

Scope of physiological and behavioural pain assessment techniques in children – a review

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Pain is an unpleasant subjective experience. At present, clinicians are using self-report or pain scales to recognise and monitor pain in children. However, these techniques are not efficient to observe the pain in children having cognitive disorder and also require highly skilled observers to measure pain. Using these techniques it is also difficult to choose the analgesic drug dosages to the patients after surgery. Thus, this conceptual work explains the demand for automatic coding techniques to evaluate pain and also it documents some evidence of techniques that act as an alternative approach for objectively determining pain in children. In this review, some good indicators of pain in children are explained in detail; they are facial expressions from an RGB image, thermal image and also feature from well proven physiological signals such as electrocardiogram, skin conductance, body temperature, surgical pleth index, pupillary reflex dilation, analgesia nociception index, photoplethysmography, perfusion index etc.

1. Introduction: The children will encounter pain resulting from injuries, disease, after surgery and other health problems. The ‘International Association for the Study of Pain (IASP)’, an interdisciplinary organisation created in 1973 to study pain and better pain management through research, training and communication. The IASP defines pain as ‘an unpleasant sensory and emotional experience associated with actual and potential tissue damage’ [1].

Pain is a highly personal and individual experience. It can generally be classified as ‘acute’ and ‘chronic’ pain. Acute pain is intense and short-lived. Chronic pain is mild or intense, but holds out longer than acute pain. In general, if pain is untreated on time important signs such as heart rate (HR), blood pressure (BP), respiration rate, O₂ and CO₂ consumption level, secretion of cortisol, adrenaline, and glucagon, ‘blood sugar level might increase and SaO₂, gastric & gut motility may go down. Therefore, individual’s normal life is being impacted directly or indirectly. In spite of its influence, pain in adult as well as in children is often underestimated and untreated [1]. Valid and reliable pain measures are needed to discern out the patients who require intervention or to appraise the efficacy of intervention.

Measurement and evaluation of pain intensity level are being carried out by researchers mainly focusing on its applications in the medical field, especially in the area of pre- and post-operative drug administration. This Letter serves as a better mediator for detecting pain in children who are static, cannot speak or even commit to memory regarding the pain they experienced so far [2]. With reference to the literature, pain measures can be classified as self-report, behavioural and physiological measures [3–6]. Pain may be influenced by factors like gender, physical status, behaviour, emotional status, pain history, and cognitive impairment. By considering all these factors a proper pain assessment model has to be designed.

From the literature survey, it is understood that the physiological measures are one of the important types of pain measures which aid to interpret the pain in infants and in young children. The autonomic nervous system (ANS) is a particular factor which affects the function of internal organs as well as the physiological activities in the body. Hence, the bio signals [ECG, photoplethysmography (PPG), electrodermal activity (EDA), galvanic skin response (GSR) and

skin temperature] and their derivatives, which directly regulated the ANS activities, are used in this Letter. These signal changes are also prominent in the postoperative pain patients. In this Letter, parameters like surgical pleth index (SPI), pupillary dilation reflex (PDR) and analgesia nociception index (ANI) are also discussed, but these parameters can be used only during surgery to assess acute pain. A few other parameters like CARDEAN index are purposefully neglected since we focus only on parameters which are widely accepted for pain measurement study and it is also not very recent. These indicators are statistically significant parameters with respect to the presence of pain, but these measures can only give qualitative information. There are several challenges in interpreting physiological measures such as medication, pathological condition, treatments, stress/depression and fear of pain may directly impact these measures and reduces reliability in pain measurement. It is also influenced by the general health and age of infant/young children. From the literature, it is understood that determining the onset of pain by only using physiological signals is not appropriate. Therefore, it is used in conjunction with other measures for better results [7].

Self-report measures are considered as the ‘gold standard’ in the pain measurement. They can be in verbal or non-verbal formats. To generate the response either in the verbal or non-verbal format all the individuals should have proper cognitive and language development. Verbal self-report measures include questionnaires; interviews etc. and Non-verbal include facial expression scales, visual analogue scales etc. [4, 8]. The ability of the children to report and describe the pain increases with growing age and experience. Facial expression scales are used frequently with young children to acquire self-report of pain [9, 10]. The available self-reporting scales for neonates & children require careful administration of age and developmental issues. Pain intensity, emotional reaction, distress, anxiety, mood etc. limits self-report measures.

The most commonly used self-report measures for children are the categorical verbal rating scale, numerical pain rating scale and visual analogue scale (VAS) [11]. This kind of self-report measure will not be applicable for infants, very young children and children with cognitive or communication disorders. Therefore, behavioural measures are used as a proxy for objective pain measurement. This includes measures of crying, facial

expressions, and body postures or mixture of these parameters. These types of pain measuring scales are simple, easy and quick to administer by the caretakers. Interpretation of these parameters is often challenging as it might represent the general distress rather than the pain [12, 13].

Most commonly used behavioural measure in children is the facial expressions. To overcome the challenges faced during behavioural measures, the detailed coding of children facial expressions are required and it can be solved using computers. There are two motor pathways which control facial movements. They are (i) a sub-cortical extrapyramidal motor system and (ii) a cortical pyramidal motor system. The cortical pyramidal motor system response will deceive most of the observers [14]. However, machine learning will help the researchers to distinguish between the deceptive facial responses and genuine facial responses.

The other simple approach to recognise pain is by monitoring temperature variations. It is estimated that the temperature variation $>0.5^{\circ}\text{C}$ indicates a possible disease or a doubtful pain. Painful regions are related to temperature not only with its intensity but also with their neighbouring regions [14]. Pain spots can be of high or low temperature compared with their close regions of the skin. Though the authentic methods of determining pain using thermal images are not practically available, the option for a thermal variation to pain correlation seems to be an important consideration. One of the objectives of this Letter is to investigate whether the integration of biophysiological signals (ECG, skin conductance level (SCL), and PPG) and visual features from RGB & thermal images can be used to determine the onset and intensity of pain which act as a personalised pain monitoring system for children.

The remainder of this work is organised as follows. In the next section, some recent research works for recognising the pain in children using facial actions have been presented. In Section 3, few research articles on physiological signals (such as ECG, HR, BP, GSR, PPG, perfusion index (PI), SPI, ANI and PDR), which enumerate their relation to pain, are discussed. In Section 4, the literature on measuring pain using thermal images are reviewed. In Section 5, few standard datasets that can be used for this Letter are discussed.

2. Facial expressions and pain recognition: Most of the literature mentions facial expressions as a good indicator of pain. However, deceptive facial responses might be misinterpreted as genuine facial responses if the coding is done manually. Hence, machine learning algorithms are introduced to effectively distinguish between the deceptive and genuine facial responses.

The facial expressions can be successfully detected only when the face is properly recognised. Therefore, in this section, a few popular literatures are discussed to detect the face. Viola-Jones [15] have proposed an algorithm to detect the face in an image as well as in the video. It is the most popularly used algorithm, which uses Haar basis function to detect the face in an image as well as in the video. Yu-Bu Lee and Sukhan Lee [16] have proposed an algorithm to detect the human face based on skin colour. It detects faces directly by setting up a window and determining the colour signature in that window. Kin Choong Yow *et al.* [17] formulated an algorithm to detect the face by detecting the feature points in a face image. These extracted feature points are grouped together, and from that true candidates are selected to identify face. Jiaming Li *et al.* [18] research articles dealing with multiple feature selections in a face image by using the AdaBoost algorithm. This algorithm divides the face into sub-regions and their orthogonal components are extracted and used to point out nose, mouth and eyes. These features decide face in an image. Jeemoni Kalita *et al.* [19] proposed the use of eigenvectors for the detection of face. From my survey, all the above techniques can be used to detect face in children as well as in adults.

In this section, we have elaborated on few research articles which detects human facial expressions. Punitha *et al.* [20] proposed a technique to recognise the facial expressions using texture information on face and trained the texture features with support vector machine (SVM) to classify the facial expressions. Schiavenato *et al.* [21] study contributes pain recognition in the RGB video of infants using computer enabled point pair and NFSC facial action methods. The study by Patil *et al.* [22] provides the information on detecting the facial expressions using the wire frame model and active appearance model (AAM).

Research by Mansor *et al.* [23] deals with an infant pain detection technique which involves an autoregressive (AR) model and fuzzy neural network (NN) algorithms. The AR model achieved 90.77% accuracy. Yuan *et al.* [24] have proposed a new algorithm to extract facial expressions using boosted Gabor filters. It achieves a recognition rate of pain versus non-pain up to 88% accuracy [25]. Zhiguo Niu *et al.* [26] have formulated an algorithm to extract local self-related features called facial action to distinguish facial expressions. Finally, the SVM algorithm is utilised to classify facial expressions. Naufal Mansor *et al.* [27] have proposed a new technique to determine infant pain. They have used gray level co-occurrence matrix (GLCM) features for classification. Hybrid genetic neural network (HGNN) & linear discriminant algorithm (LDA) are the classifiers used for the study and found HGNN as the best classifier. Naufal Mansor *et al.* [28] proposed a combination of phase congruency, local binary method and sparse method to determine pain. They have achieved 88% classification accuracy.

In previous sections, we have discussed on the extraction of general facial expressions. Understanding the facial expressions of pain by just looking at the images for a whole sequence is too coarse and it cannot be applied practically. In 2008, Prkachin and Solomon [29] proposed a technique to measure the level of pain intensity and it is termed by Prkachin and Solomon pain intensity (PSPI) scale based on the facial action coding system (FACS). Zamzami *et al.* [30] have proposed a technique to determine pain in videos of infants. It uses K-nearest neighbours (K-NN) algorithm and SVM to classify infant's expressions into pain and no-pain. It provides classification accuracy of 96 and 94% for both the classifiers. In 2016, Hong *et al.* [31] have adapted a second-order standardised moment average pooling method to extract facial features from separate frames. Recently, deep learning techniques have been used to collect the required features from separate frames as well as among adjacent frames. Jing Zhou *et al.* [32] have used the AAM to detect and track features of the face. Then, the sliding window technique is applied along the video to achieve fixed length input samples to the recurrent network. Finally, recurrent convolutional neural network (RCNN) is used to predict the pain intensity.

3. Physiological signals and pain recognition: Physiological measures represent another type of pain measure. To understand the pain in subjects, physiological measures such as ECG, PPG, SPI, ANI, PDR, HR, SpO₂, SCL, and PI are used [33]. In 1974, Peter Bankart and Elliott carried out experiments on a few healthy subjects with shock trials and their HR and SCL variations were examined. They inferred that the variations in both HR and SCL were significant and consistent under the pain condition for all the trials. Rapid habituation was evident in the case of HR with increasing trials and hence concluded to be biphasic whereas the SCL was rising monotonically. Owens and Todt [34] conducted a study on measuring the HR and crying responses of infant to different events like Heel Lance, or tactile stimulation through a non-invasive method and random stimulation. The major limitation of the procedure was the differences in responses to the stimulation for different age and sex groups. In infants, it showed a considerable variation in HR and crying was evident in each individual. In 2005, Seitsonen *et al.* proposed a hypothesis on the variation of ECG, PPG and

electroencephalography (EEG) during a study conducted on 31 women. The pain simulation was given in terms of skin incision using a knife and the variables were observed for both pre- and post-simulation for 2 min duration and their absolute difference was found out. Results showed significant differences in EEG, ECG and PPG before and after simulation.

Ahmed Hasanin *et al.* studied to find out the performance of PI in pain assessment. In this Letter, the pain index was measured by using the behavioural pain scale for non-intubated (BPS-NI) patients to compare the ability of PI to determine pain. They found that there was a significant decrease in the PI level compared with the baseline readings during pain. A better correlation result was obtained between the change of PI and the change of BPS-NI after the application of pain stimulus.

Loggia *et al.* performed intense heat stimuli over 39 healthy male candidates [35] and the associated HR, SCL, and verbal ratings were noted for the pain study. This Letter screened considerable variation in SCL and HR for the patient in pain after the stimulation and the utmost response was found soon after the stimulation is withdrawn. This Letter infers HR acts as a superior predictor of pain in subjects than the SCL. Marco *et al.* recently attempted to quantify pain with recorded biopotentials using feature extraction methods. Nearly 135 features were extracted out of which (i) peak to peak electromyography (EMG) corrugator, (ii) corrugator Shannon entropy, and (iii) heart rate variability (HRV) were given more importance in this Letter. One recent study includes the measurement of HRV and PPG derived parameters based on a pain model developed using ramped thermal stimulation, while frequent changes in BP and delayed signal processing limited the study [36]. Boser *et al.* studied different pain thresholds and graded them using both the support vector machine (SVM) classification and statistical analysis. SVM outperformed the statistical techniques in the quantification results. In addition, the same group published their revised pain intensity quantification using SVM techniques by including 'similarity' features with more accurate results.

Hamunen *et al.* studied the role of PPG pulse wave amplitude (PPGA) in assessing pain. They have measured PPGA, SPI and ANS state index (ANSSI). In this Letter, 29 healthy participants subjected to two heat stimulus and one cold stimulus were selected. They found that PPGA and its derivatives have shown a significant change with an increase in SPI and ANSSI and decrease in PI for all stimuli. Therefore PI and its derivatives can be used to assess the perioperative pain.

There are a few other parameters used for determining post-operative pain in children. They are SPI, ANI and PDR; these parameters are discussed in detail in the forthcoming section. SPI is the measure of patient's hemodynamic responses to nociceptive stimuli and analgesic medications. Ledowski *et al.* concentrated on the skin conductance (SC) and surgical stress index (SSI) to assess the post-operative pain. They recorded enough readings for no or mild pain, moderate pain, and severe pain and found that SSI failed to show promising results in the detection of moderate or severe acute post-operative pain [37]. The same team also emphasised the correlation between SPI, postoperative pain and arousal. A measure of SPI, HR, mean arterial pressure and entropy were recorded for last 10 min of surgery and the same recordings are examined after shifting patients to the postoperative ward until the patients were awake. From this observation, SPI was affected by the arousal (SPI increases from the cut-off value of SPI) and not predicting post-operative pain. An SPI value of 30 (cut-off value) will be a useful predictor of pain only when obtained during the last minutes of surgery.

Thee *et al.* studied SPI for the assessment of postoperative pain. In this Letter, pain measurement was done for no or mild pain, moderate pain and severe pain categories where they measured sympathetic activity from HR, BP, SC and SPI and found SPI measurement directly related to pain during general anaesthesia.

However, only moderate results were obtained under awake conditions [38].

Sabourdin *et al.* conducted a preliminary study on measuring ANI of children under general anaesthesia. This parameter decreases during a nociceptive stimuli mostly in lower dose analgesics. Individual ANI profile variation and absence of randomisation of target drugs limited the study. Ledowski *et al.* compared ANI scores with numeric rating scale (NRS) to measure post-operative pain and found that ANI was not effective for acute postoperative pain measurement during general anaesthesia. Only 50% sensitivity and specificity were achieved in distinguishing between no versus severe pain [39]. Boselli and Jeanne found that the ANI is a 0–100 index derived from HRV; it is the continuous measurement of the parasympathetic tone. This parameter can determine an analgesia/nociception balance. Higher values reflect parasympathetic activity and lower value correspond to nociception. When ANI was compared with NRS, significant negative correlation results were obtained [40].

Constant *et al.* tested whether the PDR might allow assessment of noxious stimulation and analgesic effect in children present in their study, pupillary dilatation (PD) increased significantly after noxious stimulation or opioid effect. PD is a more sensitive index of noxious stimulation than the commonly used variables of HR, arterial BP and bispectral index (BIS) in anaesthetised children and is independent of age [41].

Mourad Aissou *et al.* have hypothesised that PDR is significantly correlated with the pain intensity index and could guide the morphine administration in the immediate postoperative period. In this Letter, 100 patients are involved. This parameter is measured using a pupillometer. There are few issues faced during PDR measurement, one problem is that the interaction with ambient light. Another one is it is measured for a short while after surgery, because pain is influenced by anaesthetic medication. It is also affected by age, gender and type of surgery; therefore these parameters should be taken into account while measuring PDR [42]. Nadelson *et al.* have postulated that PDR can be used as an alternative approach to ANI for the assessment of postoperative pain. This technique uses an electric stimulus to achieve pupillary variation of 13%. It is a very simple technique to measure nociception. This technique is far better than ANI as it is influenced by psychological factors.

Jang *et al.* [43] proposed a study to differentiate three emotional states (frustration, pain and surprise) from physiological signals using machine learning algorithms. 217 subjects were involved in this Letter. From each subject 30 s data were collected and extracted features (statistical & geometrical in the time & frequency domain) from physiological signals (ECG, EDA, PPG, and skin temperature (SKT)). K-NN, LDA, SVM and decision-tree classification algorithms are used for classification. LDA outperformed all with a best classification rate of 74.9%. Lopez-Martinez and Picard [44] extracted 12 SC and five HR features from the BioVid database for the measurement of pain intensity based on the multi-task neural networks algorithm developed using deep learning frameworks tensor flow where 82.75 and 70.0% classification accuracy was ensured for SC and ECG features, respectively.

4. Thermal images and pain recognition: Hooshmand *et al.* applied infrared thermal imaging (ITI) for studying the thermal changes during a neuropathic pain. ITI comprehensively analysed the thermoregulatory activities for a neuropathic pain with the fact that ITI performed well in studying the surface skin temperature when compared with any other test that addresses autonomic thermal changes. The Letter points out ITI to be a better tool for not only determining superficial temperature but also for the analysis of in-depth thermal variations [45].

Another study of the same group found that being free from the effect of ionising radiation, thermal imaging serves as the best tool for the detection of breast cancer and pain, and hence thermal

changes can be studied to evaluate the pain and its intensity. Thermographs of patients were taken and pain assessment was done based on the unsymmetrical distribution of temperature from the normal symmetric pattern usually seen in healthy people. The collected images were then digitally processed and results showed high specificity [46].

Functional infrared images of the head, neck and upper dorsal at rest as well as after maximal voluntary clenching were obtained and evaluated for the diagnosis of myofascial pain (MP) by Merla *et al.* [47]. Temperature differences between sides at each time (ΔT_s) and between times for each side (ΔT_t) were calculated. This Letter shows that ΔT shows a dramatic increase in affected MP patients in all cases. This Letter reveals that temperature variation is significantly higher in patients with MP when compared with healthy people and showed an asymmetric thermal pattern.

In 2015, Bardhan *et al.* proposed that the infrared thermal images can be used for the inflammatory pain detection [48]. Any pathological abnormality can induce temperature changes in the human body. Hence, an inflammation in the skin causes abrupt changes in temperature and is radiative so that they can be perceived using an infrared detector. In this work, the authors have attempted to detect the pain due to the inflammation using infrared thermal images of more than 500 patients with neuropathic pain and some controlled volunteers.

In the same year, Irani *et al.* proposed a method for multi-model dynamic recognition of pain from RGB, depth and thermal images for three levels of pain. While RGB favours the human perception analysis (i.e. detecting face and facial landmark positions), depth analysis provides subtle changes in the expressions of the face with temperature changes being investigated through thermal images. In a word, they have fused the three types of images, extracted all the valuable information and thereby enhanced the possibility of automatic assessment of pain. The proposed method claimed to be effective for 'no pain' and 'weak pain' categories with 8 and 16% significant improvement from the previous methods while this method did not support 'strong pain' assessment efficiently [49].

5. Integrated system: Kachele *et al.* conducted a multimodal analysis for the measurement of pain when they integrated both the bio potentials and facial expression images by extracting a large set of features to determine the pain intensity [50]. The BioVid heat pain database [51] was used for the study and the features were extracted for all the signals like ECG, EMG, SCL and facial images and classified by means of 'random forest classifier'. This Letter recommends a person independent pain intensity estimation using multimodal analysis with ample accuracy for stronger pain. In 2016, a similar method was proposed by another group of researchers [52], who included body movement and crying sounds [53], claiming an accuracy of 95%.

6. Databases: For the practical work in pain recognition, many researchers used the UNBC-McMaster Shoulder Pain Expression Archive [54]. It is a publicly available image dataset with pain measures. It consists of 129 subjects which comprises of 63 males & 66 female candidates. This dataset is produced by two methods one is by initiating shoulder rotation by subject themselves and another method is by initiating shoulder rotation by a physiotherapist. For every movement, subjects have scaled their pain using the VAS and also video of each movement trial was then graded by a proficient coder using the FACS and PSPI coding techniques.

BioVid heat pain database [51] is another dataset, which is an integrated collection of both biopotentials (ECG, EMG and SCL) and video signals. Walter *et al.* published this multimodal dataset in 2013 including 90 participants from three age groups.

The pain was introduced to the subject and after setting four pain levels, the responses were recorded. Later on, they carried out a multi-model analysis for pain classification using the same data set.

7. Challenges & future work: When we discuss the challenges, the key point to be considered is patient's cooperation, real-time data capture and the dependence of biopotentials on other factors. In the case of pain via facial expression, the foremost confrontation the investigators faced is the capturing of spontaneous facial expressions of the subject. The limitations are in recording the same if the patient is conscious of the fact that his or her face is being captured. Secondly, data labelling in the machine learning approach will be exigent since its more error prone and tedious. Researchers may face some limitations in correlating the pain level to the biopotentials because they are multi-dependent. Finally, the observers might face the trouble of artefacts since the subject may not be static when they are in pain.

The researchers have to pay attention in bringing up an intelligent system which can adapt and predict the pain, even if few expressions failed to spot due to patient's movement. Introducing an automated pain detector with high accuracy and a progressively faster system which could even spot micro expressions and is also being able to extract the features more precisely would be another target for the next generations. The bio signals used for pain estimation should be more specific rather than selecting some random factors. Also, these signals should be correlated precisely with the other measurement factors in pain estimation. To make the objective measurement of pain more defined and strong, it would be suggested if researchers focus on multimodal analysis (facial expressions and biophysiological signals) with complex data learning techniques like deep learning and other big data analysis.

8. Conclusion: This report represents a literature study of the various techniques involved in recognising the pain in children. At present physicians are using subjective scores for measuring pain of any individual and also uses physiological parameters to some extent when the subjects are seduced but these measures are not an ideal method of recognising pain. Hence, computer-based pain recognition systems are developed. As discussed earlier, we can recognise pain in humans using facial expressions, but reliable pain recognition by computer using facial expressions is still a challenge. Most of the computer-based pain detection systems using facial expressions are affected by parameters such as gender, age and ethnicity and also distractions like glasses, different hair styles, facial hairs and different lightening conditions. While considering only physiological signals to measure pain, again it is not an ideal method of recognising pain as it is directly affected by the medication, pathological conditions, treatments, fear and the stress/depression of the subjects. Considering only thermal images for measuring pain is not feasible. Therefore, the data fusion of biopotentials with video signals will be a significant contribution to the quantification of pain. Hence, to conclude, multimodal analysis using big data techniques would be the most suggestible pain estimation method for the future.

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