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Pain Recognition with Physiological Signals Using Multiple Level Context Information

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ABSTRACT: Automatic pain recognition is essential in healthcare. In previous studies, automatic pain recognition methods preferentially apply the features extracted from physiological signals for conventional models. These methods provide good performance but mainly rely on medical expertise for feature extraction of physiological signals. This paper presents a deep learning approach based on physiological signals that have the role of both feature extraction and classification, regardless of medical expertise. We propose multilevel context information for each physiological signal discriminating between pain and painlessness. Our experimental results prove that multi level context information performs more significantly than uni-level context information based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset.

For Part A of the BioVid Heat Pain database, our experimental results for pain recognition tasks include Pain 0 and Pain 1, Pain 0 and Pain 2, Pain 0 and Pain 3, and Pain 0 and Pain 4. In the classification task between Pain 0 and Pain 4, the results achieve an average accuracy of 84.8 B1 13.3% for 87 subjects and 87.8 B1 11.4% for 67 subjects in a Leave-One-Subject-Out cross-validation evaluation. The proposed method adopts the ability Leave-One-Subject-Out cross-validation evaluation. The proposed method adopts the ability of deep learning to outperform conventional methods on physiological signals.

KEYWORDS: Pain recognition, physiological signals, context vector, attention module, deep learning.

I. INTRODUCTION

Pain is the body's common response to illness that requires medical attention. Traditional pain recognition methods are generally through human observations and subjective recognition. The physiotherapists assess a patient's pain through exercises during the therapy process and give reasonable exercises to the patient to overcome the disease. Pain recognition depends on the knowledge of each expert, observation, and individual perception through the patient's expression. This brings many limitations because there are no universal and reliable rules for pain recognition. Therefore, the automation of pain recognition is necessary for humans. In the medical, pain recognition applications is a health monitoring system that helps humans recover from illness through physical therapy exercises. Pain recognition systems use behavior and physiology to perform classification tasks. Measures are physiological signals, facial expressions, body movements, vocalizations, and so on, or a combination of them. In some cases, pain recognition through the patient's behavior is not reliable. The patient can intentionally control emotional expression. Furthermore, the patients express pain behavior depending on their personality. Some patients lose awareness and do not express painful emotions clearly and reliably. It is difficult to recognize pain through emotional behavior.

Therefore, pain recognition using physiological signals is essential. Pain causes the response of the relevant neural structures and alters the measures of differences in physiological signals. Measures of physiological signals related to pain response such as skin conductance, heart rate variability, resting blood pressure, and electroencephalography (EEG). Skin conductance is a signal in response to pain. The increased sympathetic outflow associated with pain secretes the sweat on the skin's surface. This is the factor to increase electrodermal activity (EDA). The increased sympathetic activity also affects heart rate, increasing heart rate variability or resting blood pressure. In addition, pain affects metabolic areas in the cerebral cortex, or muscle activity [1]. Since the publication of the BioVid Heat Pain Database [2], EDA and electrocardiogram (ECG) and (electromyogram) EMG signals have become widely used for pain recognition [1].

EDA signals show the skin conductance level, ECG represents the action potential of heart rate and the EMG signal measures muscle activity. The task of automatic pain classification remains extremely challenging. Many previous studies evaluating pain use tools to extract the dynamic characteristic composition of physiological signals to facilitate classification.

II. LITERATURE SURVEY

[1] P. Werner, D. Lopez-Martinez, S. Walter, A. Al-Hamadi, S. Gruss, and R. W. Picard, “Automatic recognition methods supporting pain assessment: A survey,” *IEEE Trans. Affect. Comput.*, vol. 13, no. 1, pp. 530–552, Jan. 2022. Pain is a complex phenomenon, involving sensory and emotional experience, that is often poorly understood, especially in infants, anesthetized patients, and others who cannot speak. Technology supporting pain assessment has the potential to help reduce suffering; however, advances are needed before it can be adopted clinically. This survey paper assesses the state of the art and provides guidance for researchers to help make such advances. First, we overview pain’s biological mechanisms, physiological and behavioral responses, emotional components, as well as assessment methods commonly used in the clinic. Next, we discuss the challenges hampering the development and validation of pain recognition technology, and we survey existing datasets together with evaluation methods.

[2] S. Walter, S. Gruss, H. Ehleiter, J. Tan, H. C. Traue, S. Crawcour, P. Werner, A. Al-Hamadi, and A. O. Andrade, “The biovid heat pain database data for the advancement and systematic validation of an automated pain recognition system,” in *Proc. IEEE Int. Conf. Cybern. (CYBCO)*, Jun. 2013, pp. 128–131.

The objective measurement of subjective, multi-dimensionally experienced pain is still a problem that has yet to be adequately solved. Though verbal methods (i.e., pain scales, questionnaires) and visual analogue scales are commonly used for measuring clinical pain, they tend to lack in reliability or validity when applied to mentally impaired individuals.

[3] Y. LeCun, Y. Bengio, and G. Hinton, “Deep learning,” *Nature*, vol. 521, no. 7553, pp. 436–444, Sep. 2015. Deep learning allows computational models that are composed of multiple processing layers to learn representations of data with multiple levels of abstraction. These methods have dramatically improved the state-of-the-art in speech recognition, visual object recognition, object detection and many other domains such as drug discovery and genomics.

[4] T. Olugbade, R. Sagoleo, S. Ghisio, N. Gold, C. D. C. Amanda, B. D. Gelder, A. Camurri, G. Volpe, and N. Bianchi-Berthouze, “The affectmove 2021 challenge—Affect recognition from naturalistic movement data,” in *Proc. 9th Int. Conf. Affect. Comput. Intell. Interact. Workshops Demos (ACIIW)*, Sep./Oct. 2021, pp. 1–5. We ran the first Affective Movement Recognition (Affect Move) challenge that brings together datasets of affective bodily behaviour across different real-life applications to foster work in this area. Research on automatic detection of naturalistic affective body expressions is still lagging behind detection based on other modalities whereas movement behaviour modelling is a very interesting and very relevant research problem for the affective computing community.

The Affect Move challenge aimed to take advantage of existing body movement datasets to address key research problems of automatic recognition of naturalistic and complex affective behaviour from this type of data.

III. EXISTING SYSTEM

The existing system for pain recognition with physiological signals using multiple level context information typically involves the integration of various physiological signals such as heart rate, skin conductance, electromyography (EMG), and electroencephalography (EEG) to capture different aspects of the pain experience.

This approach utilizes multiple levels of context information, which may include temporal dynamics, frequency domain analysis, spatial patterns, and machine learning algorithms to infer the presence and intensity of pain. The system often employs signal processing techniques to preprocess the physiological data, feature extraction methods to identify relevant patterns, and machine learning models such as support vector machines (SVM), deep learning architectures, or ensemble methods for classification and regression tasks.

IV. PROPOSED SYSTEM

In this section, we introduce the materials for the proposed method. We introduce the definitions of multi-level context information on physiological signals in pain intensity recognition.

Inspired by previous studies on the breakthrough performance of deep learning networks, the proposed architecture is built to emphasize the classification performance of deep learning networks and minimize dependence on manual designs. The work of expertise in medicine is precisely handcrafted features of physiological signals.

This is employed automatically in deep learning with hierarchical layers that carry optimal parameters and weights. In deep learning, Convolutional Neural Networks (CNN) are widely used and highly effective networks for classification tasks.

The pooling layers reduce the number of parameters to improve the calculation speed and avoid over-learning while preserving essential characteristics. Non-linearity is necessary to create non-linear decision boundaries between the output and the input, which partly helps CNN make breakthroughs.

We opt a non-linear activation function named Exponential Linear Unit (ELU) instead of ReLU to retain negative values. The Exponential Linear Unit (ELU) activation function is performed elementwise on every value from the input to saturate to a negative value when the argument gets smaller.

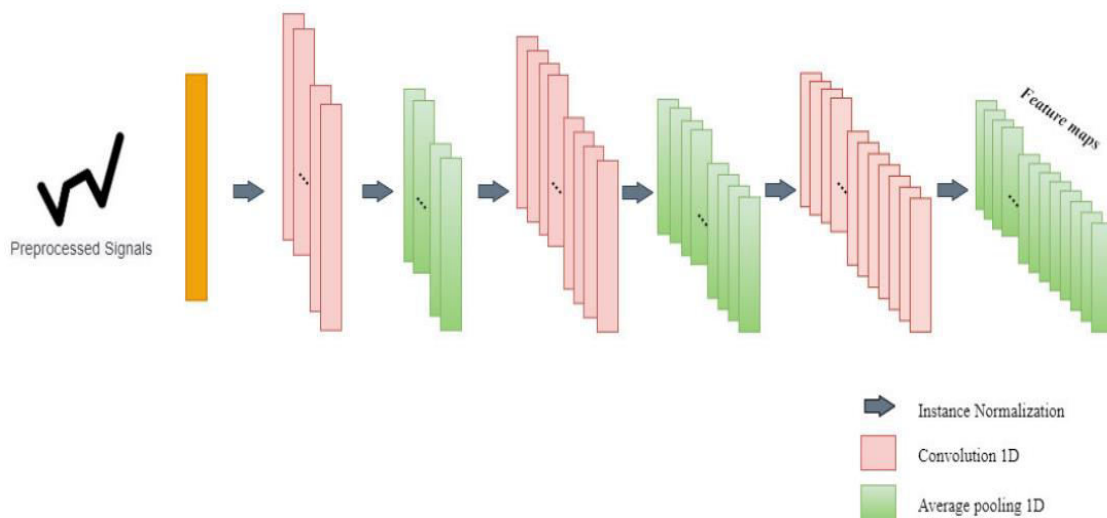


FIGURE 1. CNN spatial architecture

This section introduces a method capable of extracting multilevel representations from context information. We first perform standardization as a preprocessing step. After being preprocessed, each physiological signal modality, as shown in Figure 1, is fed into the Instance Normalization layer to normalize the input layer.

After normalization, each output is fed into a CNN block to extract spatial information. Concurrently, the pooling layers are used to reduce spatial resolution. The output of the CNN block is connected to the BiLSTMs and Bahdanau Variant Attention in the level blocks.

Levels of blocks are built based on the fluctuating information of the last hidden information, as it plays a pivotal role in creating the context information. In this work, we choose the classification of Pain 0 and Pain 4 to illustrate, that other classification tasks have similar analyses.

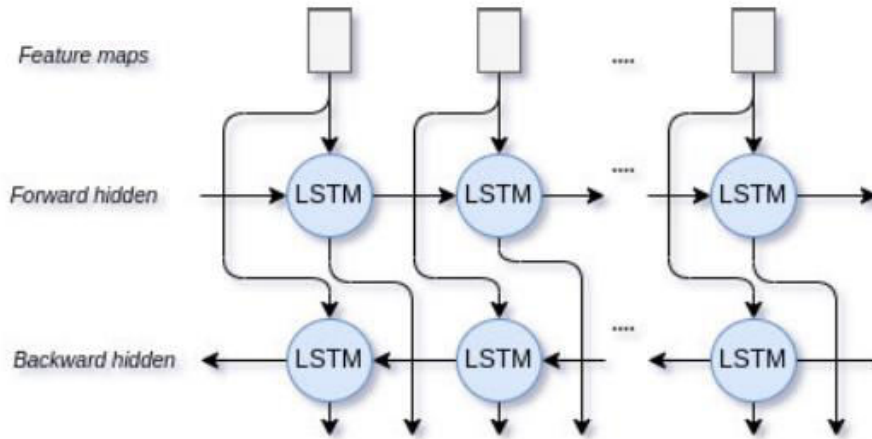


FIGURE 2: BiLSTMs architecture

We implement scaling to expand the last hidden information at the High Level and compress it at the Middle Level and Low Level before feeding it to the attention module. In each level block, the hidden information and the scaled last hidden information are fed into Bahdanau Variant Attention to extract the context vector.

Combining the scaled last hidden information and the context vector creates context information. Finally, we combine the context information of all level blocks generating multi-level context information, as shown in Figure.

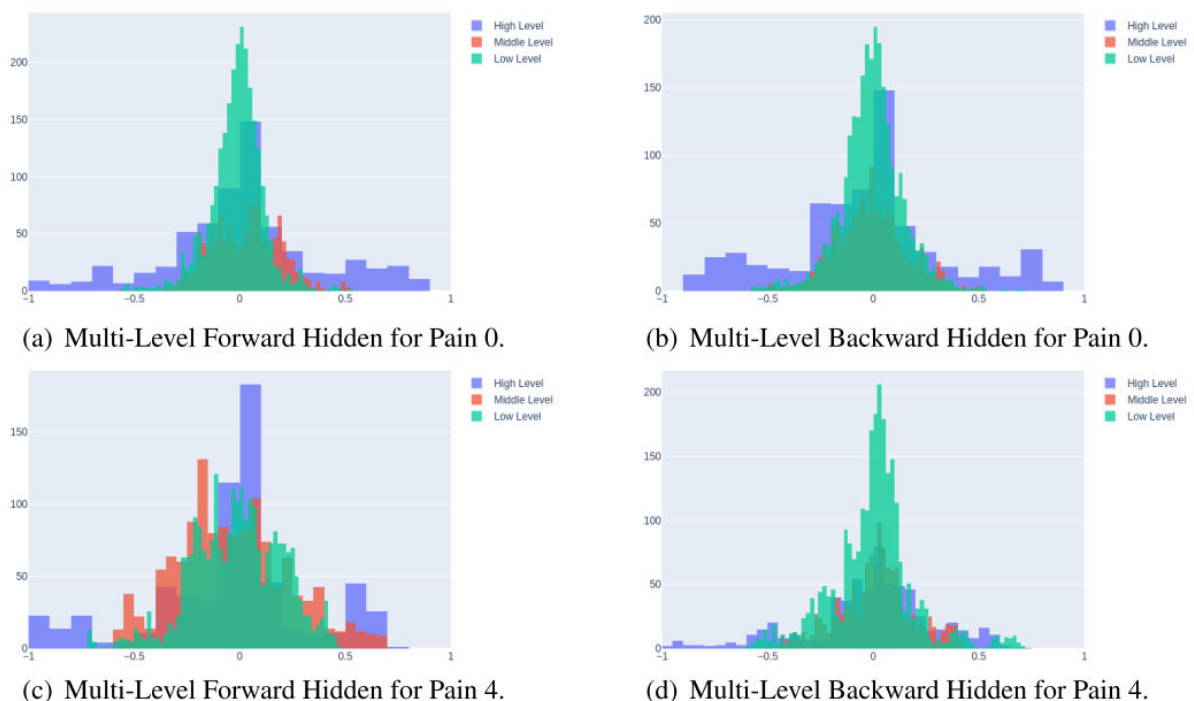


FIGURE 3: Multi-level hidden information from EDA signal

For the classification pain 0 and pain 4 of subject 071614-m-20. The training process performs LOSO cross-validation evaluation with 67 subjects. They are histogram charts with the x-axis representing the value and the y-axis representing the frequency of the hidden information. The blue, red, and green colors represent high level, Middle Level, and Low Level, respectively not improved after five executions.



V. EXPERIMENTAL RESULT

In the propose paper author employing multilevel deep learning algorithms for pain recognition as all existing uni-level traditional machine learning algorithms are not good at recognition. Multilevel algorithm giving good accuracy compare to uni-level algorithms like SVM, Random Forest, Linear Regression etc. In propose work author optimizing, selecting features and performing classification using multilevel algorithms like CNN + BI-LSTM (bi-directional LSTM).

Propose CNN + BI-LSTM is a multilevel algorithm where CNN will be using for features optimization and then BI-LSTM will select or extract relevant optimized features from CNN and then train a model for pain recognitions. To train and test all algorithms author has used different datasets like BioVid Heat Pain database and the Emopain 2021 dataset. This datasets contains two different pain signals such as EEG and EDA and author done experiment on both datasets but this datasets are not freely available to download so from GITHUB we have downloaded few subjects EEG pain signals dataset and then train with above mention algorithms.

```

In [20]: #now predict pain type using test data
testData = pd.read_csv("Dataset/testData.csv")#reading test data
testData.fillna(0, inplace = True)
temp = testData.values
testData = testData.values
test = scaler.transform(testData)#normalizing values
test = np.reshape(test, (test.shape[0], 34, 4))
predict = extension_model.predict(test)#performing prediction on test data using extension model object
for i in range(len(predict)):
    y_pred = np.argmax(predict[i])
    print("Test Data = "+str(temp[i])+" Predicted Pain Type ----> "+labels[y_pred]+"\n")

187. 228. 190. 223. 191. 218. 190. 211. 187. 207. 181. 218. 181. 223.
182. 228. 181. 238. 181. 228. 181. 223. 182. 218.] Predicted Pain Type ----> Pain0

Test Data = [ 1. 171. 129. 171. 142. 173. 155. 174. 167. 177. 180. 184. 191. 194.
200. 206. 207. 221. 210. 235. 208. 247. 203. 257. 194. 263. 184. 266.
172. 268. 160. 271. 148. 272. 136. 182. 118. 188. 111. 197. 108. 207.
109. 216. 113. 235. 114. 244. 112. 254. 113. 262. 116. 267. 124. 225.
126. 225. 135. 225. 144. 225. 153. 213. 160. 219. 162. 224. 163. 229.
163. 234. 161. 192. 128. 198. 125. 205. 125. 212. 129. 205. 130. 198.
131. 237. 131. 245. 128. 251. 128. 257. 133. 251. 134. 244. 133. 205.
178. 212. 174. 219. 172. 224. 173. 229. 172. 235. 175. 241. 180. 235.
185. 228. 187. 223. 187. 218. 186. 212. 184. 208. 178. 219. 177. 224.
178. 228. 178. 238. 179. 228. 178. 224. 179. 219.] Predicted Pain Type ----> Pain4

Test Data = [ 6. 167. 131. 167. 144. 168. 156. 169. 169. 172. 181. 179. 193. 188.
202. 200. 209. 214. 212. 228. 211. 240. 205. 250. 198. 257. 187. 260.
175. 263. 163. 266. 151. 268. 138. 176. 120. 183. 114. 192. 112. 201.
112. 210. 115. 229. 117. 238. 115. 248. 116. 256. 120. 261. 127. 219.
    
```

Figure 4: Predicted Pain Type

VI. ADVANTAGES AND APPLICATIONS

1. It can be implemented in gardens or nurseries even in balconies with minimum cost and resources. Also helps in proper utilization of the available resources and helps in avoiding wastage of electricity and water.
2. Can be easily configured and scaled up to work on larger fields.
3. Provides a user-friendly interface hence will have a greater acceptance by the technologically unskilled workers. The system is more compact compared to the existing ones, hence is easily portable and low cost. Advancements in sensor technology and control systems allow for optimal use of resources. Our aim is to design and develop newer techniques that will allow garden automation to flourish and deliver to its full potential. Thus it can be concluded that the proposed project will lessen labour, conserve water, increase crop yield, provide maximum automation and benefit the society by adopting the fast-growing IoT (Internet of Things) to implement newer and sustainable ways of farming.

VII. CONCLUSION AND FUTURE SCOPE

This paper proposes a deep learning approach based on physiological signals for pain recognition. Our method has the role of feature extraction and classification, completely replacing manual extraction methods that require highly specialized knowledge. We propose multi-level context information explored from hidden sequence information. Specifically, the architecture employs hidden information for the attention mechanism to create the context vector. We combine hidden information and context vector to create the context information. Combining context information at three levels produces multi-level context information. We perform binary classification between baseline and different pain intensities based on Part A of the BioVid Heat Pain database. In addition, we also perform binary classification based on the Emopain 2021 dataset. Our experimental results prove that multi-level context information has more significance than uni-level context information based on Part A of the BioVid Heat Pain database and the Emopain 2021 dataset. Our results demonstrate the great significance of EDA in pain classification. Combining EDA and ECG mostly provides good performance in classification tasks based on Part A of the BioVid Heat Pain database. In summary, the deep learning approach has superior potential to replace previous conventional methods in pain recognition tasks. The exploration of hidden information in the physiological signal sequence provides significant performance for classification tasks.

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