Face Behavior à la carte: Expressions, Affect and Action Units in a Single Network

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Abstract Automatic facial behavior analysis has a long history of studies in the intersection of computer vision, physiology and psychology. However it is only recently, with the collection of large-scale datasets and powerful machine learning methods such as deep neural networks, that automatic facial behavior analysis started to thrive. Three of its iconic tasks are automatic recognition of basic expressions (e.g. happy, sad, surprised), estimation of continuous emotions (e.g., valence and arousal), and detection of facial action units (activations of e.g. upper/inner eyebrows, nose wrinkles). Up until now these tasks have been mostly studied independently collecting a dataset for the task. We present the first and the largest study of all facial behaviour tasks learned jointly in a single multi-task, multi-domain and multi-label network, which we call FaceBehaviorNet. For this we utilize all publicly available datasets in the community (around 5M images) that study facial behaviour tasks in-the-wild. We demonstrate that training jointly an end-to-end network for all tasks has consistently better performance than training each of the single-task networks. Furthermore, we propose two simple strategies for coupling the tasks during training, co-annotation and distribution matching, and show the advantages of this approach. Finally we show that FaceBehaviorNet has learned features that encapsulate all aspects of facial behaviour, and can be successfully applied to perform tasks (compound emotion recognition) beyond the ones that it has been trained in a zero- and few-shot learning setting.

1 Introduction

In the early stages of automatic facial behavior analysis, the research was conducted using small, non-representative databases of posed expressions (FERET [30], CMU-PIE [32], Yale Face). It was then understood that naturalistic behaviour should be used instead of posed which led to the collection of databases such as SAL[10]. Nevertheless, these datasets were very small (in terms of people), with strict scenarios and lab-based recording environments. Recently, a lot of effort has been made towards collecting large scale databases of naturalistic behaviour captured in uncontrolled conditions, in-the-wild datasets [19][40][26][2], which is the focus of our study.

Up until now facial behaviour in-the-wild has been mostly studied by collecting a large and diverse dataset with annotations and approaching one of the tasks at a time. There a lot of works on recognition of basic emotion expressions [12] such as anger, disgust, fear, happiness, sadness, surprise and neutral in-the-wild [7][6]. Recently, continual emotion dimensions such as valence (how positive/negative a person is) and arousal (how active/passive a person is) have gained popularity (VA), as they are naturally suited to represent emotional state and its changes over time. Datasets for continual emotions are simpler to collect benefiting from human computer interactions techniques. Automatic facial analysis has been also studied in terms of the action units (AUs) coding system [13]. This system is a systematic way to code the facial motion with respect to activation of facial muscles. It has been widely adopted as a common standard towards systematically categorising physical manifestation of complex facial expressions. The dataset collection of action units is
very costly, as it requires skilled annotators to perform the
task. Nevertheless there has been a lot of effort to collect ac-
tion unit annotations and develop automatic AUs annotation
tools like [2][1].

The three aforementioned tasks of facial behaviour anal-
ysis are interconnected, as they constitute different aspects of
human affective states. In [13], the facial action coding
system (FACS) has been introduced to indicate prototypical
action units for each of the basic expressions. In [11], it
was revisited and extended to contain emotion expres-
sions beyond basic types – compound emotions (e.g. happily
surprised). In [16], the authors show that neural networks
trained for expression recognition implicitly learn facial ac-
tion units. Moreover, in [25] the authors have discovered
that valence and arousal dimensions could be interpreted
by AUs. For example, AU12 (lip corner puller) is related
to positive valence. Nevertheless, the three aspects of facial
behaviour analysis have never been addressed together in a
single framework we propose to explore in this work.

Our main contributions are as follows:

- We present the first, to the best of our knowledge, multi-
task, multi-domain and multi-label network (FaceBehaviorNet) and train it end-to-end for predicting simultane-
sously 7 basic expressions, 17 action units and valence and
arousal, which we will make publicly available. For net-
work training we utilize all publicly available in-the-wild
databases that, in total, consist of around 5M images.

- We design a novel objective function to be minimized dur-
ing network training to couple the facial behaviour tasks
via co-annotation and distribution matching.

- We show that FaceBehaviorNet outperforms each of the
single-task networks, validating that our network emotion
recognition capabilities are enhanced when it is jointly
trained for all related tasks. We further explored the fea-
ure representation learned in the joint training and show its
generalization abilities on the task of compound ex-
pressions recognition when no or little training data is
available (zero-shot and few-shot learning).

2 Related work

Multi-task learning (MTL) was first studied in [4], where
the authors propose to jointly learn parallel tasks sharing a
common representation and transferring part of the knowl-
dge learned to solve one task to improve the learning of the
other related tasks. Since then, several approaches have
adopted MTL for solving different problems in computer vi-
sion and machine learning [42, 28].

A recent approach [17] shows that MTL can be deployed
when training low-, mid- and high-level vision tasks such as
boundary detection, normal estimation, semantic segmenta-
tion, and object detection. The use of MTL for face analysis
is somewhat limited. In [37], MTL was tackled through a
neural network that jointly handled face recognition and fa-
cial attribute prediction tasks. MTL helped to capture both
global feature and local attribute information simultaneously.

One of the closest goals to ours is [5], where an in-
tegrated deep learning framework (FATAUV-Net) for se-
nquential facial attribute recognition, AU detection, valence-
arousal estimation was proposed. This framework employed
face attributes as low-level (first component) and AUs as
mid-level (second component) representations for predict-
ing valence-arousal (third component). However training of
this model is made of transfer learning and fine-tuning steps,
is hierarchical and not end-to-end.

In a similar work of [36], a two-level attention with two
stage multi-task learning framework was constructed for emo-
tion recognition and valence-arousal estimation. In the first
attention level, a CNN extracted position-level features and
then in the second an RNN with self-attention was proposed
to model the relationship between layer-level features. In
[31], a multi-task CNN-based method was proposed that
performed simultaneous face detection, alignment, verifica-
tion and recognition, pose estimation, gender and smile clas-
sification and age estimation. This work demonstrated that
subject-independent tasks benefit from domain-based regu-
larization and network initialization from face recognition
tasks. They also validated that MTL helps in learning robust
feature descriptors.

3 The Proposed Approach

We start with the multi-task formulation of the facial be-
aviour model. In this model we have three objectives: (1)
learning seven basic emotions, (2) detecting activations of
17 binary facial action units, (3) learning the intensity of the
valence and arousal continual emotions. We train a multi-
task neural network model to jointly perform (1)-(3). For a
given image \( x \in X \), we can have label annotations of ei-
ther one of seven basic emotions \( y_{\text{emo}} \in \{1, 2, \ldots , 7\} \), or
17\(^1\) binary action units activations \( y_{\text{au}} \in \{0, 1\}^{17} \), or two
continual emotions of valence and arousal, \( y_{va} \in \{-1, 1\}^{17} \).

\(^1\) For simplicity of presentation, we use the same notation
\( x \) for all images leaving the context to be explained by the la-
bel notations. We train the multi-task model by minimizing

\(^{17}\) In fact, 17 is an aggregate of action units in all datasets; typically
each dataset has about ten AUs labelled by purposely trained annota-
tors.

\(^{2}\) The datasets for action units detection are exclusively labeled with
AUs, however some datasets for studying basic emotions recognition
come with annotations of valence and arousal (AffectNet [26]).
the following objective:
\[
\mathcal{L}_{MT} = \mathcal{L}_{E\text{mo}} + \lambda_1 \mathcal{L}_{AU} + \lambda_2 \mathcal{L}_{V\text{A}} \tag{1}
\]
\[
\mathcal{L}_{E\text{mo}} = \mathbb{E}_{x,y_{\text{emo}}} [-\log p(y_{\text{emo}}|x)]
\]
\[
\mathcal{L}_{AU} = \mathbb{E}_{x,y_{\text{emo}}} [-\log p(y_{\text{au}}|x)]
\]
\[
\mathcal{L}_{V\text{A}} = 1 - \text{CCC}(y_{\text{geo}}, y_{\text{obs}})
\]
where the first term is the cross entropy loss computed over images with a basic emotion label, the second term is the binary cross entropy loss computed over images with 17 AUs activations, \(\log p(y_{\text{au}}|x) := [\sum_{i=1}^{17} \delta_i]^{-1} \cdot \sum_{i=1}^{17} \delta_i \cdot [y_{\text{au}} \log p(y_{\text{au}}|x) + (1 - y_{\text{au}}) \log (1 - p(y_{\text{au}}|x))]\) where \(\delta_i = \{0, 1\}\) indicates whether the image contains annotation for AU\(i\). The third term measures the concordance correlation coefficient between the ground truth valence and arousal \(y_{\text{va}}\) and the predicted \(\hat{y}_{\text{va}}, \text{CCC}(y_{\text{va}}, \hat{y}_{\text{va}}) = \frac{\rho^2}{\sqrt{\text{var}(\text{E}(y_{\text{va}})) \cdot \text{var}(\text{E}(\hat{y}_{\text{va}}))}}\), where for \(i \in \{v, a\}, y_i\) is the ground truth, \(\hat{y}_i\) is the predicted value and \(\rho_i =
\]
\[
2 \cdot \mathbb{E}[(y_i - \hat{y}_i) \cdot (\hat{y}_i - \hat{E}_{\hat{y}_i})]
\]

\[
\mathbb{E}^2[(y_i - \hat{E}_{y_i})^2] + \mathbb{E}^2[(\hat{y}_i - \hat{E}_{\hat{y}_i})^2] + (\hat{E}_{y_i} - \hat{E}_{\hat{y}_i})^2.
\]

**Coupling of basic emotions and AUs via co-annotation**
In the seminal work [11], the authors conduct a study on the relationship between emotions (basic and compound) and facial action units activations. The summary of the study is a table of the emotions and their prototypical and observational actions units (Table 1 in [11]) which we include in Table 1 for completeness. Prototypical are action units that are labelled as activated across all annotators’ responses, observational are action units that are labelled as activated by a fraction of annotators. For example, in emotion happy the prototypical are AU12 and AU25, the observational is AU6 with the weight 0.51 (observed by 51% of the annotators). We propose a simple strategy of co-annotation to couple the training of emotions and action unit predictions. Given an image \(x\) with the ground truth annotation of basic emotion \(y_{\text{emo}}\), we enforce the prototypical and observational AUs of this emotion to be activated. We co-annotate the image \((x, y_{\text{emo}})\) with \(y_{\text{au}}\) that contains only the prototypical and observational AUs and include this image twice, when computing \(\mathcal{L}_{E\text{mo}}\) and \(\mathcal{L}_{AU}\) in 1. We re-weight the contributions of the observational AUs with the annotators’ agreement score (from the table).

Similarly, for an image \(x\) with the ground truth annotation of the action units \(y_{\text{au}}\), we check whether we can co-annotate it with an emotion label. For an emotion to be present, all its prototypical and observational AUs have to be present. In cases when more than one emotion is possible, we assign the label \(y_{\text{emo}}\) of the emotion with the largest requirement of prototypical and observational AUs. The image \((x, y_{\text{emo}})\) that is co-annotated with the emotion label \(y_{\text{emo}}\) is included twice in 1, when computing \(\mathcal{L}_{AU}\) and \(\mathcal{L}_{E\text{mo}}\). We call this approach the FaceBehaviorNet with co-annotation.

**Coupling of basic emotions and AUs via distribution matching**
The aim here is to align the predictions of the emotions and action units tasks during training. For each sample \(x\) we have the predictions of emotions \(p(y_{\text{emo}}|x)\) as the softmax scores over seven basic emotions and we have the prediction of AUs activations \(p(y_{\text{au}}|x)\), \(i = 1, \ldots, 17\) as the sigmoid scores over 17 AUs.

The distribution matching idea is simple: we match the distribution over AU predictions \(p(y_{\text{au}}|x)\) with the distribution \(q(y_{\text{au}}|x)\), where the AUs are modeled as a mixture over the basic emotion categories:
\[
q(y_{\text{au}}|x) = \sum_{y_{\text{emo}} \in \{1, \ldots, 7\}} p(y_{\text{emo}}|x) p(y_{\text{au}}|y_{\text{emo}}) \sum_{y_{\text{emo}} \in \{1, \ldots, 7\}} p(y_{\text{emo}}|x). \tag{2}
\]
Here, \(p(y_{\text{au}}|y_{\text{emo}})\) is defined deterministically from the Table 1: \(p(y_{\text{au}}|y_{\text{emo}}) = 1\) for prototypical/observational action units, and it is zero otherwise. For example, AU2 is prototypical for emotion fearful, then \(q(AU2|x) = \frac{1}{2} (p(\text{surprised}|x) + p(\text{fearful}|x))\). In spirit of the distillation approach [15], we match the distributions \(p(y_{\text{au}}|x)\) and \(q(y_{\text{au}}|x)\) by minimizing the cross entropy with the soft targets loss term:
\[
\mathcal{L}_{DM} = \mathbb{E}_x \sum_{i=1}^{17} [-p(y_{\text{au}}|x) \log q(y_{\text{au}}|x)], \tag{3}
\]
where all available training samples are used to match the predictions. We call this approach FaceBehaviorNet with distr-matching.

A mix of the two strategies, co-annotation and distribution matching, is also possible. Given an image \(x\) with the ground truth annotation of the action units \(y_{\text{au}}\), we can first

\[\text{Here we overload slightly our notations; for co-annotated images, } y_{\text{au}} \text{ has variable length and only contains prototypical and observational AUs.}\]

| Emotion   | Protot. AUs | Observ. AUs (with weights w) |
|----------|-------------|-------------------------------|
| happy    | 12, 25      | 6 (0.51)                      |
| sad      | 4, 15       | 1 (0.60), 6 (0.55), 11 (0.26), 17 (0.07) |
| fearful  | 1, 4, 20, 25 | 2 (0.57), 5 (0.63), 26 (0.33) |
| angry    | 4, 7, 24    | 10 (0.26), 17 (0.52), 23 (0.29) |
| surprised| 1, 2, 25, 26 | 5 (0.66)                      |
| disgusted| 9, 10, 17   | 4 (0.31), 24 (0.26)           |

\[\text{4 We also tried a variant with reweighting for observational AUs, i.e. } p(y_{\text{au}}|y_{\text{emo}}) = w\]

\[\text{5 This can be seen as minimizing the KL-divergence } KL(p||q) \text{ across the 17 action units.}\]
co-annotate it with a soft label in form of the distribution over emotions and then match it with the predictions of emotions \( p(y_{\text{emo}}|x) \). More specifically, for each basic emotion, we compute the score over its prototypical and observational AUs being present. For example, for emotion happy, we compute \( (y_{\text{au}}(\text{AU12})+y_{\text{au}}(\text{AU25})+0.51*y_{\text{au}}(\text{AU6}))/ (1+1+0.51) \), or all weights equal 1 if without reweighting. We take a softmax over the scores to produce the probabilities over emotion categories. In this variant, every single image that has ground truth annotation of AUs will have a soft emotion label assigned. Finally we match the predictions \( p(y_{\text{emo}}|x) \) and the soft label by minimizing the cross entropy with the soft targets similarly to \( 3 \). We call this approach FaceBehaviorNet with soft co-annotation.

**Coupling of categorical emotions, AUs with continual emotions** In our work, continual emotions (valence and arousal) are implicitly coupled with the basic expressions and action units via a joint training procedure. Also one of the datasets we used has annotations for categorical and continual emotions (AffectNet \[26\]) and another dataset has annotations for all three tasks (Aff-Wild2 \[20,21,22\]). Studying an explicit relationship between them is a novel research direction beyond the scope of this work.

**FaceBehaviorNet structure** Fig. 1 shows the structure of our multi-task, multi-domain and multi-label FaceBehaviorNet. It is based on the 13 convolutional and pooling layers of VGG-FACE \[29\] (its fully connected layers are discarded), followed by 2 fully connected layers, each with 4096 hidden units and ReLu activation function. A (linear) output layer follows that gives final estimates for valence and arousal; it also gives 7 basic expression logits that are passed through a softmax function in order to get the final 7 basic expression predictions; lastly, it gives 17 AU logits that are passed through a sigmoid function so as to provide final predictions for each of the 17 AUs. One can see that the predictions for all tasks are pooled from the same feature space. In Fig. 1, the terms VA/AU/EXPR-BATCH refer to batches of images annotated in terms of VA/AU/7 basic expressions.

**4 Databases and Performance Measures**

In this Section, we describe the databases that we utilized in all our experiments. We selected to work with these databases because they provide a large number of samples with accurate annotations of valence-arousal, basic expressions and AUs. Training with these datasets allows our networks to learn to recognize affective states under a large number of image conditions (e.g., each database includes images at different resolutions, poses, orientations and lighting conditions). These datasets also include a variety of samples in both genders, ethnicities and races.

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**Fig. 1: The multi-task, multi-domain and multi-label FaceBehaviorNet**

**Valence and Arousal: Aff-Wild, Aff-Wild2, AffectNet**

The Aff-Wild database \[19\] \[40\] has been the first large scale captured in-the-wild database that has been annotated by 8 lay experts with regards to valence and arousal that range in \([-1,1]\). It served as benchmark for the Aff-Wild Challenge \[6\], organized in CVPR 2017. It consists of 298 Youtube videos and displays reactions of 200 subjects (130 male; 70 female). The total number of frames in this database is around 1.25M. The training set consists of around 1M frames and the test set of around 216K.

The Aff-Wild2 database \[20,21,22\] is an extension of the aforementioned Aff-Wild database (with 260 more videos with around more 1.4M frames). AffWild2 is the first large scale in-the-wild database containing annotations for all 3 main behavior tasks (valence-arousal estimation, AU detection, expression classification). It is also the first audiovisual database with annotations for AUs. In total it contains 558 videos with around 2.8M frames. All frames are annotated in terms of valence and arousal, 404K and 400K are annotated for basic expressions and AUs, respectively. In the valence-arousal set, the resulting training, validation and test subsets consist of 350, 70 and 138 videos respectively. In the AU set, the respective subsets consist of 42, 7 and 14 videos respectively. In the basic expression set, the corresponding subsets consist of 51, 11 and 22 videos respectively.

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6 [http://ibug.doc.ic.ac.uk/resources/first-affect-wild-challenge](http://ibug.doc.ic.ac.uk/resources/first-affect-wild-challenge)

7 [https://ibug.doc.ic.ac.uk/resources/aff-wild2/](https://ibug.doc.ic.ac.uk/resources/aff-wild2/)
The AffectNet database [26] contains around 1M facial images downloaded from the Internet. About 400K of the retrieved images were manually annotated by 12 human experts, for the presence of 7 discrete expressions (plus contempt) and the intensity of valence and arousal in \([-1, 1]\).

The training set of this database consists of around 321K images \(^8\) and the validation consists of 5K. The validation set is balanced across the different emotion categories whereas the training data is not.

### Seven Basic Expressions: AFEW, RAF-DB, Aff-Wild2, AffectNet

The AFEW database[8] is used in the EmotiW Challenges that focus on audiovisual classification of each video clip into the 7 basic emotion categories. It consists of 1,809 nearly real world scenes from movies and reality TV shows. The database is split into three sets: training (773 videos), validation (383 videos) and test set (653 videos).

The RAF-DB [23] contains 12.2K training and 3K test facial images downloaded from the Internet and annotated in terms of the seven basic and eleven compound emotion categories. Images in RAF-DB were labeled by 315 annotators and the final annotations were crowdsourced.

### Action Units: Emotionet, DISFA, BP4D-Spontaneous, BP4D+, Aff-Wild2

The Emotionet database [14] is a large-scale database with around 1M facial expression images collected from the Internet. It was released for the EmotioNet Challenge in 2017 [3].\(^9\) A total of 950K images were annotated by the model of [14], and the remaining 50K images were manually annotated with 11 AUs; around half of these constituted the validation and the other half the test set of the Challenge. Additionally, from these images, a subset of about 2.5K images was annotated with the 6 basic emotion expressions and 10 compound emotions.

The DISFA database [24] is a lab controlled database with spontaneous emotion expressions. It has been annotated for the presence, absence and intensity of 12 AUs. It consists of 27 subjects, each recorded while watching a four minutes video clip by two cameras. It consists of 260K video frames (130K frames from each camera).

The BP4D Spontaneous database[41] (in the rest of the paper we refer to it as BP4D) is annotated for the occurrence and intensity of 27 AUs. There are 21 subjects with 75.6K images in the training, 20 subjects with 71.2K images in the development and 20 subjects with 75.7K images in the test partition. It has been used as a part of the FERA 2015 Challenge [34], in which only AUs 1, 2, 4, 6, 7, 10, 12, 14, 15, 17, 23 were used.

The BP4D+ database [43] is an extension of BP4D described above by incorporating different modalities as well as more subjects (140). It is annotated for occurrence of 34 AUs and intensity for 5 of them. It has been used as a part of the FERA 2017 Challenge [35]. Only AUs 1, 4, 6, 7, 10, 12, 14, 15, 17, 23 have been used in the Challenge.

### Train/Validation/Test splits

Before we describe the databases, let us note that for the AffectNet, AFEW, BP4D-Spontaneous and BP4D+ databases, no test set is released, and thus we use the released validation set to test on and randomly divide the training set into a training and a validation subset (with a 85/15 split).

### Performance measures

We use:

- the CCC for Aff-Wild (as CCC was the evaluation criterion of Aff-Wild Challenge), Aff-Wild2 and Affectnet (for valence and arousal estimation, we use CCC to be consistent)
- the total accuracy for AFEW (as this metric was the evaluation criterion of the EmotiW Challenges), the mean diagonal value of the confusion matrix for RAF-DB (as this criterion was selected for evaluating the performance in this database by [23]), the F1 score for AffectNet (for evaluating the 7 basic expressions, as this metric is widely used in classification task) and Aff-Wild2
- the F1 score for BP4D-Spontaneous, BP4D+ (as this metric was the evaluation criterion of the respective FERA 2015 and 2017 Challenges), DISFA (to be consistent with the previous) and Aff-Wild2 , for the AU detection in Emotionet the Challenge’s metric that was the average between: a) the mean F1 score, across all AUs, and b) the mean accuracy, across all AUs; regarding the emotion classification it was the average between: a) the mean F1 score, across all emotion categories, and b) the unweighted average recall (UAR) over all emotion categories.

### 5 Pre-Processing

At first, we used the SSH detector [27] based on the ResNet and trained on the WiderFace dataset [38] so as to extract face bounding boxes and five facial landmarks from all images. These landmarks were used next for face alignment. All cropped and aligned images were then resized to 96 \(\times\) 96 \(\times\) 3 pixel resolution and their intensity values were normalized to the range \([-1, 1]\). Those images were used as inputs for training our networks.

### 6 Training Implementation Details

At this point let us describe the strategy that was used for feeding images from different databases to FaceBehaviorNet. At first, the training set was split into three different sets, each of which contained images that were annotated in terms of either valence-arousal, or action units, or seven basic expressions; let us denote these sets as VA-Set, AU-Set
and EXPR-Set, respectively. During training, at each iteration, three batches, one from each of these sets (as can be seen in Fig.1), were concatenated and fed to FaceBehaviorNet. This step is important for network training, because: i) the network minimizes the objective function of eq. 1; at each iteration, the network has seen images from all categories and thus all loss terms contribute to the objective function, ii) since the network sees an adequate number of images from all categories, the weight updates (during gradient descent) are not based on noisy gradients; this in turn prevents poor convergence behaviors; otherwise, we would need to tackle these problems, e.g. do asynchronous SGD as proposed in [17] to make the task parameter updates decoupled, iii) the CCC cost function (defined in Section 3) needs to be ‘aligned’. To do so, we selected the batches of these sets in such a manner, so that after one epoch we will have sampled all images in the sets. In particular, we chose batches of size 401, 247 and 103 for the VA-Set, AU-Set and EXPR-Set, respectively. The training of FaceBehaviorNet was performed in an end-to-end manner, with a learning rate of $10^{-4}$. A 0.5 Dropout value was used in the fully connected layers. Training was performed on a Tesla V100 32GB GPU and training time was around 2 days. The Tensorflow platform has been used.

7 Experiments

At first, we experimented with two state-of-the-art and broadly used networks for affective computing: ResNet-50, DenseNet-121. We trained these networks with all the databases described in Section 4 and compared their performance to that of FaceBehaviorNet. As shown in Table 2, the FaceBehaviorNet has proven to provide the best results, outperforming the ResNet-50 by 5.33% and the DenseNet-121 by 4.42%, on average (across all databases’ metrics).

### 7.1 Results on Valence-Arousal Estimation

Next, we trained a VGG-FACE network with all the dimensionally annotated databases to predict valence and arousal. This network is denoted as VGG-FACE single task in Table 3. We also trained one vanilla VGG-FACE network only on the AffectNet database. We compared these networks’ performances with the performance of the following networks: i) FaceBehaviorNet, on the Aff-Wild, Aff-Wild2 and AffectNet databases, ii) the winner of the Aff-Wild Challenge FATAUVA-Net [5] (described in Section 2), iii) the best performing CNN (VGG-FACE) on the Aff-Wild [18][19], iv) the baseline network (AlexNet) on the AffectNet database [26].

### 7.2 Results on Primary Expression Classification

We then trained a VGG-FACE network with all categorically annotated databases, to perform seven basic expression classification. This network is denoted as VGG-FACE single task in Table 4. We also trained a vanilla VGG-FACE
network only on the AffectNet database. We compared these networks’ performances with those of the following networks: i) FaceBehaviorNet on Aff-Wild2, AffectNet, AFEW and RAF-DB data-bases, ii) the baseline network (AlexNet) on AffectNet data-base [26], iii) the baseline network (non-linear Chi-square kernel based SVM ) [9] on EmotiW Challenges; iv) the VGG-FACE-mSVM [23] on RAF-DB.

In Table 4, one can see that FaceBehaviorNet’s performance is superior to those of all networks on AFEW, RAF-DB and Aff-Wild2. Here we need to mention that on RAF-DB the best performing network is the Deep Locality-preserving CNN (DLP-CNN) of [23] with a performance metric value of 0.74; this network was trained using a joint classical softmax loss - that pulls the locally neighboring faces of the same class together. This network is not listed in Table 4, since its performance is based on this different loss. Finally, on AffectNet it has the same performance as the AlexNet of [26].

7.3 Results on Action Unit Detection

Next we trained a VGG-FACE network on all databases annotated with action units, so as to perform AU detection. This network is denoted as VGG-FACE single task in Table 5. We compared these networks’ performances with the performance of the following networks: i) the FaceBehaviorNet on Emotionet, DISFA, BP4D, BP4D+ and Aff-Wild2 databases, ii) the baseline network (AlexNet) on Emotionet database [3], iii) the best performing method (I2R-CCNU-NTU-2) on Emotionet [3], iv) the Discriminant Laplacian Embedding extension (DLE extension) [39] winner of FERA 2015 on BP4D database and the [33] winner of FERA 2017 on BP4D+ database.

In Table 5, one can see that FaceBehaviorNet’s performance is superior compared to all other methods on DISFA, BP4D and BP4D+ databases (on BP4D+ it has the same performance as the winner of FERA 2017 [33]) and on Emotionet it is superior, in mean accuracy, to the method of I2R-CCNU-NTU-2 [3] (and it shows the same performance in F1 score); it also shows superior performance to all methods.

7.4 Results with Different Coupling Losses

Here, we compare the performance of FaceBehaviorNet when trained: i) with only the losses of eq. 1 and without using the coupling losses described in Section 3, ii) with co-annotation coupling loss, iii) with soft co-annotation coupling loss, iv) with co-annotation and soft co-annotation coupling losses, v) with distr-matching coupling loss, vi) with co-annotation and distr-matching coupling losses and vii) with all coupling losses (co-annotation, soft co-annotation, distr-matching). Table 6 shows the results for all these approaches.

Many deductions can be made. Firstly, when FaceBehaviorNet is trained with any coupling loss, or any combination of these, it displays a better (or in the worst case equal) performance on all databases; verifying the effect of our developed coupling losses in network training. Secondly, the performance in estimation of valence and arousal improved, although we did not explicitly designed a coupling loss for this; we only coupled emotion categories and action units. We conjecture that when action unit detection and emotion classification accuracy is improving (due to coupling), valence and arousal performance also improves, because valence and arousal are implicitly coupled with emotions via joint dataset annotations for both emotion types. Thirdly, when the soft co-annotation and distr-matching coupling losses are included in the objective function, we obtain the best results. To conclude, in all cases, there exists an increase in performance when training with the coupling losses.

7.5 Zero-Shot & Few-Shot Experiments & Results

In order to further prove and validate that FaceBehaviorNet learned good features encapsulating all aspects of fa-
Table 6: Performance evaluation of valence-aroousal, seven basic expression and action units predictions on all used databases provided by the FaceBehaviorNet when trained with/without the coupled losses

| Databases       | All-Wild | All-Wild2 | AffectNet | AFEW | RAF-DB | Emotionet | DISFA | BP4D | BP4D+ |
|-----------------|----------|----------|-----------|------|--------|-----------|-------|------|-------|
| FaceBehaviorNet  |          |          |           |      |        |           |       |      |       |
| CCC-V           | 0.55     | 0.58     | 0.60      | 0.50 | 0.68   | 0.63      | 0.94  | 0.63 | 0.55  |
| CCC-A           | 0.54     | 0.57     | 0.60      | 0.50 | 0.68   | 0.63      | 0.94  | 0.63 | 0.55  |
| Conf. matrix    |          |          |           |      |        |           |       |      |       |
| Score           | 0.50     | 0.50     | 0.50      | 0.50 | 0.50   | 0.50      | 0.50  | 0.50 | 0.50  |
| F1 Score        | 0.60     | 0.60     | 0.60      | 0.60 | 0.60   | 0.60      | 0.60  | 0.60 | 0.60  |
| Mean Conf.      | 0.60     | 0.60     | 0.60      | 0.60 | 0.60   | 0.60      | 0.60  | 0.60 | 0.60  |

7.5.1 RAF-DB database

At first, we performed zero-shot experiments on the RAF-DB’ compound set. This set includes 11 compound categories, referenced in Section 4. We computed a candidate score for each class \(y_{emo}\). This score was the sum of the terms:

\[
\sum_{k=1}^{11} \frac{1}{p(y_{emo}|x) \cdot p(y_{emo}|y_{emo})} \\
\sum_{k=1}^{11} \frac{1}{p(y_{emo}|y_{emo})} \\
\max\{ \text{emo1} \text{ and emo2} \text{ are the basic emotions that the compound class consists of, e.g., if the compound class is happily surprised then emo1 is happy and emo2 is surprised} \}
\]

The first term is the normalised sum of the FaceBehaviorNet’s predictions of only the prototypical (and observational) AUs that are associated with this compound class according to [11] (Table 1). In this manner, every AU acts as an indicator for this particular emotion class. This term describes the confidence (probability) of AUs that this compound emotion is present. The second term is the sum (no normalisation needed here) of FaceBehaviorNet’s predictions of only the basic expression classes that are mixed and form the compound class. The final term is added only to the happily surprised and the happily disgusted classes and is either 1 or 0 depending on whether FaceBehaviorNet’s valence prediction is positive or negative, respectively. The rationale behind this is that only happily surprised and (maybe) happily disgusted classes have positive valence; all other classes are expected to have negative valence as they correspond to negative emotions. Our final prediction was the class that had the maximum candidate score.

Table 7 shows the results of this approach when we used the predictions of FaceBehaviorNet trained with and without coupling loss(es). Best results have been obtained when the network was trained with all coupling losses. One can observe, that this approach outperformed by almost 5% the VGG-FACE-mSVM [23] which has the same architecture as our network and it has been trained for compound expression classification. Our approach’s performance is not as great as DLP-CNN [23] (a description along with a justification for its good performance was given previously), which was also trained for compound expression classification. We believe that from a zero-shot learning perspective, our approach achieved very good results (even outperforming a network that has been trained for this task).

Next, we target few-shot learning. In particular, we finetune the FaceBehaviorNet on the small training set of RAF-DB; In Table 7 we do a comparison with the other networks. One can verify that our fine-tuned network outperformed all other state-of-the-art networks.

7.5.2 Emotionet database

We performed zero-shot experiments on the Emotionet basic and compound set that was released for the related Challenge. This set includes 6 basic plus 10 compound categories, referenced in Section 4. Our zero-shot methodology was similar to the one described above for the RAF-DB. The results of this experiment can be found in Table 7. Best results have been obtained when the network was trained with all coupling losses. One can observe, that this approach outperformed by almost 6% and 8% in F1 score and Unweighted Average Recall (UAR), respectively, the NTech-Lab’s [3] approach. Therefore, our zero-shot approach out-
performed the state-of-the-art in both the F1 score and UAR metrics.

Table 7: Performance evaluation of generated compound emotion predictions on Emotionet and RAF-DB databases.

| Databases        | Emotionet |          |          |          | RAF-DB  |          |          |          |
|------------------|-----------|----------|----------|----------|---------|----------|----------|----------|
| Methods          | F1 Score  | Unweighted Average Recall | Mean diagonal of conf. matrix |
| zero-shot FaceBehaviorNet no coupling loss | 0.243 | 0.260 | 0.342 |
| zero-shot FaceBehaviorNet all coupling losses | 0.312 | 0.329 | 0.364 |
| fine-tuned on Emotionet or RAF-DB FaceBehaviorNet no coupling loss | 0.257 | 0.304 | 0.458 |
| fine-tuned on Emotionet or RAF-DB FaceBehaviorNet all coupling losses | 0.281 | 0.318 | 0.483 |
| NTechLab [3]†‡ | 0.255 | 0.243 | - |
| VGG-FACE-mSVM [23] | - | - | 0.316 |
| DLP-CNN [23] | - | - | 0.446 |

8 Conclusions

In this paper, we presented FaceBehaviorNet that is trained end-to-end, with over 5M images coming from many publicly available datasets, to jointly predict three facial behavior tasks (VA estimation, AU detection, classification into 7 basic expressions). We specifically designed (co-annotation and distribution matching) novel loss functions that couple these different tasks. We performed experiments comparing the performance of FaceBehaviorNet to single task networks; our network outperformed all other networks and finally we conducted zero- and few-shot experiments for compound emotion recognition.

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