Personalizing Heart Rate Based Seizure Detection Using Supervised SVM Transfer Learning

Thomas De Cooman*, Kaat Vandecasteele*, Carolina Varon Perez, Borbála Hunyadi, Evy Cleeren, Wim Van Paesschen and Sabine Van Huffel

***Abstract*—Automated seizure detection is a key aspect of wearable seizure warning systems. As a result, the quality of life of refractory epilepsy patients could be improved. Most state-of-the-art algorithms for heart rate based seizure detection use a so-called patient-independent approach, which do not take into account patient-specific data during algorithm training. Although such systems are easy to use in practice, they lead to many false alarms as the ictal heart rate changes are very patient-dependent. In practice, only a limited amount of accurately annotated patient data is typically available, which makes it difficult to create fully patient-specific algorithms. In this context, this study proposes a transfer learning approach that allows to personalize heart rate based seizure detection by using only a couple of days of data per patient. The algorithm is evaluated on 2172 hours of single-lead ECG data from 24 temporal lobe epilepsy patients including 228 focal impaired awareness seizures. The proposed personalized approach results in an overall sensitivity of 68.9% with a false alarm rate of 2.00 false alarms per hour. This is an average decrease in false alarm rate of 35% with a limited amount of patient data compared to the reference patient-independent algorithm. These results suggest that transfer learning can be a solution to fast and robust personalize heart rate based seizure detection algorithms, which can strongly improve the accuracy of wearable seizure warning systems in a practically efficient way.**

***Index Terms*—Ambulatory monitoring, Heart rate, Seizure detection, Transfer learning.**

I. Introduction

EPILEPSY is one of the most common neurological disorders, which affects almost 1% of the population worldwide [1]. Anti-epileptic drugs provide only adequate treatment for about 70% of epilepsy patients [2]. The remaining 30% of the patients continue to have seizures, which drastically affects their quality of life. This can be improved by an automated warning system, which alarms the parents or caregivers when the patient experiences a seizure. In addition, a seizure diary, automatically generated from the alarms, can be used for a follow-up of the disease and evaluation of the treatment. A seizure diary, kept by the patients or their families, is unfortunately not reliable [3].

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The key element of such a warning system is automated seizure detection. In the literature, automated seizure detection algorithms are typically based on full electroencephalography (EEG). This type of EEG recording requires wet electrodes on the scalp, which is uncomfortable for the patient [4]. More easily obtainable biomedical signals used to detect epileptic seizures include accelerometry (ACC), electromyography (EMG), galvanic skin response and electrocardiography (ECG) [5]. The most suitable modality or combination of modalities depends on the seizure type. ECG-based seizure detection for instance is ideal for the detection of focal impaired awareness seizures (FIAS), as they only result in changes in the EEG and the autonomic nervous system, making difficult to detect them with for example ACC and EMG.

Previous studies have already shown that temporal lobe seizures are often accompanied with a strong ictal heart rate (HR) increase [6], [7], [8]. Most ECG-based seizure detection systems from the literature are based on patient-independent models [9], [10], [11], [12]. For this type of models no patient-specific data is required, making them directly usable in practice. However, due to the large inter-patient differences in heart rate characteristics, the performance is too low to use in practice.

In order to increase the performance, models can be adapted to the patient heart rate characteristics [13], [14], [15]. Different options are possible. A first option is the manual setting of some parameter thresholds per patient [13], [16]. This requires manual screening of previous data, and it only works well if the parameters are easily understandable for a clinician. Simple thresholding approaches are however too simple to grasp the large complexity of the problem. Automated personalization is therefore advised, but normally requires a lot of patient-specific data in order to find a robust algorithm for a specific patient [17]. Often only a limited amount of annotated patient-specific data is available, hence often a lot of complex approaches are not useful for making fully patient-specific classifiers. Heuristic automated personalization allows for a low-complex and fast personalization, but might lead to suboptimal performances [14], [15].

A more robust and optimal solution can be found through transfer learning. In transfer learning, the solution to a classification problem is found by using the solution from a similar problem as a starting point. This way, less data for the new problem is required in order to get a robust solution. In this paper, a patient-specific heart rate based seizure detection model is trained through transfer learning by using a patient-independent classifier as a reference model. Therefore, only a limited amount of patient-specific heart rate data is required

in order to get a robust patient-specific model, obtained with a relative limited complexity.

The dataset used to evaluate the proposed transfer learning approach is presented in section II. The method for personalizing heart rate based seizure detection through transfer learning is described in section III. The results for the proposed algorithm and comparisons with other personalization options are shown and discussed in section IV and V.

II. Data Acquisition

The dataset contains recordings from refractory epilepsy patients, who underwent presurgical evaluation at the University Hospitals Leuven (UZ Leuven), Belgium and had during the evaluation at least five FIAS originating from the temporal lobe. The patients were recorded with 10-20 scalp EEG with 1 bipolar ECG channel with a sampling frequency of 250 Hz. The ECG signal was continuously unreadable due to strong noise during 4.6 (patient 13), 8.8 (patient 16) and 7.4 (patient 18) hours of data. Those segments were removed from the analysis. The remaining dataset consists of 24 patients with 2172 hours of data. In total, 228 seizures were recorded (see Table I).

A clinical expert annotated the seizure onsets and ends with the use of video-EEG data, without considering the ECG. Afterwards, a medical doctor validated the annotations. The seizure duration is defined as the time between EEG seizure onset and EEG seizure end. However, during some seizures, the end could not be determined. The fraction of the determined seizures (Determined S) is also indicated in Table I. The ethical committee of the UZ Leuven approved the study. All patients signed the informed consent for their participation in this study.

III. Methodology

The proposed seizure detection algorithm is based on the one described in [9], and it works for both the patient-independent and the personalized version. The main difference between both versions lies within the classifier training. Both approaches will be described below.

A. Preprocessing

Single-lead ECG is used as input for the proposed seizure detection algorithm. First, the heart rate is extracted from the ECG using an approach that uses a real-time R peak detection algorithm. It detects the R peaks based on the derivative signal and an adaptive threshold. Next, strong heart rate increases (HRI) caused by sympathetic activations are detected by automated slope analysis on the tachogram. HRI extraction is performed on a filtered tachogram, using a median filter with an order of 10 heart beats. If a heart rate slope is larger than 1bpm/s, a strong HRI is assumed. The beginning and end of this HRI is found by analyzing when this slope becomes negative again. The HRI is then assumed to be a strong HRI if certain thresholds on the length of the HRI, the achieved peak heart rate during the HRI and the (percentual) increase in heart rate during the HRI are exceeded [9].

B. Feature extraction

Features are extracted whenever such a strong HRI is detected in the previous step. In [9], it was shown that 4 features extracted from the HRI led to optimal patient-independent results: the peak heart rate, the heart rate at the start of the HRI, the baseline heart rate (extracted from the minute before the HRI) and the standard deviation of the baseline heart rate period. As the primary goal of this study is to lead to optimal patient-specific results with a limited amount of patient-specific data, we chose to only use the first two features in this study. The reason for this is that most of the information is already contained in these features, as explained in [9]. Adding more features to the system requires more training data for robust personalization through transfer learning. Choosing these two features leads to an optimal balance between performance and limited requirement of patient-specific data. These features are then classified with either the patient-independent (PI) or patient-specific (PS) transfer learning classifier.

C. Patient-independent classification

Let x_i, y_i be training data points extracted from patients different than the ones used for testing the algorithm, with $x_i \in \mathbb{R}^{\mathrm{d}}$ the data samples and $y_i \in \{-1, +1\}$ the corresponding labels. Let class -1 correspond to seizure samples and class +1 to non-seizure samples. Support vector machines (SVM) will map data points to a higher dimension using a (non-)linear transformation $\varphi(x)$, so that the data points can be separated in this space by the hyperplane $w^T\varphi(x)+b$, with w the unknown weight vector and b an unknown constant.

The solution for weighted SVM can be found by solving the following optimization problem

$$\begin{aligned} &\min_{w,b,\xi} \frac{1}{2}||w||^2 + C\sum_{i=1}^{N} c_i\xi_i \\ &s.t. \quad \begin{cases} y_i(w^T\varphi(x_i)+b) \geq 1-\xi_i \\ \xi_i \geq 0 \end{cases} \quad ,\forall i \in [1,N] \end{aligned} \tag{1}$$

A modification of the typical SVM is used here to remove the class imbalance from the dataset [18]. The values of c_i are defined as

$$c_i = \begin{cases} \gamma\frac{(N^+ + N^-)}{2N^-} & : y_i = -1 \\ \frac{N^+ + N^-}{2N^+} & : y_i = +1 \end{cases} \tag{2}$$

Parameter γ gives more importance to the correct classification of seizure samples compared to non-seizure samples during classifier training. In practice, the dual problem is solved, which is found by solving the Langragian

$$\begin{aligned} \mathcal{L}(w,b) = \frac{1}{2}||w||^2 + C\sum_{i=1}^{N} c_i\xi_i - \sum_{i=1}^{N}\nu_i\xi_i \\ - \sum_{i=1}^{N}\alpha_i\left(y_i\left(w^T\varphi\left(x_i\right)+b\right)-1+\xi_i\right) \end{aligned} \tag{3}$$

TABLE I
AN OVERVIEW OF THE DATASET (RD = RECORDING DURATION, SD = SEIZURE DURATION, BIHEMI = BIHEMISPHERIC, TEMP = TEMPORAL)

Patient	Seizures	RD (h)	Hemisphere	Origin	Age	Gender	Mean SD (s) [Determined S]	Range SD (s)
1	10	26	Bihemi	Temp	49	M	31 [33%]	[24 39]
2	9	63	Left	Fronto-temp	41	F	13 [11%]	[13 13]
3	13	71	Right	Temp	27	M	71 [100%]	[28 96]
4	10	25	Bihemi	Temp	15	M	19 [30%]	[14 26]
5	11	47	Right	Temp	29	F	50 [36%]	[40 60]
6	7	148	Left	Temp	26	M	63 [100%]	[32 116]
7	30	67	Right	Fronto-temp	9	M	50 [20%]	[17 90]
8	11	114	Left	Temp	38	M	39 [55%]	[19 75]
9	8	64	Left	Temp (7), Occipital (1)	28	M	23 [63%]	[11 31]
10	7	111	EEG not readable		35	M	126 [29%]	[69 183]
11	6	100	Bihemi (5), Right (1)	Temp	67	F	26 [100%]	[21 31]
12	9	91	Right	Fronto-temp	24	F	47 [89%]	[33 85]
13	8	109	Right	Temp	32	M	46 [100%]	[25 61]
14	5	100	Left	Temp	19	F	56 [40%]	[29 83]
15	13	110	EEG not readable		49	M	16 [94%]	[8 30]
16	5	96	Left	Temp	45	M	64 [100%]	[11 95]
17	7	102	Not clear (4), Right (3)	Not clear (4), Temp (3)	18	F	33 [14%]	[33 33]
18	5	84	Left (3), Right (2)	Temp	62	M	125 [100%]	[89 187]
19	15	113	Not clear		40	F	23 [93%]	[6 52]
20	5	113	Left	Temp	41	F	74 [100%]	[58 83]
21	8	103	Left (3), Right (5)	Temp (3), Fronto-temp (5)	43	M	67 [100%]	[29 99]
22	12	115	Left (4), Right (3), Bihemi (5)	Temp	35	M	27 [83%]	[17 38]
23	6	101	Right	Temp	23	F	80 [100%]	[51 108]
24	8	99	Right	Temp (1), Occipito-temp (5)	24	F	42 [100%]	[17 84]
Total	228	2172			[9-67]	14M/10F	50 ± 30 [$70 \pm 34\%$]	[6 187]

with $\alpha_i, \nu_i \geq 0$ the Langrange multipliers, leading to the dual problem

$$\begin{aligned} min_\alpha &= \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} y_i y_j \alpha_i \alpha_j K(x_i, x_j) - \sum_{i=1}^{N}\alpha_i \\ s.t. \quad &\begin{cases} \sum_{i=1}^{N} \alpha_i y_i = 0 \\ 0 \leq \alpha_i \leq C c_i \end{cases} \quad ,\forall i \in [1, N] \end{aligned} \tag{4}$$

with $K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$ the kernel function. The values of the hyperparameter C, γ and the Gaussian kernel parameter σ are taken as described in [9]. The classifier is trained using the leave-one-patient-out (LOPO) approach, training the classifier on all patients except the one used for evaluating the algorithm.

D. Personalized classification through transfer learning

The goal of this study is to personalize the seizure detection classification in order to get an optimal patient performance with a limited amount of patient-specific data. One solution for this is to use transfer learning. Transfer learning (TL) allows to train a new classifier for a problem with a limited amount of data by using a reference classifier that solves a similar problem. In this case, the previously trained patient-independent classifier discussed in section III-C is used as the reference classifier. This way, the classifier can be personalized with a limited amount of patient-specific data by using the knowledge already incorporated in the patient-independent classifier. An overview of the proposed procedure for personalizing the heart rate based seizure detection is given in Figure 1.

One way of applying transfer learning to SVM is to find a weight vector which is of sufficient resemblance compared to the one originating from the reference model, while also minimizing the misclassification error for that specific patient. The following minimization problem to create a support vector machine for the patient-specific data points $\widetilde{x}_k$ with corresponding labels $\widetilde{y}_k$ [19] is solved

$$\begin{aligned} &\min_{\tilde{w},\tilde{b},\tilde{\xi}} \frac{1}{2}||\tilde{w} - w||^2 + D\sum_{k=1}^{M} \tilde{c_k}\tilde{\xi_k} \\ s.t. \quad &\begin{cases} \tilde{y_k}(\tilde{w}^T\varphi(\tilde{x}_k) + \tilde{b}) \geq 1 - \tilde{\xi}_k \\ \tilde{\xi}_k \geq 0 \end{cases} \quad ,\forall k \in [1, M] \end{aligned} \tag{5}$$

with w the weight vector obtained from the patient-independent classifier trained using (1), defined as

$$w = \sum_{i=1}^{N} \alpha_i y_i \varphi(x_i) \tag{6}$$

by the original SVM optimization problem. The same kernel K used in the reference classifier is used here. The parameters D and $\tilde{c_k}$ are similar as C and c_i in the original patient-independent SVM problem:

$$\tilde{c_k} = \begin{cases} \widetilde{\gamma}\frac{(M^+ + M^-)}{2M^-} & : \tilde{y}_k = -1 \\ \frac{M^+ + M^-}{2M^+} & : \tilde{y}_k = +1 \end{cases},$$

with M^+ and M^- indicating the number of patient-specific non-seizure and seizure data points. Hyperparameter D allows to balance between minimizing the errors for the patient-specific data points and minimizing the difference compared to the reference patient-independent classifier (defined by w). Parameter $\widetilde{\gamma}$ is initialized to a value of 1.5. The initial value

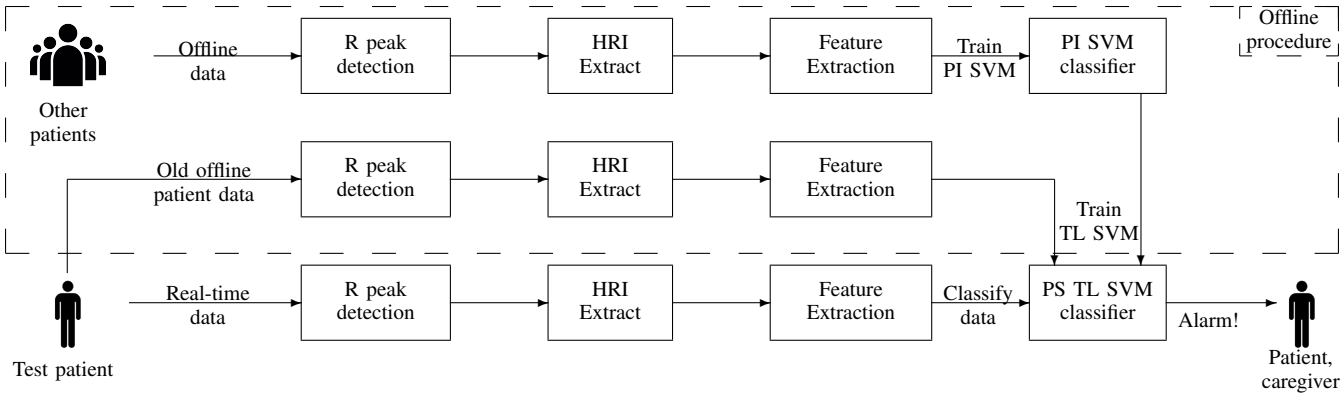

Fig. 1. Overview of the proposed transfer learning approach for personalized heart rate based seizure detection. PS TL SVM: patient-specific transfer learning support vector machine; PI SVM: patient-independent support vector machine.

for hyperparameter D depends on the amount of seizures available in the training set, and is set to 0.1 for patients with less than 10 seizures and set to 100 for patients with more than 10 seizures. These values are based on the findings of previous studies [20]. Nevertheless, these parameters should ideally be optimized per patient, based on their validation performance, but it is very challenging to get robust hyperparameter optimization results due to the low amount of patient training data. Therefore a more heuristic method is applied, which lowers the values of $\widetilde{\gamma}$ (linear decrease of 0.25) and D (exponential decrease by factor 1/10) if the resulting classifier leads 50% more false alarms than the available patient-independent approach. This reduction is repeated until the FAR is dropped below this threshold or minimal values for $\widetilde{\gamma}$ (=0.25) and D (=0.01) are reached.

The dual problem of (5) is defined as

$$\begin{aligned} min_{\widetilde{\alpha}} =& \sum_{i=1}^{N}\sum_{k=1}^{M} y_i\widetilde{y}_k\alpha_i\widetilde{\alpha}_k K\left(x_i,\widetilde{x}_k\right) - \sum_{k=1}^{M}\widetilde{\alpha}_k \\ &+ \frac{1}{2}\sum_{k=1}^{M}\sum_{l=1}^{M}\widetilde{y}_k\widetilde{y}_l\widetilde{\alpha}_k\widetilde{\alpha}_l K\left(\widetilde{x}_k,\widetilde{x}_l\right) \\ s.t. \quad & \begin{cases} \sum_{k=1}^{M}\widetilde{\alpha}_k\widetilde{y}_k = 0 \\ 0 \le \widetilde{\alpha}_k \le D\tilde{c}_k \quad ,\forall k \in [1,M] \end{cases} . \end{aligned} \tag{7}$$

Note that it can be found that

$$\widetilde{w} = w + \sum_{k=1}^{M}\tilde{\alpha}_k\tilde{y}_k\varphi(\tilde{x}_k) \tag{8}$$

which indeed indicates that the patient-specific $\tilde{w}$ is a combination of patient-independent and patient-specific information. A new data point $\tilde{x}_n$ is then classified using

$$\begin{aligned} y(\tilde{x}_n) =& sign\left(\sum_{k=1}^{M}\tilde{\alpha}_k\tilde{y}_k K(\tilde{x}_k,\tilde{x}_n) + \tilde{b}\right. \\ &\left. + \sum_{k=1}^{N}\alpha_k y_k K(x_i,\tilde{x}_n)\right) . \end{aligned} \tag{9}$$

The TL classifier is trained and tested using a 5-fold crosstesting scheme, in which 4 folds are used for training and 1 for testing. This is then repeated 5 times so that each fold is used once as test set.

E. Alternative automatic personalization solutions

The proposed transfer learning approach is also compared to two different alternatives for personalization. The first alternative includes a fully PS approach which is trained with only PS data using the SVM classifier defined by (1). The other alternative is a so-called mixed model, in which both PI and PS data are used for training an SVM classifier defined by (1), but adapting the values of c_i in (2):

$$c_i = \begin{cases} s_i\gamma\frac{(N^+ + N^-)}{2N^-} & : y_i = -1 \\ s_i\frac{N^+ + N^-}{2N^+} & : y_i = +1 \end{cases} \tag{10}$$

with

$$s_i = \begin{cases} 4 & : i \in PSdata \\ 1 & : i \notin PSdata \end{cases} \tag{11}$$

such that misclassification of PS data is more critical during training than misclassification of non-PS data. The value 4 is chosen as recommended in [14].

F. Algorithm evaluation

In order to compare the different seizure detection algorithms, four metrics were used to evaluate the seizure detection performance. The sensitivity (Se, percentage of detected seizures) and false alarm rate (FAR, expressed in false positives/hour, FP/h) were calculated. A seizure is detected when an alarm was given 30s prior to the seizure onset and 90s after the seizure onset [9]. False alarms within 1 min of each other were counted as one alarm. In order to combine the Se and FAR in one metric, the F_β-score with $\beta = 3$ was calculated with the following formula:

$$F_\beta = \frac{(1+\beta^2)TP}{(1+\beta^2)TP + \beta^2 FN + FP} \tag{12}$$

with TP, FN and FP the number of true positives (detected seizures), false negatives (missed seizures) and false positives (false alarms). The F_3-score is chosen for this application because it gives more importance to Se compared to FAR.

The detection delay indicates the time difference between the moment of detection and the seizure onset. Average measures over the entire dataset can be expressed as patient average performance (Pat.-Av.), which is the average of the performance of each patient, or overall average (Tot.-Av.), computed on the total number of seizures or recording duration. The first average measure is used, unless specifically mentioned. To prove the significant differences between the algorithms, paired t-tests were performed with a significance level of 0.05. All results were obtained retrospectively in a simulation which replicated a real-time setting.

G. Impact of number of seizures in training

One of the advantages of transfer learning is that it allows to train a new classifier with a relative limited amount of data by using a reference classifier. In one simulation, it is evaluated how many seizures are needed in order to gain sufficient added value in seizure detection performance. In this simulation, only a certain amount of seizures from the patient-specific training set are used in training (using the crosstesting scheme described in section III-D). These were chosen randomly in 100 simulations per selected amount of seizures (tested for 0-4 seizures). This simulation is done for the proposed transfer learning approach and the alternatives for personalization. Testing was performed on the same test sets used in the original evaluation tests.

IV. Results

The preprocessing procedure discussed in section III-A detected 84.71% of the seizures, which gives an indication of the amount of seizures with ictal heart rate increases. In Table II, the patient (P-Av) and overall average (T-Av) of Se, FAR and F_3-score are shown for the patient-independent (PI), fully patient-specific (PS), mixed (MIX) and transfer learning (TL) approaches. Figure 2 shows the results of the proposed TL approach and the reference PI approach for each patient. Figure 3 shows the boxplots of the different approaches for the different evaluation metrics. The PI algorithm results in an average Se of 70.75% with 3.10 FP/hour and an F_3-score of 0.204. By adapting the model to the patient characteristics with the TL algorithm, a similar Se is observed (68.93%) with 35% less false positives (2.00 FP/hour). The average F_3-score is increased to 0.283. The TL approach did not only result in an average decreased FAR, but also decreased FAR variability over the different patients. A similar effect can be seen for the F_3-score, although there is no decreased F_3-score variability in the TL approach. The alternative mixed approach results in a similar Se, but with on average 0.66 FP/h more than the proposed TL approach. The fully PS approach resulted in a decreased Se, with a slightly increased FAR (2.22 FP/h) than the TL approach.

By performing a two-sided paired t-test, the sensitivity of the PI and MIX algorithm are not statistically different from the TL algorithm (p=0.53 (PI vs. TL) and p=0.8205 (MIX vs. TL)). However, the FAR of the PI and MIX algorithm are statistically different from the TL algorithm ($p = 4.07 * 10^{-4}$ (PI vs. TL), p=0.028 (MIX vs. TL)). The fully PS approach has a significantly lower Se than the TL algorithm (p=0.019), whereas the FARs are not significantly different (p=0.46). The F_3-score of the PI, fully PS and MIX algorithm are statically lower than the TL algorithm (($p = 7.75 * 10^{-4}$ (PI vs TL), p=0.019 (PS vs TL), p=0.0091 (MIX vs TL)). This shows that the proposed transfer learning method is indeed statistically better than the other evaluated approaches for personalization. The average detection delay was 21 s.

TABLE II
RESULTS FOR THE PATIENT-INDEPENDENT (PI), FULLY PATIENT-SPECIFIC (PS), MIXED (MIX) AND TRANSFER LEARNING (TL) APPROACH. BOTH PATIENT AVERAGE (P-AV) AND OVERALL AVERAGE (T-AV) ARE SHOWN IN THE TABLE.

	Se (%)		FP/hour		F_3-score	
	P-Av	T-Av	P-Av	T-Av	P-Av	T-Av
PI	**70.75**	**72.81**	3.10	3.01	0.204	0.190
PS	56.07	57.46	2.22	2.27	0.230	0.184
MIX	69.70	71.49	2.66	2.57	0.241	0.209
TL	68.93	71.05	**2.00**	**2.06**	**0.283**	**0.242**

As explained in III-G, the influence of the number of training seizures on the TL algorithm performance is investigated. Figure 4 shows the impact on F_3-score performance in function of the number of seizures available during training. The F_3-score for the TL approach already strongly improves compared to the PI performance if only 1 patient-specific seizure is available in the training set. When 2 seizures are available, the variation between results decreases, while the average performance increases. The performance further increases by including additional seizures to the training set, while still maintaining a similar variation in results. Figure 4 also shows the effect of the number of seizures in the training set is shown for the other personalization methods.

V. Discussion

A. Performance comparison of the PI and TL approach

Table II and Figure 3 show that the mean and median sensitivity of the PI and TL approaches are similar, whereas the FAR decreases and the F_3-score increases. By looking at the patients individually (Figure 2), it can be observed that for some patients the TL approach clearly reduced the FAR (e.g. patient 4). Furthermore, for some patients, the sensitivity dropped slightly. This is due to the fact that the model adapts to the patient characteristics. However, some seizures were atypical for that patient or have a smaller heart rate increase compared to other seizures, which caused these seizures not to be detected with the TL model. An example of atypical ictal heart rate behavior within patient 13 is compared to three typical seizures in Figure 5(a). Figure 5(b) compares an atypical small heart rate increase for patient 6 with three examples of typical heart rate increases for that patient. The proposed TL approach adapts to the majority of seizures, and therefore might lead to a missed detection of these atypical seizures. However, this small decrease in sensitivity is typically accompanied with a strong decrease in FAR, justifying this small sensitivity decrease. The reverse also occurred in some patients, where borderline seizures that

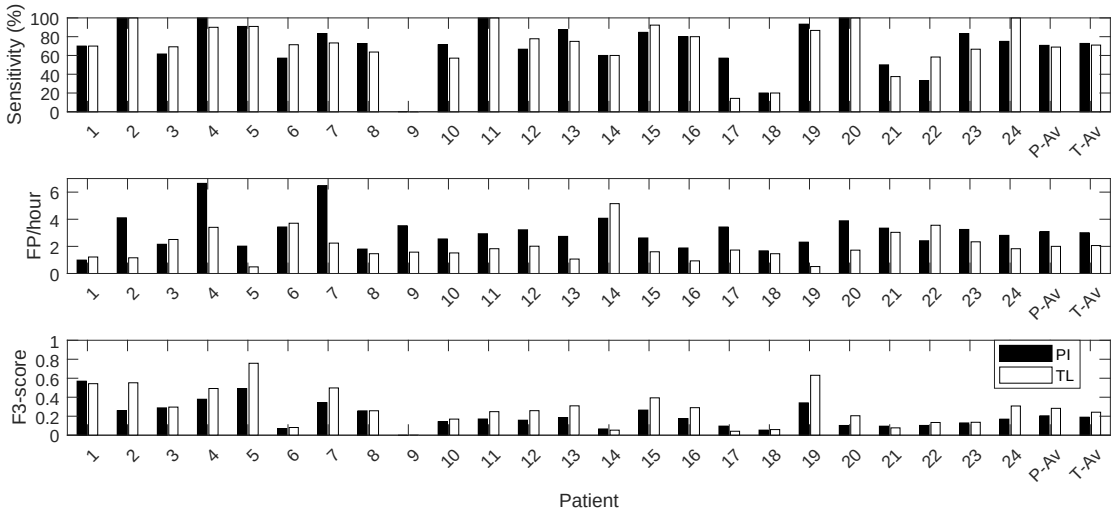

Fig. 2. Sensitivity, FAR and F_3-score per patient with patient average (P-Av) and overall average (T-Av) performances for the Patient-Independent (PI) and Transfer Learning (TL) algorithm

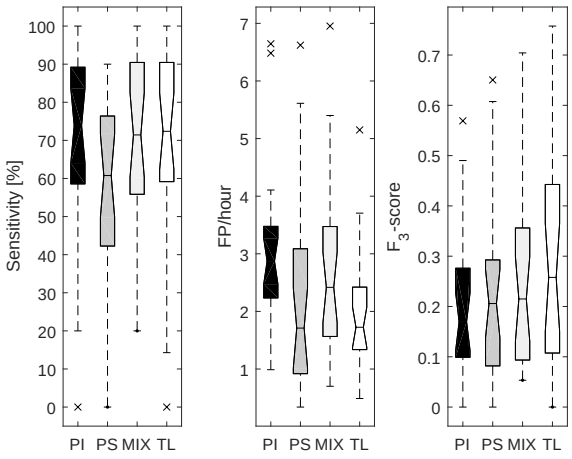

Fig. 3. Boxplots of sensitivity, FAR and F_3-score for the Patient-indpencent (PI), fully Patient-Specific (PS), mixed (MIX) and Transfer Learning (TL) algorithm

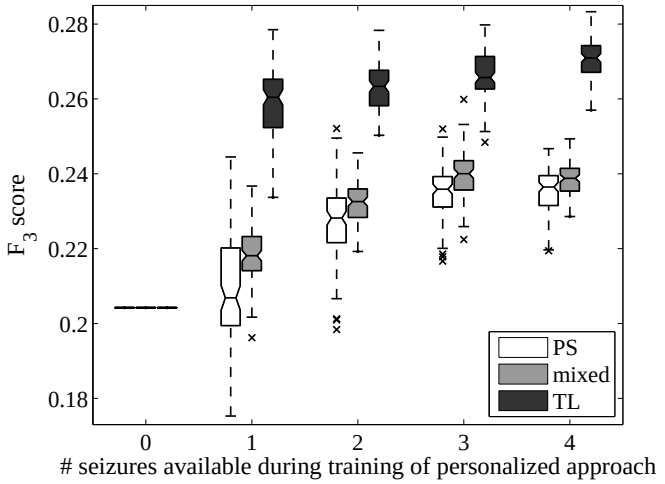

Fig. 4. Impact of the number of seizures on the F_3-score performance for the full patient-specific (PS) approach, mixed approach and transfer learning (TL) approach. In case 0 seizures are available for training, the performance of the patient-independent algorithm is shown.

were missed by the PI approach are detected by the proposed TL approach (e.g. patient 24).

Not for all patients an increase in performance is observed, for example in patient 1. For those patients, no typical ictal HR increase is observed, or the HRIs are too weak in magnitude, making it difficult to differentiate them from non-epileptic heart rate activity with the used feature set. If the seizure activity is too similar to non-seizure activity for that patient, the model can not be improved by using personalization.

Only 84.71% of seizures had ictal HRIs in the analyzed dataset, which is a similar percentage as in the literature [6], [7], [8]. Personalizing the algorithm will not help to detect these seizures without ictal heart rate changes. Also false detections or missed seizures caused by too strong ECG noise can not be avoided by the personalization [21]. Other approaches should be used to further improve the performance, such as further improved noise removal techniques [22]. These could however have a negative effect on the computation time, which is something that should be kept in mind in this real-time setting using wearable devices.

An example of the obtained classifier boundaries for patient 11 are illustrated in Figure 6. The seizure and non-seizure data points are shown together with the PI, PS and TL boundary for two different values of hyperparameter D (0.01 and 1), with a fixed $\widetilde{\gamma}$ value of 1.5. The PI boundary gives a good general indication, but lacks adaptation to the patient characteristics. The transfer learning approach adapts to these characteristics with a limited amount of available patient-specific data. By choosing a low value for D (i.e. 0.01) the TL model will be

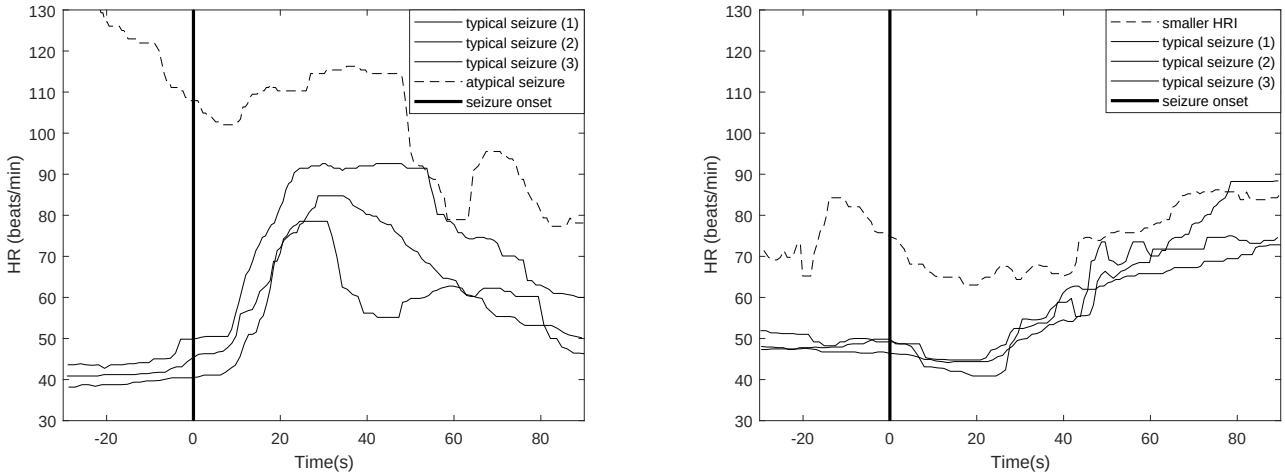

Fig. 5. Examples of atypical ictal heart rate behavior within a patient. (a) Example of 3 typical and 1 atypical ictal heart rate pattern for patient 13. (b) Example of a atypical ictal small heart rate increase and 3 normal ictal heart rate increases for patient 6. The vertical line in both figures indicate the seizure onset of the different seizures. The shown tachogram signals are filtered using the median filter discussed in section III-A.

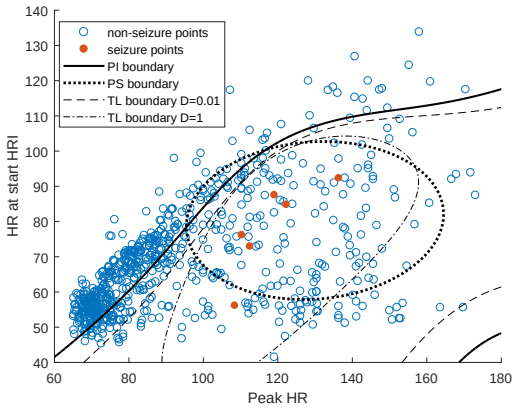

Fig. 6. Visualization of SVM boundary of the Patient-Independent (PI), Patient-Specific (PS) and Transfer Learning (TL) model for different D values (0.01 and 1).

similar to the PI model because a relative low weight is given to the errors obtained for the patient-specific data compared to the first term in (5), which quantifies how different the new model is to the original one. With a higher value of D the model adapts more to the patient-specific data (and the corresponding errors $\tilde{\xi}_k$) and shows less similarity to the PI boundary. The PS boundary is less optimal, compared to the TL solution. It can be seen from the TL boundary that it still contains information gathered in the PI classifier (especially for low values of D), indicating the added value of this approach. This way, the FAR is strongly decreased, without affecting the sensitivity.

B. Comparison of different personalization approaches

Different alternatives for personalization were implemented and evaluated in order to compare with the proposed transfer learning approach (see Table II and Figure 3). The naive approach only uses patient-specific data points for training a normal SVM classifier. Despite all patients had at least 5 seizures, this was still an insufficient amount of data for most patients in order to get a robust patient-specific classifier. In [17], it was mentioned that at least 6-8 seizures were required in order to make a personal algorithm, and the reason for this was to better include the inter-seizure variability of autonomic changes within a patient. Due to the relative low amount of patient-specific data, it often occurred that the classifier was overtrained on a limited amount of seizure data, not taking into account potential fluctuations between different seizures from a patient. This led to a strong decrease in sensitivity, although the FAR was not so much higher than the proposed TL approach. The TL approach is able to better take this inter-seizure variation into account by holding on to the knowledge described by the reference PI classifier.

The mixed model (MIX) uses a mixture of patient-specific data with data from other patients in the training set of a standard SVM training procedure. It produced more robust results than the fully patient-specific approach without strong negative outliers. However, it generated, on average, around 0.5 FP/h more than the proposed TL approach. Applying transfer learning to the reference classifier allows to better take over the information of the PI classifier and translate it to the patient-specific model, whereas the mixed approach would try to create a new model without this prior model knowledge. The proposed transfer learning method not only leads to a better performance, but is also trained faster with an optimization problem which contains less data to analyze.

C. Impact of number of seizures on personalization

Transfer learning allows to train a personalized classifier for heart rate based seizure detection. It is however important to have an idea of how much data is actually needed for this.

In the topic of seizure detection, the amount of seizures is typically the restricting factor as some patients might have a low seizure frequency. In section III-G, a simulation study was described to evaluate the impact of the number of seizures in training on the performance of the personalized approach (see Figure 4).

The proposed TL approach already leads to a strong increase in F_3 performance by only including 1 seizure in the training set. This shows that with only 1 seizure, the algorithm can already be personalized. There is a lot of variation in the results, which is caused by which seizure data is used during training. There is also a lot of variation in ictal heart rate changes between different seizures within a patient, so if an atypical seizure is used in training, this will lead to suboptimal results for that patient. By using 2 seizures during training, the F_3 performance increases slightly, and also the variability between results of different simulations decreases. However, from 3 seizures onwards, the variability is no longer strongly decreased with the proposed method. The average performance increases further up until 4 available seizures, and is expected to increase further if more seizures are included in training [17]. From a certain amount of seizures, it is however expected that the fully PS approach would lead to a better performance than the proposed TL method. Nevertheless, it is currently not known how many seizures are required for this with the proposed procedure.

Figure 4 also shows the effect of the number of seizures on the alternative personalization approaches. It can be seen that by only having 1 patient-specific seizure in the training data, the TL performance strongly increased, whereas this increase is less evident for the other approaches. For the PS approach, the median performance is increased, but a lot of results were actually worse than for the reference PI approach. This is due to the fact that the PS method is often strongly overfitting on data from 1 seizure, which is not a robust way for training a classifier. The average F_3 scores for the fully PS approach increase by adding more seizures, and the variation on performance decreases. The results however remain lower than those from the proposed TL approach when using 4 seizures. The mixed model is more robust than the fully PS approach for a limited amount of seizures, but it slightly loses its added value when more seizures are added to the training set.

D. General discussion and future work

Despite the increased performance caused by personalization through transfer learning, still a too high FAR is obtained for usage in practice. Personalization allows to solve some of the issues leading to a too high FAR, but is not able to solve all issues. Some seizures do not contain ictal heart rate changes, and still a large portion of non-epileptic heart rate changes can not be differentiated from epileptic HRIs with the current techniques. The proposed method should, however, be used as part of a multimodal algorithm, where it is combined with another modality. Accelerometers and EMG sensors could lead to an increased performance for the detection of motor seizures [23], [24]. The latter combines the different modalities with a late integration approach. Multiple modalities should generate an alarm within a certain time span, which will decrease the FAR. For the detection of non-motor focal seizures, ear EEG could be used [25]. The advantage of heart rate based seizure detection is that ECG is often monitored as well during video-EEG monitoring in the hospital, which allows to get accurately annotated heart rate data to personalize the algorithm. The algorithm can then be improved by adding either a patient-independent algorithm using a different modality, or also by applying a similar transfer learning approach to this modality in order to also personalize this algorithm.

The proposed transfer learning approach is a supervised approach, which means that annotated data was required. In practice, these annotations can be made in the hospital during, for example, presurgical evaluation, but they could also be made by the patient or their caregivers/family. Extra procedures should then be added to avoid a too big impact of incorrect annotated data as patients are not always aware about whether they actually had a seizure or not [3], [14]. Ideally, an unsupervised approach could be used [15], [20], [26], which indicate that epileptic heart rate activity can be seen as an outlier to normal heart rate activity. This is however only the case during the night [27], which makes this approach only sufficiently successful for nocturnal monitoring. Supervised approaches are thus still required for personalizing full day monitoring applications. Due to the supervised approach, still at least 1 patient-specific seizure is required in order to adapt to the patient characteristics. In patients who have a very low seizure frequency, this might still be a problem for a fast personalization. For these patients, it is then advised to have a large pool of patients, and seizures from patients with similar HRV parameters as the test patient. Then, these seizures could be added to the patient-specific data in order to be able to apply this method.

VI. Conclusion

Transfer learning allows to personalize heart rate based seizure detection in a fast and robust way by using only a limited amount of annotated patient-specific data. The false alarm rate dropped by 35% compared to the patient-independent approach while maintaining a similar sensitivity. The proposed method can be used as part of a multimodal algorithm in order to increase the performance and close the gap to usage of real-time epileptic seizure warning systems.

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