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Invited Paper

Pain Level Detection From Facial Image Captured by Smartphone

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Abstract: Accurate symptom of cancer patient in regular basis is highly concern to the medical service provider for clinical decision making such as adjustment of medication. Since patients have limitations to provide self-reported symptoms, we have investigated how mobile phone application can play the vital role to help the patients in this case. We have used facial images captured by smart phone to detect pain level accurately. In this pain detection process, existing algorithms and infrastructure are used for cancer patients to make cost low and user-friendly. The pain management solution is the first mobile-based study as far as we found today. The proposed algorithm has been used to classify faces, which is represented as a weighted combination of Eigenfaces. Here, angular distance, and support vector machines (SVMs) are used for the classification system. In this study, longitudinal data was collected for six months in Bangladesh. Again, cross-sectional pain images were collected from three different countries: Bangladesh, Nepal and the United States. In this study, we found that personalized model for pain assessment performs better for automatic pain assessment. We also got that the training set should contain varying levels of pain in each group: low, medium and high.

Keywords: pain level detection, remote monitoring, quality of life, cancer patient's pain level.

1. Introduction

More than 8 million people die suffering from cancer in this world. Most of these people face acute pain problem during their sickness [1], [2]. Current medical technology is trying to help the patient in this regards. But the adequate symptoms are necessary for the treatment. The treatment gives mediocre result if the patient is failed to provide appropriate pain intensity, which is the part of their symptoms. Health care providers cannot help the patients who has chronic situation due to the lack of their complete symptoms. In addition, the symptoms conditions are not accurate, complete, and regular. Again, the big issue for this failure is not to use validated symptom assessment that prevents communication between patients and health-caregivers to bring attention to symptoms' issues [3]. In rural area, patients are not feel free to talk over phone with doctors. In addition, doctors are found busy with their official and private patient. In this situation, doctors are talking for short period of time if the patient's call is received. For this reason, the patient tries to take the schedule, come at the office (sometimes-called chamber) of the doctor and for face to face conversation. While talking with doctor, patients are allowed to put their answers based on the written questions. In most cases, the usual way to obtain such information is to ask standard questions about their symptoms and their intensities. For patients with cancer the most widely used questionnaires are the Edmonton Symptom Assessment Survey (ESAS) or the Brief Pain Inventory [4], [5]. Common practice is to have patients provided answers on paper to these instruments when they are seen in doctors' offices. In this questionnaires, patients are asked to give their pain intensity level of a particular time. This practice of course means that the data obtained only cover the particular situation of the patient in that time. But that time the patient may have taken extra pain medicines for acute pain since they sometimes feel that they might suffer from pain while traveling. So the actual pain intensity value at different painful time is out of reach. In general, patient's verbal report on their current level of pain are compared on a visual analogue 1-10 scale. Based on the pain level the users are allowed to put any number from 1 to 10. If the user feels less pain then they write small value to present their pain intensity such as 1, 2, or 3. On the other hand, the acute level pain intensity can be input by giving 8, 9, or 10 in this system. Again, more abbreviated symptom assessment strategy has also been practiced in many cases for better understanding. Pictures are used in this case to represent different pain level. Facial expressions are varied in this scale to represent different levels of distress. However, this is a one-time and one-item assessment strategy.

Cancer patients have to send their daily assessment of problem list to the doctor for medicine adjustment or to predict the issues found in the diagnosis. But doctors need the daily pain level value with timestamp information for better pain management. Ideally, every day the data on how patients feel are necessary to monitor patients more completely and of course to make changes in treatments. For example, the medicine types, amounts and get-

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ting times are adjusted based on the data from the questionnaires every day. In the case of lung cancer, it is found that patients who have home computers and able to send daily assessments by email and get the resultant treatment adjustments have better quality of life. Patient as well as family members' satisfaction is found highly co-related to the level of patient monitoring and consequent associated prompt adjustments of symptomatic managements. These benefits are available in hospice programs settings. Note that hospice monitoring has shown better patient care than the other regular care since regular care is mostly based on patient office visits face-to-face conversation.

Another way of patient management is through phone call or email service. But the doctors are busy when they are on call and they are uncomfortable to talk over phone without having to see the patient. Teleconference is another solution in this case. But the internet bandwidth is not supporting the high quality video data transfer over mobile network. Again, the practice of medicine has historically been based on face-to-face encounters. These issues are magnified in poor and middle-income countries since they have very limited access to health care. In addition, there is no optimal quality of care and no hospice care at all in the rural area of underdeveloped country.

The paper-based questioners are not easy to maintain since the blank or filled up papers can be lost anytime. So the doctors might face an inconvenience situation without the given input data from patient. Making available the questionnaires on a cell phone as an application is one practical way. Because the patient or his/her attendant could complete at home and send by phone each day to a doctor's records/office. We have identified the problems and already developed a mobile base solution [6]. In the next phase, we are planning to introduce these facilities up into a tele-home hospice system in rural Bangladesh. We have analyzed the real life data from previous solution and found two major issues. Firstly, the chronic pain that characterizes the situation for patients with incurable cancers. We found that there is an apparent gap, sometimes called misunderstanding between what patients report about their pain levels using the standard instruments and their affect. In some culture, people talk having smiling face though they have pain and often report high pain levels. In general, this is found when they are asked face-to-face conversation. Secondly, many patients do not understand how to use the instruments since they are confused to put the values from the scale. In addition, some patents have limited cognitive abilities or other medical conditions to put the pain level when they are seriously ill in medical intensive care units. These are the major facts that inspired us to build some different solution for them. So we try to investigate whether we could reproducibly and accurately record and quantitate patients' pain levels using their face image. This is common idea since we personally also try to understand how much pain our sick beloved faces by scanning their face. People try to guess other information of the patient from their face, eye or gesture direction too. The cell phone camera images are planned to use to collect facial expression. In this research, three challenging task are appeared: Firstly, only facial images can help us to assess pain intensity among cancer patients? Secondly, which machine-learning algorithm can define pain intensity accurately? Finally, if everything works then how the full system will work?

In psychology, there are fundamental pain assessment rules from facial expression. Regarding the objectivity of self-report assessments and their susceptibility to behavioral bias, there are historical concerns [7]. For this reason, a lot of research work to identify universal cues for pain expression are going on. In the pain research [8], Prkachin et al. observed indices of facial expression change due to variations of pain. Facial Action Coding System (FACS) has been used in Ekman and Friesen's (Ekman & Friesen, 1978) to identify universal Action Units corresponding to pain expression. Researchers found a significant changes in four types of actions - brow lowering, eye orbit tightening, upperlip raising/nose wrinkling and eye closure for cold, pressure, ischemia and electric shock [10]. 'Prkachin and Solomon Pain Intensity' (PSPI) is defined by Prkachin and Solomon. The measurement is the sum of the intensities of these four actions [11]. There are multiple facial expression components (i.e., action units) that together comprise the facial expression. Therefore, it shows the intensity of pain experienced by individuals.

For most pain expressions, it is found that few specific action units correspond to pain intensities. The change in different action units might be of different magnitudes for acute and chronic pain. Using facial expressions, huge number of data for a particular target application (e.g., pain monitoring for chronic pain) improves the accuracy of pain intensity predictions [11]. It is more difficult to find the exact change in action units due to chronic pain while it is comparatively easy to identify changes in action units due to acute pain. For this reason, principal component analysis is used to extract information that would give us reasonable variance across a given data set for pain expression in this research. Principal component analysis has nice features that give four core action units comprises 0.30 or greater fraction of pain expression across all pain tests [12] supports this claim. Therefore, principal component based method is used for detection of pain expression. One of the method is called Eigenface method where each of the Eigenfaces corresponds to different levels of variance in the training data set.

In our study, both longitudinal and cross sectional study were done to measure pain intensity from facial images for chronic pain. In the previous time, many research works were accomplished to measure pain from facial expressions using principal component analysis (PCA) [13]. In those case, the accuracy level was found low. In addition, they did not use images of a single subject over long period called longitudinal data set. There are couple of benefits of longitudinal dataset. One benefit of longitudinal data is that it reduces the need for requiring a large sample. Again, longitudinal data removes individual differences in pain expression and behavioral bias of self-report pain intensity. In addition, the longitudinal data analysis would allow us to know whether a person's use of facial expressions for representing pain changes over time or they consistently use the same expressions. In this research, the idea is implemented elaborately where machine learning techniques and Eigenface method are used with proper distance measure for pain intensity measurement. The initial works and results of these research are published in the paper [44].

2. Contribution

The pain expression depends on many factors in human life [43]. For example, psychosocial and cultural assessments are considered for pain level detection in many research areas. Since this research works focus only on the rural area people in the underdeveloped country like Bangladesh, we need to consider the end user's overall situations. For example, some users are feeling shy and covering their face while capturing photo due to the religious purpose. Again, smartphone is chosen for the purpose of image capture since digital camera would costs additional money. Having all the circumstances, we have advanced our works in three ways. Firstly, we have worked on design phase of the system. Then build the mobile application that capture the facial image of the patient. Then we have deployed the mobile app for remote monitoring of pain intensity. In contrast to other systems for emotion or pain detection, we have deployed the healthcare tool that has been tested in a clinical setting. The data collection and analysis are described in the results section. In the second phase of our work, the machine learning algorithms are used for the testing and training data set to get better approximation. For better prediction, couple of issues are discussed regarding training and testing data in discussion section. In the third phase, the design challenges are discussed in design issues section that are considered to overcome the barriers to deploy the system for remote monitoring of pain intensity from facial expression.

3. Related Work

We can measure the pain level getting the users' self-reported data [7]. Extensive research is going on to detect the pain using tissue pathology, imaging procedures, testing of muscle strength, etc. [14]. Since these are highly invasive and require specialization, these procedures are not suitable for some cases. For example, many aged people can not cope with this medical treatment.

Besides, Facial expressions have also been used to detect pain [11]. Facial Action Coding Systems (FACS) are used in many affective research areas specially for pain detection from facial expressions [9]. Prkachin et al. expressed that several facial action units (AUs) like eye brow lowering, eye orbit tightening, levator contraction and eye closing to constitute pain expressions in the face [12]. This method has been developed and tested for few number of patients. The method was designed and developed for acute and chronic pain but chronic pain can be very different from acute pain [15] in clinical settings.

FACS has also been used in Ref. [16] for pain detection. Pain detection means whether the patients have pain or not. So only the presence of pain was trying to detect here. But most systems do not provide a quantitative estimate of the pain intensity.

Recently there has been a shift in research of affect detection from a lab environment to a natural environment i.e., in situ measurement of emotion. Ayzenburg et al. [17] used electro dermal activity for stress detection of a mobile user in their natural environment. Microsoft's SenseCam has also been used for logging emotional data in a natural setting. Isbister and her colleagues designed 'Yamove!' to introduce social interaction in dance games [18]. A lot of patients including pregnant women, patients suffering from shoulder pain [24], knee pain, and chronic pain etc. shows facial expressions when in pain at different age levels (neonatal, adult) [19], [20], [21], [22], [23]. However, few research works are done on automatic pain detection. Facial action units based studies have been performed by several authors [25], [26].

Facial expression gives different features that help to identify pain. These features are then given to the machine learning algorithm as input. The classifiers are also used to make different cluster of data. For example, support vector machine (SVM), AdaBooster, Gabor filter, and hidden Markov model (HMM) have been used as classifier.

Sometimes single classifier is not working good for decision making. That time combination of two or more classifiers provide greater accuracy. In some cases, active appearance models (AAM) are used to identify specific facial features associated with pain [16], [27]. To find a computationally inexpensive solution the Eigenface-based method was deployed [28]. Here, Eigeneyes and Eigenlips are also used for better classification result [29]. Sometimes artificial neural network-based back propagation algorithms showed very good result to distinguish between pain versus no pain from facial features [13], [30]. A Bayesian extension of SVM named relevance vector machine (RVM) is also used [31] to make high classification accuracy. Niese et al. and Becouze et al. used ICU/post-operative patients [32], [33] to measure pain experienced. Becouze et al. used the idea based on the hypothesis that pain results in forming extra wrinkles [32]. Photogrammetric technique is used by Niese et al. for finding features. They also get benefits using SVM filter with a radial basis function (RBF) Gaussian kernel for detecting pain [33]. Brahnam et al. worked to find pain in neonates [34], [35].

Another idea with video sequences have come from Ashraf et al. He collected all the video sequences of facial expressions and calculated the pain level [27]. UNBC-McMaster shoulder pain expression database was used here. To create active appearance models (AAM) a holistic approach was used for a face. In addition, support vector machines (SVM) were used as a classifier.

Emotion is not an objective measure [36]. It should be considered as a subjective experience. The author also mentioned that pain is obviously a subjective form of emotion and that should also be measured out of the lab.

In Ref. [42], the authors were trying to identify the visual information effectively by healthy human observers. They used the method to discriminate the facial expression of pain from the facial expression of other emotions. In addition, they used the Bubbles method that asked observers to discriminate facial emotions from randomly sampled regions of a face.

The Eigenface method is useful not only for face recognition but also for emotion recognition. It was applied in face recognition in Ref. [37] and used for emotion recognition in Ref. [38]. Moreover, this method worked well for pain and no pain condition detection [28]. Eigenfaces plays a key role here since the extracted face image was used to build the feature space. The main goal of eigenface is to make the whole process faster suing mathematical transformation. For this reason, we try to get the features in mathematical sense using instead of physical face. The training set of data is selected from the Eigenface images. So, the testing activities occurred onto the feature space when a new face is coming. Euclidean distance measurement of the weight vector is used to get the closest labeling.

For pain level detection most of the approaches has limitations and has one or more of the deficits. For example, there is a reliability issue on a clear frontal image. In addition, head position is found rotate out-of-plane. Sometimes, patients are in dilemma to select correct feature. Again, failure to use temporal and dynamic information, considerable amount of manual interaction, inability to handle noise, illumination, glass, facial hair, skin color issues, high computational cost, lack of mobility and failure to classify intensity of pain level are also remarkable problems.

4. Architectural Problems

In the rural area, people have limited access to the communication vehicle to visit doctors timely. The reason behind is the lack of financial support, mental support, family management, accompany, and transportation. In addition, patients need the doctor's appointment before visiting them. In general, doctors are available in the urban area clinics. Coping with all of these issues a patient can talk with a doctor. This is the common scenario of patient doctor situation in rural area of underdeveloped country. Having this situation, we spent couple of weeks in clinics and hospitals to see the facts in the beginning of our work. In addition, we made home visits with cancer patients in Bangladesh to learn more about their needs. Again, talking with health care professional we figured out the actual challenges. The field experiences reinforced our understanding and experiences. We found that the usual office visits for patients with advanced cancers and pain did not allow them to take better health care since their visits were not regular to the doctor. Physicians expressed significant interest to see real time "usual day and activity" symptom data of their patients. Subsequently, the developed mobile application was deployed in such a way that minimum errors are faced after installation.

4.1 Availability of Mobile Network

Couple of mobile operator are working in Bangladesh where they provide voice and data service not only in urban area but also in rural area. Mobile phone users are increasing all over the country since the cost regarding the mobile phone device and line charge are becoming reasonable. Since the developed application needs internet to send the picture to main server, we try to find out the patient who has mobile internet. We have surveyed 45 patients and selected 43 from them who have good mobile data bandwidth. Since image processing needs high computation, we send the image to the server for further processing. The mobile network is providing data transfer using internet so it is possible for us to use the cloud for photo image processing. Here we have used the advanced level software like Matlab for image processing.

4.2 Smile for the Camera

People keep their face smiling in most of the culture while capturing their photo using camera. Some people make their facial expression changed little bit from normal state when they pose for photo shooting. For example, we asked to 'pose for the camera' or 'smile for the camera' [36] when we need the photo of anybody. Getting the message to pose for photo, the facial gesture is changed since the patients are ready to pose for photo. So, image is found smiley even if the patients are suffering from pain. We have acknowledged the issues and decided to capture two pictures. One picture was taken providing the instruction. For example, the instruction was to make a facial expression that reflected their current pain level. This is called 'acted pain' and used in the next section of the paper. Second one was captured without any instruction of pose which we have mentioned as the 'real pain' in the following section of of this writing. The images were randomly selected as past of dataset subsection from 'acted pain' and 'real pain' images.

4.3 Personalized Model

Pain level detection from different training image data is not very easy task since the expression of facial image for a single pain level is varied in different culture. So the personalized model is approached here where the patient will capture their facial image for different level and input the respective pain intensity into the mobile application. In this research work, the main goal was to identify pain levels from facial expression. But we found variance in pain levels with facial expressions among individuals. For these reason, we have followed the patients longitudinally. As a result, we have taken the training database with multiple images from a single person targeting to eliminate the variance.

5. Data Collection

5.1 Image Capture

The mobile based application allows the user to give their input of pain level. In addition, they also able to capture their facial image using the smartphone camera that are uploaded to the cloud server through internet. The image as well as pain data are uploaded automatically through the mobile app. There interaction between mobile application and the remote server is accomplished through internet programming language like PHP and Javascript. Wamp server is taken to support as web server. In **Fig. 1**, two screen shots from mobile app are displayed where the first one is showing image uploading status. The second image is presenting the labels to describe the pain.

5.2 Image Collection

The Institutional Review Board (IRB) at Marquette University and the Bangladesh Medical Research Council in Bangladesh approved our data collection techniques for the longitudinal pilot study with in a small number of patients. In this case, a consent paper is given to the patient. Having their assenting acknowledgement, the next step was forwarded. As part of data collection, each patient was given a Nokia X6 phone. The mobile phone had voice and data plan form the largest telecommunication company, has about 90 percent mobile network coverage in Bangladesh, called Grameen Phone. The age distribution of patient was chosen between 35 and 48 years. Again, only the female

Fig. 1 Two screen shots of mobile application for labeling and uploading pain image. (a) shows image uploading status. (b) shows labeling of pain intensity using a sliding bar in the local language Bangla.

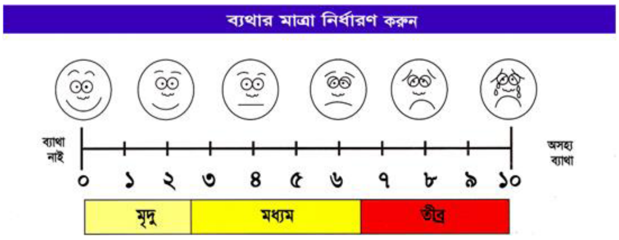

Fig. 2 Visual Analog Scale (VAS) in the local language Bangla used for training. For each of the pain intensity levels indicated on the line, the image of the face represents possible expression in the face. 0 means no pain and 10 (far right) indicates the highest possible level of pain.

patients were considered for these pilot study. So 14 women was recruited for these data collection system. Since the data collection technique is pretty new in the rural area all the patent as well as the attendant were trained how to take the pictures using the camera at the health center. The additional features of the mobile app were also shown afterwards.

The mobile application has couple of key features. The features are designed and developed for doctors as well as patients. So doctors can take picture of the subject. Some instructions are given to the user for pain input. For example, the Visual Analog Scale (VAS) describes the pain intensity with 0 being the no pain and 10 being maximum pain possible. In **Fig. 2**, the range of VAS are shown where the scale of pain intensity is explained in local language Bangla. Again, the pictures are captured having recommended light and background. The patients are not allowed to use sunglass while capturing their photo. The data collection process was run for 3 months. Finally, we found 6 patients alive from 14 patients. In this 3 months, total 454 images are found usable. The number of images are listed in the **Table 1**.

The pain level intensity data were collected by observing many subjects at the same time is called cross sectional study. In this study, we conducted cross sectional study in Bangladesh, Nepal and South Dakota in United States. The data collection protocol was approved at Marquette University and by the responsible ethical review boards in Bangladesh, Nepal and Rapid City South Dakota in the United States. In this study, patients are recruited who were presenting for a clinic visit with advanced

Table 1 Image data set size for longitudinal and cross sectional study. The entire data set for longitudinal study was used as the training data set for the cross sectional study.

Longitudinal Study			
Subject	Training Set	Test Set	Total
A	6	8	14
B	36	80	116
C	36	124	160
D	6	6	12
E	36	78	114
F	6	32	38
Total			454
Cross Sectional Study			
Location	Training Set	Test Set	
Bangladesh	454	131	
Nepal	454	311	
United States	454	71	
Total		513	

cancer. When the patient come for medical checkup two facial images are captured. First image is treated as candid and the next one was snapped after specific instructions. We have collected photographs of 131 Bangladeshi, 311 Nepali, and 71 American Indian patients. For machine learning algorithm, we need training and testing data set for better prediction. So we have taken 36 randomly images as the training set during the longitudinal study for each subject. Again, the entire dataset of the longitudinal study (454 images) was used as the training data set for the cross sectional study.

6. Methodology

6.1 Face Detection

Face detection is an important step in this study since the image processing result depends on the captured image. For example, the subjects were asked to capture the images of their face only for both longitudinal and cross sectional study. But most of the images contained significant extraneous background around the face. In this case we need to preprocess the images. For photo editing, we have used Picasa 3.0 image viewing software to create images containing only the face. Using this tool, the face portion was extracted and each image was resized to 160 times 120 pixels.

6.2 Eigenface Based Analysis

The Principal Component Analysis (PCA) is most usable method for image processing. In general, this method is preferable to the researchers since it makes less computation reducing the dimensionality of high dimensional data. Eigenface method is developed basically based on PCA. PCA identifies the principal components represented by the eigenvectors corresponding to the highest eigenvalues. IN this method, the most significant

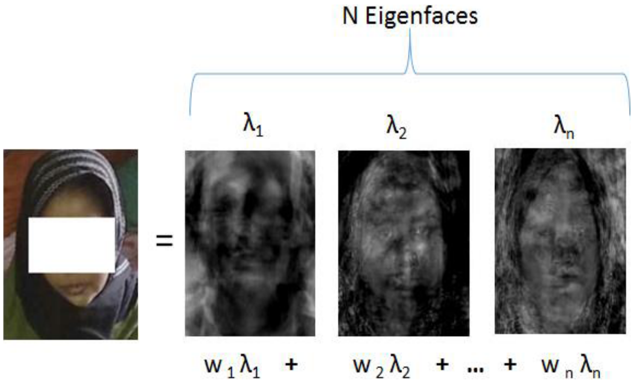

Fig. 3 N Eigenfaces for N different Eigenvalues from personalized training database.

features of an image are extracted. Since this method makes the computation inexpensive it is a perfect selection that the methods that works based on identifying action units from FACS corresponding to pain. Here some sample Eigenfaces are shown from the training database in **Fig. 3**. In this image recognition scheme, face images are decomposed into a small set of characteristic feature images. These feature images are denoted as 'Eigenfaces'. In other words, these features are the principal components of the original training face images. Now if we can project a new image into the subspace spanned by the Eigenfaces then we can classify the face by comparing its position in the face space having the positions of the known images. Since the Eigenfaces are the Eigenvectors they can be defined as numerous face features. In addition, any face feature can be represented as linear combinations of the singular vectors of the set of faces. In this research, we have also used Eigenfaces to preserve the confidentialities of the individuals.

We computed the Eigenface using a number of steps [28]. The first step is to obtain a set S with M face images. Each image is transformed to a vector Γ_n. Then we compute the mean image Ψ,

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n$$

Next, we find the difference Φ between the input image and the mean image, $\Phi_i = \Gamma_i - \Psi$.

We seek a set of M orthonormal vectors, u_M, which best describes the distribution of the data. The k^{th} vector, u_k, is chosen such that

$$\lambda_k = \frac{1}{M}\sum_{n=1}^{M}(u_k^T\Phi_n)^2$$

Where λ_k is a maximum, subject to

$$u_l^T u_k = \delta_{lk} = \begin{cases} 1, & \text{if } l = k \\ 0, & \text{otherwise} \end{cases}$$

Where u_k and λ_k are the eigenvectors and eigenvalues of the covariance matrix C. The covariance matrix C has been obtained with the following equation,

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T = AA^T$$

Where, $A = [\Phi_1\Phi_2\Phi_3\ldots\Phi_m]$. To find eigenvectors from the covariance matrix is a huge computational task. Since M is far less than N^2 by N^2, we can construct the M by M matrix,

$$L = A^TA, \text{ where } L_{mn} = \Phi_m^T\Phi_n$$

We find the M Eigenvectors, v_l of L. These vectors (v_l) determine linear combinations of the M training set face images to form the Eigenfaces u_l

$$u_l = \sum_{k=1}^{M} v_{lk}\Phi_k, \quad 1 = 1, 2, \ldots, M$$

After computing the Eigenvectors and Eigenvalues on the covariance matrix of the training image. M eigenvectors are sorted in order of descending Eigenvalues. The top eigenvectors are chosen to represent Eigenspace.

Finally, we project each of the original image into Eigenspace to find a vector of weights representing the contribution of each Eigenface to the reconstruction of the given image. To detect the pain intensity of a new image, the new image is projected onto the Eigenspace of the training images. It generates a weight vector for the new image where the image is the combination of the Eigenfaces in the training set that would create the 'best match' for the input image. Figure 3 explains this algorithm with some sample Eigenfaces. Here three Eigenfaces are shown corresponding to three eigenvalues λ_1, λ_2 and λ_n. The weight vector W is the combination of the Eigenfaces to regenerate the image or the 'best match' of the Eigenfaces for the given input image.

6.3 Weight Vectors Classification

We have used Euclidean distance, angular distance and support vector machine for the classification of the weight vectors. We have chosen different distant measures since we have to reduce the high dimensions of the weight vectors. Basically, the dimension of the weight vector is equal to the total number of images minus one in the training set. For this reason, we have 35 Eigenfaces where the weight vector was of 35 dimensions for 36 images.

Angular distance performance is better than Euclidean distance in high dimensional space. Because mean absolute error decreases in angular distance measurement. The equation for angular distance measurement is shown as following way in Ref. [39].

$$d(A, B) = \frac{A.B}{|A||B|}$$

Support vector machine (SVM) is a machine learning tool associated with learning algorithms that are used to analyze data and to recognize patterns. SVM is used for classification and regression analysis. In SVM, the series of input variables $\{X_1, X_2, X_3 \ldots X_n\}$ and their corresponding class labels $\{C_1, C_2, C_3 \ldots C_k\}$ are given. The classification problem is given to SVM with new input variable X. In general, this is a binary classification problem. But using this repeatedly we can use SVM as multiclass classifier. The classifier function to classify incoming input vector is defined as

$$y(x) = W^T\Psi(x) + b$$

Where Ψ = continuous feature space transformation, W = weight

Table 2 Mean absolute error for a 10-fold cross validation for the longitudinal study.

	Subject B		Subject C		Subject E	
Cross Val	Angular	SVM	Angular	SVM	Angular	SVM
1	0.95	1.07	0.71	0.88	1.06	0.64
2	1.02	1.142	0.71	0.77	1.01	0.67
3	0.79	0.81	0.75	0.8	1.04	0.68
4	1	1.01	0.8	0.78	0.98	0.66
5	1.12	0.97	0.83	0.83	0.98	0.72
6	1.07	0.86	0.707	0.94	1.22	0.66
7	0.88	0.94	0.82	0.87	1.09	0.62
8	0.83	0.91	0.73	0.92	1.12	0.75
9	0.92	0.73	0.78	0.82	1.04	0.53
10	1.04	1.05	0.79	0.78	0.96	0.63
Mean ± SD	0.96 ± 0.10	0.94 ± 0.12	0.76 ± 0.04	0.84 ± 0.06	1.05 ± 0.08	0.66 ± 0.05

vector and b = bias parameter. Support vector machine has used here to improve the sensitivity and specificity for each pain class.

7. Results

The levels are divided into three classes, low (L), medium (M) and high (H). Low pain level was chosen between 1 and 4. Again, medium pain level was taken between 5 and 7 and between 8 and 10 was defined as high. These three classification are similar to the Brief Pain Inventory which has been tested for different cultures (Cleeland & Ryan, 1994). The mean absolute error and, sensitivity and specificity analysis for the three pain classes are accomplished in this research. As a consequence of insufficient data for subjects A, D, and F (Table 1), the results are shown only for subjects B, C and E. Here, only 36 images in the training set were taken.

Table 3 Sensitivity and specificity of a 10-fold cross validation for the longitudinal study.

	Angular						SVM					
Subject	Sensitivity			Specificity			Sensitivity			Specificity		
B	L(0-4)	M(5-7)	H(8-10)	L(0-4)	M(5-7)	H(8-10)	L(0-4)	M(5-7)	H(8-10)	L(0-4)	M(5-7)	H(8-10)
	0.25	0.9	NaN	0.9	0.25	1	0.06	0.92	NaN	0.92	0.06	1
	0	1	NaN	1	0	1	0.16	0.88	NaN	0.88	0.16	1
	0	1	NaN	1	0	1	0.42	0.84	NaN	0.84	0.42	1
	0	1	NaN	1	0	1	0.13	0.84	NaN	0.84	0.13	1
	0.86	0.54	NaN	0.54	0.86	1	0.14	0.91	NaN	0.91	0.14	1
	0.43	0.74	NaN	0.74	0.43	1	0.14	0.94	NaN	0.94	0.14	1
	0	1	NaN	1	0	1	0.07	0.95	NaN	0.95	0.07	1
	0	1	NaN	1	0	1	0.33	0.76	NaN	0.76	0.33	1
	0.24	0.89	NaN	0.89	0.24	1	0.06	0.94	NaN	0.94	0.06	1
	0	1	NaN	1	0	1	0.27	0.92	NaN	0.92	0.27	1
Mean	0.18	0.91	NaN	0.91	0.18	1	0.18	0.89	NaN	0.89	0.18	1
C	1	0	NaN	0	1	1	0.95	0	NaN	0	0.95	1
	1	0	NaN	0	1	1	0.97	0	NaN	0	0.97	1
	1	0	NaN	0	1	1	1	0.1	NaN	0.1	1	1
	1	0	NaN	0	1	1	1	0	NaN	0	1	1
	1	0	NaN	0	1	1	1	0	NaN	0	1	1
	1	0	NaN	0	1	1	0.89	0	NaN	0	0.89	1
	1	0	NaN	0	1	1	0.92	0.13	NaN	0.13	0.92	1
	1	0	NaN	0	1	1	0.96	0	NaN	0	0.96	1
	1	0	NaN	0	1	1	1	0	NaN	0	1	1
	1	0	NaN	0	1	1	0.97	0.14	NaN	0.14	0.97	1
Mean	1	0	NaN	0	1	1	0.97	0.04	NaN	0.04	0.97	1
E	0.07	0.9	NaN	0.9	1	1	0.21	0.95	NaN	0.95	0.21	1
	0.07	1	NaN	1	0.07	1	0.14	0.97	NaN	0.97	0.14	1
	0	1	NaN	1	0	1	0.07	0.98	NaN	0.98	0.07	1
	0.07	1	NaN	1	0.07	1	0.21	0.97	NaN	0.97	0.21	1
	0	1	NaN	1	0	1	0.23	0.95	NaN	0.95	0.23	1
	0.23	0.61	NaN	0.61	0.23	1	0.23	0.97	NaN	0.97	0.23	1
	0.13	0.88	NaN	0.88	0.13	1	0.25	0.98	NaN	0.98	0.25	1
	0	0.87	NaN	0.87	0	1	0.31	0.97	NaN	0.97	0.31	1
	0.45	0.65	NaN	0.65	0.45	1	0.27	0.97	NaN	0.97	0.27	1
	0.1	0.89	NaN	0.89	0.1	1	0.5	0.95	NaN	0.95	0.5	1
Mean	0.11	0.88	NaN	0.88	0.21	1	0.24	0.97	NaN	0.97	0.24	1
Mean ± SD	0.43± 0.45	0.60± 0.44	NaN	0.60± 0.44	0.46± 0.45	1 ± 0	0.46± 0.37	0.60± 0.43	NaN	0.63± 0.43	0.46± 0.37	1 ± 0

Table 4 Sensitivity and specificity of a 10-fold cross validation for the cross-sectional study.

Angular						SVM					
Sensitivity			Specificity			Sensitivity			Specificity		
L	M	H	L	M	H	L	M	H	L	M	H
0.55	0.39	0.02	0.40	0.58	0.99	0	1	0	1	0	1

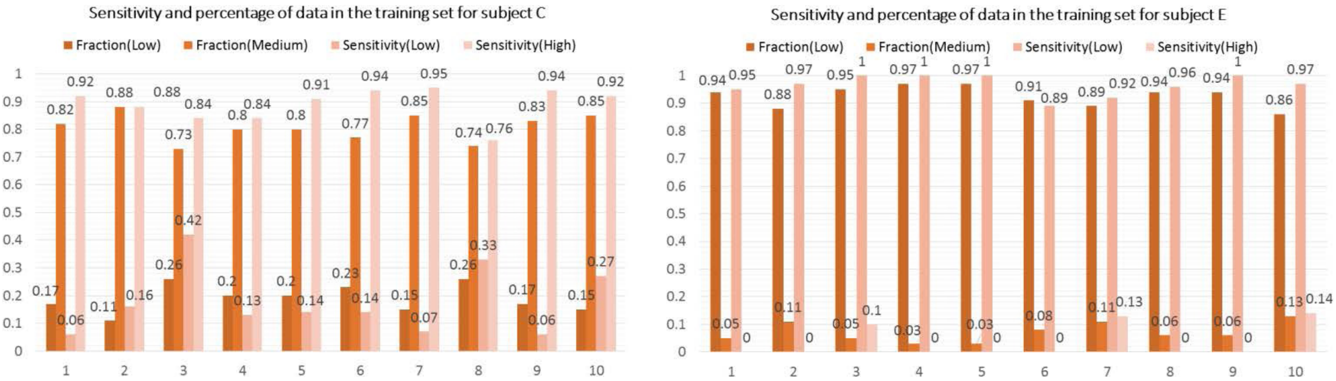

Fig. 4 Ratios of the number of images for the low and medium classes and the sensitivity for each class for the 10 fold cross validation during the longitudinal study.

7.1 Longitudinal Study (First Phase)

Longitudinal data collection means the recording of information of a similar item for long time. In medical research, scholars collect data for long time to study what changes are found over time. Since cross-sectional studies can not provide proper information regarding the main cause of some diseases and the relation between the data and effects, longitudinal studies are considered. Longitudinal studies have pretty good abilities to detect the characteristics of target population.

7.1.1 Mean Absolute Error

In the first phase of our study, we took six different training sets for the six subjects. We have taken 36 images in this longitudinal study. The training sets are made using 36 random images from subjects B, C, E of 'acted' and 'real' pain.

These training sets are named as personalized training database. As is explained earlier that longitudinal data would eliminate the individual differences in pain expression, so a personalized training database would eliminate that behavioral bias of patient. Here, each subject's images were tested against the training set of the corresponding subject. Euclidean distance, angular distance and support vector machine have been applied on the personalized training database. We have collected the data testing the classification algorithm.

When we compare the results among these algorithms we found that Euclidean distance gave poor results. For this reason, it is not reported here. The mean absolute error for angular distance and support vector machine is presented in **Table 2**. The method did not work well for subjects A, D and F since they had only six images in the training set. We have presented the results for subjects B, C and E. Over these analysis, a 10-fold cross validation was performed.

7.1.2 Sensitivity Analysis

The mean absolute error for pain level assessment needs to be optimal in clinical settings. So It is important that the input and output pain distributions are similar. On the other hand, it may be possible that the system is always giving the similar pain level as output. But the mean absolute error is low. When the input pain level distribution is similar to that of the training data set the system would perform well. But we are trying to do system performance well so that it does not depend on the input pain level distribution. This extremely necessary for robust clinical decision support system. We have shown sensitivity and specificity of three levels of pain (low, medium and high) using a 10-fold cross validation for subjects B, C, and E. The results are presented in **Table 3**.

7.2 Cross Sectional Study (Second Phase)

We have good findings in the previous longitudinal studies. Our findings could be more accurate if we had the large number of sample and different types of population. We have already mentioned that people from multiple culture express their facial expression as well as pain level differently. For this reason, different types of pain expression and behavioral bias for a single pain intensity decrease the system performance. So non-longitudinal and different population data was expected from large population. So, in the second phase of our study we had one image for each subject. In this way, we have captured the facial images of 513 subjects. We tried to experiment with different training dataset. We found mean absolute error of 2.91 when we used the entire dataset for the longitudinal study. Note that we have selected 454 images for six subjects as the training database here. The sensitivity and specificity analysis data are presented in **Table 4**.

8. Discussion and Findings

8.1 Personalized Model Works Better

For the longitudinal study, the classification method works much better since we have taken the images of one person over a long period time. We have found a mean absolute error less than 1 for the longitudinal study. This proves the subjectivity of pain expression. Again, it also reflects the behavioral bias of the subject. We also tested our data for the Eigenface method, angular distance and SVM. For these cases, we found similar result when we used with the longitudinal dataset. On the other hand, angular distance was found better for the cross-sectional study that is shown in Table 4.

8.2 Distribution of Pain Level in the Training Set

We have already mentioned that the number of image set is not very large. For this reason, we could not assign more subjects for each group: low, medium and high. So the sensitivity and specificity for each group varied for different subjects and diverse training database. For example, the sensitivity was very high for the class 'low' for subject C. Again, we found high sensitivity for subject E for the 'medium' pain level. We have shown the detail sensitivity and specificity for each class in Table 3. If do the analysis of the percentage of images for all class in the training database then we can get the answer. Since we found a high percentage of images with low pain level for subject C in the training set the accurate results are visible in this case. The **Fig. 4** shows this scenario.

8.3 Application Scenario

Pain management using mobile application is a great opportunity for the cancer patients since they do not need to regular visit to the doctor for providing the pain data regularly. This mobile application saves the users' money, time and transportation hassle. So the mobile based solution has shown that pain measurement can be used in clinical settings for the improvement of the quality of life for cancer patients.

In addition, we can use it as pain assessment tools such as Brief Pain Inventory (BPI) [5]. The main goal of this project is that we can figure out the low, medium and high level pain intensity for cancer patients though we have found fundamental challenging issues. For example, user give inadequate measurement of pain levels by different people from multicultural.

9. Conclusion

Automatic emotion detection is a renowned challenging problem. Many researchers are trying to find the emotion detection using gesture or body movement of a person. Facial expression is a key informer to detect the emotion detection though it is a challenging task. A lot of remarkable work has been done in this area during the last twenty years [40], [41]. The success of the application will be more if we can narrow down the context of the application. In addition, we need to collect more data from specific settings [11]. Although we do not have more data, we tried to show a smart phone based tool can revolutionize the remote monitoring system of pain intensity for long term. Again, this application works better that most of the pain detection system since they allow us to know whether the patient has pain or no pain. But for cancer patient the pain intensity level is a crucial information. Moreover, pain intensity detection might reduce the healthcare costs since these cost involve many hidden cost. We are continuing the research work to address the issues. The algorithm is refining having the test on appropriate training set. The usability of the mobile app and the effect on the system performance based on 'candid' and 'acted' image should be checked as future works.

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