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# Automatically Personalized Pain Intensity Estimation from Facial Expressions using CNN-RNN and HCRF in videos.

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## Abstract

1 Deep Learning methods have achieved impressive results in several complex tasks  
2 such as pain estimation from facial expressions in video sequences. Estimation  
3 pain has a difficult way to measure, it due to subjective and specifics features by  
4 each person. However, its estimation is important for clinical evaluation processes.  
5 This research paper proposes the use of Convolutional Neural Networks (CNN)  
6 with Transfer Learning and Sequence Model using GRU in order to get an accurate  
7 pain estimate. Prior to this, a preprocessing is performed using the landmarks. For  
8 a correct estimation of the automatic intensity of pain, Prkachin and Salomon Pain  
9 Intensity (PSPI) is used. However, this metric is not a personalized representation  
10 of the patient; therefore, the key contribution is Hidden Conditional Random Field  
11 (HCRFs), using PSPI, Visual Analog Score (VAS), and other scales estimate;  
12 which allows us to achieve results taking into account the evaluation metric used  
13 by specialists.

## 14 1 Introduction

15 There are several measures to estimate intensity pain like Observer Rated Pain Intensity(OPR),  
16 Sensory Scale(SEN), VAS, and Affective-Motivational Scale(AFF), these scales were given by health  
17 professionals. On the other hand, the PSPI was gotten automatically, witch has 15 scales through  
18 Actions Units (AU) from face [1]. Measuring the pain with precision is difficult because it is not  
19 easy to do a correct interpretation due to several factors. First, there are some particular cases where  
20 people cannot have a good communication (babies, dementia people, dying people and so on)[2].  
21 Second, there are some problems like mistakes with metrics, atypical signs in the face people and  
22 ambiguous definitions between patient and doctor.

23 Typical methods use: electroencephalography, magnetoencephalography, Functional Magnetic Res-  
24 onance Imaging (fMRI)[3] to estimate the pain. A disadvantage of these models is the intrusive  
25 mechanism to obtain or to measure the pain of a person. Recent approaches solve this problem by  
26 using methods using facial expressions. Our proposal is based on deep learning which demonstrated  
27 good performance in many applications of study. Although it is not widespread studied in this field,  
28 it was used to solve pain intensity.

## 29 2 Related work

30 Several research works use Handcrafted Features with great results, but this way has been quite  
31 explored for many years. Beside that approach, deep learning-based methods were also explored,  
32 achieving results close to state of the art methods like the research work using VGG and LSTM [4],

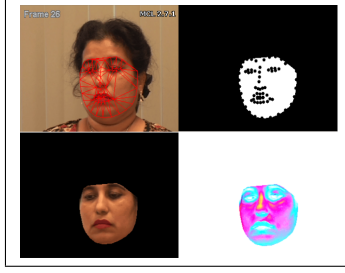


Figure 1: Preprocessing of images. First we can see Delaunay triangulation of face landmarks. Then we can see a mask. With a mask we get the warp image. Finally get from it a normalized image that feeds our model.

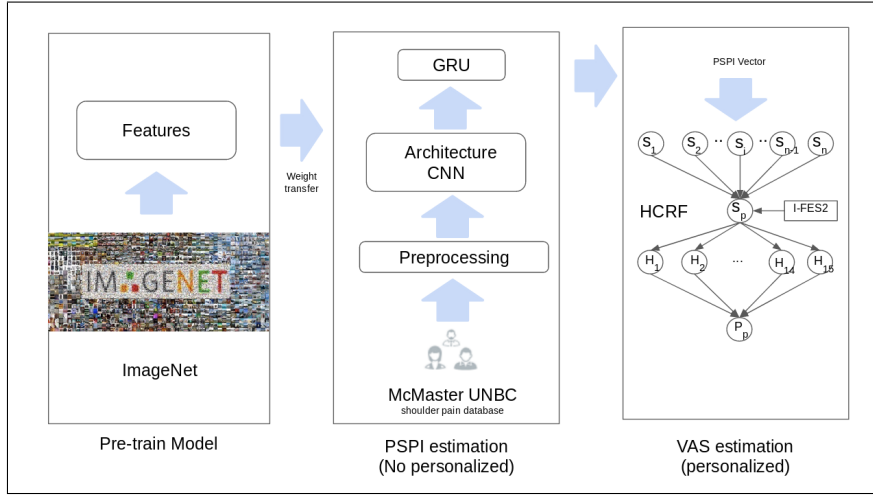


Figure 2: Graphical representation of CNN-RNN and HCRF Model to estimate personalized pain.

33 there is a proposed with the model 3D CNN by [5], another research work estimated VAS using  
 34 LSTM and HCRF[3] , furthermore, there is a research work RCNN to estimate pain[6]. For neonatal  
 35 database pain expression recognition in [7] was proposed a CNN model [7] and [8] use cGAN to  
 36 generate synthetic data to work with LSTM. Except for this research work [3], other research works  
 37 had not been treated in a personalized way, which results have a bias by person.

### 38 3 Approach and current progress

39 Our proposal approach consists of an automatically personalized estimation of pain intensity using  
 40 CNN-RNN and HCRF on facial expressions in videos. The experiments will be conducted on UNBC  
 41 McMaster database which consists of shoulder pain videos collected in three different clinics. This  
 42 database has 200 video sequences [1]. This database is unbalanced.

43 To get the personalized pain we have to follow the next steps. First, we get the most import part from  
 44 the image: The face, using the preprocessing like Figure 1. Then, we propose a Transfer Learning as  
 45 VGG16 fine tuning and GRU for dynamic facial video representation, Transfer Learning helps us  
 46 get better results and fast training. With it, we can get PSPI (no personalized pain). The next step  
 47 will be the actual personalization. We will use PSPI ( $S_i$ ) and IFES2 to fed HCRF. IFES2 is a version  
 48 witch gets the relation from other measures (AFF, VAS, SEN) with OPR. With it, we are able to get  
 49 personalized pain ( $VAS - P_p$ ) for the sequence (see Figure 2).

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