Chapter 3: A Novel Method for Automatic Detection and Intensity Estimation of Spontaneous Pain

3.1 Introduction

It is likely that research has only begun to scratch the surface of what might be learned from expressions' intensities. The occurrence and intensity of facial pain expression are both significant to what the face reveals. Although much progress has been made in respect to automatic detection of pain expression occurrence, controversy exists about the better estimation of pain expression intensity. We have compared two different methods for binary pain detection and pain intensity estimation using two large databases of spontaneous pain expressions i.e., McMaster-UNBC Pain Archive database and the self- prepared database. Scale invariant feature transforms (SIFT) and Speeded up robust feature (SURF) are used for feature extraction; Principal Component Analysis) PCA were used for dimensionality reduction; and Support vector machine (SVM) are used for prediction. The result suggests that SURF outperformed SIFT on binary pain detection. This suggests that training on intensity ground truth is worthwhile even for binary pain detection. The experimental results indicate that using SURF along with SVM as classifier can certainly improve the performance of automatic classification of pain recognition system which will aid physicians in predicting the correct level of pain intensity and thus benefit in the correct diagnosis and treatment of pain patients.

Faces in human species have evolved to express rich information for social interaction, including expressions of pain and emotions. The study of pain expression on a scientific basis was the first major attempt proposed by Darwin [Darwin, C. 1872]. His views on emotions, in general, were steady with the approach to pain. He emphasized on expressive behaviors in order to understand the functions and origin of affective states and motivation. Nonverbal communication behaviors were acknowledged through the explicit role of functional adaptations. These expressions reflect behavioral sources of evidence about pain. There are numerous psychological studies of emotion focusing on facial expressions [Ekman, P. 1980], pain [Prkachin, K.M. *et al*., 2008], and human-computer interaction [Cowie, R. 2001]. Pain is an unpleasant yet necessary signal that notifies us of actual or impending bodily damage and allows an individual to take action [Huguet, A. *et al*., 2010]. In clinical settings, this action could translate to patient diagnosis, medications or even a surgical procedure. Thus, measurement of pain is imperative for effective treatment. Several studies have shown that facial behavior can be used as a modality for prediction of internal states such as mood and confusion [Bartlett, M.S. 2005]. Estimates of pain intensity are commonly obtained in clinical settings via self-report and behavioral measures [Tomlinson, D. 2010]. The self-report measure allows an individual to verbally communicate the amount of experienced pain and suffers from several drawbacks such as subjective bias and patient idiosyncrasies. Moreover, it cannot be employed by verbally impaired patients. On the other hand, observational measures are based on inspecting non-verbal clues viz. body, face or voice of an individual in pain for reporting pain intensity. Such measures are disrupted by the presence of observer's bias, considerable demands on clinician's time, and the influence of factors such as likeability of patient [Stinson J.N., *et al.*, 2006], underestimation of pain [Prkachin, K.M., *et al.*, 1994]. To overcome this issue, some computational approaches needed to be implemented.

There are two major reasons that make the task challenging for automatic measurement of pain from the face. First, is the lack of training and testing data of un-posed, unscripted and spontaneous pain expressions and the other is the trouble of face and facial features analysis in genuine settings viz. medicinal clinics. Facial expressions, being complex in nature, are difficult to describe and quantify, as they evolve over time. Usually, they leave no record. These obstacles present a barrier to scientific analysis. Recent development in video technology which is affordable and accessible overcame this problem and stimulated the growth of the field. However, technology does not, resolve the problem of quantification.

A major advance was the development of clearly described observational systems that addressed this problem, minimizing inference and maximizing 'objectivity'. (Some element of judgment was involved in the prevalent facial coding systems applied by humans, with the inherent subjectivity that entails due to which the word 'objectivity' is in quotation marks) Ekman and Friesen's Facial Action Coding System (FACS) has been the most significant. It provides facial expressions comprising of 44 'action units', representing distinctive changes produced by the muscle combinations or by individual facial muscles. Using FACS and obtaining autonomous datasets the system's performance is tested for ground truth. Through repeated review of video recordings, observers worked from strict coding criteria to 'dissect' facial movements.

Motivation

The emerging interest in pain expression can be identified by four sources.

1. In the 1970s, psychologists working on the operant model came up with the concept of pain behavior. Based on these concepts it was proposed that almost all inferences about pain arise from behavioral observations [Fordyce, 1966] and

focused attention on those behaviors.

2. Better methods for measuring pain were sought by researchers. Human studies have relied heavily on verbal reports, despite the concerns about their objectivity, susceptibility to bias and validity. As an observable behavior related to pain experience, it was considered that facial expression offered a means of evaluating pain that have avoided the issues of self-report and yielded a more ‘objective’ measure. Once the evidence of pain can be perceived by individuals in others then can render them assistance, or to take preventive measures to protect themselves against the threat shared with the person in pain. Thus, sensitivity to evidence of pain in others should be a universal human capacity. Early research showed that indexes of facial expression could be sensitive both to variables thought to influence pain and variations in pain [Prkachin K.M. & Craig, K.D. 1985].

3. Research on emotions by [Ekman, P., *et al.*, 1969] and [Izard, C.E.1971] supported the notion of a discrete set of universal, basic emotions which are identifiable in facial expressions.

4. The last and probably the, most important influence on the field were related to the advances in methodology.

Keeping in view the above points, we have tried to classify the faces in pain. Two approaches used to classify facial pain expression are judgment-based approaches and sign based approaches. Judgment-based approaches usually are centered on the messages conveyed by facial pain expressions during facial pain expression analysis. However, during classification of facial pain expressions into a predefined number of pain states, an agreement of a group of coders is taken as ground truth. This often takes the form of classifying expressions into one of categories such as no pain, mild, moderate or severe pain. However, this involves a great deal of understanding and fails to account for the fact that facial expressions serve a communicative means [Fridlund, A.J. 1992]. Using sign-based approaches, on the other side, facial motion and deformation are coded into visual classes. The facial actions are abstracted uniquely and brief by their intensity and location. Sign-based approaches achieve more objectivity in comparison to judgment-based approaches. FACS is used in sign based approach that uses 44 action units (AUs) for the description of facial actions in accordance to their intensities and location. Pain expressions may be modeled by single action units or combinations of action unit. Much of the effort and energy have been made to study human behavior studies to identify valid pain indicators [Lucy, P. *et al*., 2011]. The studies shows the pain expression is widely characterized by the activation of a few set of facial muscles and coded by a set of action units (AUs): brow lowering (AU 4), eye closure (AU 43), levatorlabii raise (AU 9 and AU 10) and orbital tightening (AU 6 and AU 7) (see Figure 3 (a)). AU 43 being binary is taken as an exception, each of these actions are measured on a six-point ordinal scale (0 = absent, 5 = maximum) using FACS. In a study done recently Prkachin and Solomon proved and confirmed that information of pain if effectively contained in these AUs and thus defined pain intensity as the sum of their intensities. The Prkachin and Solomon pain intensity (PSPI) scale is defined as:

$$\text{Pain} = \text{AU4} + (\text{AU6} \,\|\, \text{AU7}) + (\text{AU9} \,\|\, \text{AU10}) + \text{AU43} \qquad (3.1)$$

In this part of the thesis, we have used SIFT and SURF local face descriptors to predict pain intensity using facial expressions along with testing the hypothesis that binary expression detection and expression intensity estimation require different solutions. This is explored by comparing different techniques using the same data and performance evaluation methods. We have improved upon the previous work by using sign-based approach, two large datasets of spontaneous pain expressions, and expert-coded, frame level ground truth. The techniques used for feature extraction, dimension reduction, and classification are varied systematically, enabling us to interpret which methods proved to be better. We tested binary-trained models with intensity-trained models to detect pain expression occurrence.

3.2 METHOD

Two separate datasets are considered: UNBC-McMaster Shoulder Pain expression archive database and the other self-prepared database. Both datasets were recorded and FACS coded for every participant facial expression in a clinical setting. The differences persisted in the nature and location of pain, demographic profile and the constraints placed upon data collection (e.g., illumination and head motion). Because of how its segments were selected, the self-prepared database also had more frequent and intense pain expressions. Preprocessing, feature extraction, and classification are the following stages involved in the general experimental procedures used in the experiments (Figure 3.1).

In the preprocessing stage, the original images were cropped considering the face only leaving the background, rotated, and scaled. Eyes were aligned roughly along the same axis. The original facial images, size 3008 x 2000 pixels, were also reduced to 100 x 120 pixels.

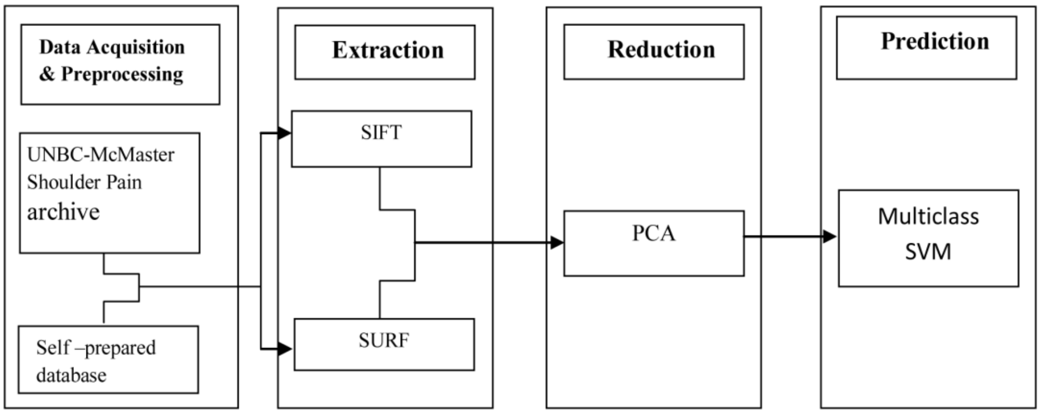

Figure 3.1: Flowchart of Automatic Pain Expression Annotation Methods

During the feature extraction stage, facial features were centered within an ellipse and color information was discarded. A feature vector of dimension 8383 was obtained by concatenating the rows within the ellipse with entries ranging in value between 0 and 255. PCA was then used to reduce the dimensions of pain images. For the best classification scores, the first 80 principle components are considered. At last, in the classification stage, the feature vectors were used as inputs to the classifiers.

3.2.1 Database

UNBC-McMaster Shoulder Pain Expression Archive Database

Researchers at McMaster University and University of Northern British Columbia captured video of participant's faces (who were suffering from shoulder pain) while they were performing a series of active and passive range-of-motion tests to their affected and unaffected limbs on two separate occasions. Using certified FACS coders each frame of this data was AU coded, and self-report and observer measures at the sequence level were taken as well. They called the database as UNBC-McMaster Shoulder Pain Expression Archive Database [Lucy, P. *et al*., 2011]. So as to promote and facilitate research into pain and augment current datasets, the publicly available portion of this database includes: 1) 200 video sequences containing spontaneous facial expressions, 2) 48,398 FACS coded frames, 3) associated pain frame-by-frame scores and sequence-level self-report and observer measures, and 4) 66-point AAM landmarks. These images had variations (in background, hair style, hair color and as shoulder movement was used some images had shoulders too along with face).

Self-prepared database

A total of 100 participants (59 male, 41 female) who were self-identified as having a problem with back, neck and knee pain were video recorded in the pain department of IMS (BHU), Varanasi, India. Facial expressions were recorded with a standard webcam (Logitech) at 30 frames per second located in front of the subject and connected to a laptop when their affected area was pressed by the practitioner.

Video recordings were converted into frames. Not all the frames were included in the study, except for those that showed major changes in the facial expressions during the various pain conditions. In this only 16 frames of each participant were taken from the video representing minor to major changes in facial expressions. Each frame of this data was AU coded by certified FACS coders. Preprocessing of images was done so as to maintain uniformity in the databases. Only the face was taken and the frame dimensions were fixed at 92x112. These faces were used as an input. Features of each image were extracted by using SIFT [Lowe, D.G. 2004] and SURF [Herbert, B. 2008].

3.2.2 Manual Expression Annotation

AU Occurrence

The UNBC-McMaster Shoulder Pain Expression database includes participant facial behaviors that are FACS coded from video by certified coders. To be precise the event onset and offset were coded for 07 commonly occurring AU (Figure 3.2(a)) contributing to pain. Inter-observer reliability for AU4, AU6, AU7, AU9, AU10, AU25 and AU43 occurrence was F_1 = 0.93. For the self-prepared database, participant facial behaviors were manually FACS coded from video by certified coders followed by event onset, offset, and apex being coded for 07 commonly occurring AU. Inter-observer reliability for AU4, AU6, AU7, AU9, AU10, AU25 and AU43 occurrence was F_1= 0.84.

(a)

No pain

Mild Pain

Moderate Pain

Severe Pain

(b)

Figure 3.2: (**a**) Shows a face in severe pain from the self-prepared database with the corresponding AUs and their intensity levels.

(**b**) Pain intensity levels defined by the FACS manual (i.e., AU4, AU6, AU7, AU9, AU10, AU25 and AU43). For both the datasets, onsets and offsets are converted to frame-level codes with 0 and 1 representing the absence and presence of the given AUs, respectively.

AU Intensity

The manual FACS coding procedures described in subsection 2.2.1were used to identify the onsets and offsets of AU4, AU6, AU7, AU9, AU10, AU25 events. The video clips were converted into frames and coded for intensity levels. This coding involved assigning each video frame an integer value between 0 and 3, with 0 representing the absence of the given above AUs and 1 through 3 representing trace through maximum intensity (Figure 3.2(b)). To establish reliability, five percent of the clips were independently coded by a second certified FACS coder, which was ICC=0.95.

3.2.3 Automatic Pain Expression Annotation

Tracking

Facial landmark points indicate the location of important facial components (e.g., eye corners, nose tip and lip corners). UNBC-McMaster Shoulder Pain Expression database consists of sixty-six facial landmarks with each video frame being FACS coded by certified FACS coder. Due to occlusion or extreme out-of-plane rotation approximately, 4% of video frames were untraceable. A global normalizing (i.e., similarity) transformation is applied to the data for each video frame to remove the variation due to the rigid head motion. Finally, each image was cropped to the area surrounding the detected face and scaled to 128x128 pixels. For the self-prepared database, sixty-six facial landmarks were tracked using active appearance models (AAM) [Cootes, T.F. 2001]. Active Appearance Model (AAM) is a computer vision system which can automatically detect pain based on facial expressions coded using FACS. The shoulder pain archive contains images of patients with rotator-cuff injuries, with spontaneous facial expressions associated with pain which are not posed or feigned. These facial actions vary in duration and intensity and often coincide with abrupt changes in head position. The AAM approach specifies that both shape (i.e. contour) and appearance (i.e. texture) are both vital for gaining accurate detection performance [Ashraf *et al*., 2009]. The normalization procedures were used on the AAM landmarks. AAM includes landmark points along the curve of the jaw whereas the other non-facial information was removed.

3.2.4 Extraction

Scale Invariant feature transform:

SIFT [David, G.L. 2004] algorithm uses local features to describe the image. We basically are extracting interesting points in the image and then computing the description of these points such that these computed key-points and descriptors are not affected by noise, illumination, and scale. The procedures followed were:

To detect key points with the different scale, we require a scalable window. That is why scale-space filtering [Witkin, A.P. 1984] is used. The scale space is defined by the function (equation 3.1 & 3.2):

$$L\ (x, y, \sigma) = G\ (x, y, \sigma) * I\ (x, y) \tag{3.1}$$

$$G\ (x, y, \sigma) = \frac{1}{2\pi\sigma r^2} e^{-(x^2+y^2)/2\sigma^2} \tag{3.2}$$

Where $G\ (x, y, \sigma)$ is a variable-scale Gaussian, * is the convolution operator and $I\ (x, y)$ is the image. In scale-space filtering, we use σ which is basically a scaling parameter. So we find maxima across the scale and space which give us a list of (x, y, σ) which means that there is a potential key point at (x, y) at σ scale. Here we use Difference of Gaussians which is obtained by blurring the image with two different σ and pσ and is given by (Koenderink, J.J. 1984) and (Lindeberg, T. 1994).

$$D\,(x,y,\sigma) = \big(G\,(x,y,p\sigma) - G\,(x,y,\sigma)\big) * I(x,y)$$

$$L(x,y,p\sigma) - L\,(x,y,\sigma) \tag{3.3}$$

After this computation, local extrema were searched in the image for a potentially key point. Once these potential key points were found, they are refined to get a more accurate result. We then use Taylor series expansion of scale space and get more accurate location of extrema, and if the intensity at this extrema is less than a threshold value, it was rejected. After this, orientation was assigned to each key point so that we achieve invariance to image rotation.

$$m\,(x,y) = \sqrt{(L(x+1,y)-L(x-1,y))^2+(L(x,y+1)-L(x,y-1))^2} \tag{3.4}$$

$$\theta(x,y) = \tan^{-1}((L(x,y+1)-L(x,y-1))/(L(x+1,y)-L(x-1,y))) \tag{3.5}$$

We then took a neighborhood around the key point location and the gradient magnitude and direction were calculated for that position (equations 3.3 & 3.4). A histogram with 36 bins dealing with 360 degrees was then created weighted by a gradient magnitude and a Gaussian-weighted circular window with σ equal to 1.5 times the scale of the key point. The highest peak in the histogram was then taken and any peak above 80% of it is also used to calculate the orientation. Now to create key point descriptor, we used a 16x16 grid around the key point which was divided into 16 sub-blocks of 4x4 sizes. Then 8 bin orientation histograms were created for each sub-block so that total of 128 bin values was created. Then we represent them in a vector to form key point descriptor.

SURF

SURF [Herbert, B. *et al*., 2008] is basically a local feature detector and is inspired by SIFT. It is quite robust and fast also. The steps involved were:

Square-shaped filters were used on the integral image. Integral image was obtained by:

$$S\,(x, y) = \sum_{p=0}^{x} \sum_{q=0}^{y} I(p, q) \tag{3.6}$$

SURF uses a hessian matrix [Christopher, M. 1992] based blob detector. Blobs were mainly detected in the place where determinant of Hessian is maximal.

$$\mathrm{H}(\mathrm{p}, \sigma) = \begin{pmatrix} \mathrm{Lxx}(\mathrm{p}, \sigma) & \mathrm{Lxy}(\mathrm{p}, \sigma) \\ \mathrm{Lxy}(\mathrm{p}, \sigma) & \mathrm{Lyy}(\mathrm{p}, \sigma) \end{pmatrix} \tag{3.7}$$

Images were then repeatedly smoothed with a Gaussian filter [Deng, G. & Cahill, L.W. 1994]. They are then subsampled to obtain the next higher level of the pyramid. Therefore, several floors or stairs “det H" with various measures of the masks are calculated:

$$\sigma\mathrm{approx} = \mathrm{Currentfiltersize} * \left(\left(\frac{\mathrm{Base\ \ Filterscale}}{\mathrm{BaseFilterSize}}\right)\right) \tag{3.8}$$

Descriptors were then computed for every point of interest. The dimension then determines its computational complexity and accuracy.

For achieving invariance against rotation, the point of interest orientation is obtained. The Haar wavelet responses in abscissa within a circular proximity of radius around the computed point of interest were calculated. The responses thus obtained was then assigned weights by using a Gaussian function which is centered at the point of interest, then plotted as points in a two-dimensional space. The dominant orientation is then calculated by obtaining the sum of all responses within a sliding orientation window of size π/3.

For descriptor extraction, we started by constructing a square region centered around the interest point and oriented along the orientation calculated above.

The result of *dx*, *dy* and their absolute are then summed as a vector given by:

$$V = \left(\sum dx, \sum dy, \sum |dx|, \sum |dy|\right) \tag{3.9}$$

These features were then stored in a cache to decrease the running time of the program. These features were then classified using SVM classifier. An SVM is a supervised learning model [Cristianini, N. & Shawe-Taylor, J. 2000] which marks an object into one category or another using the pattern learned from object supplied in training stage and this marking of the new object is called testing stage. Therefore, it is a non-probabilistic binary linear classifier. An SVM model is, therefore, a representation of the objects as points in space, mapped such that objects of the separate categories are divided by a widest possible gap. New objects are then mapped into that same space and are then classified by predicting which side of the gap they fall on.

3.2.5 Reduction

The features exhibited high dimensionality in both the cases. For reducing the dimensions, we used two which were compared on their ability to yield distinguishable features for classification. Principal components Analysis (PCA) [Wold, S. *et al*., 1987] was used to project a feature vector into a low dimensional space from a high dimensional space.

$$Yi = W_{PCA}^{T} xi \quad (where\ i = 1,2, \dots N) \tag{3.10}$$

Where W_{PCA} is the linear transformations matrix and the columns of the W_{PCA} are the p Eigen vectors corresponds to the p largest Eigen values of the covariance matrix, which is defined as:

$$Cov = \frac{1}{N-1} \sum_{i=1}^{N} (xi - ▯)(xi - ▯)^T \qquad ..... (3.11)$$

where, µ is the mean of all samples. These techniques reduced the SIFT features from 7046 dimensions per video frame to 290, and SURF features from 7452 dimensions per video frame to 302.

Cross-validation

Here we have used stratified k-fold cross-validation to prevent model over-fitting. The original sample is randomly partitioned into k equal sized subsamples. Of the k subsamples, a single subsample is retained as the validation data for testing the model, and the remaining k – 1 subsamples were used as training data. The cross-validation process was then repeated k times (the folds), with each of the k subsamples used exactly once as the validation data. The k results from the folds are then averaged (or otherwise combined) to produce a single estimation. Stratified cross-validation procedures ensure that the resultant partitions have roughly equal distribution of the target class (in this case AU4, AU6, AU7, AU9, AU10, AU25, and AU43. In this study, each video segment was assigned to one of the four partitions (called "folds"). For each iteration of the cross-validation procedure, three folds were used for training, one for testing and one for validation. The advantage of this method over repeated random sub-sampling is that all observations were used for both training and validation, and each observation was used for validation exactly once. 10-fold cross-validation was commonly used.

3.2.6 Prediction

In the current work, we have done pain classification by automatically detecting four levels of pain intensity like zero, mild, moderate and severe pain using multi-class support vector machines (SVM). They were used for binary classification. It uses the kernel trick, which uses dot product, to keep computational loads reasonable. The kernel function enables the SVM to fit a hyper-plane of maximum margin into the high dimensional feature space.

SVMs were trained using four classes corresponding to the FACS occurrence codes (0 and 1). Training sets were created by randomly sampling 11,000 frames with approximately equal representation for each class. The values above zero represent various pain intensity levels whereas negative scores reflect the absence of pain. The scores obtained were used for estimating pain intensity level by assigning threshold values. The visual classifier was trained for four different image classes (no pain, mild, moderate and severe pain). The performance of the classifier was assessed by computing a precision-recall curve for SIFT and SURF separately.

SVM models output values which were the fractions corresponding to the distance of each frame's high dimensional feature point from the class separating hyper-plane. These values were used for pain intensity estimation using the standard SVM threshold of zero to provide predictions for binary pain detection (i.e., negative values were labeled absence of AU4, AU6, AU7, AU9, AU10, AU25, AU43 and positive values were labeled as presence). Multiclass SVMs were trained using four classes corresponding to the FACS intensity codes. The output values of the multiclass classifiers were integers (scores) corresponding to each frame's estimated pain intensity level. These values were used for pain intensity estimation and also discretized to provide predictions for binary pain detection. The performance of the classifier was assessed by computing a precision-recall curve for SIFT and SURF separately (Figure 3.7 and 3.8). Figure 3.5 and 3.6 provide scores for different images. The values above 0 represent various pain intensity levels whereas negative scores represent the absence of pain (Figure 3.3 and 3.4).

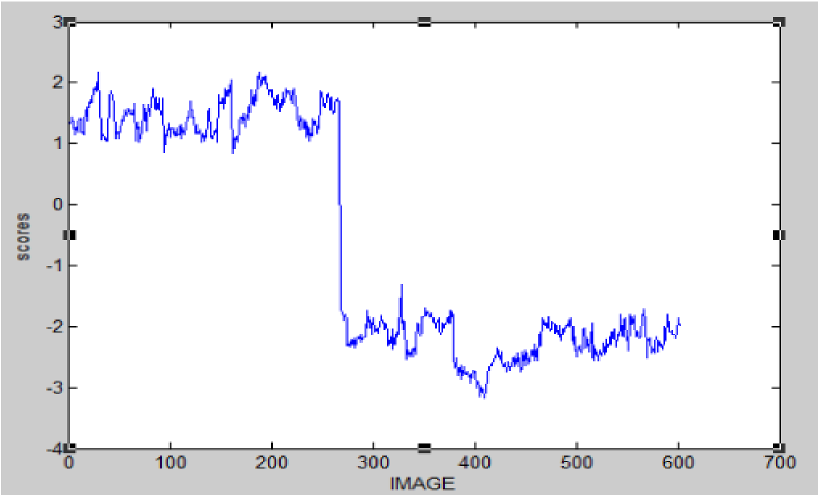

Figure 3.3: Plot of scores (y-axis) vs. image (x-axis) by using SIFT.

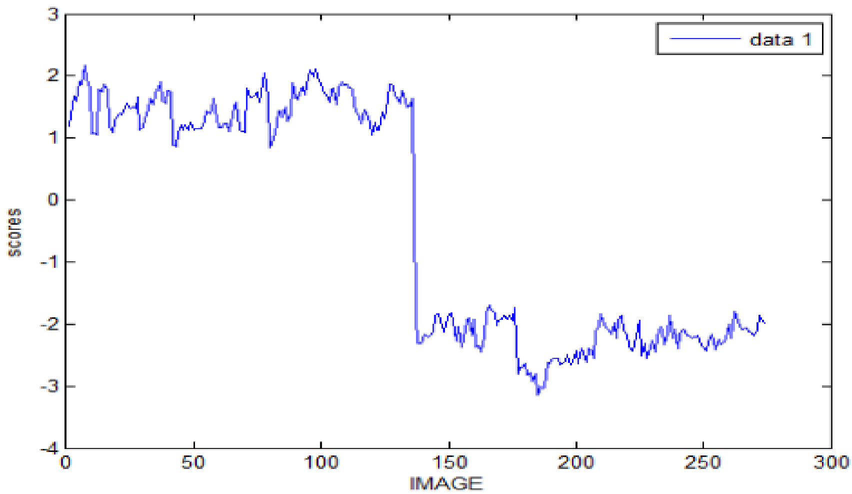

Figure 3.4: Plot of scores (y-axis) vs. image (x-axis) by using SURF.

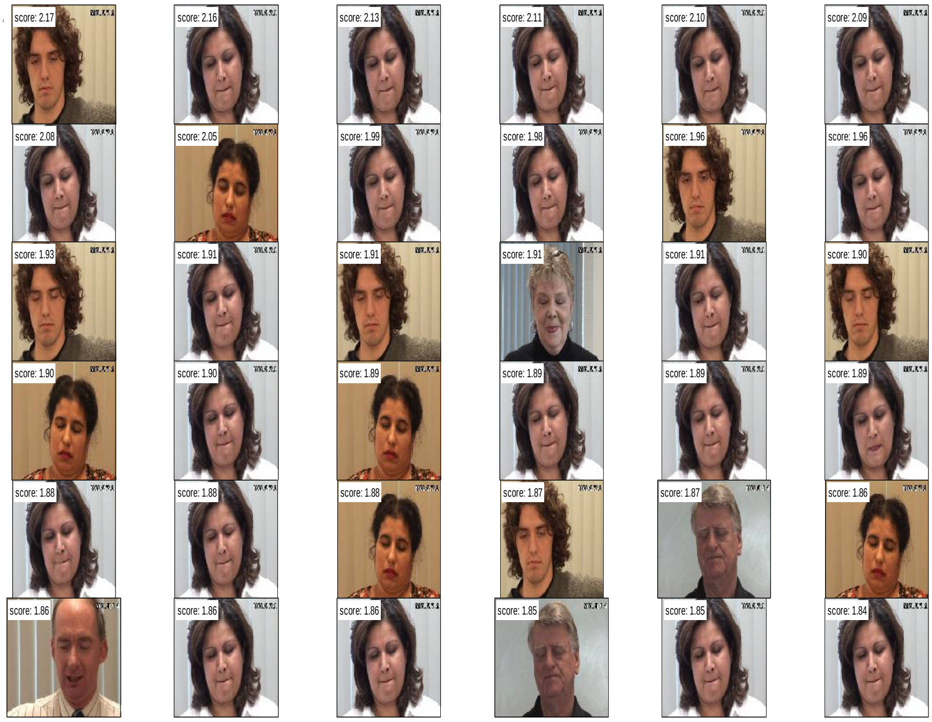

Figure 3.5: Table of patients with their scores obtained on McMaster Shoulder pain achieve

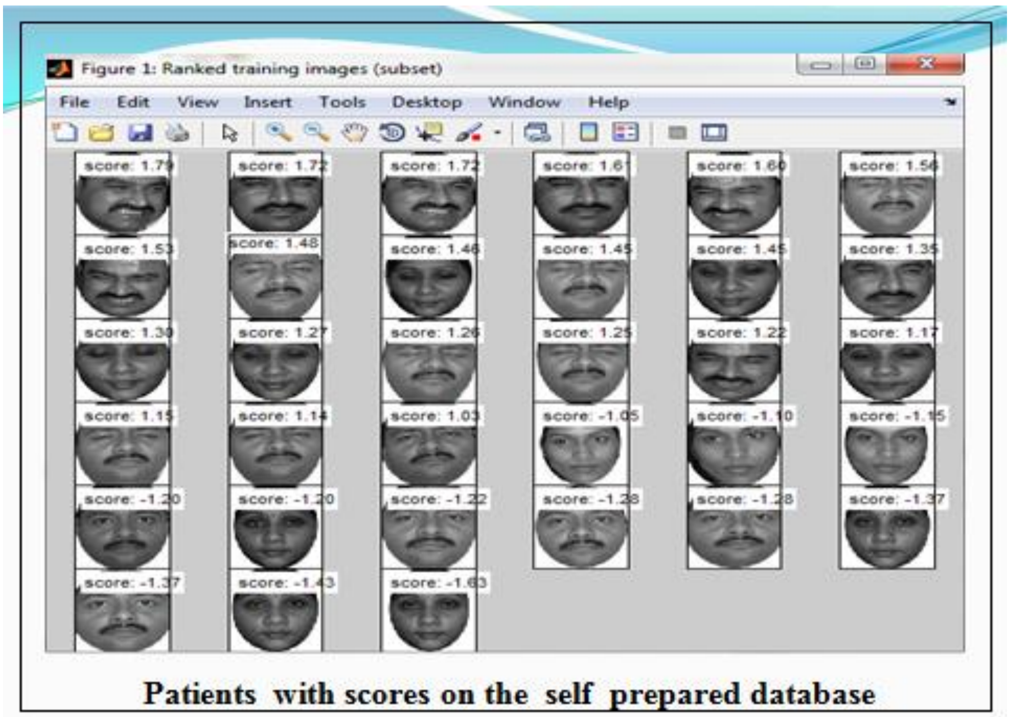

Figure 3.6: Table of patients with their scores obtained on self prepared database

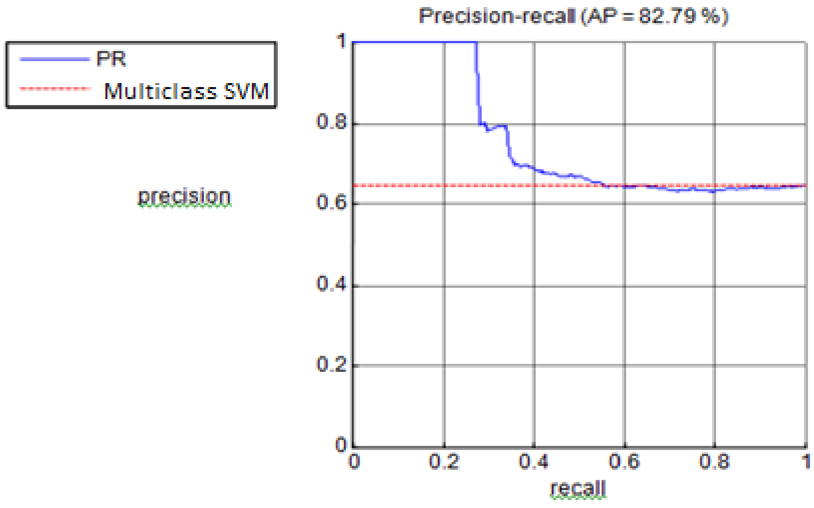

Figure 3.7: Precision recall curve using SIFT

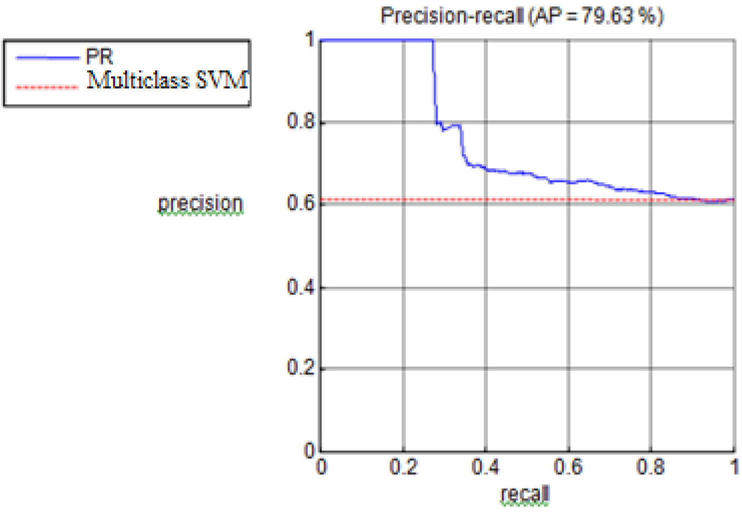

Figure 3.8: Precision- recall curve using SURF

3.3 Results and Discussion

Our findings demonstrate the feasibility of providing an automated pain detection and classification system for patients suffering from chronic pain. The images were classified into four categories viz. no pain, mild, moderate and severe pain. The accuracy of 75.79% is obtained with SIFT and 72.63% with SURF. In the past various researches have been made for the task of pain detection [Caroline, S.

et al., 2010] i.e., to check whether a person is suffering from pain or not but none were accurate in predicting how much a person is suffering and neither these studies have been used for classifying genuine and fake pain. In our approach we have shown that not only we can detect pain but can also classify it as well. The method proposed in this chapter is promising and we believe to further continue the research.

Although there was a large variation in the dataset we used for our system as an input, for example, our dataset had the shoulder of the person along with face, the different hair color and style and different background, so we initially did some preprocessing and extracted out facial expressions leaving other details as the background. This enhanced the robustness of our system. In spite of these variations, our results demonstrated that we were able to classify the images present in the dataset into four different classes namely zero, low, high and extreme pain with a greater accuracy.

Our system can use both directory of the image as well as names of images and basically improves efficiency and provides a quick response by storing features in cache making it fast and flexible as well. The result generated by the system provides hope that by further research and testing our system may produce better accuracy than traditional manual approach in which a person having a specialty of deducing pain is employed. Thus, our system being automatic can be used to monitor a person 24X7 by using video frames as an input. The present findings supports the idea of using SIFT and SURF for feature extraction. A better result was produced using SURF. The scores generated by using support vector machine basically tell the intensity based on facial expression of the person and using these scores we classified the images.

This approach had some limitations that should be kept in mind while interpreting the results and designing future studies. In some exceptional cases, where the person gives abnormal or some contradicting expression to pain the system fails as the SVM fails to classify them correctly in various pain classes. Also, if the patient is mentally or physically challenged and is unable to express himself/herself to the degree of pain then again our system fails for the same reason.

3.4 Conclusion

This suggests that training on intensity ground truth is worthwhile even for binary pain detection. The experimental results indicate that using SURF along with multiclass SVM as classifier can certainly improve the performance of automatic classification of pain recognition system in comparison to SIFT. Both the pain detection and its intensity estimation can be predicted using the same classifiers. This method is fast enough in comparison to the previously used techniques for classifying pain and thus will aid physicians to better diagnose the patients and provide drug accordingly.