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Third-Person Pain Experience Exploration Based on Multimodal Physiological Features Analysis

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Abstract. Third-person pain is an interesting empathy phenomenon that human has the ability to infer characters of other sufferers' pain by observing their behavior. In the literature, existing studies suggesting that first- person and third-person pain share common features of neuroimage, which indicates that pain behavior will cause influence on both sufferer and the observer. Consequently, it is significant to explore the third-person effects upon the observer. In this study, the evaluation and recognition of third-person pain experience was studied based on user physiological signal analysis. We built a third-person pain multimodal physiological features dataset and applied machine learning methods to explore a third-person pain experience recognition model. A classification accuracy of 95.83% was obtained in third-person pain degree recognition, which demonstrates the effectiveness of our approach. The proposed study shed light on the guiding future exploration of determinants of third-person pain process and empathy intelligence.

Keywords. Third-person pain, physiology signal, machine learning

1. Introduction

At present, user's perception need in artificial industry is becoming more and more prominent. Currently, affective and cognition intelligence are combined in AI systems. However it has some essential shortcomings that AI understands users' status based on massive data analysis, and AI could not truly understand users' emotion and give suitable responses. And artificial system's empathy ability could hardly meet users' requirement.

In order to study the problems of empathy intelligence limitations in AI system, we tried to find a research entry point for this question. Third-person pain is an interesting perception phenomenon that has a nature of empathy character, thus the recognition of third-person pain can provide a new perspective for empathy intelligence development in AI industry. Consequently, we attempt to find a method to detect and evaluate users' third-person pain experience.

Pain experience types vary with respect to the subjective and objective perception. First-person pain is a clear and subjective perception, which is also an obvious signal of

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threat and hurt. While third-person pain is an internal experience affected by observing suffers' behaviors or first-person pain response [1]. In this study, the intelligent evaluation of third-person pain can help us understand empathy mechanism and build computational model to predict the level of pain intensity.

We held experiment to investigate the physiological responses of third-person pain. We explored recognition model of third-person pain based on physiological features by machine learning algorithms. Specifically, we collected 18 video clips as third-person pain stimuli. A total of 24 participants were invited to view the stimuli videos and their physiology features were recorded to form the dataset. Several machine-learning algorithms were applied to find the optimal model of third-person pain recognition model. A 10-fold cross validation was conducted in the modeling experiment. The model results indicated that the classification accuracy is 95.83% in the best model performance based on RandomForest algorithm, which proved the effectiveness of the proposed method. The research paradigm of third-person pain model exploration is illustrated in Figure 1.

The main contribution of this work can be concluded in two aspects: (1) A novel physiology features fusion dataset of third-person pain was built; (2) An optimal model for third-person pain recognition was obtained by machine learning method.

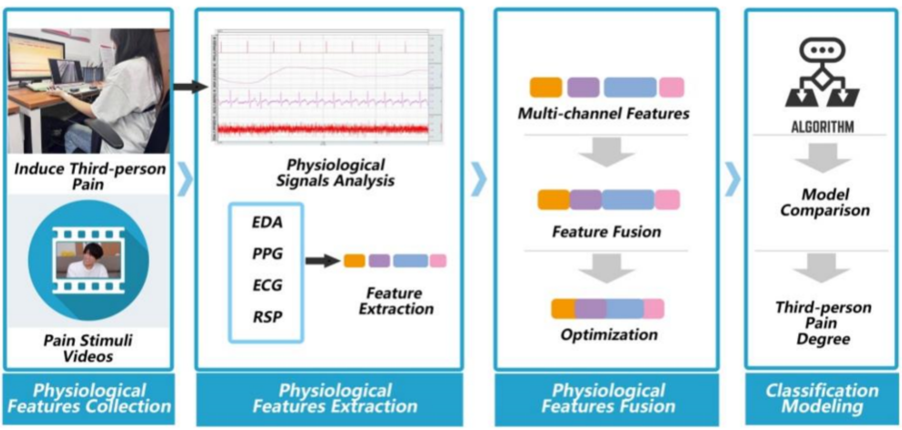


Figure 1. The research roadmap of third-person pain recognition model exploration.

This paper is organized as follows: section 2 presented the related works of third-person pain studies and existing avenues; section 3 introduces methods of different algorithms applied in the modeling experiment; section 4 shows the experiment of third-person pain stimulation and building physiology features dataset; section 5 compares the model performance of different algorithms for third-person pain recognition and discusses the experimental results; section 6 concludes with the future research directions.

2. Related Work

Recently, research interest in the phenomenon of third-person pain has steadily increased [2][3]. The advancement of AI intelligence and conceptual empathy models has accelerated this process. How socially transmitted information about an individual's internal experience is perceived by others? How can we measure the intense of third-person pain? Finding novel approaches to examine the explicit behavioral changes induced by watching suffering in others, as well as their consequences for the sufferer, should be a research goal [4]. Nowadays, technological and methodology developments have contributed to the study of the rising interest.

Researchers arranged the steps in the pain information transmission pathway from nociceptive input to social interpretation via nonverbal facial expression. According to Rosenthal's paradigm, an internal experience must first be stored in expressive behavior before pain communication may take place. Kaseweter explored the nature of the relationship and to explore the potential moderating influence of both third-person pain perception and situational factors [5]. Her findings indicated that individual differences in affective processing may moderate the relationship between empathy and social behavior, which is potentially contributing to difference in the cure of pain. The pain communication model proposed by Hajistavropoulos emphasizes that an observer may not perceive the message, perceive it appropriately, or misinterpret it, resulting in an overestimation or underestimating of the sufferer's painful state [6].

In the study of subjective pain detection aspect, studies have repeatedly shown that activation of brain regions characterized as the "pain matrix" can be triggered by the perception of painful facial expressions [7]. Whitmarsh et al. found that observation of the hand and feet in non-painful status will cause significant suppression of mu and beta oscillations over visual and sensorimotor regions. They found that viewing others' painful status compared to neutral stimuli engages both sensorimotor areas and visual areas [8]. Hein et al. examined skin conductance responses and self-reported emotion during painful electric shock exposure individuals' perception of the other's pain were positively connected with their skin conductance responses while they watched them appear to get shocks. This correlation also indicated that individuals were more likely to choose the personally costly alternative of tolerating the other's pain. It is quite interesting that the likelihood of costly aiding increased when the participant's skin conductance reactions during the observation of suffering in the other person matched their own responses [9].

3. Methodologies

In this study, we used Python to build the algorithm models with 10-folds cross-validation. In the experiment, five algorithms were implemented for the classification of third-person pain degree, including LibSVM, LibLinear, RBFNetwork, RandomTree and RandomForest. A brief introduction of these algorithms is presented below.

3.1. LibSVM

LibSVM is developed based on Support Vector Machine for solving the problems of classification and regression. Support Vector Machine (SVM) conducts classification via supervised learning method. The maximum-margin hyperplane is the decision boundary for learning approach. There are a number of extended SVM algorithms, including multi-class classification, least-square SVM, support vector regression, and semi-supervised SVM. SVM and the ensemble models that combine SVM are widely applied in artificial learning and multimedia exploration. It is outstanding in its effectiveness and superior performance in small-sample problems.

3.2. LibLinear

LibLinear is a linear classifier, which is efficient in classification of large amount of data or multiple dimensions of attributes. It is developed with classifiers of linear regression and support vector machine. Thus it has several optional classifiers, including L2-regularized classifiers, L2-loss linear SVM, and logistic regression, L1-regularized classifiers, L2-loss linear SVM and logistic regression, L2-regularized support vector regression, and L2-loss linear SVR and L1-loss linear SVR. For a sample data of (x_i , y_i), this methods can compute optimization issues without constrains:

$$\min_{\varphi} \frac{1}{2}\varphi^T \varphi + \gamma \sum\nolimits_{i=1}^{k} \beta(\varphi; x_i, y_i) \qquad (1)$$

where γ >0 is defined as a penalty value, while $\beta(\varphi; x_i, y_i)$ is the loss function. It is widely used in the classification and regression of large data sets.

3.3. RBFNetwork

RBFNetwork, the radial basis function network, is a typical neural network with three layers, including an input layer, a hidden layer and an output layer. It applies radial basis function for activation. RBFNetwork can be described as:

$$h(x) = Output(\sum_{n=1}^{N} \beta_n RBF(x, \varphi_n)) \qquad (2)$$

where φ_n is the n th center, and β_n is the corresponding weights. The functions of output can be selected according to different goal. The kernel selection of RBFNetwork is crucial in this method. This method can solve various problems of approximation, prediction, classification and regression.

3.4. RandomTree

RandomTree is a learning algorithm with a fast decision tree. It utilizes information gain/variance to construct a decision or regression tree, and it is using reduced-error pruning with backfitting approach. This method can decrease the decision tree complexity. For the given variables M and N of $\{m_1,\ldots,m_i\}$ and $\{n_1,\ldots,n_i\}$, so that the entropy and conditional entropy of N is described as:

$$E(N) = -\sum_{i=1}^{n} K(N = n_i) \log K(N = n_i) \qquad (3)$$

$$E(N|M) = -\sum_{i=1}^{t} K(M = m_i)\log K(N \mid M = m_i) \quad (4)$$

And the gain of variable M is presented by:

$$\theta(N;M) = E(N) - E(N \mid M) \quad (5)$$

The pruning process includes pre-pruning and post-pruning. The expansion of the tree will be terminated when the gain is not recognized due to division.

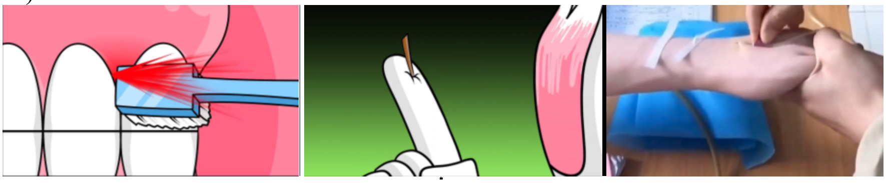
3.5. RandomForest

RandomForest is a classifier that contains multiple decision trees, and its output categories are determined by the mode of the categories output by individual trees. RandomForest method has great performance in various tasks. Its advantages can be concluded in these aspects: 1) For many types of data, it can generate high accuracy classifiers; 2) It can handle a large number of input variables; 3) It can evaluate the importance of variables when determining categories; 4) For imbalanced classification datasets, it can balance errors; 5) It has great efficiency in learning.

4. Experiment

4.1. Third-person pain stimuli

In this experiment, we collected 18 video clips (each lasts for 60 second in MPEG-4 format with a resolution of 1280*1024 dpi) to construct a third-person pain video stimuli dataset. The illustration of the screenshots of the stimuli videos are presented in Figure 2. The video clips were collected and divided into three categories according to the induced third-person pain degrees, including Pain Degree I (mild pain, score 1~3), Pain Degree Ⅱ (moderate pain, score 4~6) and Pain Degree Ⅲ (severe pain, score 7~10).



(a) Pain Degree I *(b) Pain Degree Ⅱ* *(c) Pain Degree Ⅲ*

Figure 2. The video stimuli examples of three pain degree categories applied in the experiment.

4.2. Experiment participant

Specifically, 5 college students from Digital Media Design major were invited for the video selection and classification session of the stimuli videos. Then a total of 24 participants (aged from 19 to 39, 12 males and 12 females) were invited for video viewing experiment. Each participant was asked to watch 18 video clips of different pain levels. At last, a total of 432 signal records were collected, and only 384 valid physiology signal records were obtained in the experiment. Figure 3 shows that the participant is watch video clips in the pain stimuli experiment. The participant was situated in a separate experiment room with a constant lighting environment, seated in front of a laptop computer, and the stimuli video was shown on the screen. The participant wore multi-channel sensors of EDA (electrodermal activity), PPG (photoplethysmography), RSP (respiration) and ECG (electrocardiograms), see Figure 3.

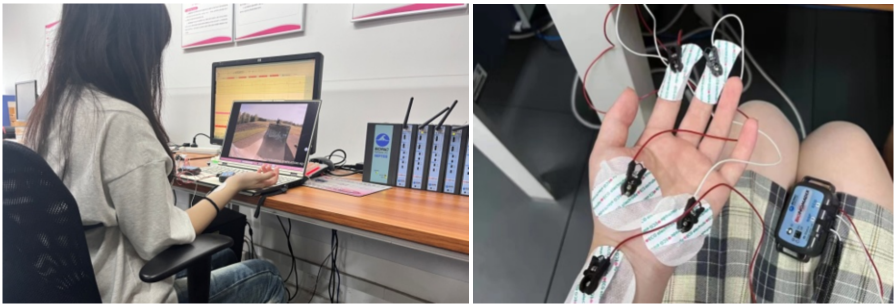


Figure 3. The participant is watch video clips in the third-person pain stimuli experiment with multi-channel sensors placed on the participant's chest and hand.

4.3. Third-person pain labeling

The most commonly evaluated index of clinical pain is its sensory intensity. There are multiple existing methods for evaluating pain intensity, including categorical scales (such as mild, moderate, and severe), numerical rating scales (NRS), visual analog scales (VAS), and validated verbal descriptive scales with excellent statistical characteristics. Due to its feasibility of scoring, NRS is the most commonly used method in clinical settings. Researchers concluded that NRS has higher usability than VAS [10][11]. Consequently, the experiment participants were asked to score the perceived pain degree in a NRS (Number Range Scare) scale of 0~10 for each video after viewing, see Figure 4.

In the scoring session, a total of 320 data samples' score results are consistent with the original pain degree classification. Inconsistent labeling mainly occurs in videos with high degree of pain. Participants reported that they could not empathize the high degree of pain while watching the videos. Since the participants' annotations are the direct reflection of their perception, in the modeling experiment, we utilized the participants' scores as the labeling for model exploration.

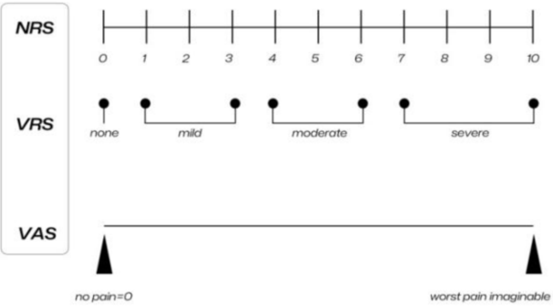


Figure 4. The pain degree scale of NRS, VRS and VAS.

4.4. Multimodal physiological features analysis

Multimodal physiological signals were collected in the experiment, including EDA, PPG, RSP and ECG, see Figure 5 of the physiological signals recorded in a video stimuli session.

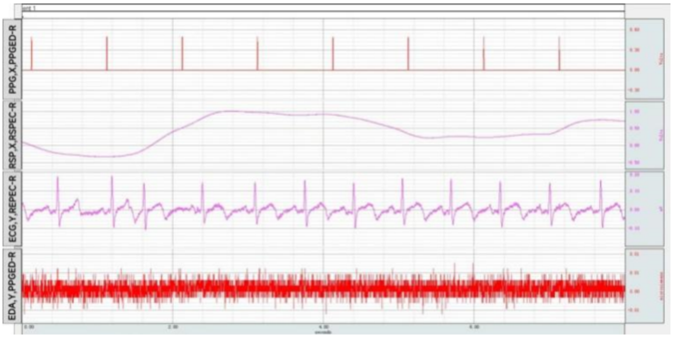


Figure 5. Multi-channel physiological signals were collected in pain stimuli experiment.

Then, the statistical features of multimodal physiology signals were applied for further modeling. The values of Average, Max, Min, Mean, Median, VAR (variance), STD (standard deviation) of the original signals were obtained to form the physiological feature dataset. Features were analyzed by CfsSubsetEvaluation method, which evaluates the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them. The experiment result shows that Min value of ECG, Average value of EDA, Median value of EDA and STD of EDA were the best features for predicting modeling. The detailed features are introduced in Table 1.

Table 1. Statistical features of the physiological signals

Feature	Description
EDA ECG PPG RSP	the statistical values of Average, Max, Min, Mean, ,Median, VAR, STD of the original signal

5. Results and Discussion

Others' pain will strike a chord in the observers' mind, and the affective response can be detected via physiology cues. In this study, we transformed the third-person pain learning question into the exploration of physiology feature analysis and modeling. Machine learning methods were applied to recognize different level of third-person pain experience based on multi-modal physiology features fusion.

5.1. Experiment results

LibSVM, RBFNetwork, LibLinear, RandomTree and RandomForest were applied to explore the model. In the results comparison, Random Forest has the best performance. According to this experiment, the third-person pain experience can be recognized efficiently by RandomForest, see Table 2.

Table 2. Third-person pain experience recognition results based on multimodal physiology features dataset

Algorithm	ACC	F-Measure	ROC	Parameters setting
LibSVM	0.8594	0.756	0.852	cost 9, gamma 2, seed 1,
RBFNetwork	0.8203	0.820	0.897	minStdDev 2, numClusters 10, Seed 1
LibLinear	0.6927	0.682	0.751	cost 1, eps 0.001, numDecimalPlaces 2
RandomTree	0.625	0.627	0.757	minNum 5, numDecimalPlaces 1, maxDepth 0, seed 1.
RandomForest	**0.9583**	**0.958**	**0.995**	Numiterations 100, bagSizePercent 100, seed =1

In the best model exploration, we compared LibSVM, RBFNetwork, LibLinear, RandomTree and RandomForest algorithms to develop the third-person pain recognition modeling. Among all the methods, Random Forest achieved an accuracy of 95.83% for the best performance, which indicated the great potential of this method.

5.2. Discussion

In this study, we investigated the possibility of third-person pain sensing utilizing multimodal physiology features fusion. The experimental results have indicated that RandomForest is effective in the third-person pain recognition modeling based on human physiology signals. This study offers possible avenue of developing computer the empathy ability of sensing the communication of pain between sufferers and the observer. And it could also provide insight for human empathy characters in social scene. In the experiment, 24 participants were invited in third-person pain stimulation and pain level labeling work. The model performance is satisfied based on the dataset of 384 third-person pain experience samples, which manifests the effectiveness of the proposed approach.

6. Conclusion and Future Work

Third-person pain was triggered by the transfer of cognition first-person pain. Sufferers' pain can be communicated to others by their facial expression, behaviors and voice. We considered that third-person pain is important socialization ability, and it can be investigated as a starting point for empathy ability mechanism.

In this study, we present a third-person pain learning model based on multimodal physiology feature analysis. A novel third-person pain physiology feature database of 384 samples was built in the experiment. Physiology features of EDA, ECG, PPG and RSP were extracted for pattern exploration. Several machine-learning approaches were utilized in the exploration of modeling, including LibSVM, LibLinear, RBFNetwork, RandomTree and RandomForest. Finally, RandomForest method achieved the best result among all the models, with a classification accuracy of 95.83%. The results of modeling experiment suggested that it is promising to develop computer empathizing pain-aware ability.

In the further study, we will conduct the third-person pain experiments and pattern exploration in several aspects. Firstly, a third-person pain aware system can be developed to verify the model. Secondly, a larger database of third-person pain physiology features will be built for method optimization. Finally, the discovery will be examined with interdisciplinary methods and extent the study to AI-empathy intelligence research as a broader scope.

7. Acknowledgments

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