an indirect measurement of $m_{\mathrm{a}}(k)$. Hence, the base value of $\bar{p}(k)$, denoted $\bar{p}_{\mathrm{base}}$ and defined as the average value of $\bar{p}(k)$ in resting state, i.e., without activating the muscles, was subtracted such that $m_{\mathrm{a}}(k) = \bar{p}(k) - \bar{p}_{\mathrm{base}}$.

In a final step, the so obtained $m_{\mathrm{a}}(k)$ is used to recognise when women made an effort to activate their muscles, i.e., squeezed in order to jump over an obstacle. In fact, when inspecting the data, these time instances could be easily recognised by abrupt increases in $m_{\mathrm{a}}(k)$. Times T_{start} where muscle activation started, i.e., when $u(k)$ increased to 1, were detected whenever $m_{\mathrm{a}}(k+1) - m_{\mathrm{a}}(k)$ was larger or equal a set threshold $m_{\mathrm{a}}^{\uparrow}$. Setting the threshold value was done manually after visual inspection of the data. In fact, all upwards jumps were easily detected using this method since the experiments were not long enough to capture full fatigue

[2]Indeed, we do not measure $u(k)$ directly, but assume that we can detect the zones where $u(k) = 1$ indirectly by checking when there exists pressure exerted by the player. For more details see Section III-E.

[3]Note that in general pressure could be introduced by other sources than muscle activity. However, in this case, women playing the game were advised to refrain from movements other than activating their PFM where needed during the game. Hence, the influence of other forces leading to pressure measurements were neglected.

of the muscles, which would have prohibited a large enough increase in $m_\mathrm{a}(k)$ despite considerable brain stimuli. This fact could easily be verified since the muscle contractions are somewhat regular due to the periodic appearance of obstacles in the game.

The end of the muscle activation period, i.e., the time T_stop when $u(k)$ decreased to 0 again, was then set to be the first time instance after $u(k)$ increased to 1, where $m_\mathrm{a}(k)$ fell below a second threshold $m_\mathrm{a}^{\downarrow}$.

IV. Results

We gathered data of three healthy, female volunteers aged between 25 and 35, here referred with fiction names to as Aby, Fay and Ida[4]. In total, data from 104 complete rounds of the game were collected: 83 from Aby, 9 from Fay and 12 from Ida. Each round lasted 90 seconds and contained 10 stones to jump over[5].

After preprocessing the sensor measurements, as described in Section III-E, the parameters $\phi_{\mathrm{a}\mapsto\mathrm{f}}$, $\phi_{\mathrm{f}\mapsto\mathrm{a}}$, $\phi_{\mathrm{a}\mapsto\mathrm{r}}$ and $\phi_{\mathrm{r}\mapsto\mathrm{a}}$ in (5) were estimated such that the difference between the measured and the estimated value of m_a is minimized using a LS approach, i.e. $\mathrm{argmin}_{\{\phi_{\mathrm{a}\mapsto\mathrm{f}},\phi_{\mathrm{f}\mapsto\mathrm{a}},\phi_{\mathrm{a}\mapsto\mathrm{r}},\phi_{\mathrm{r}\mapsto\mathrm{a}}\}} \|m_\mathrm{a} - \widehat{m}_\mathrm{a}\|$.

A. Parameter estimation with increasing test set

In a first step, Aby's 83 data sets were used to estimate the parameters $\phi_{\mathrm{a}\mapsto\mathrm{f}}$, $\phi_{\mathrm{f}\mapsto\mathrm{a}}$, $\phi_{\mathrm{a}\mapsto\mathrm{r}}$ and $\phi_{\mathrm{r}\mapsto\mathrm{a}}$, i.e., to train model (5) using a growing number of training sets to simulate a situation where it is possible to perform on-line identification of the model parameters. Initially, only the first data set was used to train the model, which was then tested using the remaining data sets. For every consecutive session we then moved one additional data set from the test set to the training set, until the test set only contained the data of the last game round (so that this was tested on a model that was trained on all previous data sets). Figure 3 shows that the resulting fit indexes[6] for the training and the test set. As it can be clearly seen, for a growing number of data in the training set, the fit indexes for the test and the training sets converge to the same value. In fact, the differences when using 30 or more of the available game sessions for training are small, which indicates that no overfitting of the data is likely to be present when using at least 30 sets for training.

Figure 4 shows the corresponding estimated parameter values, which quickly converge. Note that the outliers for $\phi_{\mathrm{a}\mapsto\mathrm{r}}$ and $\phi_{\mathrm{r}\mapsto\mathrm{a}}$ can be explained, for instance, if the fit for the outlier values is very similar to the fit of the presumed correct parameter values. Then, due to numerical inaccuracies, the fit for the outlier parameter values might be higher in some, isolated cases. Further, small inaccuracies in detecting the alleged brain forces can also lead to such isolated outliers.

[4]Note that full, informed consent has been obtained from all three women.

[5]Note that for the purpose of data collection, the game was slightly adapted. Instead of terminating the game after having missed to jump over 3 obstacles, players got infinite many "lives" in the game to allow them to finish the round with 10 obstacles despite increasing fatigue.

[6]Defined in general as $100 \cdot \left(1 - \frac{\|y - \widehat{y}\|}{\|y - \mathbb{E}\left[y\right]\|}\right)$.

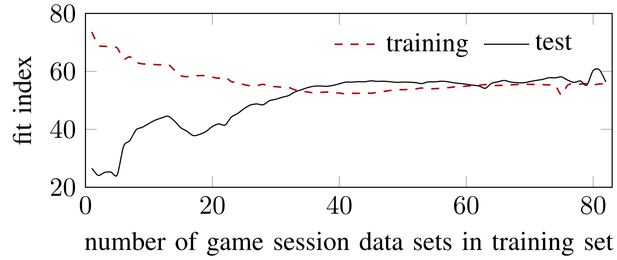

Fig. 3. Fit values for training and test sets using an increasing number of Aby's 83 data sets for training model (5) and the remaining sets for testing.

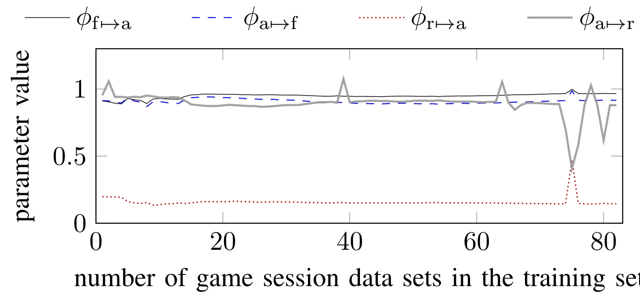

Fig. 4. Estimated parameter values using an increasing number of Aby's 83 data sets for training model (5).

Consider also Figures 8 and 9 showing the simulated pressure $\widehat{m}_\mathrm{a}$ for the training set (combination of Aby's sets 46 and 47 in Figure 8) and the test set (combination of Aby's sets 55 and 56 in Figure 9)[7].

B. Leave-one-out-cross-validation

In a second stage, we performed a standard cross leave-one-out-cross-validation by training the model on all but one of Aby's data sets and testing it on the remaining data set. This was then repeated such that each of the 83 data sets was used for testing exactly once.

Figure 5 shows the frequency of the resulting fit indexes for the training and test sets. Since almost all data are used for training the model, the fits for the training sets are very similar, i.e., between 45 and 55. However, testing the model for data of different, single game sessions leads to varying fit values. Since the vast majority still achieves fit values between 45 and 70, i.e., similar to the fit values of the training sets, we conclude that the model parameters are accurate.

This claim is supported by the frequencies of the parameter values shown in Figure 6. Indeed, in almost all of the 83 cases, the parameters are virtually the same.

C. Personalised models

Finally, we studied differences between the individual models for Aby, Fay and Ida. For this, individual models and models based on data from two players were trained using half of the available data. These were then tested against

[7]The sets were chosen such that they resemble the first two consecutive game sessions played on two consecutive days.

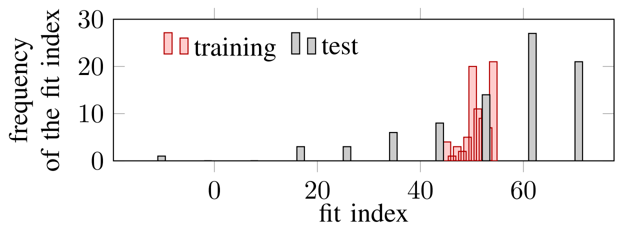

Fig. 5. Fit values for training and test sets for leave-one-out-cross-validation using Aby's 83 data sets for training model (5).

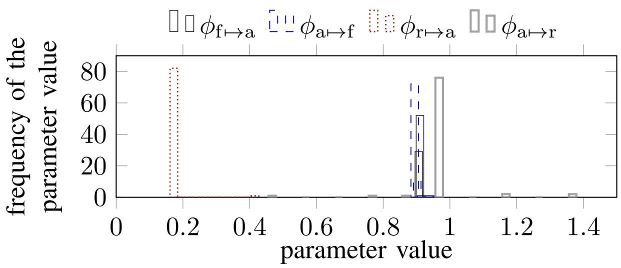

Fig. 6. Distribution of estimated parameters for leave-one-out-cross-validation using Aby's 83 data sets for training model (5).

the second half of the data for each individual player and combinations of two players. The table in Figure 7 shows the fits of individual models (first 3 rows), and models based on data from two players (last 3 rows), tested on individual data sets (first 3 columns) and combinations of two players (last 3 columns).

Specially considering the cross terms for Aby, Fay and Ida reveals that the individual models are not well suitable to describe the behaviour of other women. For instance, Ida's data can only be reproduced well with the model trained on her data. Further, Fay's model only produces positive (but still very very low) fit values for her own data. This might partly be explained by the comparatively few data available for Fay and Ida. However, considering that Aby's model (trained on much more data) still is not able to reproduce Ida's or Fay's data well, other factors must also play a role. Instead, it illustrates the fact that there exist significant individual differences between the data, and hence the models for Aby, Fay, and Ida. This issue seems also not to be alleviated by combining data sets of two players. We impute these differences to variations on the muscular physiology of the players, and not to different playing strategies (being the game mechanics the simplest possible) / different pressure sensor placement (a consideration that follows from inspecting the different traces from the different players at different times).

V. Conclusions

In this paper we studied models of effects of muscular fatigue and recovery on the capability of PFMs of exerting pelvic floor pressure while performing Kegel exercises.

Starting from an existing model for skeletal muscular fatigue from the literature, we proposed a piecewise linear model extends the original one and that can be trained using experimental data. We thus trained it using experimental data from three healthy volunteers collected using the FemFit vaginal pressure sensor and a dedicated mobile app.

The results revealed that our piecewise linear model is capable of reproducing the main dynamics of fatiguing and recovering effects of the PFMs. Even though the fit values tend to be below 60, it should be noted that several simplifying assumptions had to be made. For instance, we assumed that women either use full brain power to activate their muscle or none. However, due to the fact that no measurements of the brain activity were available, more sophisticated input values for the brain stimuli were not available. Also, the muscle fibres are likely more complex than what can be described by a piecewise linear model with two states. Despite this, the model is able to reproduce the general trend of the exerted muscular pressure and enables to predict the fatigue levels of the PFMs. The results also indicate that large differences may exist between individual women due to different fitness levels or anatomical differences, and that thus aggregating the training sets of different individuals may not lead to improvements in the generalizing capabilities of the models.

References

[1] G. Walker and P. Gunasekera, "Pelvic organ prolapse and incontinence in developing countries: review of prevalence and risk factors," *International Urogynecology Journal*, 2010.

[2] K. Bø, "Pelvic floor muscle training is effective in treatment of female stress urinary incontinence, but how does it work?" *International Urogynecology Journal*, 2004.

[3] W. McDougal, A. Wein, L. Kavoussi, A. Novick, A. Partin, C. Peters, and P. Ramchandani, *Campbell-Walsh Urology*. Saunders Elsevier, 2012.

[4] S. McCallum, "Gamification and serious games for personalized health," in *pHealth*, 2012.

[5] T. Webb, J. Joseph, L. Yardley, and S. Michie, "Using the internet to promote health behavior change: A systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy," *Journal of Medical Internet Research*, 2010.

[6] Z. Eapen and E. Peterson, "Can mobile health applications facilitate meaningful behavior change?: Time for answers," *JAMA*, 2015.

[7] A. F. Huxley, "Muscle structure and theories of contraction," *Progress in Biophysics and Biophysical Chemistry*, vol. 7, pp. 255–318, 1957.

[8] T. L. Hill, *Free Energy Transduction in Biology*. New York: Academic, 1977.

[9] S. Ross, N. Nigam, and J. Wakeling, "A modelling approach for exploring muscle dynamics during cyclic contractions," *PLOS Computational Biology*, 2018.

[10] S. Knorn, D. Varagnolo, E. Oliver-Chiva, R. Melles, and M. Dewitte, "Data-driven modelling of pelvic floor muscles dynamics," in *IFAC Symposium on Biological and Medical Systems (BMS)*, 2018.

[11] S. Knorn, D. Varagnolo, R. Melles, and M. Dewitte, "Data-driven models of pelvic floor muscles dynamics subject to psychological and physiological stimuli," *IFAC Journal of Systems and Control*, 2019.

[12] X. Li, J. Kruger, M. Nash, and P. Nielsen, "Modeling childbirth: Elucidating the mechanisms of labor," *WIREs Systems Biology and Medicine*, vol. 2, pp. 460–470, 2010.

[13] J. Liu, R. Brown, and G. Yue, "A dynamical model of muscle activation, fatigue, and recovery," *Biophysical Journal*, 2002.

[14] J. Moxnes and K. Hausken, "The dynamics of athletic performance, fitness and fatigue," *Mathematical and Computer Modelling of Dynamical Systems*, 2008.

[15] C. Klauer, M. Irmer, and T. Schauer, "A muscle model for hybrid muscle activation," *Current Directions in Biomedical Engineering*, 2015.

	Aby	Fay	Ida	Aby & Fay	Aby & Ida	Fay & Ida
Aby	56.44	22.96	-14.59	45.57	52.10	22.60
Fay	-439.1	1.57	-3339.6	-361.6	-987.7	-1292.3
Ida	30.82	7.80	43.97	24.31	32.33	15.53
Aby & Fay	56.36	25.37	-24.52	46.43	51.05	23.08
Aby & Ida	55.67	21.47	-3.93	44.55	52.42	22.77
Fay & Ida	23.97	8.12	-297.05	19.81	-8.30	-46.39

Fig. 7. Fit performance of individual models trained on datasets from the players indicated in the rows and tested on datasets from the players indicated in the columns.

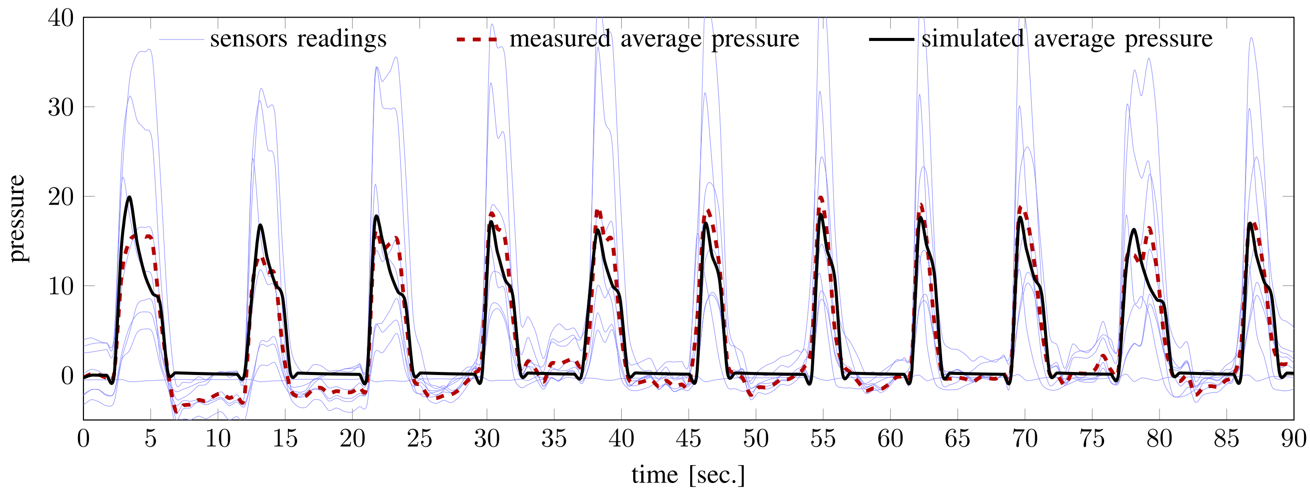

Fig. 8. Measurement data $p(t) - p_{\rm base}$ and $m_{\rm a}$ for Aby's sessions 46 and 47 as well as $\widehat{m}_{\rm a}$ for the model trained with $m_{\rm a}$ of the same data sets.

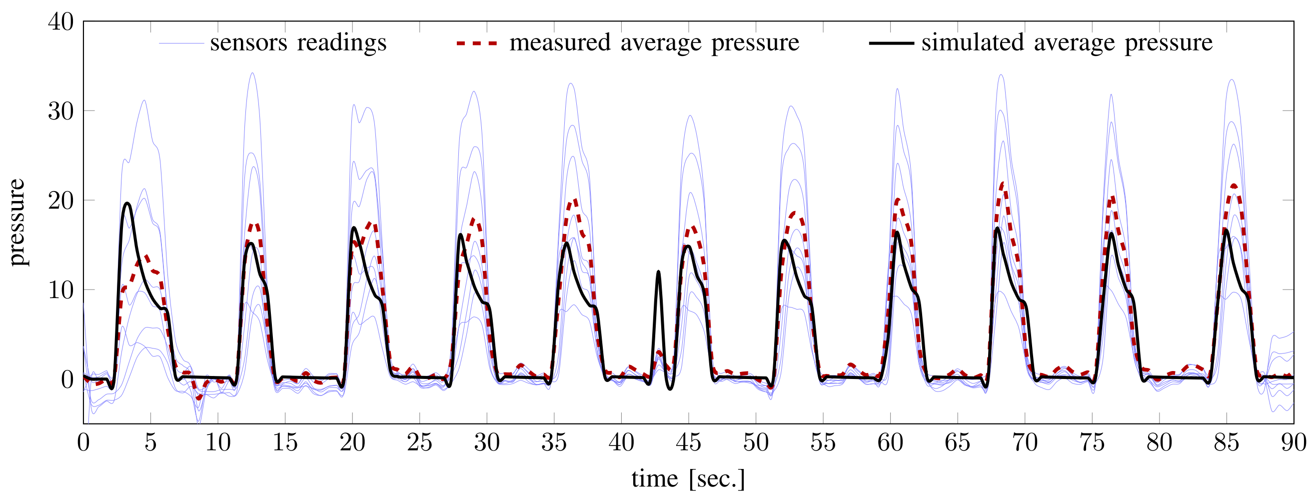

Fig. 9. Measurement data $p(t) - p_{\rm base}$ and $m_{\rm a}$ for Aby's sessions 55 and 56 as well as $\widehat{m}_{\rm a}$ for the model trained with $m_{\rm a}$ of data sets 46 and 47.