

Identification of Pelvic Floor Muscle Contraction From Non-Invasive Sensors

Ines Moudjari
Univ Rennes, INSERM,
LTSI - UMR 1099
F-35000, Rennes, France
ines.moudjari@univ-rennes.fr

Caroline Pautard
Blueback
Pacé, France
cpautard@blueback.fr

Clément Jouanneau
Blueback
Pacé, France
cjouanneau@blueback.fr

Régine Le Bouquin Jeannès
Univ Rennes, INSERM,
LTSI - UMR 1099
F-35000, Rennes, France
regine.le-bouquin-jeannes@univ-rennes.fr

Abstract—Urinary incontinence is a global health problem affecting over 200 million people worldwide. This condition is due to pelvic floor muscle dysfunction and can be treated by perineal rehabilitation. Today, biofeedback devices allow to detect and monitor the state of contraction of the pelvic floor muscle in real time. Currently, only devices using probes are available. However, this method is invasive and can be uncomfortable, justifying our proposal of a non-invasive method based on a single bipolar lead of surface electromyography to identify pelvic floor muscle contractions. This method was tested experimentally on some patients, and we obtained an average recall of 89.6% for the pelvic floor muscle. Furthermore, our method proved highly effective reconstruction, with an average correlation coefficient of 0.72 between the ground-truth and the reconstruction of the pelvic floor muscle signals. In addition, the clinical interest of this method is to provide the physiotherapist and patient with an easy-to-use, non-intrusive device for diagnosis and therapy.

Index Terms—Pelvic Floor Muscle, EMG, Detection, Classification, Reconstruction

I. INTRODUCTION

Pelvic floor muscle rehabilitation is one of the treatments for urinary incontinence. This rehabilitation enables patients to relearn how to contract their pelvic floor muscle (PFM) voluntarily and reflexively. This muscle contributes to continence in both men and women. The PFM is made up of the coccygeus muscle and the levator ani. The coccygeus forms the posterior part of the pelvic diaphragm. This muscle is triangular in shape, originating at the ischial spine and running along the posterior border of the obturator internus muscle. It inserts itself on the lowest part of the sacrum and on the lateral side of the coccyx. The levator ani is itself made up of three muscles: the iliococcygeus, the pubococcygeus and the puborectalis. The iliococcygeus muscle originates from the posterior half of the arcus tendineus and inserts on the last two segments of the coccyx and on the median line of the anococcygeal raphe. The pubococcygeus originates from the anterior half of the tendinous arch and the periosteum of the posterior surface of the pubic bone. The puborectalis is situated around the urogenital hiatus. Its contraction compresses and lifts this hiatus [1]. However, the PFM does not act alone. Indeed, Vesentini *et al.* have shown that healthy women present cocontraction of the transversus abdominis (TRA) during PFM contraction [2]. The TRA is the deepest muscle of the abdominal wall. It is the main muscle involved in the generation of intra-abdominal pressure [3]. Fibers of the TRA are horizontally

oriented which form a musculoaponeurotic belt that surrounds the abdomen. This anatomical arrangement and its insertion at the level of the lower rib cage allow the TRA to mechanically compress the abdominal wall [4]. Moreover, Sapsford *et al.* [5] found that, in healthy women, surface electromyographic (EMG) activity of the vaginal and anal muscles increased with voluntary activation of the abdominal muscles. Finally, Hung *et al.* [6] proved that coordinated training of diaphragmatic, deep abdominal and PFM could improve symptoms of urinary incontinence and quality of life. Physiotherapists currently have only two methods of checking PFM contractions and making the patient aware of them. The first is manual testing, *i.e.* vaginal examination for a woman and anal examination for a man. The second involves inserting a probe, into the vagina and the anus for women and men, respectively. Both techniques are invasive for the patient and can be uncomfortable for both the physiotherapist and the patient. In addition, the insertion of a probe leads to certain limitations of movement and therefore prevents proper functional rehabilitation when monitoring PFM contractions. However, Wu *et al.* have proved that PFM training with biofeedback of the PFM achieves better outcomes than PFM training alone in stress urinary continence management [7]. With this in mind, we propose to offer a novel non-invasive method that could be easily used by the physiotherapist to provide biofeedback of PFM. The method involves acquiring signals from only one bipolar lead consisting of two electrodes, positioned on the patient's lower abdomen. The electrodes are specific EMG-type sensors dedicated for deep detection which allows to measure EMG signals coming from deep and surface muscles in this area. After acquisition, the first step is to extract features from a 256 ms segment of the raw signal, before using principal component analysis (PCA) and support vector machine (SVM) to classify our segmented signals into three classes. These classes correspond to the schemes of co-contraction of PFM and TRA. Finally, based on these predictions, the PFM and TRA signals are reconstructed. This method is called Deep-EMG method, meaning that the system uses non invasive sensors to collect EMG signals coming from a multitude of muscles (surface and deep muscles), while the patient is in movement. Moreover this method is able to calculate the specific contribution of one deep muscle. To make this method clinically acceptable, it must be achievable in real

time, in order to provide biofeedback to both physiotherapist and patient. This contribution is structured as follows: Section II presents the materials and methods. Section III is devoted to the experimental results. In Section IV, we discuss these results and conclude this work in Section V.

II. MATERIALS & METHODS

A. Data acquisition

1) *Participants*: Data was collected in a physiotherapy practice in Caen, France. In this protocol, 8 patients were included. Each patient gave his/her consent to participate in this study.

2) *Materials*: The equipment used in this protocol to acquire the data consisted of a portable EMG device called Blueback Physio[®] and a pelvic floor muscle biofeedback device. The Blueback Physio[®], supplied by Blueback, is a CE-marked medical device. This device is composed of two bipolar leads, each with two electrodes, which are placed on the lower abdomen of the patient respectively on the left part and the right part. In this study, the use of this device serves a dual purpose. The first is to acquire the ground truth about the state of contraction of the TRA, using the main function of this device, which is to provide precise biofeedback of the TRA. The second purpose is to acquire the signals of interest, which are the raw signals acquired by the right bipolar lead of the device (arbitrary choice). The pelvic floor muscle biofeedback device is a medical device called Phenix Liberty[®], supplied by Vivaltis. This device consists of a console for data display and a vaginal probe for data acquisition. This device enabled us to acquire the ground truth about the state of contraction of the PFM.

3) *Protocol*: At the start of each acquisition session, the physiotherapist placed the Blueback Physio[®] on the patients, who then placed the vaginal probe themselves. Once the equipment had been placed, each patient was asked to perform four specific tests. The first and second tests consisted of following the PFM contraction pattern displayed on the Phenix Liberty[®] console. This pattern consisted of 5 short, rapid contractions of the PFM, followed by 3 slow, sustained contractions, and finally 5 short, rapid contractions of the PFM. The first test (Test 1) was performed in the supine position, while the second one (Test 2) was performed in the standing position. For the third and fourth tests (resp. Test 3 and Test 4), the patient has to perform a specific exercise consisting of performing 3 anterior raises with her arms, elbows extended, with a 1kg dumbbell held in both hands. This dynamic exercise can imply either a contraction of the PFM, or a contraction of the TRA, or both, depending on the patient and on the way the exercise is performed. These two tests were carried out in the supine and standing positions respectively.

4) *Ground Truth*: The ground truth of the state of contraction of the PFM is obtained thanks to the signal acquired by the vaginal probe. First, we set a threshold equivalent to 30% of the maximum of the probe signal. Next, we compared the average amplitude of the probe signal over 256 ms windows to the threshold. For all values above the threshold, the PFM

was considered contracted, otherwise the PFM was considered at rest. As explained above, the ground truth of the state of contraction of the TRA is obtained thanks to the Blueback Physio[®] proprietary algorithm, which needs two bipolar leads to operate. This algorithm returns a signal representing the contraction of the TRA only. For all values strictly positive, the TRA was considered to be contracted, otherwise it was considered to be at rest.

B. Preprocessing

The signals were acquired at a sampling frequency of 500 Hz. As said before, we only considered the signal from the right bipolar lead of the Blueback Physio[®] in the analysis. The pre-processing consisted in applying a Butterworth high-pass filter with 6 coefficients and a cut-off frequency of 55 Hz. Then, we resampled the signal at 1000 Hz and segmented it into blocks of 256 ms duration, retaining for analysis only those segments showing contractions of either the PFM or the TRA, or both. We therefore had thirty-two signals from eight patients who had completed four tests. Of these thirty-two signals, we had to reject seven, because the EMG acquisition was saturated due to either electrode detachment or poor contact with the patient's skin. In particular, we removed all the signals from Patient 07, as well as Tests 2 and 4 from Patient 01 and Test 2 from Patient 03. On these signals, we proceeded to the segmentation and to the exclusion of the segments where all the analyzed muscles were at rest, thus 3334 segments of 256 ms remained to be analyzed coming all from the right derivation of the Blueback Physio[®].

C. Feature Extraction & Selection

From a set of twenty-three features [8], including temporal, frequency and time-frequency features, we used a backward elimination algorithm to find the eight best features for classification. We chose to use 8 features, after testing different set sizes between 5 and 10. These features are presented below. For each of the following features, let us consider a vector signal \mathbf{x} of length N (with $N = 256$), corresponding to a 256 ms segmented signal acquired by the right derivation of the EMG device.

The first feature corresponds to the sum of the amplitudes of the signal \mathbf{x} , named SA :

$$SA = \sum_{i=1}^N \mathbf{x}_i \quad (1)$$

where \mathbf{x}_i is the value of the vector \mathbf{x} at index i . The second feature is the first parameter of Hjorth corresponding to the variance of the signal \mathbf{x} .

The third feature is the mean frequency, fm , which is calculated on the periodogram obtained with Welch's method considering a Hanning window of 64 points, with a 50% overlap and M frequency points. We have:

$$fm = \frac{\sum_{i=1}^M f_i \times P(f_i)}{\sum_{i=1}^M P(f_i)} \quad (2)$$

where P is the periodogram of the signal \mathbf{x} , f_i is the frequency of the periodogram at index i , and M is fixed to N . We also calculated the ratio P_1 between the sum of the powers in the [0;100] Hz band and the sum of the total power of the periodogram:

$$P_1 = \frac{\sum_{i=1}^{m_{100}} P(f_i)}{\sum_{i=1}^M P(f_i)} \quad (3)$$

where m_{100} is the index of the 100 Hz frequency in the frequency vector. The next feature is a common entropy estimator, the sample entropy.

In addition, a short term Fourier transform was calculated on \mathbf{x} . From this transform, denoted by X , we calculated three features, which were the maximum amplitude of X , its flatness, called *flatness*, (Eq. 4) and its coefficient of variation, called *cv* (Eq. 5):

$$flatness = \frac{1}{MN} \times \frac{\prod_{n=0}^{N-1} \prod_{m=0}^{M-1} X[n, m]^{\frac{1}{MN}}}{\sum_{n=0}^{N-1} \sum_{m=0}^{M-1} X[n, m]} \quad (4)$$

$$cv = \frac{\sigma}{\mu} \quad (5)$$

where μ and σ are respectively the mean and standard deviation of X .

D. Classification & Reconstruction

1) *Classification*: The first step in classification is to project the data into a new space. To do this, we use a PCA. It is a dimensionality reduction algorithm, transforming statistically correlated variables into new variables that are decorrelated from one another. The new variables correspond to a linear combination of the original variables. In the new space, the variables are represented along the directions of maximum inertia. Then, we apply a classification algorithm to this projected data. In this study, we choose to use a SVM with a radial basis function kernel to classify our signals. The principle of this algorithm is to project the data into a higher-dimensional space, in order to make the classes more separable. This algorithm was adopted on the basis of industrial constraints aimed at minimizing the computing cost and memory space required to run our method, thus imposing the choice of microprocessor.

2) *Reconstruction*: This stage consists of reconstructing the TRA and PFM signals separately. This is a very important step, as it enables physiotherapists to visualize the state of contraction of these two muscles independently, and therefore to better understand their synergies. It also allows patients to become aware of the contraction of these muscles, which is not necessarily easy. Moreover, it is common practice to standardize signals for physiotherapists, making them easier to analyze. In this respect, the amplitudes of the ground-truth signals are normalized by calibration coefficients specific to each device, leading to amplitudes in the [0;100] range. Therefore, we had to find also a calibration coefficient for our reconstruction. To this end, for a given patient on a given test, we proceeded in three steps. First of all, we took the

maximum of the raw segmented signal, \mathbf{x} . Secondly, we used a calibration coefficient, called *calib_norm*, which corresponds to the maximum amplitude of the whole signal. The ratio between these two values serves as normalized amplitude and is called *amp_reco*. In a third step, we predicted the class of \mathbf{x} . Depending on the predicted class, there are several possible cases. The first case corresponds to *PFM* prediction. In this case, the TRA signal is set to 0 all over the analyzed window, while the PFM signal is set to *amp_reco*. The second case corresponds to *TRA* prediction. In this reverse case, the TRA signal is set to *amp_reco*, whereas the PFM signal is set to 0. The last case corresponds to *PFM-TRA* prediction. In this case, the TRA signal and the PFM signal are set to *amp_reco*.

Algorithm 1 Reconstruction of $signal_{TRA}$ and $signal_{PFM}$

Input: *prediction, x, calib_norm*

Output: *point_{TRA}, point_{PFM}*

$amp_{reco} = (max(\mathbf{x})/calib_norm) \times 100$

if *prediction* = *PFM* **then**

point_{TRA} = 0

point_{PFM} = *amp_reco*

end if

if *prediction* = *TRA* **then**

point_{TRA} = *amp_reco*

point_{PFM} = 0

end if

if *prediction* = *PFM-TRA* **then**

point_{TRA} = *amp_reco*

point_{PFM} = *amp_reco*

end if

III. RESULTS

A. Definition of the classes

We consider 3 classes, corresponding to the different contractions of the muscles. The first class, called *PFM*, corresponds to signals for which only the PFM is contracted, while the second class, called *TRA*, groups signals for which only the TRA is contracted. The third class, named *PFM-TRA*, includes signals for which the two muscles are co-contracted. Here, we have 1624 signals belonging to the *PFM* class, 438 signals to the *TRA* class and 1272 signals within *PFM-TRA* class. Let's note a strong disparity between the groups. In fact, we have very few signals belonging to the *TRA* class. This is due to the configuration of the data collection. The tests carried out focused on the contraction of the PFM, with no exercise requiring a specific contraction of the TRA.

B. Performance metrics

In this section, we present the three metrics we have selected, calculated from the confusion matrix presented in Table I. The first measure is the accuracy of the classification. The second one is called PFM-score and corresponds to the recall of PFM, which is calculated from the PFM confusion sub-matrix (see Tab. II):

TABLE I
CONFUSION MATRIX

		Prediction		
		PFM	TRA	PFM-TRA
Truth	PFM	$P_{1,1}$	$P_{1,2}$	$P_{1,3}$
	TRA	$P_{2,1}$	$P_{2,2}$	$P_{2,3}$
	PFM-TRA	$P_{3,1}$	$P_{3,2}$	$P_{3,3}$

TABLE II
PFM CONFUSION SUB-MATRIX

		Prediction	
		Other	PFM
Truth	Other	$P_{2,2}$	$P_{2,1} + P_{2,3}$
	PFM	$P_{1,2} + P_{3,2}$	$P_{1,1} + P_{1,3} + P_{3,1} + P_{3,3}$

$$PFM\text{-score} = \frac{P_{1,1} + P_{3,3} + P_{1,3} + P_{3,1}}{P_{1,1} + P_{1,2} + P_{1,3} + P_{3,1} + P_{3,2} + P_{3,3}} \quad (6)$$

The third metric, named TRA-score, is the recall of TRA, which is calculated from the TRA confusion sub-matrix:

$$TRA\text{-score} = \frac{P_{2,2} + P_{3,3} + P_{2,3} + P_{3,2}}{P_{2,2} + P_{2,1} + P_{2,3} + P_{3,1} + P_{3,2} + P_{3,3}} \quad (7)$$

C. Classification

For classification, we tested the method on the seven patients. To do this, we used the signals from one patient as a test base, while the signals from the other six patients formed the training base. In Fig. 1, we observe that all PFM-scores

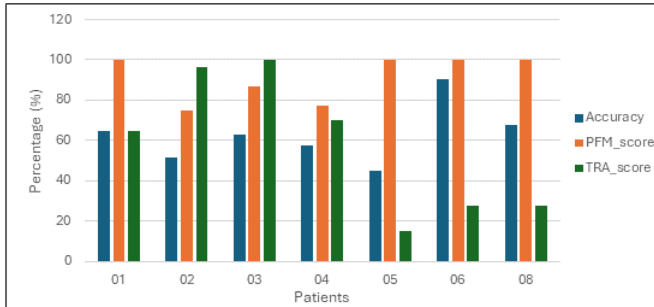


Fig. 1. Mean of classification score per patient

are above 70%. These scores show that we can clearly identify PFM contractions using only one bipolar surface EMG lead. However, the TRA-score is systematically lower whatever the patient. This misclassification of TRA contraction is partly due to the heterogeneity of the learning base. As a matter of fact, less than 3% of signals from Patients 05, 06 and 08 belong to TRA class, making the TRA-score meaningless for these patients. It should be added that the measurement protocol used focused on PFM contraction and did not address the question of deliberate contraction of the transversus abdominis muscle.

D. Reconstruction

To assess the quality of the reconstruction, we computed the correlation coefficients between the ground-truth signals and the reconstructed ones as shown in Table III. All patients, except Patient 01, show high correlation coefficients for PFM. Moreover, Patients 02 and 03 have good correlation coefficients of TRA, around 0.76 and 0.79 respectively. On average, the correlation coefficient between the PFM reconstruction and the ground truth is 0.72 ± 0.2 . For illustrative purposes, Fig. 2 and 3 show the reconstruction results for Patients 02 and 03 in Tests 1 and 4 respectively. If we examine the reconstruction in

TABLE III
CORRELATION COEFFICIENT BETWEEN GROUND TRUTH SIGNALS AND PREDICTED SIGNALS

Patients	PFM Correlation	TRA Correlation
	<i>mean</i> \pm <i>std</i>	<i>mean</i> \pm <i>std</i>
01	0.53 ± 0.26	0.58 ± 0.20
02	0.60 ± 0.13	0.76 ± 0.08
03	0.67 ± 0.16	0.79 ± 0.01
04	0.70 ± 0.15	0.61 ± 0.19
05	0.87 ± 0.03	0.36 ± 0.14
06	0.67 ± 0.34	0.28 ± 0.33
08	0.92 ± 0.01	0.21 ± 0.06

detail, we can see that the signal reconstruction for Patient 02 (Fig. 2) is fairly accurate. If there is a difference in amplitude between the probe signal and the reconstructed PFM signal, it is probably due to the difference in the normalisation methods used to produce the two signals. As for Fig. 3, it shows a slight

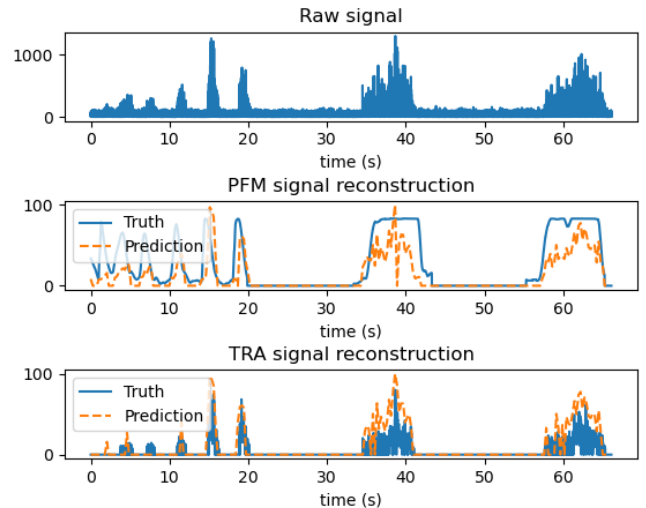


Fig. 2. Signals reconstruction: Patient 02, Test 1

shift between the reconstructed PFM signal and the probe signal. This time lag may be explained by the synchronisation of the signals during the acquisition. As a matter of fact, synchronisation between the two measurement systems was not automatic but simply based on the physiotherapist's ability

to trigger the two devices at the appropriate moment. It is therefore likely that the physiotherapist triggered the Phenix Liberty® a little early, resulting in the lag.

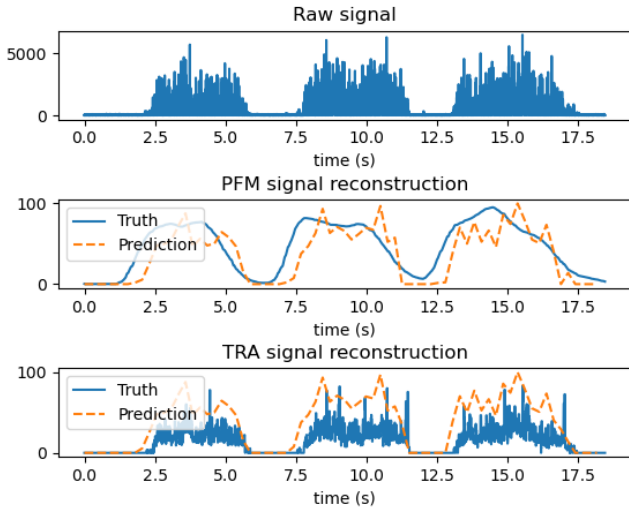


Fig. 3. Signals reconstruction: Patient 03, Test 4

IV. DISCUSSION

The main result of this study is the demonstration of the feasibility of detecting the state of contraction of the PFM by using non invasive sensors combined with a specific classification method to be applied on the measured signals. In fact, the average PFM-score of 89.6% is quite satisfying in physiotherapy practice. Regarding accuracy, the moderate mean value of 61.8% can be explained by the limited number of signals where only the TRA was contracted. However, the global performance of our method is still higher than the inter-rater reliability of manual testing using the modified Oxford Grading Scale, which reaches only 47% [9]. In addition, we have observed difference in amplitude between the probe signal and the PFM reconstruction. We think this may be due to the different normalisation algorithm between the probe signal and the reconstruction. Moreover, Bo *et al.* have shown that there are significant discrepancies in the signals acquired by different probes [10], therefore a slight difference in amplitude between a signal acquired by a probe and a signal acquired by EMG may be acceptable. In future work, we want to work more deeply on the reconstruction method. In terms of classification performance, to the best of our knowledge, there are no studies in the literature that have attempted to identify PFM contraction from non invasive EMG sensors. Nevertheless, our results can be compared with studies that use classification algorithms on surface EMG signals. In consideration of the small number of signals belonging to the TRA class, we believe that it is more interesting to compare the accuracy of the PFM confusion submatrix (83.8%) with the scores known in the literature. Wang *et al.* [11] used unsupervised domain adaptation techniques to reduce inter-subject variability. They achieved classification accuracy of 81.74% and 84.00% on two different datasets, respectively.

Unlike us, they used high density electrodes to acquire their signals. Furthermore, we can compare our results with those of Lu *et al.* [12], as they used an SVM for the classification step, as we did. They obtained $83.3 \pm 10.7\%$ accuracy. However, their study differs from ours in that their algorithm has to learn from the patient on whom it will make its prediction.

V. CONCLUSION

This contribution presented very promising results regarding the possibility of identifying pelvic floor muscle contractions from a single bipolar EMG electrode. On average, we achieved a high PFM-score. Similarly, the correlation coefficients between the ground-truth and predicted pelvic floor muscle signals enabled us to achieve good reconstruction quality. A clinical device that makes it possible to do this will make perineal rehabilitation more comfortable for both physiotherapist and patient. It could also reduce the unwillingness of some patients to undergo treatment for urinary incontinence.

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