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Automatic Recognition of Low-Back Chronic Pain Level and Protective Movement Behaviour using Physical and Muscle Activity Information

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Abstract— **Automatic recognition of low-back chronic pain and movement behaviour in humans could be a useful technology in health monitoring and providing effective rehabilitation advice. Physical and muscle activity information can be used in automating this process in combination with machine learning and feature engineering methods. This paper presents a method for automatic recognition of chronic pain and movement behaviour using our recently proposed 'Active Data Representation' (ADR) method, and applies it to two tasks of the EmoPain 2020 Challenge using physical and muscle activity features. The ADR method is used for the transformation of the physical and muscle activity features for the classification tasks. Our results show that ADR outperforms the LSTM challenge baseline model in terms of Matthew correlation coefficient (0.43) and F score (61.21) for the recognition of chronic pain and movement behaviour respectively in hold-out validation settings. Although a decrease in performance is observed on the test dataset, ADR still outperforms the challenge baseline for the recognition of chronic pain and movement behaviour tasks.**

I. INTRODUCTION

Chronic Low-Back Pain (CLBP) is a continuous pain unrelated to a specific injury, with no existing lesion or persisting past healing. Physical activity is essential for rehabilitation [4] but subjective aspects (anxiety, perceived exacerbation, etc.) can hamper regular practise with adversarial consequences[14]. Patient's engagement to physical exercise plans need to take into consideration psychological aspects and provide effective rehabilitation advises [13]. The detection of the patient's perception is essential in this effort to improve care plans.

Avoidance of physical activity is expressed through protective behaviour, also referred as guarded movements - body movement aimed at avoiding strain [14]. Automatic detection of these movements can enable the development of support tools complementing physiotherapists, in clinical settings or for self-management. Movement-based automatic recognition of protective behaviour is performed at different temporal scopes: sequence labelling is interested in the overall classification, and frame by frame labelling aims to characterise specific movement. Posture and movements are recorded using sensors on the whole body. Movements are decomposed in frames, and joints angles and energy are extracted for each time step.

In an overview of the literature, Aung et al. [2] found that although pain expression classification has been studied, body expression recognition has been neglected.

Classification of pain related expression from body movement is based on the work in recognition of affective states from body movements and posture [7].

Movement-based automatic recognition of protective behaviour is performed at different scopes: frame by frame labelling to characterise the temporal structures and sequence labelling for the classification of the overall movement.

Aung et al.[1] investigated Movement Behavior Classification, classifying *guarding* in two movements: sit-to-stand and one-leg-stand using posture and velocity based features. A Random Forests classification was performed, with overall F1-scores of 0.81 and 0.73.

This work was expanded in an exploratory study after the collection of the EmoPain data set [2]. A Random Forest classification was performed on the main combinations of labels/exercises, suggesting contextual factors in the differences observed between the combinations themselves and between the type of exercise (instructed vs non instructed). In a follow-up study, a deep learning architecture (BodyAttentionNet)[16] was developed to capture spatial and temporal cues. Compared to the state of the art, the system drastically improved the performances (F1-score: 0.572 vs 0.844). Compared to other LSTM-based architectures[15], the BodyAttentionNet neural network achieved a better F1-score (0.812 vs 0.844), and required a much lower number of hyperparameters (2.1k vs 40.9k). Separating the results of the spatial and temporal subsystems suggested a more important role for the former, although the combined performance hints to their complementarity.

Pain classification is based on similar body features. Initial classification using three pain levels (control, low, high) with Support Vector Machine on body motion and muscular activity combined with feature selection [10] showed good results. Feature sets of both modalities achieved similar F1 scores (movement: 0.63, muscles: 0.69), while their combination lead to a large improvement (F1 = 0.8). Investigation on the inclusion of a depression score as an additional input feature [11] did not improve the performances, however the results further stressed the prominence of the context (movement and type of exercise) in the classifier's performance. In their study on the relevance of features based on linear mixed model analysis, Olugabe et al. [12] further investigated the discriminative power of specific body features. The resulting optimised feature set allowed further improvement. Additionally, the study investigated the potential of ubiquitous monitoring through the use of a minimal set of features from low-cost sensors. In this last experiment, they achieved an F1-score of 0.78 on a reduced two-level pain classification.

II. Data Set Description

The movement challenge data set used for the 'Pain Recognition' and 'Movement Behaviour Classification' is based on the EmoPain dataset [2]. It contains movements from 30 participants carrying out physical activity, described by two types of features: full body motion capture and muscle activity. Body motion is tracked though bodily joints (13 angles and corresponding energies) and the muscle activity is tracked using Surface Electromyography (sEMG), a non-invasive method to record the electric activity of muscles. The dataset for pain recognition Task labels each movement for chronic pain using three levels : none, low, high. The dataset for the movement behaviour recognition task is provided with continuous binary labels of protective behaviour (PB) for each of the 180 frames constituting a movement. PB labels were generated in the EmoPain data set from the fusion of six (5 + null) behaviour categories temporally segmented by experts in CLBP. The data set is slightly imbalanced (≈60/40) in terms of number of subjects, featuring 18 participants with CLBP and 12 healthy participants. The population was divided randomly into three sets (see table I).

TABLE I
MOVEMENT CHALLENGE DATASET.

Set	**Participants - total**	**CLBP**	**Healthy**
Training	16	10	6
Validation	7	4	3
Test	7	4	3

III. Experimentation

This section describes the features sets of the of EmoPain Data for pain and movement behaviour recognition tasks, the training of the feature extraction model, the generation of a feature vector for the recognition tasks, the classification methods and the evaluation metrics.

A. Feature Sets

Each frame is a single data vector at each time step containing 30 features: 13 joint angles, 13 joint energies and 4 electromyography from lower and upper back. In total the data consists of 514545 frames (356107 and 158438 in the training and validation sets respectively). The Classification is performed on time intervals (T), i.e. sequences of frames. The Challenge Organisers use a different time interval for each task, as described below:

Pain Recognition from Movement: $size = I \times T \times d$

1) I = the total number of instances of exercise;
2) T = the number of frames in each segment = variable, depends on the length of the exercise;
3) d = the number of dimensions of each frame = 30.

Movement Behavior Classification: $size = W \times T \times d$

1) W = the total number of window segments over all exercise instances;
2) T = the number of frames in each segment = 180;
3) d = the number of dimensions of each frame = 30.

B. Active Data Representation

In this section, we describe our active data representation method briefly [5], [6]. This is the first study which evaluates the ADR using physical and muscle activity information. Previous studies [5], [6] evaluates ADR using audio and visual information only. It involves the following steps:

1) *Clustering* of frames: Self-Organising Maps (SOM) [8] are employed for clustering of all the frames using 30 features. The number of clusters was determined through a grid search hold-out-validation procedure with a hyperparameter space of $m \in \{5, 10, \ldots, 100\}$. An example of clustering (i.e. feature extraction model) is shown in Figure 1.
2) *Generation* of the Active Data Representation (ADR_{Ai}) vector is done by first calculating the number of segments in each cluster for each I or W (Ai), that is, creating a histogram of the number of frames ($nADR_{Ai}$) present in each of the m clusters for each I/W. Then, to model temporal dynamics we calculate the mean and standard deviation of the rate of change with respect to the clusters associated with the frames for each I/W ($cADR_{Ai}$), where the rate of change is given by an approximation of derivative
$$vADR_{Ai} = \frac{\partial cADR_{Ai}}{\partial t},$$
with respect to time (t).
$$nADR_{Ai_{norm}} = \frac{nADR_{Ai}}{\|nADR_{Ai}\|_1} \quad (1)$$
3) *Fusion*: the $ADR_{Ai_{norm}}$ feature set encompasses the features of $nADR_{Ai_{norm}}$, and $vADR_{Ai}$. Therefore a feature vector with dimensionality of $m{+}2$ is generated to represent each instances ($WorI$) for classification.

C. Classification Methods

The classification experiments were performed using four different methods, namely decision trees (DT, with leaf size of 20), nearest neighbour (KNN with K=1), linear discriminant analysis (LDA) and Random Forest (RF, with leaf size of 30 and 250 number of trees for pain recognition task, and with leaf size of 2 and 12 number of trees for movement behaviour recognition task). The classification methods are implemented in MATLAB[1] using the statistics and machine learning toolbox. A hold-out validation setting was adopted, where the training data do not contain any information of validation subjects. The pain recognition task is a three class problem as follow:

1) 0: Healthy,
2) 1: Low-level pain,
3) 2: High-level pain.

The movement behaviour recognition task is a two class problem as follow:

1) 0: Not protective,
2) 1: Protective.

[1]http://uk.mathworks.com/products/matlab/ (Jan 2020)

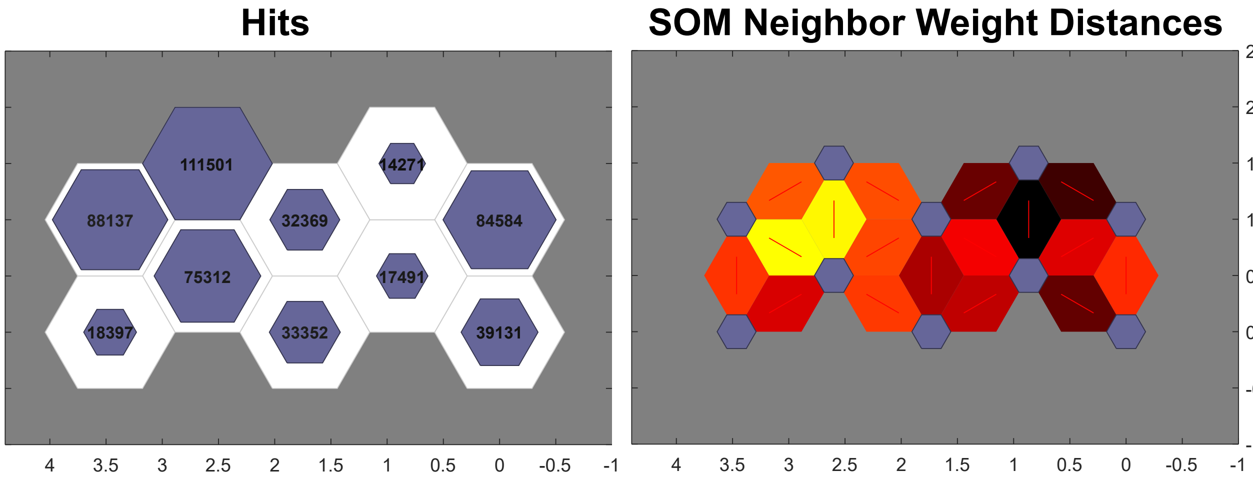

Fig. 1. ADR feature extraction model with $m = 10$ which provides the best result of 0.43 (MCC) for Pain Recognition task with RF classifier. Left figure indicates the number of frames present in each cluster (hexagon i.e. neuron) and right figure indicates the distance between clusters (blue dots i.e. neurons) and darker color indicates greater distance between clusters. The red lines connect neighboring neurons.

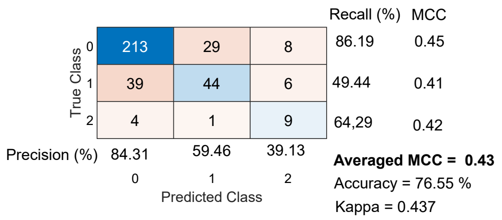

Fig. 2. Pain Recognition: Hold-out validation Results

TABLE II

RESULTS OF PAIN RECOGNITION TASK IN HOLD OUT VALIDATION: MCC

		Base-SVM	**Base-KNN**	LDA	KNN	DT	RF
	m	-	-	10	10	35	10
Valid.	class (0)	-	-	0.36	0.32	0.16	0.45
	class (1)	-	-	0.47	0.24	0.25	0.41
	class (2)	-	-	0.29	-0.06	0.11	0.42
	average	0.19	0.05	0.38	0.16	0.18	**0.43**
test	class (0)	-	-0.04	0.14	-	0.16	0.23
	class (1)	-	-0.06	0.03	-	-0.09	-0.01
	class (2)	-	0.16	0.03	-	0.16	0.14
	average	-	0.02	0.07	-	0.08	**0.12**

D. Evaluation Matrices

To assess the classification results, we used the average of Matthew Correlation coefficient (MCC) for pain recognition task as shown in Equation 2 and Averaged F_{Score} for movement behaviour recognition task in hold-out-validation setting.

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \quad (2)$$

IV. RESULTS AND DISCUSSION

This section describes the results of machine learning models for pain and movement behaviour recognition task of EmoPain challenge.

A. Results: Pain Recognition

The results (i.e. MCC) of pain recognition task are shown in Table II. The results indicate that the RF (the feature extraction model is shown in Figure 1) provides better averaged MCC of 0.43 than the other classifiers. The results indicated that the LDA provides the best MCC of 0.47 for class (1). The results also indicates that RF provides the best results for class (0) and class (2) with an MCC of 0.45 and 0.42 respectively. For further insights, confusion matrices of the best result is shown in Figure 2 along with precision, recall of each class, overall accuracy, UAR and Kappa [9]. We have submitted top three results (i.e. RF, LDA and DT) for test pupose to the challenge organisers and the results are also shown in Table II.

B. Results: Movement Behaviour Recognition

The results (i.e. F_{Score}) of movement behaviour task are shown in Table III. The results indicate that the RF (0.6121) provides better averaged F_{Score} (the feature extraction model is shown in Figure 3) than the other classifiers and the challenge baseline of 0.4811 [3]. The results showed that RF provides the best F_{Score} of 0.9677 and 0.2564 for class (0) and class (1) respectively. For further insights, confusion matrices of the best result is shown in Figure 4 along with precision, recall of each class and overall accuracy, F_{Score} and Kappa [9]. We have submitted top three results (i.e. RF, LDA and DT) for test purpose to the challenge organisers and the results are also shown in Table III.

TABLE III

RESULTS OF MOVEMENT BEHAVIOUR RECOGNITION TASK ON VALIDATION AND TEST DATA : $F_{Score}(\%)$

		Base-LSTM	LDA	KNN	DT	RF
	m	-	75	25	15	25
Valid.	class (0)	96.22	95.98	94.55	95.06	96.77
	class (1)	-	25.13	21.40	23.01	25.64
	Averaged	48.11	60.56	57.97	59.03	**61.21**
test	class (0)	90.29	92.01	-	91.64	93.40
	class (1)	24.65	21.63	-	24.52	18.57
	Averaged	57.45	56.82	-	***58.08***	55.98

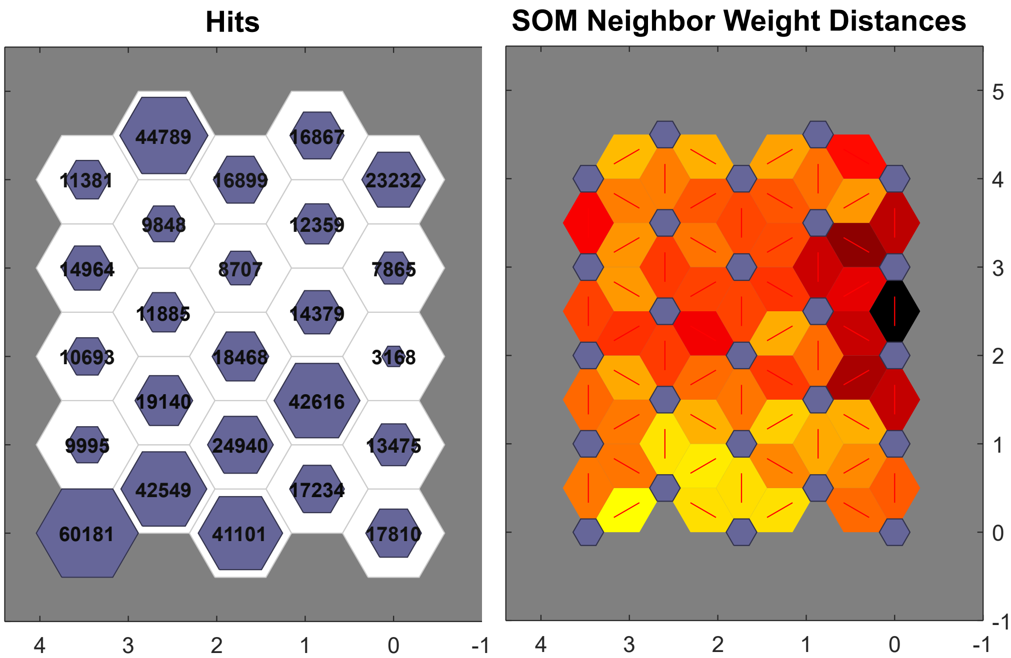

Fig. 3. ADR feature extraction model with $m = 25$ which provides the best result of 0.6121 (F_{Score}) for Movement Behaviour Recognition task with RF classifier. Left figure indicates the number of frames present in each cluster (hexagon i.e. neuron) and right figure indicates the distance between clusters (blue dots i.e. neurons) and darker color indicates greater distance between clusters. The red lines connect neighboring neurons.

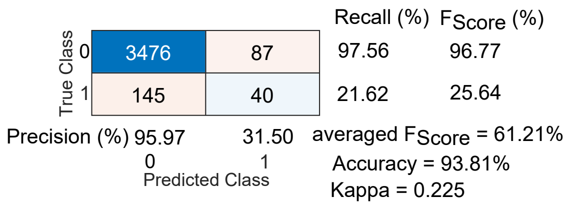

Fig. 4. Movement Behaviour Recognition: Hold-out Validation Results.

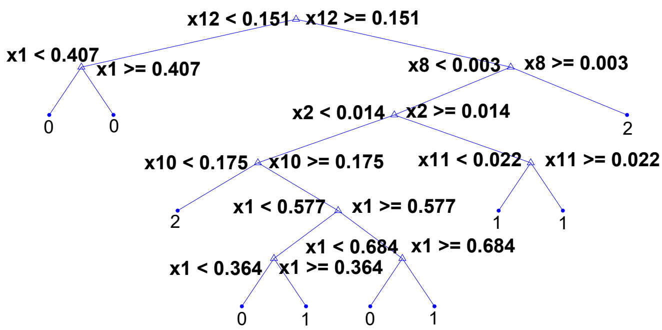

Fig. 5. Pain Recognition: An example of a tree from the RF which provides the best MCC of 0.43. In this case,the ADR has a dimensionality of 12 with m =10.

C. Discussion

To get further insight of results we draw a tree from the RF classifier as shown in Figure 5. As the ADR is generated with different number of clusters (m) and $m = 10$ provides the best results (MCC of 0.43) for pain recognition task. The dimensionlity of the ADR is $m + 2$ which is represented in Figure 5 as $x1, x2, x3, \ldots, x12$. Where $x11$ and $x12$ represents the $vADR_{Ai}$ and $x1, x2, \ldots, x10$ represent $nADR_{Ai_{norm}}$.

In the baseline study [3], authors uses the KNN and SVM classifiers for the pain recognition's tasks. They reported an MCC of 0.05 and 0.19 for KNN and SVM respectively in LOSOCV settings on training data. However a decrease in MCC is observed for KNN (0.02) and SVM on test data In this study, we used hold-out validation settings. For movement behaviour recognition task, the authors uses the hold-out-validation and uses the stacked-LSTM algorithm for classification. The reported results are almost close to blind guess (i.e. $F_{Score} = 48.11\%$ on validation and $F_{Score} = 57.45\%$ on test). However, It is a very challenging machine learning problem as the classes of the data-set are highly imbalanced.

V. Conclusions

This study demonstrate the results of 'Active Data Representation' (ADR) method for 'low-back chronic pain' and 'protective movement behaviour' recognition tasks of EmoPain challenge. The results reported in this paper outperform the baseline of *EmoPain* challenge with an MCC of 0.43 and averaged F_{Score} of 61.21% on validation dataset, and an MCC of 0.12 and averaged $F_{Score}L$ of 58.08% on test data. In future we intend to evaluate the performance of the ADR method for multiple feature sets and compare the results with other feature extraction methods such as VGGNet and GoogleNet.

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