Exploring speaker enrolment for few-shot personalisation in emotional vocalisation prediction

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Abstract

In this work, we explore a novel few-shot personalisation architecture for emotional vocalisation prediction. The core contribution is an ‘enrolment’ encoder which utilises two unlabelled samples of the target speaker to adjust the output of the emotion encoder; the adjustment is based on dot-product attention, thus effectively functioning as a form of ‘soft’ feature selection. The emotion and enrolment encoders are based on two standard audio architectures: CNN14 and CNN10. The two encoders are further guided to forget or learn auxiliary emotion and/or speaker information. Our best approach achieves a CCC of .650 on the ExV o Few-Shot dev set, a 2.5% increase over our baseline CNN14 CCC of .634.

1. Introduction

The modelling of emotional expression through non-verbal vocalisations is recently undergoing a paradigm shift following the introduction of a new coding scheme that imposes a continuous scale over several emotion categories (Cowen et al., 2019). Research findings suggest that humans are better able to perceive positive emotions from non-verbal vocalisations than prosody (Hawk et al., 2009; Sauter et al., 2013) and emerging speech emotion recognition (SER) approaches utilise that information to improve SER performance (Huang et al., 2019; Hsu et al., 2021). To that end, the ICML Expressive Vocalisations Workshop & Competition 2022 (ExVo) (Baird et al., 2022) presents an excellent opportunity for studying the automatic recognition of emotion through vocalisations.

The present contribution targets the ExVo-FEW-SHOT task, whose goal is to study the efficacy of personalisation techniques using two-shot adaptation. Emotion researchers have long investigated individualistic effects in emotional expressivity, which is attributable to differences in personality, childhood, and context (Larsen & Diener, 1987; Barr et al., 2008). Accordingly, several prior works have attempted to incorporate those differences in the automatic recognition of emotion (Rahman & Busso, 2012; Rudovic et al., 2018; Yin et al., 2020; Li et al., 2020; Triantafyllopoulos et al., 2021; Moine et al., 2021; Sridhar & Busso, 2022; Fan et al., 2022). Our approach is mostly inspired from Li et al. (2020); Triantafyllopoulos et al. (2021); Moine et al. (2021); Fan et al. (2022). In particular, like (Triantafyllopoulos et al., 2021; Moine et al., 2021; Fan et al., 2022), we use an auxiliary network that conditions a main classification network based on two enrolment utterances from the same speaker; in that sense, we are most similar to (Triantafyllopoulos et al., 2021; Fan et al., 2022), as Moine et al. (2021) extracts the conditioning information from the same utterance while those two get it from a neutral enrolment utterance. In our case, however, the enrolment utterance is not neutral (and thus does not represent a speaker ‘baseline’ as per (Triantafyllopoulos et al., 2021; Fan et al., 2022)) but contains itself some emotion (that we attempt to remove using adversarial adaptation (Ganin et al., 2016)). Furthermore, we draw from Yin et al. (2020); Li et al. (2020), which induce invariance to speaker characteristics using auxiliary adversarial subnetworks. Thus, our main contribution can be summarised as follows: we explore the use of enrolment-based conditioning for few-shot personalisation using auxiliary guiding losses. Our methodology is described in detail in Section 2. This is followed by our results in Section 3 and a conclusion in Section 4.

2. Methodology

Our work is targeted towards the ExVo-FEW-SHOT task introduced in the ICML Expressive Vocalisations Workshop & Competition 2022 (Baird et al., 2022). ExVo-FEW-SHOT is based on the The Hume Vocal Burst Competition Dataset (H-VB) (Cowen et al., 2019), a novel dataset of emotional vocalisations. It contains over 36 hours of data
from 1702 speakers from four countries crowdsourced in ‘in-the-wild’ conditions. Each burst was annotated for the ten different emotions of Amusement, Awe, Awkwardness, Distress, Excitement, Fear, Horror, Sadness, Surprise, and Triumph, each annotated on a scale of [1 – 100] for each burst; thus, the main goal of E\textsuperscript{X}Vo is multitask regression for all ten targets. Performance is evaluated by taking the average concordance correlation coefficient (CCC) over each category as a holistic score, $\bar{C}$. The goal of E\textsuperscript{X}Vo–FEW-SHOT is to improve this score by providing 2 annotated bursts per speaker in the test set. These bursts serve as ‘enrolment’ utterances and enable adaptation to the individual characteristics of each speaker.

An overview of our proposed methodology is presented in Figure 1. Our architecture consists of three core constituents: an emotion encoder, $g(\cdot)$, an enrolment encoder, $\tilde{g}(\cdot)$, and an emotion classifier, $f(\cdot)$. Several variants are explored by additionally utilising a set of optional components during the training phase: an adversarial speaker classifier, $h(\cdot)$, attached to the emotion encoder, as well as an adversarial emotion classifier, $\tilde{f}(\cdot)$, and a speaker classifier $\bar{f}(\cdot)$ attached to the enrolment encoder. The rationale and function of each component is explained below.

The emotion encoder $g(\cdot)$ is tasked with extracting emotional information from input vocalisations; its input $x$ (with label $y$ obtained from speaker $s$) is the target vocalisation on which the model is trained/evaluated. The encoder consists of several differentiable layers which generate an emotional embedding $z$. In the baseline variant of our approach, this emotional embedding is fed into the emotion classifier $f(\cdot)$, which generates the emotion estimates $\tilde{y}$ – these are then used to train the system by forming the input to the loss function $L_{\text{emo}}(y, \tilde{y})$.

Our core contribution is the introduction of an enrolment encoder $\tilde{g}(\cdot)$, which is tasked with adapting (personalising) to the target speaker $s$. It accepts as input a small set of exemplar enrolment utterances $\tilde{x}$ (with label $\tilde{y}$) from speaker $s$ (the same speaker who generated the target utterance $x$). The encoder consists of several differentiable layers which generate an adaptation embedding $\tilde{z}$. Ideally, this embedding should encode information about how the target speaker is expressing their emotions through vocalisations. In this work, we use $\tilde{z}$ to impose a soft feature selection process on $z$ through the use of dot-product attention (Bahdanau et al., 2015): $\tilde{z}$ is first passed through a softmax layer to obtain $\tilde{\alpha}$ which is then multiplied with $z (z \cdot \tilde{\alpha})$ to highlight the parts of $z$ that are most relevant for this particular speaker. In order to stabilise the performance of the dot-product attention, we introduce a residual connection, so the input to the emotion classifier is $e = z + z \cdot \tilde{\alpha} − z$ as is often done in other works using attention (Vaswani et al., 2017).

The other three components of our architecture are optional and are introduced in an attempt to help the emotion and enrolment encoders learn their intended functions: the emotion encoder should learn a speaker-agnostic embedding $z$ that the enrolment encoder will help personalise through a speaker-aware embedding $\tilde{z}$. This conceptualisation offers the following design principle: we should guide the emotion encoder to ‘forget’ any speaker information and help the enrolment encoder learn more of it. This is achieved by the additional speaker classifiers, $h(\cdot)$ and $\bar{h}(\cdot)$, respectively. Both accept as input the corresponding embeddings $z$ and $\tilde{z}$ and output a predicted speaker label $\tilde{s}$; they are then trained with a speaker loss $L_{sp}(c, \tilde{s})$. However, there is one crucial difference: the speaker classifier attached to the emotion encoder is preceded by a gradient reversal layer. This layer was introduced by Ganin et al. (2016) for domain adaptation, and has been widely used to remove undesired information from learnt representations – including for speaker-invariant SER (Li et al., 2020). The functionality of this layer is simple: it merely inverts the gradients forcing the emotion encoder to perform gradient ascent (as it continues to minimise the error which now corresponds to the inverse of the speaker loss).

Finally, the last optional component of our architecture is an (adversarial) emotion classifier, $\bar{f}(\cdot)$, attached to the output of the enrolment encoder. This is introduced to solve a further challenge imposed by E\textsuperscript{X}Vo–FEW-SHOT: unlike other works which relied on enrolment utterances lacking emotion (i.e., neutral ones) (Triantafyllopoulos et al., 2021; Fan et al., 2022), the utterances provided here are themselves emotional and using them to adapt to the target speaker might inadvertently remove relevant information. Thus, we hypothesise that a gradient reversal layer which removes emotional information from the enrolment encoder will be beneficial for generalisation to new speakers.

All-in-all we explore:

1. $g \circ f$ (baseline), which uses only the emotion encoder and classifier,
2. $g \circ f \circ (−h)$, which forces the emotion encoder to forget speaker information but makes no use of enrolment,
3. $g \circ f \circ \tilde{g}$, which additionally introduces enrolment to the baseline,
4. $g \circ f \circ \tilde{g} \circ h$, which guides the enrolment encoder with speaker information,
5. $g \circ f \circ \tilde{g} \circ (−\bar{f})$, which guides the enrolment encoder away from emotional information,
6. $g \circ f \circ \tilde{g} \circ h \circ (−\bar{f})$, a combination of 4) and 5)
7. $g \circ f \circ \tilde{g} \circ (−h) \circ h \circ (−\bar{f})$, a combination of 2), 4), and 5).

We note that none of the approaches investigated here requires annotated emotional information during test time; it is merely enough to provide 2 unlabelled enrolment utterances of the target speaker.
Given its multiple components, our architecture comes with several knobs to twist. In the present work, we limit ourselves to fairly generic hyperparameters and leave a more thorough ablation study for follow-up work. Thus, for the learnable components, we rely on standard auditory architectures. The emotion encoder is identical to (the convolution part of) CNN14 and the enrolment one to CNN10, both introduced in Kong et al. (2020). Both these architectures have proven successful in a variety of tasks – including SER (Triantafyllopoulos & Schuller, 2021). The classifiers are accordingly identical to the output parts of CNN14 and CNN10. Specifically, $f(\cdot)$ and $h(\cdot)$ are 2-layered feed-forward neural networks (FFNNs) each with 2048 hidden units and an appropriate output dimension, while $	ilde{f}(\cdot)$ and $	ilde{h}(\cdot)$ are also 2-layered FFNNs with 512 hidden units.

All models are trained for 120 epochs. We used a batch size of 8, a stochastic gradient descent (SGD) optimiser with Nesterov momentum of 0.9, and a starting learning rate of 0.001, which is reduced by a factor of 0.1 whenever the development set score stops decreasing for 5 epochs. The best model is selected based on the development set performance, which is evaluated at the end of each epoch. $L_{sp}(\cdot, \cdot)$ is set to the standard cross-entropy loss; $L_{emo}(\cdot, \cdot)$ to the CCC loss commonly used in dimensional SER tasks – including the ExVo baseline (Baird et al., 2022). Whenever multiple classifiers are used, their losses are simply averaged to procure the final loss with which the entire architecture is optimised (finding a more appropriate combination of weights for all losses is another knob that could be tweaked to further improve performance). Moreover, for each instance in the training, the enrolment encoder is fed with 2 utterances from the same speaker selected randomly; this randomisation is there to improve generalisation to test set conditions where the enrolment utterances are a priori unknown. To make our results reproducible, the development set results are obtained by selecting the first 2 utterances per development set speaker as they appear in the H-VB data. Finally, as bursts can be of different length, we randomly crop both the target and the enrolment utterances to 2.5 s (average burst duration is 2.23 s; longer utterances are randomly cropped; silence is randomly added to the start and/or end times of shorter utterances). During evaluation, we use a batch size of 1, so the target utterances can be fed in whole, while the shorter of the enrolment utterances is zero-padded to match the duration of the longest one. The gradient reversal layer
requires additional tuning (Ganin et al., 2016). Specifically, like Ganin et al. (2016), we gradually introduce gradient reversal in our training using a warm-up schedule. For the first 10 epochs of training, the λ hyperparameter is set to −1, while from epoch 10 to 60 we linearly increase λ to 1.

3. Results

In Table 1, we present development set results for all investigated architectures, as well as test set results for our top-5 architectures as found on the development set. In addition to the standard score metric of EXVo-FEW-SHOT, the average CCC of all ten emotions (C), we also show 95% confidence intervals (CIs) for the development set, obtained via 1000-sampled bootstrapping (with replacement) and relative gain over our baseline. Our first observation is that our baseline, which comprises solely of CNN14, vastly outperforms the official EXVo-FEW-SHOT baseline, which relied on 1D-CLSTM networks trained on raw audio inputs (Tzirakis et al., 2017), with a C of .634 on the test set, compared to a baseline of .444. This indicates that 2D-CNN architectures based on log-Mel spectrograms might be more suitable for the analysis of emotional vocalisations. Interestingly, inducing speaker invariance by adding an auxiliary adversarial speaker classification output to the main emotion encoder branch (g ◦ f ◦ (−h)) substantially reduces development set performance.

Adding enrolment-based personalisation yields small improvements, though in most cases the development set CIs do not overlap with those of our baseline, lending some importance to them. The highest improvement is obtained by adding the enrolment encoder without any classifiers attached to it (g ◦ f ◦ ̂g); this results in a +2.5% increase to a C of .650. This is slightly better than adding an adversarial emotion classifier to the enrolment branch, which yields a C of .647, followed by adding a speaker classification decoder (C of .639) and using both decoders (C of .642). Further adding an adversarial speaker classifier in the main encoder branch (g ◦ f ◦ ̂g ◦ h) actually decreases development set performance (C of .636) – which is attributable to the negative effect observed by adding (−h) to the main branch.

Overall, it seems that most of the gain is obtained by adding the enrolment encoder, with the auxiliary outputs that guide it to learn more speaker information and forget emotional information adding marginal improvements over that on the development that do not translate well to the test set. This indicates that the additional information injected to the embeddings of the emotion encoder is sufficient for adapting to the new speaker. The relative gain of +2.0% is comparable with that reported in previous work: for example, Sridhar & Busso (2022) report a +13.5% for valence, but only +1.8% for arousal and +1.2% for dominance, while Li et al. (2020) and Fan et al. (2022) report a +4.2% / 3.3% gain for categorical emotion recognition, respectively.

4. Conclusion

We presented a novel, few-shot personalisation architecture for emotional vocalisation prediction. Our results show that the proposed approach can overcome a standard adversarial loss which induces speaker invariance. We included a comprehensive ablation study of the different components of our architecture and conclude that most of the improvement stems from the enrolment encoder. Given that our model consists of multiple parts, further work is needed to tune them and improve their combination.

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