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Online, data-driven detection of human position during Kegel exercising

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Abstract: This paper proposes an online, data-driven method to detect in which position (lying or standing) a women is performing Kegel exercises from measurements collected with a vaginal pressure sensor array. Pressure data has been collected with the vaginal pressure sensor from women performing Kegel exercises by playing a dedicated mobile app, which is controlled by contracting their pelvic floor muscles. Depending on their position while playing (lying or standing), the recorded pressure patterns exhibit different characteristics in terms of intensity, location and width of the pressure peak, which may be used to detect the human position. For this, the recorded data is filtered, opportune features are extracted and a suitable classifier is trained to distinguish the two positions. The results show that the human position can be accurately detected online when using individual models for each patient (in our experiments, up to 1% of false positives and 4% false negatives), whereas the detection capabilities might decrease drastically when considering the same classifier for another women (e.g., up to 95% of false positives).

Keywords: physiological modelling, activity recognition, activity classification, pelvic floor muscles

1. INTRODUCTION

The Pelvic Floor Muscles (PFM) support several inner organs such as the bladder, the bowel and, in females, the uterus. Several factors can contribute to damaged or weak PFM, including pregnancy, childbirth related injuries, and aging. Weakened PFM may lead to urinary incontinence; estimated to affect one third of women, Walker and Gunasekera [2010]; or pelvic organ prolapses. Moreover, these conditions frequently intensify after the menopause.

To strengthen the PFM, and hence alleviate or even cure the issues above, women are encouraged to perform so called “Kegel exercises” consisting of repeated contractions and relaxations of the PFM, Bø [2004]. Advice on how to practice these exercises are often given by health practitioners as verbal instructions, brochures, or videos. To be effective, Kegel exercises must be repeated over long periods of time and be performed correctly. Consequential, they tend to be experienced as tiring or boring, leading to many women either neglecting, or failing to exercise sufficiently often.

In order to encourage women to exercise their PFM sufficiently and regularly, we have developed a game app that uses real time data from an array of pressure sensors and motivates women through an appropriately chosen game design (see more details on the game and the vaginal pressure sensor array in Section 2). Indeed, gamified treatment strategies, including game mechanisms such as rewarding- and sanctioning systems, compels the user to remain invested in the task at hand, McCallum [2012]. 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. This is in line with positive evidence that *mHealth* based interventions (i.e., medicine supported by mobile devices) improve health outcomes [Webb et al., 2010, Eapen and Peterson, 2015].

Apart from being perceived as tedious or boring; leading to many women not exercising as regularly as require; approximately 30% of the women do the exercises incorrectly, McDougal et al. [2012]. This may be due to the location of the muscles and the inability to recognize if the pelvic floor muscles are being activated, as opposed to the surrounding pelvic, abdominal or hip muscles. This is particularly important since using the abdominal muscles instead of PFM means “pushing down” onto the pelvis, which might damage the PFM rather than training them. Hence, being able to distinguish between correct Kegel exercises and incorrect muscle contractions is important to prevent harm and give feedback to women to encourage correct execution of Kegel exercises.

Since the used pressure sensor (described further in Section 2.1) can distinguish between muscle activity from the PFM and the abdominal muscles, data recorded through the game app can be used to understand which muscles the player has been using when playing the game. Indeed, when inspecting data recorded from women playing the game app, we could distinguish between different muscle patterns. For instance, it appeared that women were more likely to use their abdominal muscles rather than their PFM when standing (compared to lying) since Kegel exercises are considered more difficult to initiate correctly when standing, especially after fatigue during a prolonged game play. Intuitively, the players may resort to contract their abdominal muscles when the PFM contractions are too hard or too tiring, and in this way miss the desired medical outcome (i.e., training the PFM). It is desirable thus to detect such behaviour and prevent it whenever possible.

As one option, when detecting that women mostly use their abdominal muscles, the game dynamics could account for this effect by automatically lowering the difficulty to indirectly encourage women to use their PFM. In a more direct fashion, the game could issue a warning message to the player informing her of the detected muscle activity. Alternatively, the game dynamics might be adapted to include a sanctioning system for using the abdominal muscles.

In any case, it is important to develop real-time algorithms that use measurements from wearable and portable units [1] that can detect which muscles are being activated. To this purpose, it is essential to note that the muscular activation patterns depend on several factors, such as:

- the position in which the game is being played (lying, sitting, or standing);
- the muscular tonicity, and the current fatigue levels.

Being able to estimate these latent variables; for example, by estimating the playing positions from the data; clearly enables more detailed analyses of the gaming patterns. However, differentiating between these factors, which contribute in a non-deterministic way to the measured pressure, requires careful modelling of the dynamics of the measured system.

Regarding this modelling step, we note that the dynamical model of the PFMs of interest associates muscular stimulation levels with the corresponding pressure (or force) outputs. For the general problem of associating stimuli to pressure (or force), researchers have developed many generic models of variable complexity. These include, among others: *i) physiologically based models*, which relate the input output maps as interactions of the fibers at a microscopic level, Huxley [1957], *ii) Hill-type models*, which relate stimulation levels and corresponding forces through mechanically-inspired concepts such as mass-spring-damper systems, Hill [1977], and *iii) black-box models*, that relate input-output relations starting from numerical evidence. The most common strategies in this case use *Hammerstein-Wiener* or *Nonlinear autoregressive exogenous (NARX)* models, including neural networks and fuzzy models. We notice that physiological models of muscular dynamics are typically nonlinear; for this reason, nonlinear identification approaches tend to provide better results than linear ones.

In this paper, we consider the very specific case of control-oriented PFM muscular models. As for the literature, we recall the model derived in Knorn et al. [2018], analysing the effects of dilation using a vaginal dilator of adjustable size, and proposing a data-driven dynamical model of the muscular response as a response to the vaginal dilation patterns. The model in Knorn et al. [2018] uses time-series data 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 model was then extended in Knorn et al. [2019], where the authors included psychological input signals in the dynamics (namely, subjective assessments of pleasure/discomfort levels).

We also note that there exist a plethora of non-control-oriented models of the behaviour of the pelvic floor muscles in other situations, e.g., in connection with childbirth [Li et al., 2010]. Considering the specific case under investigation in this paper, we report the existence of several models focusing specifically on fatigue. For example, the authors of Liu et al. [2002] 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 Moxnes and Hausken [2008], instead, 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 trained further. As for the specific case of PFM fatigue, to the best of our knowledge, the first model was presented in Kask et al. [2019]; here the authors built their model on the one that was derived in Liu et al. [2002] to allow for non-constant brain stimuli.

Contributions The medical literature advocates the need for using physiologically sound Kegel exercising principles, and for following a progression of PFM rehabilitation (training) that starts in the lying position, and continues towards standing positions (sometimes passing through a 'supported standing' phase where she supports herself against a wall or something, before going to a completely free standing) when the person is more confident about how to correctly activate her muscles [Bø, 1995].

Our goal is to determine effective information flows that enable the real-time detection of a player's human position (standing or lying), a stepping stone towards algorithms that can *i)* suggest the players whether to change their playing position, and *ii)* induce adaptations in the game mechanics (e.g., thresholds) and statistical data analysis

[1] To this point we note that there exist some literature about EMG biofeedback devices for the training of PFM; however to the best of our knowledge EMG-based approaches do not guarantee the comfort levels that wearable and portable PFM status units may bring.

routines (that may indeed need to be adapted depending on the position of the person while playing).

As a constraint, we aim at understanding how the game is being played without using information from other sensors embedded in the mobile device (e.g., accelerometers and gyroscopes), but rather only through measuring the pressure field. Our intuition is indeed that it is intuitively better to avoid including external variables that may be spuriously correlated with the intended estimands, and inspect instead what can be obtained using the quantities that are for sure involved in the investigated process.

We thus propose and assess an online classification algorithm that discriminates the players' current gaming positions using only vaginal pressure field measurements. The approach is based on a combination of: *1)* treating the pressure field as a spatiotemporal Gaussian random field, and filtering it using standard regularized regression approaches; *2)* extracting opportune features from the filtered data; *3)* training a standard Support Vector Classifier, using thus a supervised learning approach on top of some opportunely labelled datasets; *4)* testing the trained classifier online on non-labelled data.

Postponing the numerically oriented claims on the efficacy of the approach, we can summarize the main result as follows: the here proposed information flow constructed leads to confusion matrices and Cohen's Kappa values that are very promising (e.g., sum of false positives and false negatives rates that are below 5%), *but only if we consider "personalized" classifiers.* In other words, if both training and test data are from the same player, then the approach returns the desired results. But *if using the classifier from one person on an other person, the results are completely meaningless.* Degradations were actually expected: different players have different physiological statuses, and this calls for having individually trained procedures. However, the assessed sheer of degradation is, at least for us authors, exceeding the expectations. Summarizing, the specific application that we are considering seems needing much more individualization and tailoring than initially forecasted.

Organization of the manuscript The paper continues with the description of the sensor and the gamified app in Section 2. The proposed estimation algorithms (together with the relative results from the field tests) are given in Section 3. The paper closes then with some concluding remarks in Section 4.

2. EXPERIMENTAL SETUP

2.1 The FemFit pressure sensor

The femfit®, see Figure 1, is an intra-vaginal pressure sensor array that can be used to gain detailed insights into PFM dynamics. The device has been developed by the Auckland Bioengineering Institute, University of Auckland (NZ), and includes a sensor array of eight evenly spaced pressure sensors, connected to a flexible Printed Circuit Board (PCB) encapsulated in a soft medical grade silicone, and with a range from 0 kPa to 5 kPa. The PCB is attached to a telemeter encased in plastic which sits outside the body that transmits the measurements from the pressure

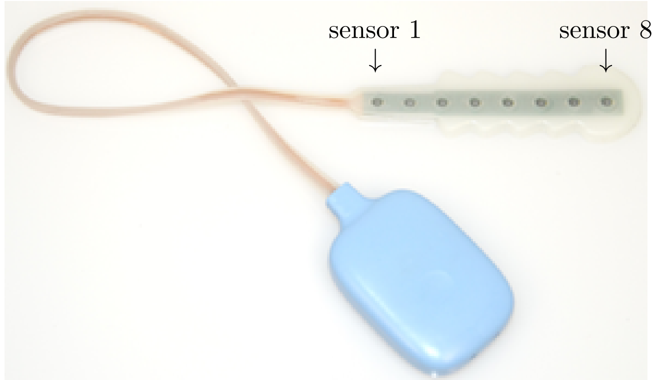

Fig. 1. Photo of a femfit® pressure sensor. The device is 80 mm long, 24 mm at its widest point and 4 mm thick and contains eight pressure sensors within a soft medical grade silicon enclosing (in gray), connected to a Bluetooth communication module (in light blue) through a dedicated flexible wiring.

sensors above via a Bluetooth connection. The femfit® is flexible and able to conform to the vaginal anatomy, and enables measuring in real-time the pressure profile along the length of the vaginal duct. For the sake of interpreting the subsequent results, the sensors at the most distal end of the vaginal canal (sensors 7 and 8) measure abdominal pressure, while sensors 3 to 6 are most likely to measure the pressures due to pelvic floor muscles activity. Sensors 1 and 2 tend to be placed towards the introitus, and typically do not contribute with information regarding the PFM dynamics. The ability of distinguishing abdominal vs. pelvic floor activity when wearing the femfit® and while performing Kegel exercises enables determining whether the Kegel exercises are being performed correctly, e.g., contracting the PFM rather than the abdominal muscles.

2.2 The gamified biofeedback application

As mentioned in the introduction, the here described game app is designed to motivate and encourage women to exercise their PFM sufficiently and regularly. The game is an android mobile application featuring a female character (called Juno) immersed in a fictive world. The user wears the femfit® and uses the pressure sensor as a game controller: indeed the application is driven by the measurement data collected by the femfit® and communicated via Bluetooth. Thus, by contracting the PFMs, the user triggers Juno to jump upwards to avoid some incoming obstacles (as in the screenshot shown in Figure 2). Before playing the game, the user can calibrate her personal maximum contraction pressure through a dedicated routine. This registered pressure acts as a threshold: while playing, the user shall exceed this pressure if she wants to make Juno jump. In each game session players are awarded one point for each avoided obstacle; in contrast, when failing to jump over an incoming obstacle, the player loses one health point. The session terminates at the fourth lost health point or when the player decides to exit. The aim of the game is thus to avoid obstacles, and in this way promote exercising. The most relevant parameters of each gameplay are therefore the required length and frequency of the jumping actions, combined with the number of jumping actions required from the user to finish the session.

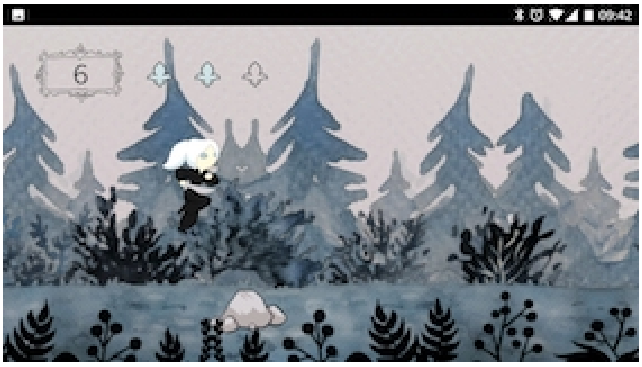

Fig. 2. In-game screenshot from an exercising session.

2.3 Collected data

During each gaming session, the pressure time series from the eight pressure sensors are recorded. The vector of pressure measurements is denoted with

$$\boldsymbol{p}(t) = \left[p_1(t), p_2(t), \ldots, p_8(t)\right]^{\mathrm{T}}.$$

The scalar components of $\boldsymbol{p}(t)$ refer to the individual pressure sensor measurements, according to the numbering introduced above – hence $p_1(t)$ is the pressure at the introitus, while $p_8(t)$ is the abdominal pressure. In the following we will treat $\boldsymbol{p}(t)$ as the measurement process over a spatiotemporal random field defined over the (continuous) spatial domain $[1, 8]$, and the (continuous) temporal domain $[0, T]$ (i.e., where the units refer to seconds, 0 refers to the start of the game, and T the end of the game – that, as written before, may depend on the gameplay itself). This means considering formally $\boldsymbol{p}(t)$ as induced by the spatio-temporal pressure field

$$f_x(t) = \text{value of the field } f \text{ at height } x \text{ and at time } t \tag{1}$$

and the measurement model

$$p_x(t) = \text{measured pressure field at height } x \text{ at time } t \tag{2}$$

connected through

$$p_x(t) = f_x(t) + \nu_x(t) \qquad x \in \{1, \ldots 8\} \tag{3}$$

with $\nu_x(t)$ a zero-mean Gaussian i.i.d. measurement noise with variance σ_ν^2 that shall be identified from the data.

Importantly, given the fact that the muscles fatigue in time, the spatial covariance

$$\operatorname{cov}\left(p_x(t), p_{x'}(t)\right) := K\left(x, x'\right) \tag{4}$$

should be modelled as potentially time-varying. For the sake of our purposes (see also Section 3.1), though, we did not (yet) identify structures that help achieving better statistical performances, and for this reason in the remainder of the paper we ignore this refinement.

We finally note that, actually, there are two other indexes associated to each measurement stream $\boldsymbol{p}(t)$: *i)* the player, and *ii)* the actual starting date of the session. Given the purposes of this paper, it is safe to omit them for the sake of readability.

3. DETECTION ALGORITHMS

As mentioned in the introduction, our aim is to detect whether a game is being played standing or lying by inspecting the evolution of the measured pressure field $\boldsymbol{p}(t)$. Note that since each gameplay may last several minutes, the users may well change their position while playing. Approaches for which a user informs about her posture via the app are impractical, since relying on the user having to remember when and how she changed her position while playing. We thus aim at automating this detection step.

We also recall that different players have different physiological statuses and dynamics, and that this calls for having individually trained estimators. Condensing all these intuitions, the proposed strategy is in practice to verify if the same player has distinct and recognizable behaviors when playing in different positions. More verbosely, the overall algorithm can be divided into the following four steps, each described and illustrated in the following subsections:

(1) filtering the pressure field $\boldsymbol{p}(t)$;
(2) extracting opportune features from the filtered signal;
(3) using these features to train an opportune gaming position classifier;
(4) using this classifier to perform online classification tasks.

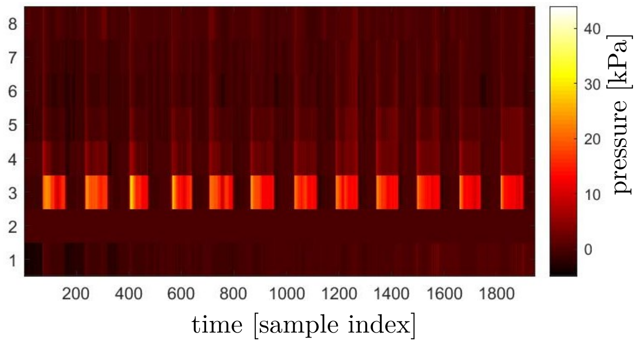

Fig. 3. Example of a pressure field typically measured when a player is playing in position "Lying". Here the y axis corresponds to the sensor index.

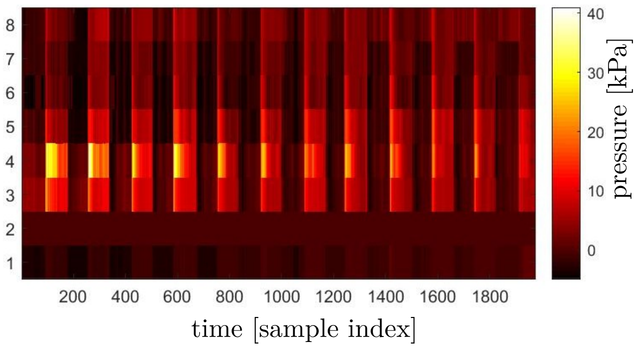

Fig. 4. Example of a pressure field typically measured when a player is playing in position "Standing". Here the y axis corresponds to the sensor index.

To give a qualitative intuition as to why the overall scheme is feasible, we consider Figures 3 and 4, that plot the detrended field $\boldsymbol{p}$ for a subset of time indices t for a specific player (say, "Amy") in two consecutive days (so that the overall tiredness levels and fit levels of the person can be considered constant) but playing in different positions. Note that $\boldsymbol{p}$ is here detrended, in the sense that the plot actually shows the actual pressure minus the pressure measured in resting state (a baseline that for the purpose of this paper is non-informative).

Figures 3 and 4 highlight the two alternating behaviors: the inactive zones, i.e., when the player does not need to jump because there are no incoming obstacles (qualitatively speaking, the periods corresponding to "darker" colours), and the activity zones (the ones corresponding to "lighter" colors), that occur when the player is jumping. Comparing the two figures, and recalling that they are relative to the very same player in equivalent fatiguing & fit conditions, one can immediately see a known effect in Kegel exercising, i.e., the fact that exercising while in a standing position is more difficult than when lying, because standing involves additional, involuntary contractions of the abdominal muscles as an inherent effect of human balancing efforts.

3.1 Filtering $\boldsymbol{p}(t)$

Given the assumptions in Section 2.3, a natural approach for smoothing and interpolating the individual pressure profiles $\boldsymbol{p}(t)$ is to formulate the problem as a Gaussian smoothing one, defined over the various t's independently of each other. More precisely, assuming that $K(\cdot,\cdot)$ in (4) and $\nu(t)$ in (3) have been estimated from the data, then the point estimate $\widehat{p}_{x'}(t)$ over a generic $x' \in \mathbb{R}$ (thus not restricted anymore to $1,\ldots,8$) can be defined as the conditional expectation

$$\begin{aligned} \widehat{p}_{x'}(t) &:= \mathbb{E}\left[f_{x'}(t) \mid \boldsymbol{p}(t)\right] \\ &= K\left(x', \boldsymbol{x}\right)\left(K\left(\boldsymbol{x}, \boldsymbol{x}\right) + \sigma_\nu^2 I\right)^{-1} \boldsymbol{p}(t) \end{aligned} \tag{5}$$

with $\boldsymbol{x} := \{1,\ldots,8\}$ and $x' \in \mathbb{R}$ (see, for example, [Rasmussen and Williams, 2006, chap. 2] for more details and additional probabilistic information for the computation of $\widehat{p}_{x'}(t)$). Instrumental to our real-time computation needs, we also note that given the structure of our problem, the term $\left(K\left(\boldsymbol{x}, \boldsymbol{x}\right) + \sigma_\nu^2 I\right)^{-1}$ shall be computed only once, after the hyperparameters of K and σ_ν^2 have been estimated.

Regarding the estimation of these two last quantities,

- for K, it is sufficient to consider a simple squared exponential
$$K\left(x, x'\right) = \sigma_f^2 \exp\left(-\frac{1}{2}\frac{\left(x - x'\right)^2}{\ell^2}\right) \tag{6}$$
with hyperparameters $\left[\sigma_f^2, \ell\right]$ estimated using a Maximum Likelihood 2 (see, for example, [Rasmussen and Williams, 2006, chap. 5]) and 20% of the whole available dataset;
- for estimating σ_ν^2 in a real-time fashion, we may exploit the structure of our experimental setup in the following sense: we assumed that the measurement noise is homoskedastic, and thus its variance does not change between the periods where there is brain activity (i.e., when the player is pressing her PFM) and when there is not. Periods of no brain activity are easily detectable and the variability of the signal is almost only due to noise effects (especially if we de-trend the baselines of the measured pressure signals). We thus estimate σ_ν^2 by first detecting inactivity periods using simple thresholding, and then compute the variance of the measurement noise directly by assuming the true $\boldsymbol{p}(t) = 0$ during that period.

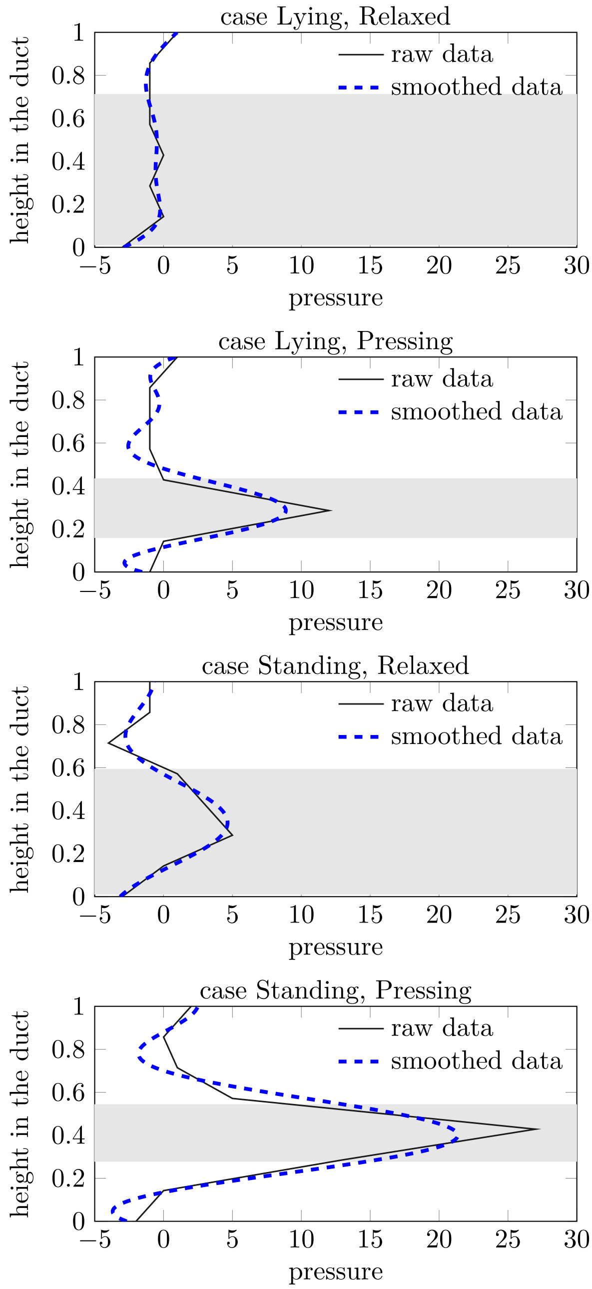

Fig. 5. Raw and filtered data for the various cases "playing position, pressing the PFM or not". Note that these signals are de-trended (i.e., subtracted of the baseline pressure that is measured just before playing a game). Data from the same player as in Figures 3 and 4.

To give a qualitative intuition of the type of results one obtains when implementing the regression problem as explained above, we plot in Figure 5 the four possible combinations of pressure profiles that are typically obtained while either lying or standing, and while either relaxing or pressing the PFM. For the sake of completeness, in these figures we highlight in gray the extent of the feature "*peak width*", a quantity that will be defined and motivated in Section 3.2.

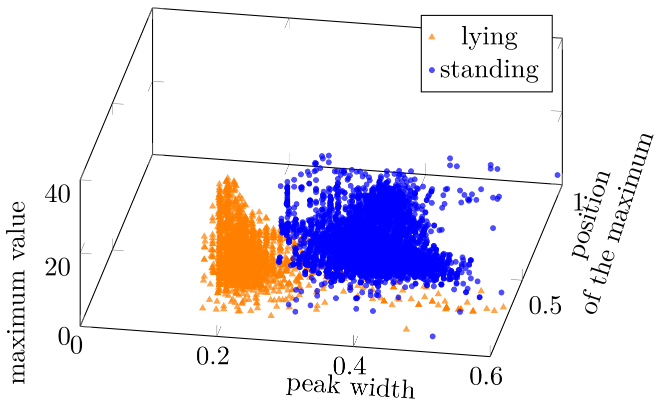

Fig. 6. Qualitative summary of the features that are typically measured when considering two typical game sessions played in different conditions by the same player. Data relative to player Amy.

The plots in Figure 5 are typical and representative of what happens when a person is exercising correctly, in the sense that:

when relaxing the PFM, if lying, we cannot distinguish any muscular activity from the measurements; if standing, instead, it is possible to see a broad peak whose maximum value tends to be placed at the height of the PFM;

when pressing the PFM, it is similarly possible to see a peak in the measured field, whose maximum value is again typically placed at the height of the PFM.

Importantly, the qualitative behavior of this peak changes sensibly depending on the situation: when standing and pressing, this peak is typically much higher and wider than all the other cases (with the width feature defined more precisely in Section 3.2). When lying and pressing, instead, the peak is still relatively high, but much more defined (i.e., "narrower"), indicating that in the specific "lying, pressing" case the person seems to be more able to control their PFM.

3.2 Extracting features from the filtered $\boldsymbol{p}(t)$

The considerations above lead to identifying three natural features that may be first extracted from the filtered field $\widehat{\boldsymbol{p}}$ and then used in the considered estimation problem: *i)* maximum value of $\widehat{\boldsymbol{p}}(t)$, *ii)* spatial location of the maximum (here assumed to be unique, and actually always identified as unique in our dataset of hundreds of hours of gameplays), *iii)* width of the peak informally introduced above, and mathematically defined as the smallest contiguous interval containing the maximum above representing 50% of the $L2$ norm of the estimated pressure field $\widehat{\boldsymbol{p}}$.

To illustrate the type of results that can be obtained using these features, we consider Figure 6, where we scatter-plot the features measured in two different gameplays (i.e., data recorded in separate sessions) in different positions from Amy, i.e., the same player considered in Figure 5. Qualitatively speaking, the results are as expected, in the sense that the data exhibit clearly separated patterns, making it meaningful to perform classification tasks.

3.3 Using the extracted features to train a Support Vector Classifier

Several classification algorithms may be used in our specific situation. Among them, we choose to consider a linear Support Vector strategy, i.e., focus on finding separating hyperplanes directly in the original input space represented in Figure 6. While this may look simplistic, it is in a sense a crude way of preventing overfitting (in the sense that, after all, we are presenting the first results that have been obtained - and thus avoided testing competing strategies for then selecting the best one). We also note that this strategy enables performing very easy comparisons of the models that are obtained for different players, since corresponding to simple hyperplanes in the original input space. Besides this, the decision boundaries are also *i)* immediately explainable, something that is desirable in our medical setup, *ii)* requiring a negligible computational overhead (both in terms of storage allocation and computational requirements), helping thus the implementation of the schemes in real-time settings.

3.4 Performing online classification

Testing the classifier trained on the data shown in Figure 6 on the rest of the datasets from the very same person led to the confusion matrix reported in Table 1. It can be noted that, despite using no statistical sophistication whatsoever (cf. the "standard" kernel structure in (6) and the linear SVC in Section 3.3), the results are very good.

Table 1. Confusion matrix when used to classify games played by Amy using the classifier trained using data from the very same Amy.

	actually lying	actually standing
estimated as lying	0.96	0.01
estimated as standing	0.04	0.99

One may feel then optimistic, and believe that this strike of obtaining good results with minimal efforts will continue; however, testing the classifier trained on the data from Amy on data from a different person (say, Ida), we get the confusion matrix in Table 2.

Table 2. Confusion matrix when used to classify games played by Ida using the classifier trained using data from Amy.

	actually lying	actually standing
estimated as lying	0.05	0.00
estimated as standing	0.95	1.00

Clearly, the classifier trained on Amy is useless when considered on Ida. Indeed, if we plot in Figure 7 the same plot of Figure 6 but this time for player Ida, we note that her features have a different distribution; in particular, they are so that Amy's classifier considers almost all of them as standing.

Note that this might be explained by Amy having well-trained PFMs, which is known to lead to better coordination of the muscles, leading to more targeted muscle activation and hence narrower peaks. Since Ida's muscles seem to be not as well-trained, the peaks when lying are wider and hence are categorized as standing. This also

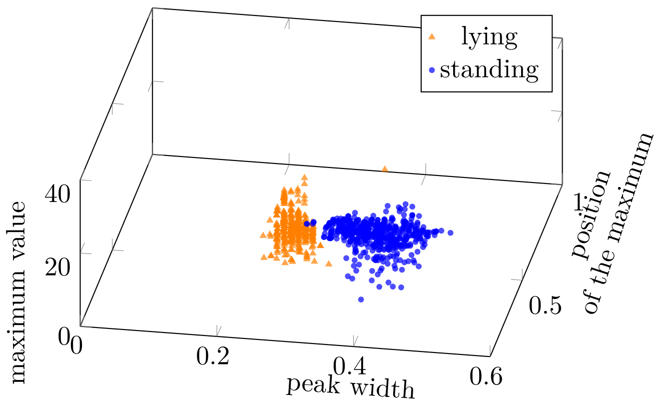

Fig. 7. Qualitative summary of the features relative to player Ida.

hints that the SVC might change over time due to training effects. Indeed, it may even be expected that upon further training, the peaks in Amy's data when standing might get narrower making the distinction between lying and standing harder. This might be less of a practical problem since we wish to distinguish between the two positions to detect when a player resorts to activating her abdominal muscles due to fatigue and tiring, which is expected to affect the player more when standing. Instead, once the PFMs are trained further, so that the player is less likely to resort to her abdominal muscles, the peaks also become narrower in the standing position. These narrow peaks may prevent correct detection of human position; however, the risk of harm due to incorrect muscle activation is reduced, which make this a less pressing issue.

4. CONCLUSIONS

We considered the problem of detecting activities of persons that are performing gamified Kegel exercises, an issue whose practical importance lies on being a stepping stone for implementing adaptable game dynamics.

We followed a rather standard information processing approach for discriminating these activities, composed of standard filtering, feature extraction, training and testing of the activities classifier, and found results that are notable in two distinct ways:

- the first is the surprising effectiveness of the strategy when considering the case of individualized classifiers: the overall strategy is based on standard estimation building blocks and even in this case, the quantitative results are well beyond what were expected;
- the second is the surprising decay of performance when doing cross-training (i.e., training on one person, testing on an other). Decays were actually expected: different players have different physiological statuses, and this calls for having individually trained procedures. However, in our examined cases, cross-training is leading to practically useless results.

This means that the application that we are considering needs more individualization and tailoring in the estimation step than initially forecasted, and this is in some sense undesirable – therapies will likely require the inclusion of several estimator training steps.

We note that we are still considering datasets comprising of limited numbers of persons (below 10). Planned medical trials are expected to provide information from several hundreds of players; it may then be that with that amount of information, we may discover patterns that are currently undetectable.

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