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A novel approach for pain intensity detection based on facial feature deformations ☆

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ABSTRACT

The pain intensity detection approach proposed in this paper is based on the fact that facial features get deformed during pain. To model facial feature deformations, Thin Plate Spline is adopted that separates rigid and non-rigid deformations very well. For efficient pain level detection, we have mapped the deformation parameters to higher discriminative space using Distance Metric Learning (DML) method. In DML, we seek a common distance metric such that the features belonging to the same pain intensity are pulled close to each other and the features belonging to the different pain intensity are pushed as far as possible. The assessment of the proposed approach is carried out on the popularly accepted UNBC-McMaster Shoulder Pain Expression Archive Database by using Support Vector Machine as a classifier. To prove the efficacy of the proposed approach, it is compared with state-of-the-art approaches mentioned in literature.

1. Introduction

Faithful pain intensity detection is the key concern of clinical practitioners since last many years. The most widely used techniques for pain detection used so far include patient self reports, visual analog scale (VAS) [1] and clinical interviews as they are convenient and does not require any special skill or advanced technology. For pain intensity, the scale is most commonly anchored by "no pain" (score of 0) and "pain as bad as it could be" or "worst imaginable pain" (score of 100 [100-mm scale]) [2–4].

The self reporting methods are popularly used, but they suffer from drawbacks like reactivity to suggestion, efforts at impression management, deception, difference between patients and the clinician conceptualization of pain [5]. To solve issues related to self report measures, observer rating method is adopted. The main drawback of observer rating is its impracticability and inefficiency to cases where monitoring is required for a lengthy period of time like monitoring a person in an intensive care unit [6]. In addition, the methods of observer measure and self report are highly subjective.

The other methods of pain assessment such as analysis of tissue pathology, neurological "signature", imaging procedures, testing of muscle strength are highly invasive and need binding to the patients. Another important issue raised by Hadjistavropoulos et al. [7] is that naive human subjects are marginally capable of differentiating real pain from fake pain. A potential solution to above discussed issues proposed by researchers is to use facial expressions for pain detection. For the past couple of decades, efforts have been made to isolate such facial actions [8].

A measure of pain based on the facial action coding system (FACS) on a frame by frame basis is proposed by Prkachin and Solomon [9] and results in a reliable measure of pain. The information obtained from such systems can be used for training a real-time automatic system that provides a significant advantage in sufferer's care and cost reduction [10–12].

Several groups have worked hard and designed the systems that can automatically distinguish pain and no-pain [13,10,11]. With the advancement of automatic systems and their clinical and real time usages, researchers are oriented to measure the intensities of pain [14]. The most common database used to assess pain detection algorithms is UNBC-McMaster Shoulder Pain Expression Archive. A brief summary of the methods evaluated on the above said database is presented in Table 1.

It is clear from the table that most of the researchers have used pixel based methods for representation of pain features which may

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Table 1
Brief summary of the recent methods proposed for pain detection.

Sr. no.	Author name	Feature descriptors	Pain levels	Measures of pain intensity	Classifier	Performance measure	Accuracy
1	Ashraf et al. [10]	S-PTS, S-APP, C-APP + S-PTS	2	OPI PSPI	SVM	Leave One Out CV	82%
2	Lucey et al. [15]	PTS, APP, PTS + APP	2	PSPI	SVM	Leave One Out CV	78%
3	Lucey et al. [12]	PTS, APP	2	PSPI	SVM	Leave One Out CV	78%
4	Lucey et al. [11]	SAPP SPTS CAPP SAPP + SPTS + CAPP	2	PSPI	SVM + LLR	Leave One Out CV	75% 77% 81% 85%
5	Hammal and Kunz [13]	CAPP	4	PSPI	SVM	Leave One Out CV	82%
6	Kaltwang et al. [16]	DCT,LBP,PTS, DCT + LBP	16	PSPI	RVR	Leave One Out CV	MSE = 1.39, PCC = 0.59
7	Lucey et al. [8]	AAM + SVM	2	PSPI OPI	SVM	Leave One Out CV	84%
8	Khan et al. [17]	PLBP, PHOG	2	PSPI	SVM,2NN, Random Forests, Decision tree	10-fold CV	96% 97%
9	Florea et al. [18]	Histogram of Topographical features	16	PSPI	SVM	Leave One Out CV	MSE = 1.18, PCC = 0.55

S-PTS: Similarity Normalized Shape, S-APP: Normalized Appearance, C-APP: Canonical Appearance, PTS: Normalized Shape, APP: Appearance, DCT: Discrete Cosine Transform, LBP-Local Binary Pattern, PLBP: Pyramid LBP, PHOG: Pyramid Histogram of Orientation Gradients, SVM: Support Vector Machine, PCC: Pearson Correlation Coefficient, RVR: Relevance Vector Regression, NN: Nearest Neighbor, MSE: Mean Square Error, LLR: Linear Logistic Regression, PSPI: Prkachin and Solomon Pain Intensity, CV: Cross Validation, AAM: Active Appearance Model, OPI: Observer Pain Intensity.

get effected by illumination, scaling and rotation. In order to extract the features which are illumination, scale and rotation invariant researcher have adopted S-PTS, S-APP and C-APP. Being inspired from high accuracy achieved by these methods we have adopted model based method to represent the deformation of facial features during pain. Our contribution in the pain detection field is three fold:

1. We have used Thin Plate Spline (TPS) mapping for modeling the deformation of facial features. TPS gives both rigid(affine) and non-rigid warping parameters for various pain levels, which can be separated as well [19]. By using non-rigid warping parameters to represent facial feature deformations caused by pain and ignoring the rigid parameters, we extract only those deformations which are caused by pain.
2. Since computing the TPS mapping function is single step closed form solution [19], feature extraction using TPS is quite simple process.
3. Motivated by the fact that facial feature deformations at different pain levels are very similar and often misclassified, we aim to map them to higher discriminative space. A distance metric learning method is adopted, which is capable of mapping the data to higher discriminative space.

Thin Plate Spline (TPS) is a spline based technique for smoothing and interpolation. The use of TPS for mapping between two frames was introduced by Bookstein [19]. The motivation behind using TPS is its capability to compute global rigid and local non-rigid parameters between points of two different frames as TPS consist of affine as well as non-affine transformations. Consequently, it is applied for medical image deformation [20], image registration [21], gait recognition [22] and pose invariant affect analysis [23]. We have explored TPS for computing the facial feature deformation caused due to the pain.

There exist a lot of metric learning methods in the literature that have received attention of researchers working in the field of computer vision. The distance metric learning methods can be broadly classified as supervised and unsupervised methods. The popular methods under supervised category include principal component analysis (PCA) [24], local linear embedding (LLE) [25] and laplacian eigenmaps [26] and under unsupervised category include neighborhood component analysis, relevance component analysis, pseudo metric online learning algorithm and transfer metric learning.

Recently, Lai et al. [27] introduce a novel method of discrimination by giving a sparse approximation to eigen subspace. A new framework named sparse 2-D projections for image feature extraction is presented which learns the sparse projection matrix by using singular value decomposition and elastic net regression. Later Lai et al. [28] extends the multilinear discriminant analysis to a sparse case by proposing sparse tensor discriminant analysis (STDA). In this method, multiple interrelated sparse discriminant subspaces are obtained by introducing $L1$ and $L2$ norms into an object function of STDA. The details of the DML methods are presented by Yang and Jin [29] and Bellet et al. [30] and can be referred for detailed description. Motivated by the discriminative mapping using DML methods, we have proposed the DML which pulls the data belonging to the same class as close as possible and that belonging to the different class as far as possible simultaneously.

The overview of the proposed work is presented in Fig. 1.

The rest of the paper is organized as follows. Section 2 describes facial feature extraction using TPS. In Section 3, basic algorithm of proposed DML is explained in detail. The classifier for pain intensity level detection, SVM, is explained in Section 4. The database used for evaluating the proposed method is well introduced in Section 5. The assessment of the proposed approach presented in Section 6. Finally, conclusion and perspective are introduced in Section 7.

2. Feature extraction by Thin Plate Spline

Feature extraction performs two basic tasks: transformation of input image into a feature vector and its dimension reduction for efficient classification. A well-defined feature extraction algorithm ensures more robust and efficient classification or recognition. The requirement of real time applications further adds stringent constraints on the efficiency of this task. In the proposed work this task is accomplished using TPS.

In literature, deformations of facial features have been parameterized by several methods like geometric features and appearance