Facial Expression Analysis for Estimating Pain in Clinical Settings

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ABSTRACT

Pain assessment is vital for effective pain management in clinical settings. It is generally obtained via patient's self-report or observer's assessment. Both of these approaches suffer from several drawbacks such as unavailability of self-report, idiosyncratic use and observer bias. This work aims at developing automated machine learning based approaches for estimating pain in clinical settings. We propose to use facial expression information to accomplish current goals since previous studies have demonstrated consistency between facial behavior and experienced pain. Moreover, with recent advances in computer vision it is possible to design algorithms for identifying spontaneous expressions such as pain in more naturalistic conditions.

Our focus is towards designing robust computer vision models for estimating pain in videos containing patient's facial behavior. In this regard we discuss different research problem, technical approaches and challenges that needs to be addressed. In this work we particularly highlight the problem of predicting self-report measures of pain intensity since this problem is not only more challenging but also received less attention. We also discuss our efforts towards collecting an in-situ pediatric pain dataset for validating these approaches. We conclude the paper by presenting some results on both UNBC Mc-Master Pain dataset and pediatric pain dataset.

Keywords

machine learning; pediatric pain; machine learning; regression; facial action coding system; expression analysis

Categories and Subject Descriptors

H.5.1 [**Information Interfaces and Presentation (e.g. HCI)**]: Multimedia Information Systems; I.4.9 [**Image Processing and Vision Applications**]: Applications; G.1.1 [**Numerical Analysis**]: Probability and Analysis

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1. INTRODUCTION

Pain is an unpleasant yet necessary signal that warns us of actual or impending bodily damage, and allows an individual to take action [8]. In clinical settings, this action could translate to patient diagnosis, medications or even a surgical procedure. Thus measurement of pain is imperative for effective treatment. Despite its significance, clinical pain is often misunderstood and underestimated, which makes its management difficult [8, 21, 24, 7]. It was also highlighted in a recent survey that pain management in children demands more attention due to lack of evidence based studies and also since ineffective pain management in children can lead to long-term undesirable effects [7].

Estimates of pain intensity are commonly obtained in clinical settings via self-report and behavioral measures [25, 22, 23]. The self-report measure allows an individual to verbally communicate the amount of experienced pain and suffers from several drawbacks such as subjective bias and patient idiosyncrasies. Moreover, it cannot be employed by verbally impaired patients. On the other hand, observational measures are based on inspecting non-verbal clues (such as the face, body or voice of an individual) related to pain for reporting pain intensity. Such measures are disrupted by the presence of observer's bias, considerable demands on clinicians time, and the influence of factors such as likability of patient [10], underestimation of pain [17]. Since pain is inherently a subjective and internal experience, self-report measures are preferred over others and considered the gold-standard for conveying pain intensity [23, 28, 6].

The field of facial expression analysis has recently seen significant progress due to advancements in machine vision. Several studies have shown that facial behavior can be used as a modality for predicting internal states such as mood, confusion, [13, 3]. Case studies on understanding pain have also established relationship between facial behavior and experienced pain. In particular the Facial Action Coding System (FACS) has been shown to provide objective indicators of facial expressions that are correlated with self-report measures of pain [17, 6]. Other works have also explored approaches for facial expression analysis that do not require FACS coding. These methods employed discriminative features such as Local Binary Patterns (LBP), Bag of Words (BoW), Active Appearance Model (AAM), for representing facial behavior [20, 16, 27].

Our work is focused towards developing an automated system for predicting pain. We propose to use facial expression information to objectify the process of both detecting and measuring pain intensity in clinical settings. Since pain is a complex signal such a system should be able to capture both the appearance variation and temporal dynamics of pain expression. This system will be evaluated on the task of predicting both postoperative ongoing pain and experimentally induced acute pain. Since appropriate datasets are required to validate computer vision algorithms for prediction pain, we are also collecting an in-the wild clinical dataset that could be used to validate the posed research question. Such automated methods for measuring pain intensity could be used to aid clinical staff in long-term patient monitoring. Moreover, machine observers could be used to alert clinicians to instances of pain and thus free up resources for more efficient allocation of clinical attention. Such systems are also useful in cases where verbal self-report ratings are not available.

2. RELATED WORK

Over the years there have been significant research efforts towards automatic facial expression analysis (AFEA). This progress has been fueled by improvements in fields such as computer vision and by the availability of research datasets such as Extended Cohn-Kanade (CK+) and UNBC Pain dataset [14, 15]. Initially the field focused on analyzing posed facial expressions, obtained under controlled laboratory settings, where subjects were instructed to perform certain expressions. The AFEA research is now shifting towards spontaneous expressions that differ from posed facial expression in a number of ways and are inherently challenging owing to head-motion, low-intensity expressions and temporal variations [3]. Since pain expression is spontaneous in nature, designing algorithms to recognize and quantify pain expression is a step forward in the research on AFEA.

A significant contribution towards research on spontaneous pain expression was the public release of UNBC-McMaster Pain dataset [15]. This dataset contains video sequences of subjects experiencing shoulder pain. They were asked to perform a series of active and passive movements of their affected and unaffected shoulders while being videotaped with a front-facing camera. Each sequence was annotated with several labels: (1) patient self-report, and (2) expert observers rating referred to as Observer Pain Index (OPI). The dataset also included FACS code for certain AUs for each frame. The first computer vision work on this dataset was to design a system to predict pain/no-pain for each sequence [2] and use the binarized observer ratings observers ratings (OPI) as the ground-truth. Their approach began by first extracting AAM based features from each frame. The AAM features from each video were then clustered and a video was represented by these cluster centers. This was followed by assigning the label of the video to each clustered frame and using the data was used to train a Support Vector Machine (SVM). During prediction the SVM classifier was used to assign a score to each test-frame. A video was classified as pain if the average score of its member frames was above a threshold. Lucey et al. [16] showed improvement on this work by compressing the AAM-based features using a Discrete Cosine Transform (DCT) instead of clustering them. Sikka et al. [20] later proposed multiple segment representation in combination with weakly supervised learning to address the inherent drawbacks in these approaches. Weakly supervised learning addressed the problem of label-level ambiguity introduced by assigning each frame the label of the sequence. Multiple segment representation was used to add temporal information in the decision process and also to handle the ambiguity in the location and duration of pain signal in a sequence. Their work showed significant improvement in performance over previous approaches.

Another problem addressed via this dataset involves continuous per-frame pain intensity estimation. The ground-truth employed for this task is the Prkachin and Solomon pain intensity index (PSPI) that combines intensities of four pain-related AUs and returns a pain intensity score between $0 - 16$. Kaltwang et al. [9] trained multiple regression models using relevance vector machines for shape and appearance based features. The outputs from these models were later combined to obtain a continuous estimate of pain intensity. Later Rudovic et al. [18] proposed a model based on Conditional Ordinal Random Fields to incorporate the ordinal nature of pain intensities and their temporal dynamics.

These studies focused on either predicting binary observer's ratings or anatomically defined pain intensity ratings such as PSPI. None of these studies targeted the problem of predicting self-report measures of pain intensity. This could be because alternate pain ratings seem to be more objective and have less subjective bias relative to self-report ratings. Moreover designing accurate machine learning based approaches for making continuous estimates of self-report measures, in clinical settings, requires a massive amount of data, which might be difficult to obtain. As discussed in the Introduction Section, however, self-report ratings are considered to be the primary source of information in clinics; this work places a special attention to the problem of predicting self-report measures.

2.1 METHODOLOGY

In this section we have discussed the data collection procedure, proposed approach and related technical challenges.

2.2 Data Collection

Data are being collected in collaboration with Rady ChildrenâĂŹs Hospital, San Diego, California. The participants for this study were children, aged between 5 and 18, who had undergone an appendectomy within the past 24 hours. The participants were selected without any history of medication in past six months and without any mental disorder.

Videos of study participants are recorded while they lay in an upright position on the hospital bed. Although care is taken to obtain the face video in frontal position, we observe significant out-of-plane head rotations. In order to collect pain behavior at different intensities, we record video samples at different times after the surgery. Samples for both ongoing pain (five minute rest period) and experimentally induced acute pain are collected. At the end of each pain period, the children are asked to provide pain ratings by pointing out a number between $0 - 10$ on the Numerical Rating Scale. Several studies have validated the use of NRS for recording children's self-report measures of pain intensity. We also obtain observer or proxy ratings from parents and nurses using the NRS. Both of them are asked to look at the participant and point out to a number on the NRS that corresponds to maximum severity of pain experienced by the children. Children's ratings were not available to the proxy participants.

We shall refer to this dataset as pediatric pain dataset. The data is currently being collected and a manuscript highlighting the data-collection procedure, population demographics and statistics will be released soon. As mentioned earlier collecting relevant data is one of the major challenges involved in this project. The data should not only adhere to certain guidelines but also represent the variability in input-output space for learning accurate models.

2.3 Automatic Facial Expression Analysis

AFEA approaches can be categorized into static, space-time and sequential approaches. A very similar taxonomy was also employed for classifying human action recognition in videos [1]. Static approaches work by first extracting static features such as LBP or Gabor in individual images (or video frames). This is followed by either a temporal pooling strategy or feature extraction from the apex frame in order to obtain a vector representation. Finally a ML classifier such as SVM is used for the AFEA task. Although these approaches happen to be the starting point for any AFEA system, they are not suited for spontaneous expressions since they fail to incorporate temporal information into the decision process. On the other hand, space-time approaches extract features by treating a video as a XYT volume, such as LBPTOP or spatio-temporal gabor [26]. Although these approaches perform better than static approaches, they still do not explicitly encode temporal information leading to performance loss. Moreover, as mentioned by Sikka et al. [20], such approaches are known to work well with uniform actions that span the entire video (CK dataset). However, their performance falls down when actions have high intra-class variations and are localized in the video (UNBC Mc-Master Pain dataset). Sequential methods model a video as a sequence of observations and employ dynamic models such as Hidden Markov Models for modeling both appearance and transitions space of a video or expression class [5]. These methods suffer from drawbacks such as over-fitting due to many parameters and poor generalization performance on unseen test data as the model is limited by underlying probabilistic assumptions. In this work we briefly discuss an approach for predicting self-report pain intensity measures using AFEA.

We propose to employ FACS-based image attributes for predicting self-report measures of pain. To meet the requirements of an automated system, the FACS code are computed using the Computer Expression Recognition Toolbox (CERT) [12]. CERT is a software tool that codes each frame in a video with respect to a set of continuous dimensions that describe facial actions from the FACS and also returns other parameters such as probabilities of 6 basic emotions and 3D pose information. CERT works by first detecting a frontal face in a video and warping it to a canonical frame. The registered face is then convolved with a gabor filter bank to obtain image features. These features, along with labeled data, are then used to train separate SVMs for each AU. During run-time these pre-trained models are used to report activations for different AUs in a face containing image. The CERT output for a segment containing facial expression will be a time-series for different AUs. Since training a ML model requires a vector representation for each sample, an approach is required to summarize the time-series into a compact vector representation. A static approach to accomplish this is to summarize the time-series using naive statistics, such as mean, maximum and minimum, followed by feature concatenation [11]. It is also possible to use space-time approaches, such as "bag of temporal features" as used by Bartlett et al. [4], for obtaining a vector representation. Since our system is expected to predict continuous outputs, we need to train an appropriate regression model. The regression model should be (1) robust to noisy self-report labels, and (2) robust to over-fitting since the available data is not sufficient to handle complexities in input and output space. This requirement could be made possible in any regression model by adding a penalty factor over learned weights and obtaining a sparse solution such as Relevance Vector Machines [9], $\epsilon-$SVM [19], regression based feature selection via AdaBoost.RT [19].

3. EXPERIMENTAL ANALYSIS

In this section we discuss the experimental analysis performed on both the pediatric pain dataset and UNBC Mc-Master Pain dataset.

3.1 Pediatric Pain Dataset

In order to substantiate the viability of the proposed method, we conducted some basic statistical analyses on a subset of the dataset. These analyses were used to test two specific hypotheses: (1) do AU measurements differ between pain and no-pain periods, and (2) are AU intensities and self-report measures correlated. These experiments were conducted on a subset containing 40 children, aged between 5-15 (mean age: 12 years), with their facial expressions recorded in clinical pain (within 24 hours of surgery) and no-pain (after clinical resolution) situations. This analysis was performed on the video segments corresponding to the 5 minute ongoing pain (or rest) period. These video segments were passed as input through CERT and activation for AUs related to pain were extracted (AUs $4, 6, 7, 9, 10, 25, 43$). The time-series for each AU was consolidated into a single number using the mean statistic. The pain ratings provided by children on NRS scale were used as the self-report ratings. We found in our results that the mean difference between pain and no-pain periods is statistically significant for AU4, AU 7, AU9, AU25 and AU45. The AUs that had significant correlation with self-report measures were AU4 (r=0.22), AU9 (r=0.47), AU25 (r=0.3) and AU45 (r=0.39). The testes are conducted at 5% significance level.

3.2 Self-Report Predictions on UNBC Mc-Master Pain Dataset

We designed a self-report pain intensity prediction task on this dataset (200 videos and 25 subjects), which assessed the ability of a system to predict pain intensity. Since our approach is based on FACS coding, the feature representation for this dataset was also constructed over FACS. This dataset is provided with manual FACS codes for several pain related AU (AU$4, 6, 7, 9, 10, 12, 20, 25, 26, 43$). The time-series for each AU was summarized using mean statistic and finally a video was represented by vector containing the mean measurement for different AUs. This feature representation was employed to train a regression model (SVM with rbf kernel) using self-report ratings on VAS scale as the ground-truth. The experiments were conducted in a leave-one-subject-out cross validation format by partitioning the data into subsets (called folds) that contain data from only one subject. The data from one fold were held for testing and the model is trained on the remaining folds, and the process was repeated for all folds. The first performance metric used for evaluation in this work was Mean Absolute Error (MAE), which is the mean difference between the predictions and the true labels. The second metric calculated the Pearson correlation coefficient between the predictions and the true labels. Instead of calculating metrics separately for each fold, we calculated them by concatenating the predictions from different folds into a single vector, as was done by Ashraf et al. [2].

The results for self-report prediction experiments on the UNBC Mc-Master Pain dataset are show in Figure 1 as a plot between true labels (X-axis) and prediction along with standard error (Y-axis). The plot reveals that (1) there is a positive correlation between the true labels and the predictions, (2) the trend between the true and the predicted labels is non-linear, and (3) local regions of constant predictions can be observed on Y-axis. Since the number of training samples is less for self-report ratings with higher intensity, the prediction error seems to increase with higher intensities. The MAE is 2.28 and the Pearson correlation coefficient is 0.51. The chance prediction in this experiment corresponds to predicting 5 (mean value of self-report intensities) in all cases. The MAE for chance classification is 3.05 and the correlation coefficient is undefined owing to zero variance in the predictions. This shows that the SVM-based regression is performing better than chance classification. It is also interesting to note that the correlation between Observers' ratings (OPI) and self-report is 0.66, which is higher than the correlation obtained using our model predictions. However it should be noted that these ratings were performed by expert observers and the correlation in case of inexperienced observers are known to be reduced [17].

3.3 Pain Detection on UNBC Mc-Master Pain Dataset

We would also like to highlight our recent work on automatic pain recognition in videos [20]. This approach tackled the joint problem of, (1) classifying the expression in a video as pain/no-pain, and (2) detecting pain in each video frame. The problem was challenging since the algorithm was trained with limited ground-truth that informed about only the absence or presence of pain in the video without any information about its location. Our approach consisted of using a latent model (called multiple instance learning) for learning visual patterns related to pain. This was combined with a novel method of representing each video as bags of multiple segments (or sub-sequences) in order to address temporal information. Rigorous experiments demonstrated that our method obtained state-of-the-art results on the task of pain classification compared to previous approaches. Moreover it was also able to achieve promising results on the task of pain localization compared to algorithms trained using complete ground-truth.

4. DISCUSSION

The results on the pediatric pain dataset highlight that certain AUs show a statistically significant difference between their measurements at pain and no-pain events and also have significant correlation with the self-report measures. We are hopeful that more data will allow us to perform more thorough analyses and yield interesting insights into the problem of predicting self-reports in pediatric pain. It is also evident from the results on the UNBC Mc-Master Pain dataset that machine learning models built over FACS coding are capable of predicting self-report measures of pain intensity. Moreover there are various way for extending the naive system presented in this paper and improving performance. Lastly our previous work on pain detection showed that the problem of estimating pain can benefit by using high-level machine learning approaches that can effectively encode the underlying assumptions in a problem.

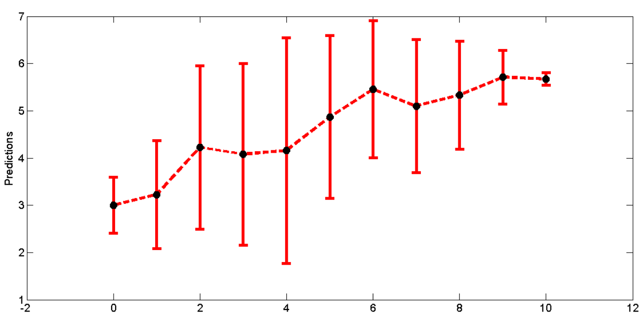

Figure 1: Plot between true labels and predictions for the task concerning prediction of self-report measures on the UNBC Mc-Master Pain dataset.

4.1 Progress and Future Work

We wish to explore multiple research avenues for the problem of estimating pain using AFEA. Firstly we are in the process of preparing a detailed manuscript for presenting our initial findings on the pediatric pain dataset. With this work we wish to explore interesting questions pertaining to AFEA for pain expression such as: (1) which action units contribute towards predicting self-report measures in pediatric population, (2) difference in facial behavior during ongoing and acute pain, (3) is it possible to design an automatic system that can perform equivalent or better than human observers such as parents and nurses, (4) possibility of using multiple source of pain intensity groundtruth such as self-reports and observer ratings, and (5) is it possible to predict time since surgery using facial expression information. In addition this work also requires working with robust regression models that can handle noisy labels and variations in data. As a future plan we plan to combine visual information along with Electrodermal activity (EDA) for predicting pain.

As an extension of our previous work on detecting pain using multiple instance learning, we are also investigating the application of various latent models for improving expression recognition in video in natural environments. This involves choosing apt underlying assumptions for a particular problem and also making the inference and learning procedures tractable. We believe that the analysis of the underlying patterns discovered by models involving latent variables will be of significant interest. We are also interested in discovering novel machine learning methods for modeling the temporal dynamics in a video. This would require either modifying previous algorithms to include temporal information as done by Sikka et al [20] or using robust sequential models [5]. The student is in the process of presenting his thesis proposal to a committee.

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