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Pain intensity estimation by a self-taught selection of histograms of topographical features☆

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ABSTRACT

Pain assessment through observational pain scales is necessary for special categories of patients such as neonates, patients with dementia, and critically ill patients. The recently introduced Prkachin–Solomon score allows pain assessment directly from facial images opening the path for multiple assistive applications. In this paper, we proposed a system built upon the Histograms of Topographical (HoT) features, which are a generalization of the topographical primal sketch, for the description of the face parts contributing to the mentioned score. We further propose a semi-supervised, clustering oriented self-taught learning procedure developed on the Cohn–Kanade emotion oriented database by adapting the spectral regression. To make use of inter-frame pain correlation we introduce a machine learning based temporal filtering. We use this procedure to improve the discrimination between different pain intensity levels and the generalization with respect to the monitored persons, while testing on the UNBC McMaster Shoulder Pain database.

1. Introduction

The International Association for the Study of Pain defines pain as "an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage" [1]. Assessment of pain was shown to be a critical factor for psychological comfort in the periods spent waiting at emergency units [2]. Typically, the assessment is based primarily on the self-report and several procedures are at hand; details can be retrieved from [3] and from the references therein. Complementary to the self-report, there are observational scales for pain assessment and a review may be followed in [4]. If both methods are available, the self report should be the preferred choice [5].

Yet, there are several aspects that strongly motivate the necessity of the observational scales: (1) Adult patients typically self-assess the pain intensity using a no-reference system, which leads to inconsistent properties across scale, reactivity to suggestion, efforts at impressing unit personnel etc. [6]; (2) Patients with difficulties in communication (e.g. newborns, patients with dementia, and patients critically ill) cannot self-report and assessment by specialized personnel is demanded [4,7]; (3) Pain assessment by nurses encounters several difficulties. The third criteria is detailed by Manias et al. [8] by naming four practical barriers emerged from thorough field observations: (a) nurses encounter interruptions while responding to activities related to pain; (b) nurses' attentiveness to the patient cues of pain varies due to other activities related to the patients; (c) nurses' interpretations of pain vary, while the incisional pain is the primary target of attention, and (d) nurses' attempt to address competing demands of fellow nurses, doctors and patients. To respond to these aspects, automatic appraisal of pain by observational scales is urged.

Among the multiple observational scales existing at the moment, for pain intensity, the revised Adult Nonverbal Pain Scale (ANPS-R) and the Critical Care Pain Observation Tool (CPOT) have been consistently found reliable [9–11]. Both scales include evaluation of multiple factors, out of which the first is the dynamic of the face expression. Intense pain is marked by frequent grimace, tearing, frowning, wrinkled forehead (in ANPS-R) and, respectively, frowning, brow lowering, orbit tightening, levator contraction and eyelid tightly closed (in CPOT).

1.1. Prkachin–Solomon pain index

The mentioned facial dynamics, in fact, overlap some of the action units (AU) as they have been described by the seminal Facial Action Coding Systems (FACS) introduced by Ekman et al. [12]. Prkachin [13] following a study on facial pain expressions concluded that four

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actions — brow lowering (AU_4), orbital tightening (AU_6 and AU_7), levator contraction (AU_9 and AU_{10}) and eye closure (AU_{43}) — carried the bulk of information about pain. In a more recent follow up, Prkachin and Solomon [14] found more action units to be relevant but confirmed that these four "core" actions contained the majority of pain information. They defined pain as the sum of intensities of brow lowering (AU_4), orbital tightening (maximum effect of AU_6 — Cheek Raiser and AU_7 — Lid Tightener), levator contraction (AU_9 — Nose Wrinkler, AU_{10} — Upper Lip Raiser) and eye closure (AU_{43}). Consequently the Prkachin–Solomon Pain index [15] quantifies in 16 discrete pain levels (0 to 15) the 6 contributing face AUs[1] :

$$Pain = AU_4 + \max(AU_6, AU_7) + \max(AU_9, AU_{10}) + AU_{43} \tag{1}$$

The Prkachin–Solomon formula has the cogent merit of permitting direct appraisal of the pain intensity from digital face image sequences acquired by regular video-cameras and image analysis. It has been used to manually annotate the UNBC-McMaster Shoulder Pain database [16]. Thus, it clears the path for multiple applications in the assistive computer vision domain. For instance, in probably the most intuitive implementation [17], by means of digital recording, a patient is continuously monitored and when an expression of pain is detected, an alert signal triggers the nurse's attention; he/she will further check the patient's state and will consider measures for pain alleviation. Such a system may be employed in intensive care units, where its main purpose would be to reduce the workload and increase the efficiency of the nursing staff. Alternatively, it could be used for continuous monitoring of patients with communication disabilities (e.g. neonates) and for reducing the cost for permanent caring.

Following further developments (i.e. reaching high accuracy), in both computer vision and pain assessment and management, automatic systems that use the information extracted from video sequences could be applied to infer the pain intensity level and to automatically administer the palliative care.

In this paper we propose a system for face analysis and, more precisely, for pain intensity estimation, as measured by the Prkachin–Solomon formula, from video sequences. To properly place it in a context, we will review prior art on pain intensity estimation from visual data and, taking into account that one of the major technical contributions is the introduction of a new image descriptor, we will also summarize the major results within this direction.

1.2. Related work

1.2.1. Pain estimation from visual data

Although other means of investigation (e.g. biomedical signals) were discussed [18], in the last period significant efforts have been made to identify reliable and valid facial indicators of pain, in an effort to develop non-invasive systems. Mainly, these are correlated with the appearance of three databases:

- Classification of Pain Expressions (COPE) database [19] which focuses on classification of pain expressions on infants,
- Bio-Heat-Vid [18] database containing records of induced pain, and
- UNBC McMaster Pain Database [16] with adult subjects suffering from shoulder pain.

[1] For a better visualization of the Action Units and the contributing muscles, we suggest the reader to visit the following page:http://www.cs.cmu.edu/∼face/facs.htm.

As said in the introduction, the majority of the face-based pain estimation methods exploit the Action Unit (AU) face description, previously used in emotion detection, and to which is correlated. A detailed review of the emotion detection methods is in the work of Zeng et al. [20] and, more recently, in the work of Cohn and De La Torre [21]. A summary of methods reporting pain measurements from facial expression may be followed in Table 1.

Pain detection. On the *COPE* database, Brahnam et al. [19] exploited Discrete Cosine Transform (DCT) for image description followed by Sequential Forward Selection (SFS) for reducing the dimensionality and nearest neighbor classification for infant pain detection. On the same database, Gholami et al. [22] relied on relevance vector machine (RVM) applied directly on manually selected infant faces for improved binary pain detection. Guo et al. [23] used Local Binary Pattern (LBP) and its extension for improved face description and accuracy. We note that the COPE database, containing 204 images of 26 neonates is rather limited in extent and it is marked with only binary annotations (i.e. pain and no-pain).

While testing on the *BioVid Heat Pain* database, Werner et al. [18] fused data acquired from multiple sources and information from a head pose estimator to detect the triggering level and the maximum level of pain supportability. One of their contributions was to show that various persons have highly different levels of pain triggers and of supportability levels, thus arguing for pain assessment with multiple grades in order to accommodate personal pain profiles.

Pain recognition from facial expressions was referred in the work of Littlewort et al. [24], who applied a previously developed AU detector complemented by Gabor filters, AdaBoost and Support Vector Machines (SVM) to separate fake versus genuine cases of pain; their work is based on AUs, thus anticipating the more recent proposals built in conjunction with the UNBC McMaster Pain Database.

The *UNBC McMaster Pain* Database, due to its size and the fact that it was made public with expert annotation, is currently the factum dataset for facial based pain estimation. Yet many solutions used for performance assessment in pain detection. In this direction, Lucey et al. [15] used Active Appearance Models (AAM) to track and align the faces on manually labeled key-frames and further fed them to a SVM for frame-level classification. A frame is labeled as "with pain" if any of the pain related AUs found earlier by Prkachin [14] to be relevant is present (i.e. pain score higher than 0). Chen et al. [25] transferred information from other patients to the current patient, within the UNBC database, in order to enhance the pain classification accuracy over Local Binary Pattern (LBP) features and AAM landmarks provided by Lucey et al. [15]. Zen et al. [30] and Sanginieto et al. [26] trained a person specific classifier augmented with transductive parameter transfer for expression detection with applicability in pain.

We note that all these methods focus on binary detection (i.e. pain/no pain) thus experimenting only with the first level of potential applications. Furthermore, pain (i.e. true case) appears if at least one of the AU from Eq. (1) is present, criteria fulfilled by other expressions too. For instance, AU 9 and 10 are also associated with disgust [31]. Another corner case is related to the binary AU 43 which signals the blink; obviously not all blinks are related to pain and the annotation of the UNBC database acknowledges this fact.

Pain estimation. Multi-level pain intensity is estimated by the methods proposed in [27] and [32]. Kaltwang et al. [27] jointly used LBP, Discrete Cosine Transform (DCT) and AAM landmarks in order to estimate the pain intensity either via AU or directly by processing all frames from a sequence. Rudovic et al. [32] introduced a Conditional Random Field that is further particularized for each subject, for the expression dynamics and for timing in order to obtain increased accuracy. Hong et al. [28] aggregates local descriptors into global