FENP: A Database of Neonatal Facial Expression for Pain Analysis

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Abstract—In this article, we introduce a new neonatal facial expression database for pain analysis. This database, called facial expression of neonatal pain (FENP), contains 11,000 neonatal facial expression images associated with 106 Chinese neonates from two children's hospitals, i.e., the Children's Hospital Affiliated to Nanjing Medical University and Second Affiliated Hospital Affiliated to Nanjing Medical University in China. The facial expression images cover four categories of facial expressions, i.e., severe pain expression, mild pain expression, crying expression and calmness expression, where each category contains 2750 neonatal facial expression images. Based on this database, we also investigate the pain facial expression recognition problem using several state-of-the-art facial expression features and expression recognition methods, such as Gabor+SVM, LBP+SVM, HOG+SVM, LBP+HOG +SVM, and several Convolutional Neural Network (CNN) methods (including AlexNet, VGGNet, GoogLeNet, ResNet and DenseNet). The experimental results indicate that the proposed neonatal pain facial expression database is very suitable for the study of both neonatal pain and facial expression recognition. Moreover, the FENP database is publicly available after signing a license agreement (the users can contact Jingjie Yan (yanjingjie@njupt.edu.cn), Guanming Lu (lugm@njupt.edu.cn)) or Xiaonan Li (xnli@njmu.edu.cn).

Index Terms—Facial expression recognition, neonatal pain, facial expression database

1 Introduction

Facial expression recognition is one of the most active research topics in affective computing and computer vision communities. A major target of facial expression recognition is to classify the facial expression images into one of the predefined expression categories, e.g., happy, sad, surprise, fear, sad, neutral, and disgust. Over the past several years, facial expression recognition received increasing interest among the researchers in the affective computing, computer vision and psychology fields [1], [2], [3], [4], [5], [6]. Nevertheless, it is notable that the previous facial expression recognition works have the following three major characteristics [1], [2], [3], [6], [7], [8], [9], [10], [11], [12]:

1) Most facial expression recognition researches mainly focus on the adult subjects, and only a few studies focus on children or neonates [1], [3], [6], [13], [14]. Since there are major differences between the facial expressions of adult and children (especially neonates), the existing facial expression recognition approaches that are designed for adults may not be applicable for children or neonates, and performing facial expression recognition of children or neonates may be much more challenging [15], [16], [17], [18].
2) Most facial expression recognition researches focus on classification of six basic facial expression categories (happy, sad, disgust, surprise, fear and angry). Only a few researchers investigate the non-basic expression categories such as the pain expression category of neonates and the contempt expression category [13], [15], [19], [20], [21], [22], [23], [24].
3) Most facial expression recognition researches are based on acted facial images such as film clips or facial expression images taken under the experimental environments. Only a few works focus on the facial expression recognition under the real environment. It is notable that spontaneous facial expression recognition would be much more challenging.

As a challenging and difficult research topic in facial expression recognition area, facial expression recognition of neonatal pain gets more and more attention from the researchers of the affective computing, computer vision, life sciences

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and neuroscience field in recent years. Due to the lack of large and reliable facial expression database of neonatal pain, however, the progress of the facial expression recognition of neonatal pain is very slow and the relevant works are very rare so far. Nevertheless, the research of pain expression recognition had received increasing attention in recent years because of the importance of pain expression to human beings, especially for neonates. According to the conclusion of many medical and neuroscience researches, facial expression is the most reliable and important pattern to assess the pain of neonates [13], [14], [15], [16], [17], [19], [21], [25], [26], [27], [28].

Although the experience of the pain emotion has less influence on adults in most cases, it will frequently produce different levels of influence or damage on neonates [13], [14], [16], [17], [29], [30], such influences or damages including developmental retardation, damage of central nervous system and so on [16], [25], [26], [29], [30], [31]. If the degree of the pain is severe and continuous, the influence or damage on neonates would be greater, and if the degree of the pain is fair, the influence or damage on neonates is relatively little. To alleviate or remove those influences or damages, doctors often adopt pain management on the basis of pain type and intensity in clinical medicine [13], [14], [16], [25], [26], [29]. For example, pediatricians often give neonates pharmacological drugs (analgesic) for the severe pain, or take nonpharmacological measures such as taking the sucrose solution to neonates for the mild to moderate pain. However, before taking the correspondingly protective or analgesic measures, the most key problem is that doctors must take pain assessment to determine variation in the intensity of pain.

Although it is very important to recognize neonatal pain, it is still a very challenging issue to recognize the expression of neonatal pain [13], [14], [15], [16], [19], [21], [32]. At present, the commonly used method to evaluate neonatal pain is based on the manual coding method, such as using the tool of neonatal infant pain scale (NIPS) [33] or neonatal facial coding system (NFCS) [25], [26] to get the score of the neonatal pain, and then based on the score, to evaluate whether the newborn is suffering from pain and the degree of pain. This approach based on manual coding may lack objectivity, because different coding studies may have bias in coding the same pain expression. In addition, it is worth noting that pain assessment methods based on manual coding often have time-consuming problems and hence they may not satisfy the real-time assessment [14], [15], [16], [21]. To overcome the limitations of the traditional methods of pain recognition based on manual coding, it is very essential of using automatic facial expression recognition for neonatal pain assessment. Consequently, it is necessary to establish a neonatal pain database for neonatal pain facial expression recognition research.

Although some facial expression recognition databases have been built over the past several years, many of them focus on adult facial images, such as the Ekman's POFA database [8], [34], the JAFFE database [35], [36], the CK+ database [37], [38], the MMI database [39], [40], the Multi-PIE database [11], [41], [42], the BU-3DFE [40], [43] the UNBC-McMaster database [44], the STOIC database [45], [46], the BioVid database [47] and so on. In these databases, only a few of them are related to the pain expressions, such as the UNBC-McMaster database, the STOIC database, and the BioVid database. Nevertheless, it should be noted that the facial images of the three pain expression databases are collected from adults. Currently, the COPE database [13], [14], [17], YouTube database [48] and APN-db [49] database are the three public and reliable facial expression databases of neonatal pain [50]. However, they are all small database and have not collected the data under different degrees of pain. Moreover, Zamzami *et al.* [18], [20], [21] build the other facial expression database of neonatal pain, but it has the same limitation.

In this paper, we focus our attention to building a new neonatal pain expression database, called facial expression of neonatal pain (FENP), which contains more than 10,000 neonatal pain facial images and more than 100 subjects.[1] The FENP database is publicly available after signing a license agreement (the users can contact Jingjie Yan (yanjingjie@njupt.edu.cn), Guanming Lu (lugm@njupt.edu.cn)) or Xiaonan Li (xnli@njmu.edu.cn).[2] Compared with the existing neonatal expression databases [13], [18], the new database provides much more data samples and hence would be much more useful for the research to the neonatal pain expression recognition. To build such a large database, we spent many years to collect the data of neonatal pain facial expression from two children's hospitals, i.e., the Children's Hospital Affiliated to Nanjing Medical University and the second Affiliated Hospital Affiliated to Nanjing Medical University of China. In this case, we collect 11,000 neonatal facial expression images in total from 106 Chinese neonates, which covers four emotion categories including severe pain, mild pain, crying and calmness and each emotion category contains 2,750 neonatal facial expression images. To evaluate the recognition performance of several baseline facial expression recognition methods, we also conduct some experiments based on the Gabor feature, local binary patterns (LBP) feature, and histogram of gradient (HOG) feature, respectively, where the traditional support vector machine (SVM) is used to serve as the classifier. In addition, we also investigate to use the state-of-the-art convolutional neural network (CNN) methods (AlexNet, VGGNet, GoogLeNet, ResNet and DenseNet) to evaluate the recognition performance on the proposed database.

The rest of the paper is organized as follows: In Section 2, we review some related facial expression databases including nine facial expression databases of adult pain and three facial expression databases of neonatal pain. In Section 3, we specify the detailed information of the proposed FENP database. Section 4 devotes to the experimental evaluation on the FENP database. Finally, in Sections 5 and 6, we discuss and conclude the paper, respectively.

2 Existing Databases

In this section, we briefly overview two kinds of pain facial expression databases, i.e., the adult pain facial expression databases versus the neonatal pain facial expression databases.

1. FENP is a database of acute pain expressions which responses to injections/blood draws, and is not a database of chronic pain expressions which often responses far injury

2. It was approved by the neonate's caregivers

2.1 Adult Pain Facial Expression Databases

The UNBC-McMaster [44] database is a facial expression database about adults' pain. It contains 200 facial expression video clips and 48,398 facial expression images from 25 adults. Those videos and images contain the pain and non-pain emotion.

The STOIC database [45], [46] is another facial expression database of pain. It is an acted database that does not include genuine pain expression. Besides the pain emotion, this database also contains six basic emotion categories and the neutral emotion. It collects 1088 facial expression videos from 34 adults and contains about 130 pain expression videos.

Different from the above two facial expression databases of pain, the BioVid [47] database is a facial expression database of heat pain based on adults. Besides the facial expression data, it also contains the physiological data from 90 adults.

The X-ITE Pain database [51] is a multi-modal pain database which includes facial expression, body gesture and physiological signals. This database focuses on the different intensity and duration of pain.

The MIntPAIN database [52] is a video-based facial expression database of pain which includes color, depth and thermal data. It contains 9,366 facial expression videos and 187,939 facial expression images from 20 subjects in total.

The SenseEmotion database [53] is another multi-modal pain database which includes facial expression, biopotentials and audio signals. The database records approximately 1,350 min data from 45 subjects.

The EmoPain database [54] is also a multi-modal pain database covering facial expression videos, audio signals, body gesture and electromyographic signals. This database is collected from 21 Chronic Lower Back Pain (CLBP) patients and 28 healthy subjects.

Moreover, the BP4D database [55] is a spontaneous facial expression database which contains a part of physical pain data. On the base of the BP4D database, the BP4D+ database [56] comprises the multi-modal spontaneous datasets which cover the emotion category of physical pain, happiness, surprise, sadness, angry and so on.

2.2 Neonatal Pain Facial Expression Databases

So far, the COPE database [13], [14], [17] is a public and reliable facial expression database of neonatal pain. It in total contains 204 pain facial expression images from 25 neonates. It contains 60 facial expression images of severe pain and 144 facial expression images of non-pain [50].

Zamzami *et al.* [18], [20], [21] also built a facial expression database of neonatal pain. Different with the COPE database, their database is a video-based facial expression database of neonatal pain. It comprises 10 videos from 10 neonates in total.

YouTube database [48] is another public facial expression databases of neonatal pain. It comprises 142 videos from YouTube and those videos are uploaded by parents, nurses and so on.

Moreover, APN-db [49] database also is a public facial expression database of neonatal pain. It contains more than 200 videos of infants and they are all labeled in different pain intensity.

The major limitation of the above four facial expression databases of neonatal pain is that they are all small database and have not collected the data under different levels of pain.

3 The FENP Database

Based on the overview of the existing facial expression databases, we know that, although most of the adult subject based facial expression databases (e.g., UNBC-McMaster) are large size databases, the existing facial expression databases of neonatal pain (e.g., COPE and [18]) are small size ones. This is because it is very difficult and challenging to build a large facial expression database of neonatal pain compared to the facial expression database based on adults, e.g., the facial expression database is a spontaneous database rather than an induced or acted one and hence it should be collected from the real environment (such as newborn room).

With the help of the Children's Hospital Affiliated to Nanjing Medical University and Second Affiliated Hospital Affiliated to Nanjing Medical University, we have persistently collected the data of neonatal pain facial expression for about five years. This study had been approved by the Independent Ethics Committee (IEC) of Nanjing Children's Hospital Affiliated to Nanjing Medical University (Approval Number: 201603032-1) before the collection of this database in the hospitals. Currently, we have built a large facial expression database of neonatal pain which contains 11,000 images. In what follows, we will address this database in details.

3.1 Data Collecting Equipment and Environment

We use two equipments including a digital single lens reflex camera and IPHONE 6 to collect the facial expression videos and images of neonatal pain in the newborn room of the Children's Hospital Affiliated to Nanjing Medical University and Second Affiliated Hospital Affiliated to Nanjing Medical University. These two hospitals are all located in Nanjing city of China. Fig. 1 is the collecting environment in the newborn room of the Children's Hospital Affiliated to Nanjing Medical University.

In most cases of the data collection, we use the IPHONE 6 equipment to collect the videos. As nurses and doctors are very busy in the real newborn room environment, and they frequently need to keep working while photographing neonates. Therefore, the IPHONE 6 equipment is convenient for nurses and doctors in the newborn room.

3.2 Procedure of Video Collection

The FENP database contains four major categories of pain emotions, i.e., severe pain, mild pain, crying and calmness. For each emotion category, we need to find suitable scene to collect the corresponding neonatal videos in the real newborn room environment. According to the actual situation of the newborn room and the scene designed in the COPE database [13], [14], [17], we choose the following scenes to collect neonatal videos. For pain emotion category (including severe pain and mild pain), we collect videos when neonates suffered from intramuscular injection or blood sampling on their heels. For the

Fig. 1. The collecting environment in the newborn room of the Nanjing Children's Hospital Affiliated to Nanjing Medical University.

category of crying emotions, we select the scene of changing the baby crib of neonates and other crying situations not caused by pain (such as neonates are hungry or fear and so on). For the calmness category, we collect videos when neonates are sleeping or calm [14], [15], [16], [22], [57], [58], [59].

It should be noted that the four emotion categories in our FENP database (severe pain, mild pain, crying and calmness) are different. It is easy to understand that the calmness emotion category is different from the severe pain, mild pain and crying emotion category. However, it may be hard to understand that the pain emotion category (severe pain and mild pain) is also different from the crying emotion category. There are many reasons for crying, such as pain, hungry, fear and so on. Most of neonates will cry when suffering from the pain stimulation, but some neonates may not. According to the conclusion of many medical and neuroscience researches, when neonates suffered from the pain stimulation (in this case, neonates may cry or not cry), its facial expression is different from that of the neonates crying (in this case, neonates are not pain) when neonates

Fig. 2. The video sequence of the collected pain emotion category.

suffered from non painful conditions such as hunger, fear, and so on [13], [16], [25], [26], [29], [30], [31]. Moreover, the purpose of establishing FENP database is to research facial expression recognition of neonatal pain approaches in future which can distinguish between pain related crying and non pain related crying. Therefore, we chose the scene of changing the baby crib of neonates and other crying situations (such as neonate is hungry or fear and so on) which are not caused by pain, and the collected data is labeled as the crying emotion category in this case. On the contrary, when neonates suffered from the pain stimulation, the data collected is labeled as pain emotion category (in this case, neonates may cry or not cry).

During the photographing process, in order to collect the frontal facial expression videos of neonates as much as possible, the camera lens or IPHONE lens is opposite to the neonates' face and follows neonates' head movement. Due to the complexity of the real newborn room environment, nurses may often need to continue to work when photographing neonates, so the collected video often has occlusion problems such as the occlusion of arms, cloth, medical devices and instruments, especially for the emotional category of crying and pain. Finally, the length of each video is between 20 seconds and 60 seconds.

Fig. 2 is a video sequence of collected pain emotion category. As described above, it can be see that one frame is occluded by the medical apparatus and instruments from the Fig. 2. Therefore, we use the FFmpeg tool to cut each video and obtain a series of image frames. Among those image frames, we manually select those clear, representative and non-occluded frames as the data of the FENP database.

3.3 Assessing the Degree of Pain

After obtaining the neonatal images under different scene, we need to give a label for all the neonatal images. For the neonatal images of the crying and calmness emotion category, we already know the label when collecting the corresponding neonates videos. Because the videos of these two categories are collected on the condition of no injections, so doctors and nurses assign the corresponding label in realtime when collecting the videos of crying and calmness emotion category. However, for the neonatal images of the pain emotion category, we need to assess the degree of pain and give them the label of severe pain or mild pain. Because the aim of the FENP database is to build a large facial expression database of neonatal pain which can be used to study the degree of neonatal pain.

Fig. 3. The example of rotating and cropping the neonatal image.

To accurately assess the degree of pain for each neonatal pain image, 5 doctors and 5 nurses of the new pediatric coming from Children's Hospital Affiliated to Nanjing Medical University and Second Affiliated Hospital Affiliated to Nanjing Medical University are selected to assess the degree of pain in the manual form. They use the tool of neonatal facial coding system [25], [26], [27] to get the score of each neonatal pain image. In the procedure of assessing, except the facial expression, doctors and nurses also refer to the health state of the corresponding neonates to improve the degree of assessing accuracy. As we want to classify the neonatal pain images into two degrees of pain (severe pain or mild pain), the score between 6 and 10 is assigned to the label of the severe pain emotion category, and the score between 1 and 5 is given the label of mild pain emotion category [15], [16], [57], [58], [59]. Since the assessed scores of each neonatal pain image for different doctors and nurses have certain difference, so we only keep those neonatal pain images which have the consistent score and get rid of those neonatal pain images which have inconsistent score (About 78 percent of images the raters agreed on) [22], [59].

3.4 Image Preprocessing

Because the real newborn room environment is very complicated, the collected video often has interference information such as occlusion, noise, complex background information and lighting changes. As can be seen from Fig. 2, the background information is complex and the lighting changes are significant. In addition, the face of the collected neonatal image is not always frontal, and angular deflection often exists to a certain extent [16], [58], [59].

Therefore, we manually rotate the neonatal images with angular deflection to ensure that the face is straight, then remove the background area and retain the newborn face area [59]. Fig. 3 is an example of rotating and cropping a neonatal image. Finally, scale normalization, grayscale normalization and equalization are performed on the rotated and cropped neonatal images [15], [16], [19], [58].

3.5 The Result of the FENP Database

At last, the FENP database in total collets 11,000 neonatal facial expression images from 106 Chinese neonates. Those 106 Chinese neonates are all about two days to four weeks old. The image resolution is $256 * 256$ and the image format is JPEG. Besides, it covers four emotion categories including severe pain, mild pain, crying and calmness, and each emotion category has 2,750 image samples. Fig. 4 is the image sample of the severe pain, mild pain, crying and calmness emotion category on the FENP database.

Moreover, we also compare the FENP database with the existing two facial expression databases of neonatal pain in Table 1. From Table 1, we can see that our FENP database is a very large database and is far larger than the COPE [14] and Zamzami *et al.* [18] database no matter the subjects or the number of samples. The neonatal age range of the FENP database is also wider than the other two existing databases. Our FENP database contains two different degrees of pain data (severe pain and mild pain), and the other three existing databases have no different degree of pain data. But the Zamzami *et al.* [18] database contains the acute pain and chronic pain data. In addition, our FENP database is based

Fig. 4. The image sample of the severe pain, mild pain, crying and calmness emotion category on the FENP database. The first, second, third and fourth row correspond the severe pain, mild pain, crying, and calmness emotion category respectively.

TABLE 1
The Information of the FENP Database and the Other Existing Neonatal Pain Facial Expression Database

Database	Subjects	Age	Samples	Resolution	Categories	Race
FENP	106	two days to four weeks	11000 images	256×256	Sever Pain; Mild Pain; Crying; Calmness	Chinese
COPE [14]	26	18 hours to three days	204 images	3008×2000	Pain; Friction; Air Stimulus; Cry; Rest	Caucasian
Zamzami et al. [18]	10	About 36 weeks	10 videos	Unknown	Acute Pain; Chronic pain	Caucasian; Hispanic; African American; Asian; others
YouTube [48]	Unknown	0, 2, 4, 6 or 12 months	142 videos	Unknown	Pain	Unknown

on the Chinese neonates, and the COPE database is based on Caucasian neonates.

4 Experiment

After establishing the FENP database, we need to do some testing and verification experiments on the FENP database. In this section, the traditional facial expression recognition method and the state-of-the-art method such as deep learning method are utilized to perform recognition experiments on the FENP database. The traditional facial expression recognition method used in this experiment is the Gabor [60] combination Support Vector Machine [61] (Gabor+SVM), Local Binary Patterns [62] combination SVM (LBP+SVM), Histogram of Oriented Gradient [63] combination SVM (HOG+SVM) and LBP+HOG+SVM (combination of LBP and HOG at feature level). The state-of-the-art method of deep learning used in this experiment is Convolutional Neural Network [64] based on the AlexNet [64], VGGNet [65], GoogLeNet [66], ResNet [67] and DenseNet [68]). Moreover, we use the training data of the FENP database for fine tuning based on the pre-trained model for AlexNet, VGGNet, GoogLeNet, ResNet and DenseNet.

In the experiment, we use the subject-independent strategy to perform recognition experiments on the FENP database. We randomly select 80 subjects as the training data set (9,751 images) and the remaining 23 subjects as the test data (1,249 images).

To effectively test the FENP database, we take the following four sets of experiment on the FENP database. In the first set of experiment, we divide all the samples of the FENP database into two emotion categories including calmness and non-calmness. The samples of the non-calmness emotion category are constituted by the samples of severe pain, mild pain and crying emotion category of the FENP database. Table 2 is the result of the first set of experiment (non-calmness/calmness) on the FENP database. From Table 2, we can see that the recognition rate of nine approaches on the FENP database are all very high, which indicates the calmness emotion category of the FENP database is obviously different from the non-calmness emotion category (severe pain, mild pain and crying). Moreover, the recognition rate of AlexNet, VGGNet, GoogLeNet, ResNet and DenseNet are all better than Gabor +SVM, LBP+SVM, HOG+SVM and LBP+HOG+SVM.

In the second set of experiment, we divide all the samples of the FENP database into two emotion categories including pain and non-pain. The samples of pain emotion category are constituted by the samples of severe pain and mild pain emotion category of the FENP database. The samples of non-pain emotion category are constituted by the samples of crying and calmness emotion category. Table 3 is the result of the second set of experiment (non-pain/pain) on the FENP database. From Table 3, we can see that the recognition rate of non-pain/pain is lower than non-calmness/calmness for all nine methods on the FENP database.

In the third set of experiment, we divide all the samples of the FENP database into three emotion categories including pain, calmness and crying. The samples of pain emotion category are constituted by the samples of severe pain and mild pain emotion category of the FENP database. Table 4 is the result of the third set of experiment (crying/pain/calmness) on the FENP database. From Table 4, we can see the similar result of the first set and second set experiment,

TABLE 2
The Experimental Results of Non-Calmness and Calmness Expressions Over the Various Methods

Methods	Average classification accuracies (%)		
	Non-calmness	Calmness	All
Gabor+SVM	91.00	82.00	89.27
LBP+SVM	91.00	85.00	89.51
HOG+SVM	91.00	82.00	89.35
LBP+HOG+SVM	91.00	85.00	89.99
AlexNet	97.00	92.00	95.44
VGGNet	98.00	96.00	97.60
GoogLeNet	97.00	87.00	95.04
ResNet	98.00	93.00	96.80
DenseNet	98.00	92.00	96.64

TABLE 3
The Experimental Results of Non-Pain and Pain Expressions Over the Various Methods

Methods	Average classification accuracies (%)		
	Non-Pain	Pain	All
Gabor+SVM	83.00	81.00	82.15
LBP+SVM	81.00	84.00	82.15
HOG+SVM	80.00	93.00	85.27
LBP+HOG+SVM	80.00	92.00	85.35
AlexNet	84.00	97.00	89.75
VGGNet	90.00	91.00	90.39
GoogLeNet	92.00	89.00	90.63
ResNet	87.00	96.00	90.79
DenseNet	90.00	92.00	91.03

TABLE 4
The Experimental Results of Three Kinds of Expressions (Crying/Pain/Calmness) Over the Various Methods

Methods	Average classification accuracies (%)			
	Crying	Pain	Calmness	All
Gabor+SVM	54.00	85.00	82.00	73.50
LBP+SVM	45.00	91.00	81.00	72.30
HOG+SVM	51.00	93.00	79.00	74.94
LBP+HOG+SVM	50.00	93.00	84.00	75.90
AlexNet	63.00	91.00	87.00	80.46
VGGNet	73.00	87.00	86.00	82.07
GoogLeNet	61.00	94.00	89.00	80.94
ResNet	69.00	94.00	88.00	83.67
DenseNet	72.00	90.00	86.00	82.95

TABLE 5
The Facial Expression Recognition Results With Respect to Four Kinds of Expressions (Crying/Mild Pain/Severe Pain/Calmness) Over the Various Methods

Methods	Average classification accuracies (%)				
	Crying	Mild Pain	Sever Pain	Calmness	All
Gabor+SVM	59.00	42.00	46.00	80.00	57.17
LBP+SVM	45.00	57.00	58.00	81.00	57.97
HOG+SVM	50.00	61.00	56.00	78.00	59.81
LBP+HOG+SVM	50.00	59.00	64.00	83.00	61.97
AlexNet	49.00	61.00	75.00	88.00	65.73
VGGNet	63.00	65.00	62.00	89.00	68.69
GoogLeNet	75.00	54.00	53.00	82.00	67.41
ResNet	55.00	71.00	71.00	90.00	69.66
DenseNet	72.00	72.00	55.00	86.00	71.02

and the recognition rates of deep learning method (AlexNet, VGGNet, GoogLeNet, ResNet and DenseNet) are all better than Gabor+SVM, LBP+SVM, HOG+SVM and LBP+HOG+SVM. Moreover, taking the ResNet method as an example, we show the confusion matrix of the ResNet method for the third set of experiment (crying/pain/calmness) on Fig. 5.

In the last set of experiment, we take the experiment to classify four emotion categories including crying, mild pain, severe pain and calmness. Table 5 is the result of the last set of experiment (crying/mild pain/severe pain/calmness) on the FENP database. From Table 5, we can see that the recognition rate of crying/mild pain/severe pain/calmness is lower than non-calmness/calmness, non-pain/pain and crying/pain/calmness for all nine methods. The recognition rate of the deep learning method (AlexNet, VGGNet, GoogLeNet, ResNet and DenseNet) is better than Gabor+SVM, LBP+SVM, HOG+SVM and LBP+HOG+SVM. Moreover, we show the confusion matrix of the DenseNet method for the last set of experiment (crying/mild pain/severe pain/calmness) on Fig. 6.

Moreover, from the result of the above four sets of experiment, we can see that the calmness emotion category is easy to recognize, but the crying emotion category is hard to recognize. We also can see that the recognition rate of the pain emotion category (including severe pain and mild pain) is high, but severe pain and mild pain are also hard to recognize.

5 Discussion

In the procedure of the collecting neonatal videos, we also simultaneously record the crying sound and body gesture data except the facial expression data. According to [20], [27], [69], [70], the crying sound and body gesture also can reflect the neonatal pain and other emotion. As we collect the neonatal videos in the real newborn room environment, so the voice data is complex and not clear, and it contains various voices such as the crying sound of multiple neonates, the voice of doctors and nurses and so on. Moreover, due to the complexity of the real newborn room environment, the collected videos frequently exist the problem of the occlusion such as the occlusion of the arm, cloth, medical apparatus and instruments (It is shown in Fig. 2), so the body gesture data is also not good. We may will collect effective crying sound and body gesture data of neonates in the next step.

6 Conclusion

In this paper, we introduce a novel database FENP for facial expression recognition of neonatal pain to carry forward the research of the facial expression recognition of neonatal pain. The FENP database in total collets 11,000 neonatal facial expression images from 106 Chinese neonates in the Children's Hospital Affiliated to Nanjing Medical Univer-

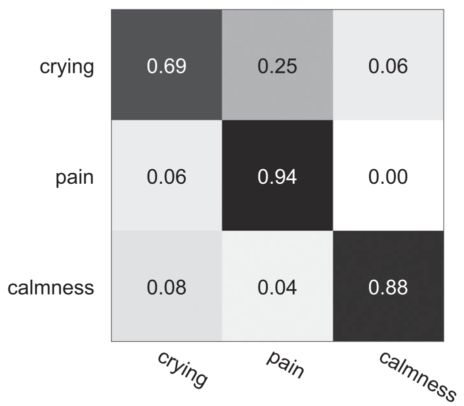

Fig. 5. The confusion matrix among the crying, pain and calmness expressions using the ResNet method on the FENP database (The values are row-normalized percentages, the rows and columns correspond to labels and predictions respectively).

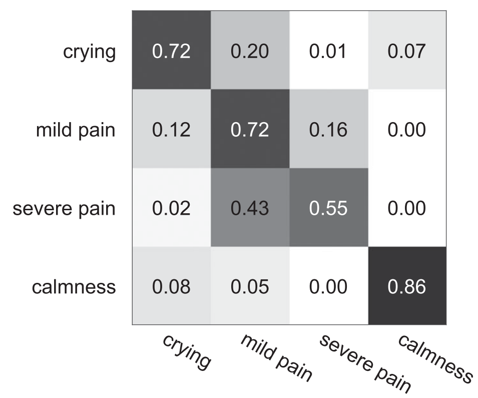

Fig. 6. The confusion matrix among the four expressions (crying/mild pain/severe pain/calmness) using the DenseNet method on the FENP database (The values are row-normalized percentages, the rows and columns correspond to labels and predictions respectively).

sity and Second Affiliated Hospital Affiliated to Nanjing Medical University in China. Besides, it covers four emotion categories including severe pain, mild pain, crying and calmness, and each emotion category has 2,750 image samples. At last, the gabor+SVM, LBP+SVM, HOG+SVM, LBP +HOG+SVM, Convolutional Neural Network method (AlexNet, VGGNet, GoogLeNet, ResNet and DenseNet) test and verify the FENP database.

The main contribution of this paper is to build a large facial expression database of neonatal pain. Compared to the existing facial expression database of neonatal pain, our FENP database has the following three advantages or characteristics, i.e., (1) our FENP database is a very large database, and it is far larger than the existing facial expression database of neonatal pain. (2) our FENP database contains two different degrees of pain data (severe pain and mild pain), and the other existing facial expression database of neonatal pain has no different degrees of pain data. (3) our FENP database is based on the Chinese neonates, and the other facial expression databases of neonatal pain are mainly based on Caucasian neonates.

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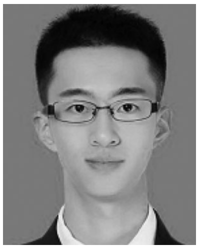

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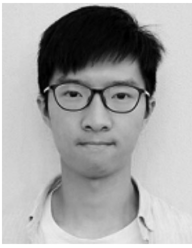

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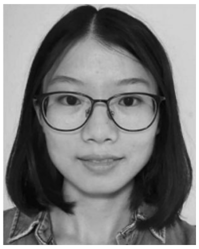

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