Deep Multi-Facial patches Aggregation Network for Expression Classification from Face Images

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Abstract

Emotional Intelligence in Human-Computer Interaction has attracted increasing attention from researchers in multi-disciplinary research fields including psychology, computer vision, neuroscience, artificial intelligence, and related disciplines. Human prone to naturally interact with computers face-to-face. Human Expressions is an important key to better link human and computers. Thus, designing interfaces able to understand human expressions and emotions can improve Human-Computer Interaction (HCI) for better communication. In this paper, we investigate HCI via a deep multi-facial patches aggregation network for Face Expression Recognition (FER). Deep features are extracted from facial parts and aggregated for expression classification. Several problems may affect the performance of the proposed framework like the the small size of FER datasets and the high number of parameters to learn. For That, two data augmentation techniques are proposed for facial expression generation to expand the labeled training. The proposed framework is evaluated on the extended Cohn-Konade dataset (CK\textsuperscript{+}) and promising results are achieved.

Keywords: Human-Computer Interaction, Face Expression Recognition, Deep Visual learning, multi-facial patches, Conditional Generative Adversarial Network, CK\textsuperscript{+} database.

1. Introduction

Human face conveys a significant information about identity, gender, ethnicity, age and emotion. It is extremely expressive and able to communicate countless emotions without saying a word. Besides, all humans communicate six basic internal emotional states (happy, surprise, fear, disgust, anger, and sad) using the same facial movements according to the universality hypothesis of facial expressions of emotion established since Darwin’s seminal works \cite{1}. Facial expressions provide substantial evidence of the level of interest, the level of understanding and support and a continuous feedback of agreement or disagreement.

The human face exhibits information pertaining to identity as well as to attributes such as age, gender and ethnicity. Evaluating the performance of cross-domain FER systems is a challenging topic. For example, by studying crossing facial expressions and ethnicity using artificial intelligence on big data face images, it can help to solve the longest debates in the biological and social sciences of the universality of facial expressions emotion using cross-cultural comparisons \cite{1}.

In fact, a computer could interact more intelligently with human users by understanding facial expressions. Thus, emotion recognition from face images has attracted considerable attention and a wide range of applications has been developed in Human-Computer Interaction (HCI), biometrics, Health informatics and computer-vision applications.

However, Automated Facial Expression Recognition (FER) has remained a challenging problem because of in-the-wild environmental conditions and most of existing methods lack generalizability when applied to images captured in wild. Others difficulties exists related to illumination variation, occlusions and non-frontal head poses. Facial expressions is person-dependant and the intensity of the expressions depends on the person.

Psychological studies has shown that not all facial regions contributes on facial expressions. In fact, the most contributing regions are nose, mouth and eyes.
regions [2]. Motivated by this fact, a multi-task network is proposed for FER. Several facial landmarks are used to generate many local patches of the most contributing regions on facial expressions. Face images are then cropped into many patches and feed into Convolutional Neural Networks (CNN). The aggregation of the deep multi-patches network decide about the class of expression from face image.

Aiming to improve the performance of the proposed Multi-Facial patches-based CNN and to avoid overfitting, two data augmentation techniques are carried out to increase and to diversify the input data and then to expand the labeled training. A Conditional Generative Adversarial Network and Transformation Functions are proposed for Facial Expression Generation.

An overview of the rest of the paper is as follows: in Section 2 the literature of FER is reviewed. Section 3 describes the proposed method. Section 4 presents quantitative results. A conclusion and future perspective works are given in Section 5.

2. Related work

Since the early 1970s, the universality and the cultural differences in facial expressions of emotions have been studied and it has been shown an evidence of cross-cultural agreement in the judgment of facial expression and another evidence to support universality in facial expressions [22]. These ‘universal facial expressions’ are those representing happiness, sadness, anger, fear, surprise, and disgust. First, a manual labelling of facial behavior using the Facial Action Coding System (FACS) is proposed by Ekman et al. [23]. In FACS, facial movements in terms of atomic facial actions called Action Units (AUs) are measured and then used for the recognition of effective states and emotions. Ekman’s work inspired many researchers to develop automatic approaches to analyze facial expressions based on image and video processing.

Several works have been proposed for facial emotions classification from static images [24] [7] [25] [26] [27] [28] [29] [30] [31] [32] [33] [34] [35] [36] [37] [38] or from continuous video input [29] [40] [41]. A system that automatically finds faces in the visual video stream and codes facial expression dynamics in real time with seven dimensions (Neutral, anger, disgust, fear, joy, sadness, surprise) is proposed in [29]. To demonstrate the potential of the proposed system, a real time ‘emotion mirror’ is developed to render a 3D character in real time that mimics the emotional expression of a person. Then, the real time system has been deployed in a variety of robotic platforms. Another system for classification of facial expressions from continuous video input is proposed in [40] to learn from both labeled and unlabeled data.

Traditionally, emotion recognition databases are acquired on laboratory-controlled conditions where subjects posed a particular emotion. The face images are generally taken with static backgrounds, controlled and invariant illumination and without any movement [8] [13] [12] [11] [10]. Emotion recognition from facial images in wild conditions is a relatively new and challenging problem in face analysis. Several datasets have been proposed in recent years without any lab-controlled conditions and where photos of the subjects are acquired in real-world scenarios [9] [3] [4] [5] [6] [7]. For that, methods should be robust to indoor, outdoor, different color backgrounds, occlusion, background clutter and face misalignment.

Happy People Images (HAPPEI) [5], Acted Facial Expressions in the Wild (AFEW) [42], Static Facial Expressions In the Wild (SFEW) [24] and GENKI [6] are recent databases for emotion recognition in the wild with real-world scenarios. The existing databases for emotion recognition presents mainly universal emotions like angry, disgust, fear, happy, neutral, sad and surprise. Recent databases use continuous labelling in the arousal and valence scales. An overview of the facial expression datasets is given in Table 1.

Common approaches to facial expression recognition presents two main steps : (1) features extraction and (2) classification. For that, several Hand-crafted and learned features have been proposed. Deep learned features usually perform better than hand-crafted features. Thus, facial expression recognition methods can be generally categorized into three groups:

**Hand-crafted features based**: various hand-crafted feature schemes have been proposed for facial emotion classification: action units (AUs) [29], Gabor magnitude representation using a bank of Gabor filters [39], histogram of gradients (HOG) [27] [39] and local phase quantisation (LPQ) features for encoding the shape and appearance information [25], Facial Animation Parameters (FAPs) [26], motion features [40] [41] and texture descriptors like Gray Level Co-occurrence Matrix [28].

**Metric learning based**: multiple metric learning
| Dataset          | Challenge          | Samples       | Nb subjects/Faces | Nb expressions | lab-controlled |
|------------------|--------------------|---------------|-------------------|----------------|----------------|
| AFEW 7.0 [3]     | EmotiW 2017        | 1809 videos   | -                 | 7              | NO             |
| SFEW [4]         | EmotiW 2015        | 1766 images   | -                 | 7              | NO             |
| HAPPEI [5]       |                    | -             | 4886              | 8500           | NO             |
| GENKI [6]        |                    | -             | 63,000 images     | approximately as many different human subjects | 3 | NO             |
| GEMEP-FERA [7]   | FERA Emotion sub-ch | 289 videos    | 13 sub            | 5              | NO             |
| MMI [8]          |                    | -             | 740 images + 848 videos | 19 | AUs | YES             |
| FER2013 [9]      | ICML 2013          | 35887 images  | -                 | 7              | NO             |
| CK+ [10]         |                    | -             | 593 sequences     | 123            | 7 | YES             |
| JAFFE [11]       |                    | -             | 213               | 10             | 7 | YES             |
| Oulu-CASIA [12]  |                    | -             | 2880 videos       | 80             | 6 | YES             |
| MultiPIE [13]    |                    | -             | 750000            | 337            | 6 | YES             |

Table 1: An overview of the facial expression Datasets.

approaches have been proposed for facial emotion recognition. In [30], two-stage multi-task sparse learning (MTSL) framework is proposed to efficiently locate discriminative patches. Two multi-task extensions of Metric learning for kernel regression (MLKR) for facial action unit intensity prediction is proposed in [31]. The Hard Multi-task regularization for MKLR introduce a more constrained common representation between tasks than a standard multi-task regularization. An adaptative discriminative metric learning (ADML) is also proposed for facial expression recognition by imposing large penalties on interclass samples with small differences and small penalties on interclass samples with large differences simultaneously [32].

Deep learning based: recently, high-level semantic features are designed based on deep neural networks architectures for facial emotions recognition. The multi-level neural networks perform a series of transformations on the face image. On each transformation, a denser representation of the face is learnt. More and more abstract features are learnt in the deeper layers and can allow a better prediction of the class of emotion. A comparison between a suite of Deep Belief Network models (DBN) and baseline models shows improvement in audio-visual emotion classification performance when using DBNs models. Further, the three-layer DBN outperforms the two-layer DBN models [33]. In [34], the approach aims to go deeper using deep neural networks, a network of two convolutional layers each followed by max pooling and then four inception layers is proposed and shows an improvement of performance on seven publically available facial expression databases.

Different deep networks architectures are proposed for facial emotion learning. Among these, those which study the spatial and the temporal information and incorporate them into different networks. A Deep evolutional spatial-temporal networks (PHRNN - MSCNN) is proposed in [14], it is a fusion of temporal network for modelling dynamical evolution called Part-based Hierarchical Bidirectional Recurrent Neural Network (PHRNN) and a spatial network for global static features called Multi-signal Convolutional Neural Network. In the PHRNN, facial landmarks are divided into four parts based on facial physical structure and fed to the BRNN models. While, the MSCNN takes pairs of frames as the input with both recognition and verification signals and fed the frame to a CNN. Like the PHRNN-MSCNN, the Deep Temporal Appearance-Geometry Network (DTAGN) [19] com-
| Method                | Approach                                                                 | Dataset       | Accuracy   |
|----------------------|--------------------------------------------------------------------------|---------------|------------|
| Zhang et al. (2017)  | Deep evolutional spatial-temporal networks (PHRNN-MSCNN)                 | CK+           | 98.5%      |
|                      |                                                                          | OULU-CASIA    | 86.25%     |
|                      |                                                                          | MMI           | 81.18%     |
| Sun et al. (2017)    | Multi-channel Deep spatial-Temporal feature fusion neural network (MDSTFN)| CK+           | 98.38%     |
|                      |                                                                          | RaFD          | 99.17%     |
|                      |                                                                          | MMI           | 99.59%     |
| Kuo et al. (2018)    | frame-based and frame-to-sequence FER framework                         | CK+ (frame-based) | 97.37%   |
|                      |                                                                          | CK+ (frame-to-seq) | 98.47%   |
|                      |                                                                          | Oulu-Casia (frame-based) | 88.75%   |
|                      |                                                                          | Oulu-Casia (frame-to-seq) | 91.67%   |
| kim et al. (2017)    | deep generative-contrastive networks                                    | CK+           | 97.93%     |
|                      |                                                                          | Oulu-Casia    | 86.11%     |
|                      |                                                                          | MMI           | 81.53%     |
| Yang et al. (2018)   | Identity-Adaptive Generation (IA-gen)                                   | CK+           | 96.57%     |
|                      |                                                                          | OULU-CASIA    | 88.92%     |
|                      |                                                                          | BU-3DFE       | 76.83%     |
|                      |                                                                          | BU-4DFE       | 89.55%     |
| Jung et al. (2015)   | Deep Temporal Appearance-Geometry Network (DTAGN)                        | CK+           | 97.25%     |
|                      |                                                                          | OULU-CASIA    | 81.46%     |
|                      |                                                                          | MMI           | 70.24%     |
| Yu et al. (2018)     | Deeper Cascaded Peak-piloted Network (DCPN)                              | CK+           | 98.60%     |
|                      |                                                                          | OULU-CASIA    | 86.23%     |
| Zhao et al. (2016)   | Peak-piloted deep network (PPDN)                                        | CK+           | 97.3%      |
|                      |                                                                          | OULU-CACIA    | 72.4%      |

Table 2: An overview of deep learning-based approaches for FER.
bines deep temporal geometry network (DTGN) which extracts temporal geometry features from temporal facial landmark points and deep temporal appearance network (DTAN) which extracts temporal appearance features from image sequences. Another Multi-channel Deep spatial-Temporal feature fusion neural network (MDSTFN) is proposed and in which he temporal information is defined as the optical flow from the peak expression face image and the neutral face image, while the spatial information is defined by the gray-level image of emotional face [15].

Others deep networks consider a peak-piloted feature transformation by using the peak expression images to supervise the intermediate responses of non-peak expression images [21, 20]. The Conditional Generative Adversarial Network (CGAN) are also used to generate basic facial expressions in the Identity-Adaptive Generation (IA-gen) network [18]. Then, features are extracted using the pre-trained CNN and the query image is labeled as one of the six basic expressions based on a minimum distance in feature space. More complex and original architecture is proposed in [17] through a deep generative-contrastive networks. It is a combination of a generative model, a contrastive model and a discriminative model. The contrastive representation is calculated at the embedding layer of deep network by comparing a given (query) image with the reference image. An overview of deep learning-based approaches for FER is given in Table 2.

Others approaches combine data from different modalities for emotion recognition and sentiment analysis. For instance, in [35], the convolutional recurrent multiple kernel learning model combines features extracted from video, speech and text, a convolutional RNN is used for extracting features from video data. A large amount of labeled data is required to train deep neural networks. However, emotion recognition dataset are relatively small and do not have a sufficient quantity of data. To overcome this problem, transfer learning approaches are proposed by a first pre-training on related task dataset and fine-tuning on datasets relevant to facial expression [36, 37]. In the literature, several works propose various methods for deep facial expression recognition. A survey on deep FER including datasets and algorithms is given in [38].

3. Proposed Method

The structure of the proposed framework is shown in Fig 1. Given a face image, facial landmarks are detected. Facial patches are then cropped around facial landmarks (Section 3.1) and they are fed to the multi-patches based convolutional neural networks (Section 3.2). The response of the sub-networks of all patches are aggregated at two dense layers to classify the facial expression (Section 3.2). FER datasets are relatively small. To overcome this problem, two data augmentation techniques are performed (Section 3.3 and Section 3.4). The details of the proposed framework are described in the following contents.

3.1. Multi-facial patches Extraction

Facial expression is presented by the dynamic variation of key parts of the human face (e.g. eyes, nose and mouth). The variation of local parts are fused to form the variation of the whole face.

The first step of the proposed framework concerns the extraction of local aligned facial patches. The face image is cropped into many local patches. A facial landmark detector is used in this work (Sagonas et al., 2013; Kazemi and Sullivan, 2014). Facial landmarks are used to localize and to represent salient regions of the face (eyes, eyebrows, nose, mouth and jawline). A fully discriminative model based on a cascade of boosted decision forests to regress the position of landmarks from a sparse set of pixel intensities is performed and it provide accurate landmarks in the majority of cases.

The alignment is simply a transformation from an input coordinate space to an output coordinate space such that all the faces are centered, eyes lie on a horizontal line, and faces are scaled such that the faces sizes are nearly identical. Facial landmarks show better performance for face alignment than Haar cascades or HOG detectors since the bounding box provided less precision to estimate the eye location as compared to landmarks indexes.

Seven patches are extracted around the facial landmarks and they represent right eye, left eye, nose, mouth, left eyebrow, right eyebrow and jaw. The extracted facial patches forms key parts of human face and can allow the study and the comparison of their dynamic variation for each facial expression.

3.2. Multi-facial patches based Convolutional neural networks

The seven extracted patches from each face image are fed to seven sub-networks. Their responses are
Figure 1: The diagram of the proposed approach

Figure 2: Multi-Facial Patches based Convolutional Neural Networks (MFP-CNN). For each image, the face is detected and aligned. Facial landmarks are extracted from each aligned face. Facial patches are extracted around facial landmarks and they are fed each to a sub-network. The structure of each sub-network is shown in Fig. 3.
fused and concatenated in two dense layers separated by a dropout layer. Fig. 2 shows the architecture of the proposed multi-facial patches-based convolutional neural network (MFP-CNN). Particular features are learnt from each patch using different sub-networks and the concatenate layer aggregate all sub-networks together. The sub-network for each patch is composed by three convolutional layers. Each convolutional layer is followed by a max pooling layer and finally a dropout is performed. The structure of each sub-network for each patch is shown in Fig 3.

Implementation details and overfitting problem: Many parameters may affect the performance of the MFP-CNN such as the number of layers in each sub-network. In this work, our proposed architecture of each sub-network is not very deep because of the small size of patches. The number of channels of the first convolutional C1 and the max pooling layers are 6. While, the number of channels of the second convolutional C2 and the max pooling layers are 16 and the number of channels of the third convolutional C3 and the max pooling layers are 120. The filter size of C1 layer is 5 \times 5 pixels and the stride of the max pooling layer is 2. The C2 and C3 layers have the same filter size and the same stride value as C1 layer. The output of the each sub-network has 120 \times 31 \times 31 = 115320 dimensions. Therefore the input of the first dense layer has 7 \times 115320 = 807240 dimensions. The activation functions are ReLU for the first dense layer and Softmax for the second dense layer. The MFP-CNN is optimized using RMSProp optimizer with a learning rate of 10^{-3}.

3.3. Conditional Generative Adversarial Network for Facial Expression generation

To generate more facial expression images, the conditional version of the generative adversarial networks (GANs) are considered in this work [43]. cGANs enable the generation of fairly realistic synthetic images by forcing the generated images to be close statistically to the real ones. It consists of two ‘adversarial’ models:

- Generator G: that captures the data distribution,
- Discriminator D: that estimates the probability that a sample come from the training data rather than G.

The generator maximizes the log-probability of labeling real and fake images correctly while the generator minimizes it. From an observed image x and a random noise vector z, cGAN learn a mapping to y : G(x, y) \rightarrow y and the final optimization is to solve the min-max problem:

\[ G^* = \arg \min_G \max_D L_{GAN}(D) + \lambda L_{GAN}(G) \] (1)

Where \( L_{GAN}(D) \) is the loss function of the discriminator and \( L_{GAN}(G) \) is the loss function of the generator G as defined in the following:

\[ L_{GAN}(G) = 1/N \sum_{i=1}^N \mathcal{L}_{ad} + \alpha \mathcal{L}_{MSE} + \beta \mathcal{L}_{PEP} \] (2)
where N is the total number of training images, $L_{\text{ad}}$ is the adversarial loss, $L_{\text{MSE}}$ and $L_{\text{PEP}}$ are the pixel-wise MSE loss and the perceptual loss between the regenerated and training samples respectively as defined in [44]. The loss function of the discriminator can be expressed as:

$$L_{\text{GAN}}(D) = \frac{1}{N} \sum_{i=1}^{n} \log D(x, y) + \log(1 - D(x, G(x, z)))$$

(3)

The structure of the generator G and the discriminator D are summarized in Fig. 4.

3.4. Patches generation for data augmentation

The technique of artificially expanding labeled training sets by transforming data points in ways which preserve class labels known as data augmentation has quickly become a critical and effective tool to handle labeled data scarcity problem.

A second technique for data augmentation that leverages user-domain knowledge in the form of transformation operations is adapted. The problem is formulated as a generative model over a set of transformation functions (TFs) which are user-specified operators representing geometric transformations to data points. Five TFs are considered and could rotate the facial patch by 90 and 180 degrees, translate it, shift it and transformed it with ZCA whitening.

In addition to the generated images using cGAN, more patches are generated for data augmentation and for increasing the robustness of the model to random transformations. FER datasets contains very often data with imbalanced classes.

4. Experiments and results

4.1. Datasets

Several datasets have been used in our experiments:

The main dataset: The extended Cohn-Kanade dataset (CK+) [10] is the main dataset used in our experiments mainly because it is one of the largest publicly available dataset for FER and then it can be considered on deep learning-based approaches. It is a complete dataset for action unit and emotion-specified expression. It include 593 sequences from 123 subjects. The image sequence vary in duration between 10 and 60 frames and go from the onset (neutral face) to peak facial expression. Frontal face images of seven discrete emotions, consisting of synchronous views of the posed expression from an angle of 30 degrees, are collected. The CK+ is not balanced in term of gender and ethnicity with 69% female, 81%.Euro-American, 13% Afro-American, and 6% other groups. In our experiments, all the frames per sequence are considered for training and testing. The first seven frames are labeled as Neutral, while the label is provided to the last three frame with high-intensity expression.

Datasets to evaluate the generalization of the proposed model to other datasets: Two datasets are considered.

- JAFFE [11]: is the first dataset. It is acquired on laboratory-controlled conditions exactly like the main dataset used to train the model. Ten subjects posed six facial expressions (happiness, sadness, surprise, anger, disgust, fear) and a neutral face for a total of 219 images. Only Japanese female participate to the data collection.

- SFEW [4]: is the second dataset and it is acquired in the wild conditions which could be more challenging when the dataset is trained with a laboratory-controlled dataset. Static Facial Expression in the Wild (SFEW) 2.0 dataset is introduced during the sub-challenge of EmotiW 2015. It contains 1766 facial expressions images of seven discrete emotions. It is created from AFEW 5.0 videos dataset. A semi-automatique technique based on k-means clustering is performed for the data labelling.

4.2. Experimental results

4.2.1. MFP-CNN framework evaluations

Evaluation of the baseline MFP-CNN on the CK+:

Several experiences are performed to assess the performances of the proposed MFP-CNN-based approach for FER as shown in Table 3. In the first experience, the performance of the baseline MFP-CNN is evaluated on the well-known benchmark of the CK+. We divide the subjects frames into 10 subsets and we avoid subjects appearing in both the training and the test simultaneously. The overall accuracy of 10-fold subject-independent cross-validation protocol is 89.77%. The results shows that the baseline MFP-CNN is robust in learning facial expression on a relatively small dataset. Nevertheless even without expanding labeled training sets and without transferred features from other tasks and datasets, the accuracy is quiet good. The corresponding confusion matrix is shown in Fig. 7a. The misclassified face images are mainly neutral faces. As the neutral face images correspond to the first seven frames of the image sequence which
Table 3: MFP-CNN performances through several experiences and setups.
go from the neutral face to the peak face expression, face images of the third frame, labeled as neutral are close in term of the intensity of facial expression and the dynamic variation of key parts of the human face to the face images of the fourth frame, labeled as the peak expression and then it can be misclassified as the class of the peak face expression.

**Evaluation of Data augmentation:** The FER dataset are relatively small. To expand the labeled training sets, two techniques for data augmentation are performed as described in (Section 3.3 and Section 3.4.) In the second experience, we evaluate the performance of generating more facial images using cGAN. As shown in Figure 5, the generated facial images are fairly realistic, the different facial expressions can be identified visually by human while the identity-related information is preserved. The regenerated images using cGAN are used in the second expression with the original images of the CK+ to train the MFP-CNN. The augmented dataset is divided into 80% for training and 20% for testing. During the training phase, 90% of the training set is used for learning the weights and 10% is used for validation. Subjects do not appear in both the training and the test simultaneously. This second experience outperforms the first experience with an accuracy of 96.60% and it shows that data augmentation improve the accuracy the proposed MFP-CNN-based approach. The corresponding confusion matrix is shown in Fig. 7b. Only three facial expression classes are misclassified: neutral, sad and contempt. There were not large difference between these facial expressions in term of the dynamic variation of key parts of the human face, also, posing them in lab-controlled conditions could be hard to succeed.

In the third experience, we evaluate the performance of augmenting training data by generating more patches to train the MFP-CNN. Some examples of the generated patches using the five transformation functions are shown in Figure 6. Like in the second experience, the dataset is also divided into 80% for training and 20% for testing. The accuracy in this experience is equal to 97.96%. It has been increased by 8.25% comparing to the baseline framework of MFP-CNN in the first experience and it confirms the impact of augmenting pre-training data sets in this framework of FER. The corresponding confusion matrix is shown in Fig. 7c.

In the fourth experience, the two data augmentation techniques are considered and more facial images and facial patches are generated using cGAN and the transformation functions, respectively. Like in the second and in the third experience, the dataset is divided into 80% for training and 20% for testing. This
Figure 7: Confusion matrices of the MFP-CNN on the CK+ database of four different experiments. (a) Experience 1: 10-fold cross-validation with the baseline MFP-CNN. (b) Experience 2: 80% for training and 20% for testing of the augmented CK+ with cGAN. (c) Experience 3: 80% for training and 20% for testing of the augmented CK+ with the transformation functions. (d) Experience 4: 80% for training and 20% for testing of the augmented CK+ with cGAN and the transformation functions.
experiences outperforms all the previous ones and an accuracy of 98.07% is obtained. The corresponding confusion matrix is shown in Fig. 7d, the misclassified samples belong to sad, neutral and contempt. Thus, data augmentation is very important in the proposed FER framework and more data can give a more accurate FER model.

4.2.2. Generalization of the proposed model to other datasets

FER datasets presents a big variability due to the variations in facial expressions among different persons, the different ways of data labeling and the different conditions of acquiring data. A robust model learn from known examples and generalize from those known examples to new examples. The generalization of the proposed model is evaluated under dataset bias. Thus, the MFP-CNN trained on CK+ dataset is tested on other datasets. CK+ is a standard dataset acquired on laboratory-controlled conditions where face images are taken in same conditions. Two experiments are performed:

- **Training on CK+ dataset and testing on JAFFE dataset:** in the first experiment, the generalization of model to a dataset acquired in laboratory-controlled conditions is evaluated. The test dataset presents same gender and same ethnicity, unlike the train dataset which contains different ethnicities and two genders. An accuracy of 61.97% is achieved and the corresponding confusion matrix is shown in Fig. 8a. The misclassification comes mainly from two facial expressions: disgust and neutral. 61.54% of disgust face images and 51.63% of neutral face images are misclassified and they are confused with all facial expressions present in JAFFE dataset. Despite the big difference between the JAFFE and the CK+ databases in term of image resolution, number of face expressions, conditions of acquisition, gender and ethnicity, the learned MFP-CNN on CK+ is still able to predict correctly the facial expression in 62% of cases. It is a promising result.

- **Training on CK+ dataset and testing on SFEW dataset:** in the second experiment, the test dataset is collected in the wild for unconstrained FER. Training on laboratory-controlled dataset and testing on labeled facial expressions in the wild dataset is more hard and challenging. Training on CK+ and testing on SFEW gives an accuracy of only 32.7% as shown in confusion matrix of Fig. 8b. When a fine-tuning is applied, the accuracy of FER increases considerably and it achieves 86.36% as shown in the Confusion matrix of Fig. 8c. The transition from ideal condition of face acquisition (CK+) to faces in the wild conditions (SFEW) shows an increased error rate, a fine-tuning improved considerably the results.

4.2.3. Comparison with existing methods

In this section, we compare the performance of the proposed method with state-of-the-art FER methods on the CK+. Only deep neural networks-based architectures are reported in this comparison as they are performing better than shallow learning-based methods on FER methods. The top performing methods in FER literature exceeds 98% [20, 14, 15, 16]. Two factors that could impact strongly the performances of FER methods on CK+ database, are not standard in the existing FER methods:

- Data selection: the number of frames to consider,
- Sequence-based methods outperform frame-based methods [16, 20].

In [16], the high performance is achieved thanks to the extending of their proposed framework to a frame-to-sequence approach by exploiting the temporal information with gated recurrent units. Their frame-based approach achieve only 97.37%. The use of peak expression to supervise the non-peak expression improves the performance of the proposed framework in [20]. Also learning spatio-temporal features that capture the dynamic variation of facial physical structure and the dynamic temporal evolution of expression [14, 15] boosts the performance of FER method. In [15], only 6 universal emotional faces are tested. Neutral and Contempt facial expressions are ignored. We have reported in Section 4.2.1 that the misclassified samples belong mainly to these two classes. Also, they do not use three consecutive face images to reduce the sample correlation caused by two similar face images. This can explain the achieved high good performance.

Our frame-based approach achieves an accuracy of 98.07% on 8 facial expressions. To the best of our knowledge, it is the only approach reported in the FER literature that consider neutral facial expressions despite its correlation with the rest seven facial expressions on the CK+ database. Despite the correlation between the third frame labeled in our experiments as neutral and the fourth frame labeled as the facial expression, the
MFP-CNN framework performs well among existing FER methods.

5. Conclusion and future works

In this paper, we propose a Multi-Facial Patches-based Convolutional Neural Networks (MFP-CNN) for Face Expression Recognition (FER). Further, we propose to expand the labeled training by generating facial expressions images and patches. Two techniques are considered for that by using the Conditional Generative Adversarial Networks and a set of transformation functions. The proposed method achieves significantly good performance in comparison to others existing approaches on the CK+ database. For the future work, we plan to make the model more generalizable to others databases acquired in different conditions and in real-world scenarios.

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Figure 8: Confusion matrices of the MFP-CNN trained the CK+ database and tested on others FER databases.
| Method               | Descriptor                               | Data selection                                      | Expressions | Accuracy |
|---------------------|------------------------------------------|-----------------------------------------------------|-------------|----------|
| Zhang et al. (2017) | PHRNN - MSCNN                             | -                                                   | 7 expressions | 98.50%   |
| Sun et al. (2017)   | MDSTFN                                   | 1st frame (neutral) + seven successive (peak)       | 6 expressions | 98.38%   |
| Kuo et al. (2018)   | frame-to-sequence approach               | 9 frames                                            | 7 expressions | 98.47%   |
| Kim et al. (2017)   | deep generative-contrastive network      | -                                                   | 7 expressions | 97.93%   |
| Yang et al. (2018)  | Identity-Adaptive Generation (IA-gen)    | last three frames                                   | 7 expressions | 96.57%   |
| Jung et al. (2015)  | Deep Temporal Appearance-Geometry Network (DTAGN) | -                                                   | 7 expressions | 97.25%   |
| Yu et al. (2018)    | Deeper Cascaded Peak-piloted Network (DCPN) | 7th to 9th (weak) last one to 3 frames (strong)     | 7 expressions | 98.6%    |
| Zhao et al. (2016)  | Peak-Piloted Deep Network (PPDN)         | last 3 frames (peak)                                | 7 expressions | 97.3%    |
| Our method          | Multi-Facial patches-based convolutional Neural Networks (MFP-CNN) | 1st to 3rd (neutral) + 4th to last frame (expression) | 8 expressions | 98.07%   |

*Table 4:* Comparisons of the FER methods by the proposed CNN architectures and the state-of-the-art methods on CK+ database.
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