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An Approach for Automated Multimodal Analysis of Infants' Pain

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***Abstract*—Current practices of assessing infants' pain depends on the observer's subjective and potentially inconsistent judgment and requires continuous monitoring by care providers. Therefore, pain may be misinterpreted or totally missed leading to misdiagnosis and over/under treatment. To address these shortcomings, current practices can be augmented with a machine-based assessment system that monitors various pain cues and provides an objective and continuous assessment of pain. Although several machine-based pain assessment approaches have been introduced, the majority of these approaches assess pain based on analysis of a single pain indicator (i.e., unimodal). In this paper, we propose an automated multimodal approach that utilizes a combination of both behavioral and physiological pain indicators to assess infants' pain. We also present a unimodal approach that depends on a single pain indicator for assessment. Recognizing pain using a single indicator yielded 88%, 85%, and 82% overall accuracies for facial expression, body movement, and vital signs, respectively. Combining facial expression, body movement, and changes in vital signs (i.e., the multimodal approach) for assessment achieved 95% overall accuracy. These preliminarily results indicate that utilizing both behavioral and physiological pain indicators could provide a better and more reliable assessment of infants' pain.**

I. Introduction

Pain is defined as: "The unpleasant sensory and emotional experience caused by an actual or a potential tissue damage or injury" [1]. The assessment of pain helps care providers to understand patients' medical conditions and develop suitable treatments. However, the assessment of pain in infants can be difficult, because it requires a continuous monitoring by care providers and depends on the observer's bias. Care provider misinterpretation or lack of attention to infants pain may lead to misdiagnosis and over or under treatment. Therefore, it is crucial to utilize an accurate and continuous assessment of infants' pain.

Several traditional pain assessment scales have been developed to evaluate pain and estimate pain intensity. The most popular assessment scale is the patient self-evaluation in which the patient provides a verbal description of his/her pain intensity. Another scale to nonverbally communicate pain is the Visual Analog Scale (VAS), which has faces or numbers for different levels of pain [2]. Although the verbal and non-verbal self-evaluation of pain is the gold standard for assessing pain, they are not applicable for individuals with communicative/neurological impairments (e.g., dementia) and infants. To assess pain in this population, care providers observe specific behavioral and physiological (e.g., changes in vital signs) indicators that are related to pain [3], [4]. Figure 1 summarizes the common pain indicators that are considered when assessing infants' pain.

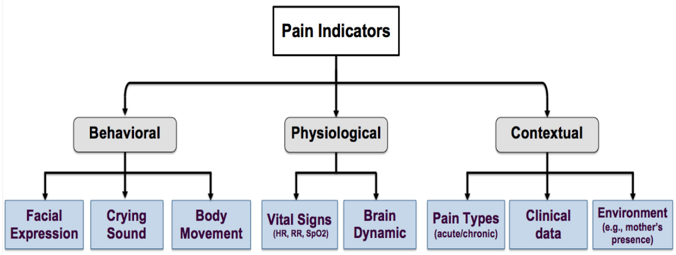

Fig. 1. Tree diagram for various pain indicators.

Assessing pain using the traditional indicator-based scales may not be efficient or reliable since it is noncontinuous and threatened by variation in clinical judgment, which can lead to poor treatment. Studies have found that poor treatment of infants' pain might cause permanent neuroanatomical changes, developmental, and learning disabilities [5], [6]. A possible way to provide an objective and continuous pain assessment is to develop an automated system that observes and analyzes different behavioral/physiological indicators related to pain. This system can be used by care providers in the neonatal intensive care unit (NICU) to continuously assess pain. It can also be used in homes as a pain-monitoring system or in the developing countries where medical professionals and resources are scarce.

Several works have been presented to assess infants' pain using signal processing and machine learning techniques. One of the first works, known as the COPE project, to assess infants' pain based on analysis of facial expressions is presented in [7]. The accuracy of classifying facial expressions as pain/no-pain expression using standard classification methods (e.g., SVM) was approximately 88%. Other works that used COPE dataset to analyze pain expressions in infants are presented in [8], [9]. A noticeable limitation of these works is the use of a 2D static images dataset (COPE) to classify facial expressions of pain. Static images ignore the expression's dynamic and temporal information and therefore developing a method to dynamically measure and classify pain expression was needed.

Zamzmi et al. [10] presented an optical-flow based algorithm to detect and classify pain expressions from video sequences of infants undergoing acute painful procedures. The algorithm yielded 96% accuracy in classifying facial expressions as pain/no-pain expressions using K-nearest-neighbors classifier. Another behavioral pain indicator that has been used to assess pain automatically is crying [11]–[13]. We are not aware of any existing machine learning based approach that analyzes infants' body movement automatically for the purpose of assessing pain.

Various methods are presented to assess infants' pain based on analysis of physiological pain indicators. Lindh et al. [14] proposed a method to assess pain in infants undergoing heel-lancing procedure by analyzing heart rate variability (HRV) and heart rate mean (HR_{mean}) in frequency domain. The results from the statistical analysis performed on the extracted heart rate data showed a significant increase in HR_{mean} during the heel-squeezing painful event. Other automated methods that analyze physiological indicators of pain can be found in [15]–[17]. As a side note, pain recognition using machine learning methods is a wide area of research, but since this paper presents a method for analyzing infants' pain, we focus primarily on related works that analyze pain for infants population.

Although there are several machine learning based approaches to assess infants' pain, existing approaches utilized a single pain indicator (i.e., unimodal) for assessment. Studies [18], [19] have found that pain causes behavioral and physiological changes and suggested to consider both changes when assessing infants' pain. Also, it has been found [18], [20] that physiological changes such as an increase in heart rate are less specific for pain (i.e., they can be associated with other emotional conditions such as discomfort or stress), and thus are not sufficient for pain assessment. Additionally, some infants have limited ability to behaviorally express pain due to specific disorders or physical exertion (e.g., exhaustion after a surgery). Therefore, we believe it is important to consider both behavioral and physiological pain indicators for assessing infants' pain.

In this paper, we present an automated approach to dynamically measure and assess pain in infants based on analysis of behavioral and physiological pain indicators. Specifically, we present a decision-level fusion approach that combines infants' facial expression, body movement, and vital signs modalities to classify the infant's state into no pain, moderate pain, or severe pain. As far as we know, we are the first to propose a multimodal machine learning based approach that combines several behavioral and physiological modalities for automatic recognition of infants pain. Figure 2 depicts a general overview for the multimodal pain assessment system (MPAS) we are proposing.

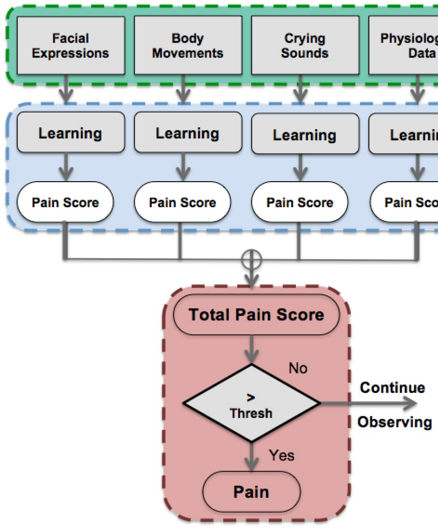

Fig. 2. Multimodal Pain Assessment System (MPAS)

II. METHODOLOGY

A. Facial Expression

Our method to evaluate facial expressions exploits the non-rigid facial motions that occur during facial expressions to estimate the magnitude of facial tissue deformations (i.e., strain magnitude) [21], [22]. There are two ways to estimate the strain magnitude: (i) integrate the strain definition into the optical flow equations, or (ii) derive strain directly from the flow vectors. Since the second method allows post-processing the flow vectors before calculating the strain (i.e., reduce the effects any errors incurred during the optical flow estimation), it is used to estimate the optical strain. The equations to compute the flow vectors and the strain magnitude (ϵ_M) can be found in [21], [22].

The strain-based method that is used to detect facial expressions of infants consists of two main stages: (i) face tracking, and (ii) expression segmentation. Figure 3 provides an overview of the strain-based method to detect and extract facial expressions' features.

In the face tracking stage, the infant's face in each video frame is detected using a Viola-Jones face detection method [23]. We built an infant's face classifier (i.e., using a cascade of boosted Haar-like classifiers) trained with images of infants' face under different poses and occlusions. The classifier was able to successfully detect faces with frontal/near-frontal views. Faces with severe poses/strong occlusions were missed and thus are excluded from further analysis. After the face images were obtained, we applied the facial landmark points algorithm implemented in [24] to extract 68 points. These points are used then to align the face, crop it, and divide it into four regions as illustrated in Figure 3.

The algorithm for facial expressions segmentation consists of the following steps. First, optical flow is calculated between consecutive frames of a video for each region of the face. Then, optical strain is estimated over the flow fields to generate the strain components of the strain tensor. Next, the strain

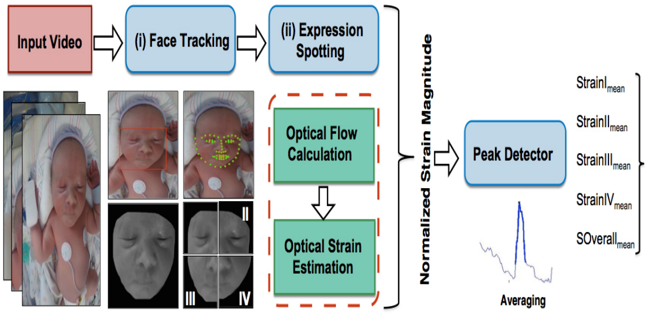

Fig. 3. Facial expression segmentation based on strain analysis

magnitude (ϵ_M) is calculated for each region of the face along with the overall face region; each region generates a sequence corresponding to the amount of strain observed over time. Lastly, a peak detector method is applied to the strain plots obtained for each region from I to IV to detect the points of maximum strain, which correspond to facial expressions. To form the features vector for classification, we compute the mean of the strain values for each of the segmented expression (i.e. $StrainOverall_{mean}$, $StrainI_{mean}$, $StrainII_{mean}$, $StrainIII_{mean}$, and $StrainIV_{mean}$).

B. Body Movement

Our method to detect and evaluate body movement depends on the motion image. Motion image is a simple and efficient method to estimate an infant's body movement in video sequences [25]. It identifies the change of each pixel value between consecutive frames. Each pixel in the motion image $M(x, y)$ has a value of 0 to represent no movement or 1 to represent movement.To analyze the infant's body movement, we computed the motion images between consecutive video frames. Then, we applied a median filter to reduce noise and get the maximum visible movement.

In assessing infants' pain, care providers focus on observing the amount of body movement along with the speed and pattern. Hence, we used the amount of body motions in each video frame as the main feature for analyzing infants' body movement. This feature is computed as follows:

$$A_m = \frac{1}{N_x N_y} \sum_{x=1}^{N_x} \sum_{y=1}^{N_y} M(x, y) \tag{1}$$

Where N_x and N_y represent the image's height and width. Figure 4 displays the amount of motion as a curve plotted over frames for an infant in a pain state; the curve that represents the amount of motion for the same infant in normal state ranges from 0 to 0.0005. To find the total amount of motion in each video sequence, we summed A_m as:

$$Total_{motion} = \sum_{k=1}^{F} A_m^k \tag{2}$$

Where F is the total number of frames. For classification, thresholding is applied on $Total_{motion}$ to classify body movements as pain related movement (score of 1) or no pain related movement (score of 0).

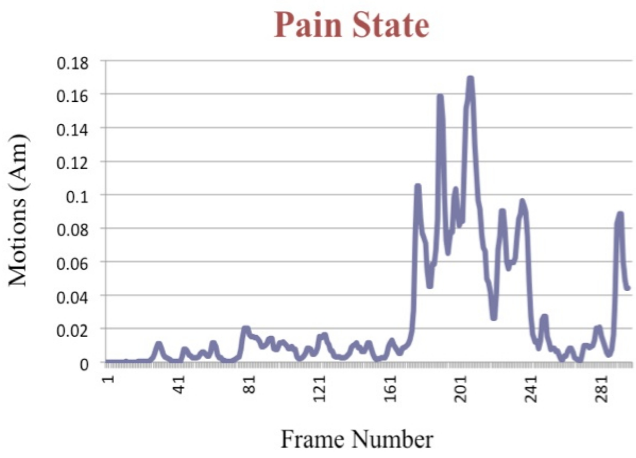

Fig. 4. Motions A_m per frame for an infant in a pain state

C. Vital Signs

The steps to assess pain using vital signs (VS) data are summarized as follows: 1) VS data (i.e., heart rate *HR*, respiratory rate *RR* and oxygen saturation levels *SpO2*) were extracted from the VS monitor; 2) These numbers were filtered and averaged to get three features, which are HR_{mean}, RR_{mean}, and $SpO2_{mean}$.

III. Implementation and Results

In this section, we discuss our dataset and the recording procedure. Then, we describe the score predication for various pain indicators, namely facial expression, body movement, and vital signs. We also present unimodal and multimodal approaches to assess infants' pain and report their results.

A. Data

Various behavioral and physiological pain indicators were recorded in NICU at Tampa General Hospital. Specifically, facial, vocal, and vital signs data were recorded for eighteen infants (Dataset1); age of the infants was 36 [32, 41] (avg. [min, max]) gestational weeks. Twelve infants out of the eighteen had their body (i.e., arms and legs) recorded along with the facial, vocal, and vital signs data (Dataset2).

The recorded infants were receiving routine painful procedures (e.g., heel lancing) during their hospitalization. Prior to recording the painful procedure, informed consent was obtained from the infant's parents. The painful procedure's recording is divided into seven time periods:

- T0: 5 minutes pre-procedure to provide the baseline state.
- T1: actual painful procedure (e.g., heel lancing).
- T2: 1 minute after the completion of the painful procedure.
- T3: 2 minute after the completion of the painful procedure.

- T4: 3 minute after the completion of the painful procedure.
- T5: 4 minute after the completion of the painful procedure.
- T6: 5 minute after the completion of the painful procedure.

NIPS (Neonatal Infant Pain Scale) pain scores were documented by a trained nurse at the beginning of each time period to provide the ground truth labels. The score for each of the pain indicators is 0 or 1 except for crying pain indicator, which is scored as 0, 1, or 2. After documenting the score for each of the pain indicator, the scores were combined to predict the infant's final state as no pain, moderate pain, or severe pain. In this paper, we analyze infants' pain using only facial, body, and vital signs data; we are currently developing a method to analyze infants' sounds and incorporate it as a modality for pain assessment.

B. Infant Pain Assessment

Using the above-described datasets, we predicted the score for three pain indicators: facial expression (score of 0 or 1), body movement (score of 0 or 1), and vital signs (score of 0 or 1). Then, we used each of these indicators individually (i.e., unimodal) to predict the infant's final state as no pain (class 0), moderate pain (class 1), or severe pain (class 2). In the multimodal approach, a decision-level fusion of behavioral and physiological pain indicators is used for pain assessment; this automated and multimodal approach is similar to the current practice for assessing infants' pain in NICU. Both unimodal and multimodal approaches along with the score predication are discussed below.

1) Score Prediction: To classify the facial expression of infants as pain expression (score of 1) or no pain expression (score of 0), the strain-based algorithm discussed previously (Section II-A) is applied to extract five features (i.e., $StrainOverall_{mean}$, $StrainI_{mean}$, $StrainII_{mean}$, $StrainIII_{mean}$, and $StrainIV_{mean}$) for each expression in Dataset1. The extracted features are then used to train different classifiers, namely K-nearest-neighbors (KNN), support vector machine (SVM), and Random Forest trees.

To evaluate the trained model and estimate its generalization performance, we performed leave-one-subject-out cross-validation (LOSOXV). For each training fold, feature selection was performed to select the most relevant features. KNN achieved the highest accuracy (91%) in classifying the facial expression as pain expression (score of 1) or no pain expression (score of 0); no pain expressions are the expressions occurred during no pain epochs. The first row of Table I shows the performance measures. The confusion matrix is given in Table II.

It is worth pointing out that the lower accuracy compared to our previous work (96%) might be attributed to the model evaluation method, which is LOSOXV. As discussed in [8], LOSOXV evaluation method is considered more realistic for pain assessment in clinical applications, but it can lead to lower classification accuracy. Another reason might be the inter-infants variation in expressions due to their age, health status, or habituation of the infant to the pain stimulus.

TABLE I
PERFORMANCE FOR SCORE PREDICATION

	Accuracy	Recall	Precision
Facial Expression	91%	87%	89%
Vital Signs	96%	97%	94%
Body Movement	92%	89%	90%

TABLE II
FACIAL EXPRESSION

N = 116	Score 0	Score 1
Score 0	85	4
Score 1	6	21

TABLE III
VITAL SIGNS

N = 116	Score 0	Score 1
Score 0	74	5
Score 1	0	37

TABLE IV
BODY MOVEMENT

N = 116	Score 0	Score 1
Score 0	66	3
Score 1	4	18

For vital signs analysis, Dataset1 is used to extract three features (i.e., HR_{mean}, RR_{mean}, and $SpO2_{mean}$) as described in section II-C. These features are then used to train Random Forest trees. For the classifier evaluation, LOSOXV was performed as discussed above. The second row of Table I shows the classifier performance; the confusion matrix is shown in Table III.

To predict the score of the body movement indicator, the total motions $Total_{motion}$ feature is extracted from each video sequence (i.e., pain/no-pain epochs) in Dataset2. Thresholding is then applied on this feature to predict the score. The accuracy of classifying the infant's body movement as pain related movement (score of 1) or no pain related movement (score of 0) is 92% (Table I, third row). The performance is shown using a ROC curve (Figure 5) comparing the true positive rate (TPR) and false positive rate (FPR), by varying the threshold; the confusion matrix is presented in Table IV.

To summarize, the results of predicating the scores for facial expression, body movement, and vital signs pain indicators are presented. The overall accuracies are 91% and 92% for facial expression and body movements, respectively; vital signs achieved the highest accuracy, which is 96%. It is important to note that this result is for the score predication of vital signs readings as 1 (i.e., change in vital signs) or 0 (i.e., no change) but not for the final assessment of infants' pain. As discussed in [26], changes in vital signs are not specific to the presence or absence of pain since they can be affected by underlying illness, homeostatic changes, medications, and other factors. Using vital signs readings to assess an infant's final state does not give the highest result, as we will see in the next subsection.

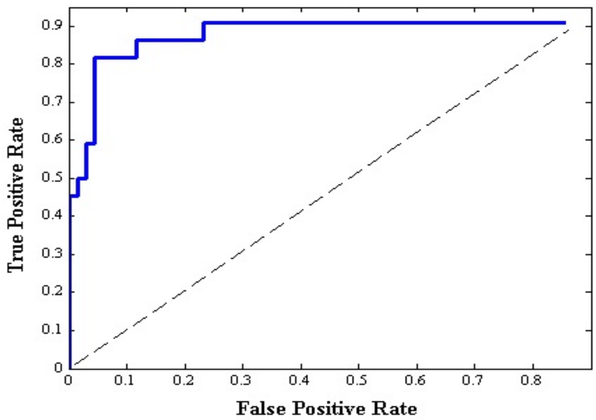

Fig. 5. ROC Curve for Body Movement Indicator

2) Unimodal Infant Pain Assessment: In the unimodal assessment, each of the pain indicators is used individually to predict the infant's final state as no-pain (class 0), moderate pain (class 1), or severe pain (class 2). For facial expression indicator, the five strain features are used to train different state of the art classifiers. To analyze the association between changes in vital signs and pain, HR_{mean}, RR_{mean}, and $SpO2_{mean}$ features were extracted and used to train random forest trees. Classifiers of both pain indicators are evaluated using LOSOXV evaluation method. The body movement's feature $Total_{motion}$ was also used to predict the infant's final state. The first three columns of Table V summarize the results of assessing pain in infants using each of the pain indicators individually.

As shown in Table V, facial expression achieved the highest overall accuracy (88%) in predicating the infant's final state as no pain, moderate pain, or severe pain. This result supports previous finding [27] that facial expression might be the most specific and frequent indicator of pain.

3) Multimodal Infant Pain Assessment: We present a decision-level fusion method that combines the scores of different behavioral pain indicators and physiological changes to predict the final state as no pain (class 0), moderate pain (class 1), and severe pain (class 2). Particularly, we combined the class labels (i.e., 0, 1, or 2) for each individual pain indicator or modality together. Then, we employed the majority-voting method in the combination to decide the final prediction.

In the majority-voting scheme, each pain indicator or modality contributes by one vote (i.e., class label) to the final predication; and the major class in the combination is chosen as the final assessment of pain. If the combination of different indicators has a tie, we chose the class that has the highest confidence score as the final assessment of pain. For example, the final predication for a combination of two pain indicators (facial expression FE and vital signs VS) is decided as presented in Table VI. As illustrated in the table, if the class of both indicators are the same, this class is chosen to be the final assessment (bolded in the table). If the indicators' labels (i.e., class label) make a tie, the final assessment's class is the class with the highest confidence score.

TABLE V
UNIMODAL AND MULTIMODAL PAIN ASSESSMENT PERFORMANCE SUMMARY

	Unimodal			Multimoda			
Facial Expr.	X			X		X	X
Body Move.		X		X	X		X
Vital Signs			X		X	X	X
Accuracy	**88%**	86%	82%	90%	86%	89%	**95%**
Recall	57%	55%	52%	86%	70%	58%	98%
Precision	58%	52%	54%	61%	64%	60%	71%

TABLE VI
VOTING PROCEDURE TO COMBINE PAIN INDICATORS

VS\FE	**0**	**1**	**2**
0	**0 (no pain)**	tie	tie
1	tie	**1 (moderate pain)**	tie
2	tie	tie	**2 (severe pain)**

Using Dataset1 and Dataset2, four combinations of pain indicators (i.e., modalities) were generated to predict the infant's final assessment of pain. These combination are: 1) facial expression and body movement; 2) body movement and vital signs; 3) facial expression and vital signs; and 4) facial expression, body movement, and vital signs. The last four columns of Table V present summary of performance for these four combinations.

As can be seen from the table, combining both behavioral and physiological pain indicators for assessment achieved the higher overall accuracy (95%) with 98% recall and 71% precision. This result supports preceding evidence that demonstrated the association between pain and several behavioral/physiological pain indicators and recommended the use of both for an efficient and accurate pain assessment. An important point to consider here is that care providers in NICU use a multimodal approach to assess pain of infants. Our automated approach provides a continuous assessment of pain similar to the current practice.

IV. CONCLUSIONS AND FUTURE RESEARCH

The traditional assessment of infants' pain depends on utilizing subjective tools that fail to meet rigorous psychometric standards. Since untreated pain in infants can cause long-term impairments, it is crucial to develop a quantitative and continuous system for assessment. In this paper, we present an automated approach to assess infants' pain. Specifically, we present automated unimodal and multimodal approaches for infants' pain assessment. Combining different pain indicators for assessment (i.e., multimodal) achieved the highest overall accuracy, which is 95%. This result suggests the feasibility of developing an automated and multimodal approach for pain assessment in infants.

Several directions exist for future research.

One direction is to evaluate our method on similar datasets and compare the results. As a part of this direction, we also want to evaluate our method on a larger dataset. We are currently working on collecting several behavioral and physiological data for approximately 300 infants during acute and chronic painful procedures.

Another direction is to investigate a feature-level fusion method for assessment of infants' pain. We believe that this direction is challenging and difficult to implement in practice due to features incompatibility, curse of dimensionally, and missing data handling.

Finally, we plan to include crying sounds as a behavioral pain indicator and the near infrared spectroscopy (NIRS) data as a physiological pain indicator along with the other pain indicators for assessment. Recent studies [28], [29] found that pain caused hemodynamic changes in specific cortical regions of the brain in infants and claimed that measurements of the brain activity provide important information about the infant's pain state. We also plan to incorporate contextual information (e.g., age and presence of the mother) into the assessment approach to refine the classification process.

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