BALANCED DEEP CCA FOR BIRD VOCALIZATION DETECTION

Sumit Kumar¹, B. Anshuman¹, Linus Rüttimann², Richard H.R. Hahnloser², Vipul Arora¹

¹Department of Electrical Engineering, Indian Institute of Technology, Kanpur, India.
²Institute of Neuroinformatics, University of Zürich and ETH Zürich, 8057 Zürich, Switzerland.

ABSTRACT

Event detection improves when events are captured by two different modalities rather than just one. But to train detection systems on multiple modalities is challenging, in particular when there is abundance of unlabelled data but limited amounts of labeled data. We develop a novel self-supervised learning technique for multi-modal data that learns (hidden) correlations between simultaneously recorded microphone (sound) signals and acceleromer (body vibration) signals. The key objective of this work is to learn useful embeddings associated with high performance in downstream event detection tasks when labeled data is scarce and the audio events of interest — songbird vocalizations — are sparse. We base our approach on deep canonical correlation analysis (DCCA) that suffers from event sparseness. We overcome the sparseness of positive labels by first learning a data sampling model from the labelled data and by applying DCCA on the output it produces. This method that we term balanced DCCA (b-DCCA) improves the performance of the unsupervised embeddings on the down-stream supervised audio detection task compared to classical DCCA. Because data labels are frequently imbalanced, our method might be of broad utility in low-resource scenarios.

Index Terms— self-supervised learning, representation learning, multi-modal, DCCA, data imbalance

1. INTRODUCTION

Supervised learning techniques have produced very promising results in speech signal processing. But supervised learning tends to be inadequate in low-resource fields such as animal communication research where large datasets of labelled vocalizations are very time-consuming and costly to produce. In such Sound Event detection (SED) tasks, both the event classes and the events’ timelines (onsets and offsets) need to be labeled, which is a tedious task in noisy environments. In contrast, in self-supervised learning (SSL), models themselves generate supervisory labels from unlabeled data, with the benefit of reducing the dependence on supervisory labels. By learning from unlabeled data, unsupervised models leverage the underlying data structure.

Self-supervised learning on multi-modal data can be implemented on Siamese Networks [1]. These networks are generally trained using a contrastive loss [2], [3]. In their objective function, Jure et al. [4] used the correlation between two distorted views of the same image as distance metric. In natural language processing, word2vec [5], BERT [6] are popular techniques for learning the relationship between words in a self-supervised manner; these techniques are based on the concept of masking. Recently, the field of audio signal processing has adopted SSL because of its success in computer vision and natural language processing. Inspired by word2vec, Steffen et al. proposed wav2vec [7]. In the case of multi-view or multi-modal data, Wang et al. used Deep Canonical Correlation Analysis (DCCA) [8] to learn the correlated acoustic features [9]. In [10], the authors extracted the (hidden) correlation between the audio, video, and text features using the proposed ICCN network. In [11], the correlated features obtained from DCCA are used for the emotion recognition task. The obtained features are fused in different ways and used for various downstream tasks [12].

We aim to apply SSL for SED task using multi-modal data. DCCA can be used to leverage the underlying correlation between different modalities of data. The dataset used for this task is highly sparse. Therefore, DCCA-based approaches fail to perform. To address this issue, we propose a novel balanced deep canonical correlation analysis (b-DCCA) model where the DCCA model is balanced over the classes. Our model requires a very limited amount of labeled data in order to bootstrap the DCCA model. The labeled data used for the downstream task can be used for bootstrapping the DCCA model. The main contributions of this paper are summarized as follows.

1. This paper proposes a novel self-supervised learning model called balanced deep canonical correlation analysis (b-DCCA) that deals with sparse datasets by maximizing the entropy of training batches through a binning technique.

2. We also show the proposed b-DCCA model trained on both modalities of the data may require only a single modality at the time of inference, thus further reducing the cost of data collection.

3. We release a dataset named TwoRadioBirds for birds vocalization detection task. The dataset can be accessed using the link: https://doi.org/10.5281/zenodo.7253729

Our codes are available on https://github.com/madhavlab/2022_icassp_krsumit

2. DATASET

The bird vocalization dataset TwoRadioBirds contains accelerometer and microphone recordings of an adult male and an adult female zebra finch (Taeniopygia guttata) that were housed in a home cage where they could freely behave. All experimental procedures were approved by the Cantonal Veterinary Office of the Canton of Zurich, Switzerland (license numbers ZH045/2017). All methods were carried out in accordance with relevant guidelines and regulations (Swiss Animal Welfare Act and Ordinance, TSchG, TSchV, TVV). Vibration transmitter devices were mounted on the back of the birds with a rubber band harness [13]. The vibration transducer (Knowles Bu-21771-000 accelerometer) on the transmitter functioned as a contact microphone and selectively recorded vocalizations of the bird that carried the transmitter. The sensor signal was routed into a high-pass filter (-3dB: 15Hz) and then transmitted as a frequency
modulated FM radio signal. The vibration transducer signal picks up frequencies from vocalizations up to 7kHz in the best case and up to 1kHz in the worst case, depending on factors like e.g. how well the skin contact is. Additionally the transmitter devices picks up movement signals from e.g. wing flaps and radio noises [13]. An additional, modified transmitter device, where the vibration transducer was replaced by a Knowles FG-23329-D65 microphone, was mounted on the wall of the home cage, it delivered the microphone signal. The radio signals from the vibration and microphone transmitter device were received and demodulated by a software defined radio receiver.

The dataset was annotated by visual inspection of accelerometer vibration spectrograms, which was separately performed for the male and the female vibration data. In the first step, candidate vocalizations were extracted as described in [14]. In the second step, the candidate vocalizations were manually corrected by discarding them as noise or by manually shifting the vocalization onset and offset times to their correct positions. In a third step, we looked for missed vocalizations by using the positive examples thus far obtained as templates and by performing a brute-force nearest neighbor search across the entire dataset of candidate vocal segments (the latter were templates and by performing a brute-force nearest neighbor search)

of eleven data files of 1 hr. duration each, out of which three are defined as the regions of supra-threshold vibration signal amplitudes, across the entire dataset of candidate vocal segments (the latter were templates and by performing a brute-force nearest neighbor search).

The radio signals from the vibration and microphone transducer was replaced by a Knowles FG-23329-D65 microphone, was used for the microphone channel. The up movement signals from e.g. wing flaps and radio noises [13]. An optimal solution of the CCA objective as defined in eq. 2 is given as 

\[ A_1 = C_{11}^{-1/2}U_1, C_{22}^{-1/2}V_k, \]

where \( U_1 \) and \( V_k \) are left and right singular matrices of \( T, \) and \( T = \hat{C}_{11}^{-1/2}C_{12}C_{22}^{1/2}. \)

The linear projections are given as \( H_1 \) and \( H_2 \in \mathbb{R}^r, \) where \( H_1 = X^t_1A_1 \) and \( H_2 = X^t_2A_2. \)

CCA can compute only linear projections which certainly limits its utility. Considering this limitation, Andrew et al. developed DCCA [9] which utilizes neural networks to learn the non-linear transformations of two views of data such that the embeddings obtained are highly correlated. Data from both of the views is transformed by passing through several nonlinear layers. Let \( \theta_1, \theta_2 \) be the parameters of networks \((f_1, f_2)\) as shown in fig. 1. For \( m \) number of samples, \( H_1 = f_1(X_1), H_2 = f_2(X_2) \in \mathbb{R}^{(o \times m)} \) are the outputs of DCCA network where \( o \) is the number of neurons in the final layer of the network. Both \( H_1 \) and \( H_2 \) are centered about mean. \( \hat{C}_{11} = \frac{1}{m-1}H_1H^t_1 + r_1I \), \( \hat{C}_{12} = \frac{1}{m-1}H_1H^t_2 \), \( \hat{C}_{22} = \frac{1}{m-1}H_2H^t_2 + r_1I \) are the estimated covariance matrices for both the views.

A regularizer \( r_1 > 0 \) is added to ensure that the estimated matrices are positive definite. Summing up top \( k \) singular values of \( T \) matrix gives the total correlation of top \( k \) components of \( H_1 \) and \( H_2. \) If \( k = o \), the objective of DCCA is

\[
\text{corr}(H_1, H_2) = \|T\|_F = \text{trace}(TT^T)^{1/2}
\]

where \( \|T\|_F \) represents trace norm of \( T. \) The parameters \( (\theta_1, \theta_2) \) are iteratively updated using the objective defined in eq. 3

4. DATA PREPROCESSING

We merge the data from the male and female bird’s accelerometer channels to create the first view of the DCCA, with the data from the microphone channel serving as the second view. For merging the data, we take the average over both the accelerometer channels. Now, having two channels, i.e., microphone and accelerometer, the labeled dataset is represented as \( D_l = \{(X^m, X^a), y\} \), and unlabeled as \( D_u = \{(X^m, X^a)\}. \) Superscripts \( m \) and \( a \) are used to denote data from microphone and accelerometer channels respectively throughout the paper.

Each file in the dataset is segmented into clips of smaller duration. For each clip, the spectrogram \( X \in \mathbb{R}^{\mathbb{F} \times 1} \) is calculated by squaring the magnitude of the spectrogram obtained by applying the short-time Fourier transform. \( f \) and \( t \) are the number of frequency bins and the number of time frames, respectively. Each time-frame \( t \) of the spectrogram \( X \in \mathbb{R}^T \) is labeled using a binary value \( b, \) where \( b \in \{0, 1\}. \) The frames with the label 1 indicate the presence of a sound event in that particular time frame and those with the label 0 indicate the absence of the sound event. Since the dataset is highly sparse, class imbalance makes the task more challenging. For labeled dataset, the class imbalance is minimized by data augmentation technique, SpecAugment [17].
5. PROPOSED METHODOLOGY

5.1. Module 1: Supervised Learning Module

Deep convolutional recurrent neural network (DCRNN) [18] is used for the downstream task, i.e., birds vocalization detection. Let \( f_\theta \) be the binary classification DCRNN model where the model parameters \( \theta \) are randomly initialized. From \( D_t \), the spectrograms of the accelerometer channel, \( \tilde{X}^a \in \mathbb{R}_t^{T \times m} \) are given as an input to the model for bootstrapping the DCCA network as explained in following Section 5.2. For detection of birds vocalization, microphone channel of labeled dataset is used. For the given input, the model predicts \( \hat{y} \in \mathbb{R}^t \).

The parameters \( \theta \) are updated using the gradient descent algorithm: \( \theta \leftarrow \theta - \alpha \nabla_\theta L(f_\theta) \), where \( \alpha \in \mathbb{R}^+ \) is the learning rate and \( L \) is the binary cross entropy loss. The trained model is then used to generate labels for unlabeled data as shown in fig. 2 in order to bootstrap the DCCA module.

5.2. Module 2: Balanced Deep Canonical Correlation Analysis (b-DCCA)

Fig. 3. Module 2: Illustration of binning technique used in proposed b-DCCA model

The model parameters of DCCA, \( (\theta_1, \theta_2) \) as in discussed in Section 3 are updated using the gradient descent algorithm using mini-batches. These mini-batches represent data distribution over all the classes present. For effective training, the mini-batches should contain data samples from each class with equal probability. Since the TwoRadioBird dataset is highly sparse, the majority class dominates over the minority class in most of the mini-batches used for training the model. Therefore, the model learns biased solutions. In order to solve this issue, the proposed b-DCCA algorithm, which maximizes entropy across training batches over the classes of interest is discussed as follows.

First, the model \( f_\theta \) from Module 1 is trained on accelerometer data from labeled dataset. Then the trained \( f_\theta \) is used for the inference on \( \tilde{X}^a \in D_t \). The predicted values obtained from \( f_\theta \) are binarized using a unit-step function \( U \) such that \( \hat{y}^a = U(f_\theta(\tilde{X}^a) - \mathcal{T}) \), where \( \mathcal{T} \) is the threshold on the values of \( f_\theta(\tilde{X}^a) \) and \( \tilde{X}^a \in D_t \). Since, these values are just used for bootstrapping the DCCA model and not for the actual downstream task, i.e., birds vocalization detection, therefore the overall performance of the bird vocalization detection does not degrade. Using the binarized \( \hat{y} \), the total number of sound events in a spectrogram can be calculated as \( m = \sum_i \hat{y} \) where \( 0 \leq m \leq t \). The value of \( m \) is calculated for each spectrogram in \( D_t \). Out of all the calculated values of \( m \), the maximum value is denoted by \( M \). Further, the range \([0, M]\) is divided into \( B \) equal parts. Based on the value of \( m \), each spectrogram is allotted a bin index \( n \) as defined below,

\[
 n = \left\lceil \frac{m}{M} \right\rceil \quad (4)
\]

where \( n \in \{1, \ldots, B\} \). The spectrograms are uniformly sampled from each bin to create training batches for b-DCCA as shown in fig. 3. The spectrograms in the higher order bins have very low count due to sparsity in dataset therefore those are augmented using SpecAugment [17]. Since both of the channels are synchronized, corresponding spectrograms are selected from the microphone channel also. The parameters \( \theta_1 \) and \( \theta_2 \) of the b-DCCA networks are updated using the following objective

\[
 L_{\text{cor}} = \text{corr}(f_{\theta_1}(\tilde{X}^a), f_{\theta_2}(\hat{X}^a)) \quad (5)
\]

The proposed b-DCCA model is explained in Algorithm 1.

5.3. Detection

As shown in the fig. 4, the embeddings \( H_1 \) obtained from trained b-DCCA model is used for bird vocalization detection task using Deep CRNN model as explained in Section 5.1.

6. EXPERIMENTS

We clip each file into 4-second segments. For calculating the STFT of the segments, we use 1024 point FFT using a 43 ms Hanning window and a hop size of 21.5 ms. The obtained spectrograms have dimension \((f \times t)\), where \( f = 257 \) and \( t = 375 \). In all of the three methods discussed below, the performance of the trained classifier (DCRNN) is evaluated on the test data created by random train-test split by sklearn [19] The experiments shown in Table 1 are discussed below.

DCRNN: Using the DCRNN [18] classifier, we classify each time frame of the spectrogram \( \tilde{X}^m \in D_t \) and obtain a vector \( \hat{y} \in \mathbb{R}^t \).
Algorithm 1 Algorithm for b-DCCA

Input: Spectrograms: \((\hat{X}^m, \hat{X}^a) \in \{D_l \cup D_u\}\) and DCRNN model \(f_\theta\) trained on \(\hat{X}^a \in D_l\)

Output: Correlated and balanced embeddings: \(H_1\)

1. for each \(\hat{X}^a \in D_u\) do
2. Detect \(\hat{y}^a\) using trained DCRNN model \(f_\theta\)
3. Calculate \(m\) on binarized values of \(\hat{y}^a\) such that \(m = \sum_t \hat{y}^a_t\); \(t = \) number of time frames in \(\hat{X}^a\)
4. Assign a bin number \(n\) for each \(\hat{X}^a \in D_u\) based on \(m; n = B(\hat{X}^a); \) where \(B\) is binning function as defined in eq. 4
5. Create training batches by sampling uniformly from each bin: \(\hat{x}_u \sim U(\{\hat{X}^{(n)}_u\}); \) where \(n \in \{1, \ldots, B\}\) for \(b\) number of bins
6. Since both the channels are synchronized, sample the corresponding spectrograms \(\hat{x}^m \in D_u\)
7. Train b-DCCA \((f_{\theta_1}, f_{\theta_2})\) with the batches created by samples obtained in Step 5, 6
8. end for
9. Using trained b-DCCA model, obtain the embeddings of \(\hat{x}^m \in D_l\) as \(H_1 = f_{\theta_1}(\hat{x}^m)\)
10. return \(H_1\)

We use 3 Conv2D layers followed by BatchNormalization, relu activation, and Maxpooling2D layers. The features extracted from convolutional layers act as the input to bidirectional GRU. We use single bi-GRU layer followed by dense layer with sigmoid activation.

DCRNN*: We use the same architecture and training hyperparameters for training DCRNN* model as described above in DCRNN. For DCRNN* model, we use accelerometer channel data \(\hat{x}^a \in D_l\) as input along with the labels. We are not using DCRNN* as a baseline because it is trained on accelerometer data therefore performs better; while other models in Table 1 are trained on microphone data.

DCCA: We implement DCCA [8] baseline using 4 Conv1D layers followed by BatchNormalization and relu activation layer for each view. The DCCA models \(f_{\theta_1}\) and \(f_{\theta_2}\) are trained using \(\hat{x}^m\) and \(\hat{x}^a\) in \(D_u\) respectively. Using trained DCCA, we obtain \((H_1, H_2)\), each having size \((50 \times 375)\). We select top 50 dimensions along frequency axis while preserving the temporal dimension. For bird vocalization detection task, another DCRNN classifier is trained on labeled data with \(H_1\) as input.

b-DCCA: The architecture and training hyperparameters of the proposed b-DCCA model are similar to that of the DCCA model described above. We train the b-DCCA model using the training batches created by the binning technique as discussed in Section 5.2. Using trained b-DCCA model for inference, we use \(\hat{x}^m \in D_l\) to obtain \(H_1\). \(H_1\) is further used for birds vocalization detection task using the above discussed DCRNN classifier.

7. RESULTS

To evaluate the b-DCCA against the baseline, segment-based F1 score is used as the evaluation metric. We use sed_eval library [20] for evaluation.

We report P, R, and F1 in Table 1. The labeled microphone channel of the dataset is used for the sound event detection task. We select microphone channel for bird sound vocalization task because collecting the data from microphone sensor is easy as compared to accelerometer sensor. The microphone channel contains noisy audio recordings. So, the spectrograms obtained from the microphone channel data does not have high fidelity. Therefore, the supervised DCRNN classifier does not perform very well on this data as reported in Table 1. The other modality in dataset, i.e., the accelerometer channel is more reliable as compared to microphone channel data. We quantify the fidelity of data by comparing the DCRNN classifier’s performance on both of the channels individually. The performance of DCRNN using accelerometer channel data is given in Table 1 as DCRNN*.

Since, both the microphone and accelerometer channels record the same sound event therefore both of these channels have some hidden correlation. To capitalize on the hidden correlation between both channels, we use DCCA. DCCA extracts useful features from both channels by maximizing the correlation between them. The major issue with DCCA is that due to the high sparsity in data, it learns the solution which is biased towards the majority class, i.e., silence which degrades the results of DCRNN classifier. To address this problem, we applied the proposed b-DCCA on our dataset and demonstrated that the embeddings obtained by the b-DCCA model perform much better than other baseline models.

8. CONCLUSION

This paper proposes a novel self-supervised algorithm called b-DCCA which uses canonical correlation to learn the hidden relationships between the microphone and accelerometer channel recording the same audio event simultaneously. The obtained results demonstrate that the model generates better embeddings when it learns with a substantial amount of data. Naturally, there is a lot of potential for development. In future works, we hope to move forward with the development of an end-to-end model which performs both of the tasks, i.e., maximizing the canonical correlation between the two views as well as the downstream tasks. Moreover, instead of using sigmoid activation on the final layer of DCRNN classifier, we plan to try other convex functions to make the spectrograms more uniformly distributed across all the bins.

Table 1. Performance of the Proposed b-DCCA Model

| Methods       | Precision | Recall | F1 Score |
|---------------|-----------|--------|----------|
| DCRNN [18]   | 0.76      | 0.77   | 0.76     |
| DCRNN [18]*  | 0.89      | 0.94   | 0.92     |
| DCCA [8]     | 0.53      | 0.67   | 0.59     |
| b-DCCA       | 0.98      | 0.72   | 0.83     |

Fig. 5. Visualization of detected bird vocalizations using b-DCCA model. **Top:** Spectrogram of microphone channel data. **Middle:** Ground Truth **Bottom:** Predictions
9. REFERENCES

[1] R. Hadsell, S. Chopra, and Y. LeCun, “Dimensionality reduction by learning an invariant mapping,” in 2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’06), vol. 2. IEEE, 2006, pp. 1735–1742.

[2] S. Chopra, R. Hadsell, and Y. LeCun, “Learning a similarity metric discriminatively, with application to face verification,” in 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’05), vol. 1. IEEE, 2005, pp. 539–546.

[3] T. Chen, S. Kornblith, M. Norouzi, and G. Hinton, “A simple framework for contrastive learning of visual representations,” in International conference on machine learning. PMLR, 2020, pp. 1597–1607.

[4] J. Zhontar, L. Jing, I. Misra, Y. LeCun, and S. Deny, “Barlow twins: Self-supervised learning via redundancy reduction,” in International Conference on Machine Learning. PMLR, 2021, pp. 12310–12320.

[5] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, “Distributed representations of words and phrases and their compositionality,” Advances in neural information processing systems, vol. 26, 2013.

[6] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, “Bert: Pre-training of deep bidirectional transformers for language understanding,” arXiv preprint arXiv:1810.04805, 2018.

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

[8] G. Andrew, R. Arora, J. Bilmes, and K. Livescu, “Deep canonical correlation analysis,” in International conference on machine learning. PMLR, 2013, pp. 1247–1255.

[9] W. Wang, R. Arora, K. Livescu, and J. A. Bilmes, “Unsupervised learning of acoustic features via deep canonical correlation analysis,” in 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2015, pp. 4590–4594.

[10] Z. Sun, P. Sarma, W. Sethares, and Y. Liang, “Learning relationships between text, audio, and video via deep canonical correlation for multimodal language analysis,” in Proceedings of the AAAI Conference on Artificial Intelligence, vol. 34, no. 05, 2020, pp. 8992–8999.

[11] Y.-T. Lan, W. Liu, and B.-L. Lu, “Multimodal emotion recognition using deep generalized canonical correlation analysis with an attention mechanism,” in 2020 International Joint Conference on Neural Networks (IJCNN). IEEE, 2020, pp. 1–6.

[12] Y. Lu, W.-L. Zheng, B. Li, and B.-L. Lu, “Combining eye movements and eeg to enhance emotion recognition,” in Twenty-Fourth International Joint Conference on Artificial Intelligence, 2015.

[13] L. Rüttimann, J. Rychen, T. Tomka, H. Hörster, M. D. Rocha, and R. H. Hahnloser, “Multimodal system for recording individual-level behaviors in songbird groups,” bioRxiv, 2022.

[14] C. Lorenz, X. Hao, T. Tomka, L. Rüttimann, and R. H. Hahnloser, “Extracting extended vocal units from two neighborhoods in the embedding plane,” bioRxiv, 2022. [Online]. Available: https://www.biorxiv.org/content/early/2022/09/27/2022.09.26.509501

[15] H. Harold, “Relations between two sets of variates,” Biometrika, vol. 28, no. 3/4, p. 321, 1936.

[16] K. Mardia, “Jt kent. and j. m. bibby,” Multivariate Analysis, 1979.

[17] D. S. Park, W. Chan, Y. Zhang, C.-C. Chiu, B. Zoph, E. D. Cubuk, and Q. V. Le, “Specaugment: A simple data augmentation method for automatic speech recognition,” arXiv preprint arXiv:1904.08779, 2019.

[18] A. Mesaros, T. Heittola, T. Virtanen, and M. D. Plumbley, “Sound event detection: A tutorial,” IEEE Signal Processing Magazine, vol. 38, no. 5, pp. 67–83, 2021.

[19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, “Scikit-learn: Machine learning in Python,” Journal of Machine Learning Research, vol. 12, pp. 2825–2830, 2011.

[20] A. Mesaros, T. Heittola, and T. Virtanen, “Metrics for polyphonic sound event detection,” Applied Sciences, vol. 6, no. 6, p. 162, 2016.