Exploring the Effectiveness of Self-supervised Learning and Classifier Chains in Emotion Recognition of Nonverbal Vocalizations

Detai Xin † Shinnoesuke Takamichi † Hiroshi Saruwatari †

Abstract

We present an emotion recognition system for nonverbal vocalizations (NVs) submitted to the ExVo Few-Shot track of the ICML Expressive Vocalizations Competition 2022. The proposed method uses self-supervised learning (SSL) models to extract features from NVs and uses a classifier chain to model the label dependency between emotions. Experimental results demonstrate that the proposed method can significantly improve the performance of this task compared to several baseline methods. Our proposed method obtained a mean concordance correlation coefficient (CCC) of 0.725 in the validation set and 0.739 in the test set, while the best baseline method only obtained 0.554 in the validation set. We publicate our code at https://github.com/Aria-K-Alethia/ExVo to help others to reproduce our experimental results.

1. Introduction

Nonverbal vocalizations (NVs), also called affect bursts, refer to short and expressive vocalizations containing no linguistic information like laughter, sobs, and screams (Scherer, 1994; Trouvain & Truong, 2012). NVs are important for spoken language processing, since (1) NVs play an important role in expressing emotions in spoken languages (Hall et al., 2009; Scherer & Scherer, 2011), and (2) they are common components of human communication existing in different cultures and languages (Sauter et al., 2010). Although both emotional prosody and NVs contribute to emotional expressions in speech, NVs are ignored by most previous research on speech emotions (Lima et al., 2013), which necessitates further work in this field.

The ICML Expressive Vocalizations Competition (hereafter ExVo) launched in 2022 aims to develop technologies for the recognition, generation, and personalization of NVs (Baird et al., 2022). The competition includes three tracks: ExVo Multi-Task, ExVo Generate, and ExVo Few-Shot, which correspond to the three goals of recognizing, generating, and personalizing NVs, respectively. Specifically, the ExVo Multi-Task track aims to recognize not only emotions but also demographic information like the age and native country of the speakers from NVs. In the ExVo Generate track, the participants need to generate NVs of various emotions. Similar to the Multi-Task track, the ExVo Few-Shot track also aims to recognize emotions from NVs, but further requires the prediction systems to adapt to new speakers which are not in the training set. All tracks are evaluated by appropriate subjective and objective metrics to reflect the performance of the proposed systems.

In this paper, we describe our emotion recognition system for NVs submitted to the ExVo Few-Shot track. Our system consists of two components: a feature extractor and a classifier chain (CC). As the feature extractor, we use a self-supervised learning (SSL) model like Wav2vec2 (Schneider et al., 2019; Baevski et al., 2020) or HuBERT (Hsu et al., 2021a). The extracted feature is then fed to a classifier chain, which predicts the score for each emotion sequentially. The proposed classifier chain predicts the score by conditioning on both the extracted feature and the predicted scores in previous steps, so can utilize information from label dependency. We conducted comprehensive experiments to verify the effectiveness of these two components, and show that the proposed method can significantly improve the performance compared to several baseline methods. Our contributions can be summarized as follows:

- We propose an emotion recognition system for NVs using SSL models and CC, and conduct experiments to show the effectiveness of the proposed method.
- We conduct experiments to show the best SSL models for this task.
- We analyze the prediction results and give insights for future research.

2. The ExVo Few-Shot track

The task of the ExVo Few-Shot track is recognizing emotions from NVs for unseen speakers that are not in the training set. During the training phase, the participants can train their emotion recognition models on the data of the seen speakers. In the test phase, two samples for each unseen
speaker will be provided by the organizer, and the participants can then adapt their models to unseen speakers by few-shot learning.

ExVo provides a large-scale multilingual (Chinese, English, Spanish) NVs dataset (Cowen et al., 2022), which contains approximately 36 hours NVs uttered by 1,702 speakers from the USA, China, South Africa, and Venezuela. Ten emotions consisting of amusement, awe, awkwardness, distress, excitement, fear, horror, sadness, surprise, and triumph are covered by the dataset. Each NV is annotated with ten emotion scores ranging from 0 to 1 by crowdsourcing. Some statistics of the dataset are summarized in Table 1. The participants should submit the predictions of their models on test samples. Concordance correlation coefficient (CCC) is used to evaluate the performance, which can measure the agreement between the ground-truth (GT) and predicted emotion scores.

Table 1. Statistics of the dataset. Some terms are not available for the participants.

|                | Train  | Validation | Test  | ∑    |
|----------------|--------|------------|-------|------|
| Duration (hrs) | 12.32  | 12.10      | 12.37 | 36.78|
| Speakers       | 571    | 568        | 563   | 1702 |
| Audio clips    | 19,990 | 19,396     | 19,815| 59201|
| Audio clips    | 4-201  | 4-168      | –     | –    |
| per speaker    | (Avg. 35) | (Avg. 34) | –     | –    |

Figure 1. Architecture of the proposed method. FC denotes a fully connected layer.

Although previous work has shown that pretrained SSL models were effective on speech emotion recognition in verbal communication (Pepeino et al., 2021; Chen & Rudnicky, 2021; Wang et al., 2021; Wagner et al., 2022), since most of the SSL models were trained on speech corpora that rarely contain NVs, whether these models are effective on NVs remains unknown. Therefore, in the experiments, we select several SSL models and verify their effectiveness in the task of recognizing emotions from NVs.

3. Proposed method

In this section, we describe the proposed method. We first introduce the general architecture of the proposed method and then describe each component separately.

3.1. Architecture

The architecture of the proposed method is illustrated in Figure 1. Specifically, the NVs are first fed to the SSL model to extract sequential features from them. Then, an attentive pooling module is used to collect information over the time axis and convert the sequential features into fixed-length features. Finally, a CC is used to predict the score for each emotion sequentially. Each emotion has a separate predictor, which contains a fully connected (FC) layer followed by a sigmoid activation. The predictor in the CC not only uses the extracted feature as input, which can thus utilize information of label dependency.

3.2. Self-supervised learning models

SSL is a popular and powerful method to leverage large-scale unlabeled data. The idea of SSL is to set a sophisticated pretext task to learn nontrivial data representations. Recently, several works based on SSL have been proposed in speech processing, which showed promising results in speech-to-text and other speech-based tasks (Schneider et al., 2019; Baevski et al., 2020; Conneau et al., 2020; Hsu et al., 2021b:a). Although previous work has shown that pretrained SSL models were effective on speech emotion recognition in verbal communication (Pepeino et al., 2021; Chen & Rudnicky, 2021; Wang et al., 2021; Wagner et al., 2022), since most of the SSL models were trained on speech corpora that rarely contain NVs, whether these models are effective on NVs remains unknown. Therefore, in the experiments, we select several SSL models and verify their effectiveness in the task of recognizing emotions from NVs.

3.3. Classifier chain

The task of the ExVo Few-Shot track is a multivariate regression problem. While similar tasks like continuous speech emotion recognition usually use separate predictors to predict the emotions independently (Atmaja & Akagi, 2021), it is noteworthy that the emotion labels in the provided dataset have an intrinsic dependency. For example, if the score of amusement is high, the scores of negative emotions like sadness and fear may be low, which implies the possibility to utilize information from label dependency. To this end, we propose to use CC (Read et al., 2011), which has been proved to be useful for modeling label dependency in multilabel classification (Dembczynski et al., 2010; Dembczynski et al., 2010; Nam et al., 2017).

Formally, denoting the predictor of the \( i \)-th emotion and the extracted feature as \( f_i(\cdot) \) and \( z \), respectively, the emotion score \( \hat{y}_i \) is computed by: \( \hat{y}_i = \sigma (f_i(z \oplus \hat{y}_{<i})) \), where \( \sigma (\cdot) \) is the sigmoid function, \( \oplus \) is the vector concatenation operator, and \( \hat{y}_{<i} \) indicates a vector concatenating previously predicted emotion scores. During training, we feed GT emotion scores \( y_{<i} \) to the predictor to prevent error propagation.

While it is possible to use powerful sequential models like a recurrent neural network to implement the predictor \( f_i \) in CC (Nam et al., 2017), in the preliminary experiments we found simple linear CC was more stable than other models,
Table 2. Average CCC of different SSL models in 5-fold cross-validation. Bold indicates the best score.

| SSL Model         | CCC    |
|-------------------|--------|
| Wav2vec2-base     | 0.699 ± 0.013 |
| HuBERT-base       | 0.703 ± 0.013 |
| Wav2vec2-robust   | 0.709 ± 0.012 |
| Wav2vec2-large    | 0.709 ± 0.009 |
| HuBERT-large      | 0.718 ± 0.011 |
| XLSR              | 0.722 ± 0.012 |

Table 3. Average CCC of the proposed method using CC and data augmentation in 5-fold cross-validation. Bold indicates the best score.

| Model              | CCC    |
|--------------------|--------|
| CC HuBERT-large    | 0.722 ± 0.012 |
| CC HuBERT-large Aug.| 0.722 ± 0.012 |
| CC XLSR            | 0.724 ± 0.012 |
| CC XLSR Aug.       | 0.726 ± 0.013 |

features include: the 6373-dimensional ComParE set from the 2016 Computational Paralinguistics Challenge (Schuller et al., 2016) and the 88-dimensional extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) (Eyben et al., 2015) extracted by openSMILE toolkit (Eyben et al., 2010), the Bag-of-Audio-Words (BoAW) representations with a 2000 codebook size extracted by openXBOV toolkit (Schmitt & Schuller, 2017) from the low-level descriptors of ComParE set, the 4096-dimensional spectrum representations extracted by the DeepSpectrum toolkit (Amiriparian et al., 2017). We used multi-layer neural networks with LeakyReLU activation (Maas et al., 2013) to process each of the features. Batch normalization (Ioffe & Szegedy, 2015) was used in each layer to normalize the features.

To verify the effectiveness of SSL models and find the best model for NVs, we selected six SSL models: Wav2vec2-\{base, large\} (Baevski et al., 2020), HuBERT-\{base, large\} (Hsu et al., 2021a), Wav2vec2-robust (Hsu et al., 2021b), and XLSR (Conneau et al., 2020). Wav2vec2-\{base, large\} and HuBERT-\{base, large\} are common models used in previous work (Chen & Rudnicky, 2021; Wang et al., 2021). The Wav2vec2-\{base, large\} and HuBERT-large were trained on the Librispeech (Panayotov et al., 2015) corpus containing 960 hours of audio, while the HuBERT-large model was trained on the Libri-Light (Kahn et al., 2020) corpus containing 60k hours of audio. These corpora are all from clean audiobooks that rarely contain NVs. Also, since the NVs in the dataset were recorded by the speakers themselves and sometimes contain noises, we selected Wav2vec2-robust that was trained on not only the Libri-Light corpus but also noisy telephone corpora including Switchboard (Godfrey & Holliman, 1997), Fisher (Cieri et al., 2004), and CommonVoice (Ardila et al., 2019). Finally, to handle multilingual NVs we select XLSR, which is a multilingual version of Wav2vec2 trained on 56k hours of multilingual audio (multilingual Librispeech (Pratap et al., 2020), CommonVoice, and Babel (Gales et al., 2014)) covering 53 languages.

Instead of using the original train-validation split, we first combined the train and validation sets and then used 5-fold cross-validation to train all models. To ensure the validation

thus we use linear CC in the proposed method. Chain order is another critical problem for CC since it determines what information can be utilized by each classifier (Read et al., 2021). In our implementation, we adopt a heuristic method in which we first train ten separate base predictors for each emotion, then use the descending order of the performance of the base predictors as the chain order. This method can intuitively alleviate the error propagation problem by first predicting emotions with high confidence, hence can improve the performance (Read et al., 2021).

3.4. Loss function

We use CCC as the objective for the model training. Previous work has demonstrated that CCC was better for speech emotion recognition than error-based loss functions like L1 loss (Atmaja & Akagi, 2021). Generally, given a set of paired data \(\{(s_j^i, t_j^i)\}_{j=1}^n\) with length \(n\), the CCC between them is defined as: \(\text{CCC}(\{s_j^i\}_{j=1}^n, \{t_j^i\}_{j=1}^n) = \frac{2\sigma^2_{\text{C}} + \sigma^2_{\text{S}} + \sigma^2_{\text{C}}}{\sigma^2_{\text{C}} + \sigma^2_{\text{S}} - \sqrt{\sigma^2_{\text{C}} + \sigma^2_{\text{S}}}}\). In the proposed method the objective value of a mini-batch is computed by averaging CCC values of all emotions. Formally, denoting the number of emotions and the mini-batch size as \(C\) and \(B\), respectively, the loss function of the proposed model is defined as: \(\mathcal{L} = \frac{1}{C} \sum_{i=1}^C \text{CCC}(\{y_i^j\}_{j=1}^B, \{\hat{y}_i^j\}_{j=1}^B)\), where \(y_i^j\) and \(\hat{y}_i^j\) are GT and predicted scores of the \(i\)-th emotion of the \(j\)-th sample in the mini-batch, respectively.

3.5. Data augmentation

To improve the robustness of the model, we additionally use data augmentation. Specifically, we use two strategies: pitch-shifting and speaking-rate-changing (Saeki et al., 2022). Pitch-shifting raises or lowers the pitch of NVs, and can change the speaker identity of NVs. Speaking-rate-changing slows down or speeds up the NVs. We tune the shifting range and the speaking-rate-changing range so that the emotion of the augmented NVs has little difference from the original ones.

4. Experiments

4.1. Experimental Setup

We constructed several baseline systems based on the features provided by the organizer (Baird et al., 2022). These systems provided promising performance for emotion recognition.
We select the top-2 SSL models (XLSR and HuBERT-large) to evaluate their effectiveness. We first evaluate all SSL models to verify their effectiveness and find the best model for NVs. To avoid the influence of SSL models and CC. Besides, it can be observed that all models have difficulties to recognize some emotions like awkwardness, triumph, distress.

### 4.2. Evaluations of SSL models

We first evaluate all SSL models to verify their effectiveness and find the best model for NVs. To avoid the influence of SSL models and CC, the XLSR model obtained the best performance. We suppose this is because the multilingual XLSR model can handle more phonetic tokens of different languages, unlike other SSL models that are only trained on English corpora. Also, large models are always better than base models, which is consistent with the results of previous work (Wagner et al., 2022).

### 4.3. Evaluations of CC and data augmentation

We select the top-2 SSL models (XLSR and HuBERT-large) in the previous experiment as the feature extractors to evaluate CC and data augmentation (“Aug.”). The results are shown in Table 3. It can be seen that CC consistently improves the performance compared to the results in Table 2. The data augmentation brings improvements for the XLSR model but failed to improve the performance of the CC HuBERT-large model.

### 4.4. Evaluations for each emotion

We then evaluate the proposed method for each emotion. We selected the best performing model CC XLSR Aug. obtained in previous experiments. All baseline models were trained using cross-validation for comparison. After training, we combined the inference results on all 5 splits of each model and computed the CCC value for each emotion. The result is demonstrated in Table 4. It can be seen that the proposed method significantly outperformed all baseline methods on all emotions, which indicates the effectiveness of SSL models and CC. Besides, it can be observed that all models have difficulties to recognize some emotions like awkwardness, triumph, distress.

### 4.5. Evaluations on test set

We finally fine-tuned the best model (CC XLSR Aug.) on the test samples provided by the organizer. Our best CCC on the test set is 0.739, which demonstrates the proposed method has a strong generalization ability.

### 5. Conclusions

This paper described an emotion recognition system for NVs submitted to the Few-Shot track of the ICML ExV o competition. The proposed method uses a SSL model to extract contextual speech representations from NVs, and uses a CC to predict emotion scores by utilizing the features and the emotion scores predicted in previous steps together. Experimental results demonstrated that the proposed method significantly outperformed several baseline methods.

**Acknowledgements:** This work was supported by JST SPRING, Grant Number JPMJSP2108. Part of this work was also supported by JSPS KAKENHI Grant Number 21H04900 (for implementation) and JST Moonshot R&D Grant Number JPMJPS2011 (for evaluation).
Exploring the Effectiveness of SSL and CC in Emotion Recognition of Nonverbal Vocalizations

References

Amiriparian, S., Gerczuk, M., Ottl, S., Cummins, N., Freitag, M., Pugachevskiy, S., Baird, A., and Schuller, B. Snore sound classification using image-based deep spectrum features. *Proc. Interspeech 2017*, pp. 3512–3516, 2017.

Ardila, R., Branson, M., Davis, K., Henretty, M., Kohler, M., Meyer, J., Morais, R., Saunders, L., Tyers, F. M., and Weber, G. Common voice: A massively-mulilingual speech corpus. *arXiv preprint arXiv:1912.06670*, 2019.

Atmaja, B. T. and Akagi, M. Evaluation of error-and correlation-based loss functions for multitask learning dimensional speech emotion recognition. In *Journal of Physics: Conference Series*, volume 1896, pp. 012004. IOP Publishing, 2021.

Baevski, A., Zhou, Y., Mohamed, A., and Auli, M. wav2vec 2.0: A framework for self-supervised learning of speech representations. *Advances in Neural Information Processing Systems*, 33:12449–12460, 2020.

Baird, A., Tzirakis, P., Gidel, G., Jiralerpspong, M., Muller, E. B., Mathewson, K., Schuller, B., Cambria, E., Keltner, D., and Cowen, A. The icml 2022 expressive vocalizations workshop and competition: Recognizing, generating, and personalizing vocal bursts. *arXiv preprint arXiv:2205.01780*, 2022.

Chen, L.-W. and Rudnicky, A. Exploring wav2vec 2.0 fine-tuning for improved speech emotion recognition. *arXiv preprint arXiv:2110.06309*, 2021.

Cieri, C., Miller, D., and Walker, K. The fisher corpus: A resource for the next generations of speech-to-text. In *LREC*, volume 4, pp. 69–71, 2004.

Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, É., Ott, M., Zettlemoyer, L., and Stoyanov, V. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 8440–8451, 2020.

Cowen, A., Baird, A., Tzirakis, P., Opara, M., Kim, L., Brooks, J., and Metrick, J. The hume vocal burst competition dataset (h-vb) — raw data [exvo: updated 02.28.22] [data set]. *Zenodo*, 2022. doi: https://doi.org/10.5281/zenodo.6308780.

Dembczynski, K., Cheng, W., and Hüllemeier, E. Bayes optimal multilabel classification via probabilistic classifier chains. In *ICML*, 2010.

Dembczynski, K., Waegeman, W., Cheng, W., and Hüllemeier, E. On label dependence in multilabel classification. In *LastCFF: ICML Workshop on Learning from Multi-label data*, 2010.

Eyben, F., Wöllmer, M., and Schuller, B. Opensmile: the munich versatile and fast open-source audio feature extractor. In *Proceedings of the 18th ACM international conference on Multimedia*, pp. 1459–1462, 2010.

Eyben, F., Scherer, K. R., Schuller, B. W., Sundberg, J., André, E., Busso, C., Devillers, L. Y., Epps, J., Laukka, P., Narayanan, S. S., et al. The geneva minimalistic acoustic parameter set (gemaps) for voice research and affective computing. *IEEE transactions on affective computing*, 7(2):190–202, 2015.

Gales, M. J., Knill, K. M., Ragni, A., and Rath, S. P. Speech recognition and keyword spotting for low-resource languages: Babel project research at cued. In *Fourth International workshop on spoken language technologies for under-resourced languages (SLTU-2014)*, pp. 16–23. International Speech Communication Association (ISCA), 2014.

Godfrey, J. J. and Holliman, E. Switchboard-1 release 2. *Linguistic Data Consortium, Philadelphia*, 926:927, 1997.

Hall, J. A., Andrz ejewski, S. A., and Yopchick, J. E. Psychosocial correlates of interpersonal sensitivity: A meta-analysis. *Journal of nonverbal behavior*, 33(3):149–180, 2009.

Hsu, W.-N., Bolte, B., Tsai, Y.-H. H., Lakhotia, K., Salakhutdinov, R., and Mohamed, A. Hubert: Self-supervised speech representation learning by masked prediction of hidden units. *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, 29:3451–3460, 2021a.

Hsu, W.-N., Sriram, A., Baevski, A., Likhomanenko, T., Xu, Q., Pratap, V., Kahn, J., Lee, A., Collobert, R., Synnaeve, G., et al. Robust wav2vec 2.0: Analyzing domain shift in self-supervised pre-training. *arXiv preprint arXiv:2104.01027*, 2021b.

Ioffe, S. and Szegedy, C. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *International conference on machine learning*, pp. 448–456. PMLR, 2015.

Kahn, J., Rivi ère, M., Zheng, W., Kharitonov, E., Xu, Q., Mazaré, P. E., Karadayi, J., Lipchinsky, V., Collobert, R., Fuegen, C., Likhomanenko, T., Synnaeve, G., Joulin, A., Mohamed, A., and Dupoux, E. Librilight: A benchmark for asr with limited or no supervision. In *ICASSP 2020 - 2020 IEEE International
Exploring the Effectiveness of SSL and CC in Emotion Recognition of Nonverbal Vocalizations

Conference on Acoustics, Speech and Signal Processing (ICASSP), pp. 7669–7673, 2020. https://github.com/facebookresearch/libri-light.

Kharitonov, E., Rivi`ere, M., Synnaeve, G., Wolf, L., Mazaré, P.-E., Douze, M., and Dupoux, E. Data augmenting contrastive learning of speech representations in the time domain. arXiv preprint arXiv:2007.00991, 2020.

Kingma, D. P. and Ba, J. Adam: A method for stochastic optimization. In Proc. ICLR, San Diego, USA, May 2015.

Lima, C. F., Castro, S. L., and Scott, S. K. When voices get emotional: A corpus of nonverbal vocalizations for research on emotion processing. Behavior research methods, 45(4):1234–1245, 2013.

Maas, A. L., Hannun, A. Y., and Ng, A. Y. Rectifier non-linearities improve neural network acoustic models. In ICML Workshop on Deep Learning for Audio, Speech and Language Processing, 2013.

Nam, J., Loza Mencía, E., Kim, H. J., and Fürnkranz, J. Maximizing subset accuracy with recurrent neural networks in multi-label classification. Advances in neural information processing systems, 30, 2017.

Panayotov, V., Chen, G., Povey, D., and Khudanpur, S. Librispeech: an asr corpus based on public domain audio books. In 2015 IEEE international conference on acoustics, speech and signal processing (ICASSP), pp. 5206–5210. IEEE, 2015.

Pepino, L., Riera, P., and Ferrer, L. Emotion recognition from speech using wav2vec 2.0 embeddings. arXiv preprint arXiv:2104.03502, 2021.

Pratap, V., Xu, Q., Srim, A., Synnaeve, G., and Collobert, R. Mls: A large-scale multilingual dataset for speech research. arXiv preprint arXiv:2012.03411, 2020.

Read, J., Pfahringer, B., Holmes, G., and Frank, E. Classifier chains for multi-label classification. Machine learning, 85(3):333–359, 2011.

Read, J., Pfahringer, B., Holmes, G., and Frank, E. Classifier chains: a review and perspectives. Journal of Artificial Intelligence Research, 70:683–718, 2021.

Saeki, T., Xin, D., Nakata, W., Koriyama, T., Takamichi, S., and Saruwatari, H. Utmos: Utokyo-sarulab system for voicemos challenge 2022. arXiv preprint arXiv:2204.02132, 2022.

Sauter, D. A., Eisner, F., Ekman, P., and Scott, S. K. Cross-cultural recognition of basic emotions through nonverbal emotional vocalizations. Proceedings of the National Academy of Sciences, 107(6):2408–2412, 2010.