NEURAL AUDIO FINGERPRINT FOR HIGH-SPECIFIC AUDIO RETRIEVAL BASED ON CONTRASTIVE LEARNING

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ABSTRACT

Most of existing audio fingerprinting systems have limitations to be used for high-specific audio retrieval at scale. In this work, we generate a low-dimensional representation from a short unit segment of audio, and couple this fingerprint with a fast maximum inner-product search. To this end, we present a contrastive learning framework that derives from the segment-level search objective. Each update in training uses a batch consisting of a set of pseudo labels, randomly selected original samples, and their augmented replicas. These replicas can simulate the degrading effects on original audio signals by applying small time offsets and various types of distortions, such as background noise and room/microphone impulse responses. In the segment-level search task, where the conventional audio fingerprinting systems used to fail, our system using 10x smaller storage has shown promising results. Our code and dataset will be available.

Index Terms — acoustic fingerprint, self-supervised learning, data augmentation, music information retrieval

1. INTRODUCTION

Audio fingerprinting is a content summarization technique that links short snippets of unlabeled audio contents to the same contents in the database [1]. The most well-known application is the music fingerprinting system [1,8] that enables users to identify unknown songs from the microphone or streaming audio input. Other applications include detecting copyrights [3], deleting duplicated contents [9], monitoring broadcasts [1,10], and tracking advertisements [11].

General requirements for audio fingerprinting system are discriminability over a huge number of other fingerprints, robustness against various types of acoustic distortions, and computational efficiency for processing large-scale database. To achieve these requirements, most of conventional approaches [1–7] employed a novelty function to extract sparse representations of spectro-temporal features from a pre-defined audio window. These sparse representations, or acoustic landmarks [5], used to be coupled with binary hashing algorithms [1,2,12] for scalable search in hamming space.

Still, the representation learning approach to audio fingerprinting has not been discovered well. Now-playing [8] has been pioneering work in the direction. They trained a neural network using semi-hard triplet loss, which derived from face recognition [13]. In their setup [8], Now-playing could identify songs within 44h long audio database. In our benchmark, we could replicate this semi-hard triplet approach and compare it with our work in a new setup: high-specific audio retrieval in a 180 times larger database.

We present a neural audio fingerprinter for robust high-specific audio retrieval based on contrastive learning. Our fingerprinting model in Figure 1 differs from the prior works in three key aspects:

- Prior works [1,8] have focused on song-level audio retrieval from a music excerpt; we challenge a high-specific audio search by allowing miss-match less than 250 ms from a few seconds input.
- We introduce the contrastive learning framework for simulating maximum inner-product search (MIPS) in mini-batch.
- We employ various types of data augmentation methods for generating acoustic distractors and show their benefits to training a robust neural audio fingerprinter.

2. NEURAL AUDIO FINGERPRINTER

Our neural audio fingerprinter in Figure 1 transforms and maps the segment-level acoustic features into $L^2$-normalized space, where the inner-product can measure similarities between segments. It consists of a pre-processor and neural networks.

As a first step, input audio $X$ is converted to time-frequency representation $S$. It is then fed into convolutional encoder $f(.)$ which is based on the previous study [8]. Finally, $L^2$-normalization is applied to its output through a linear projection layer $g(.)$. Thus, we employ $g ∘ f : S → Z^d$ as a segment-wise encoder that transforms $S$ into d-dimensional fingerprint embedding space $Z^d$. The d-dimensional output space $Z^d$ always belongs to Hilbert space $L^2(\mathbb{R}^d)$; the cosine similarity of a pair unit such as $\cos(z_a, z_b)$ becomes inner-product $z_a \cdot z_b$, and due to its simplicity, $L^2$ projection...
has been widely adopted in metric learning studies \cite{8, 13, 14}.

The $g\circ f(.)$ described here can be interpreted as a reorganization of the previous audio fingerprinting networks \cite{8} into the common form employed in self-supervised learning (SSL) \cite{14, 17}. However, our approach differs from the typical SSL that throws $g(.)$ away before fine-tuning for the target task: we maintain the self-supervised $g(.)$ up to the final target task.

2.1. Contrastive learning framework

From the previous section, we can use the inner-product as a measure of similarity between $z_i \in \mathbb{Z}^d$ for any time step $t$. Without losing generality, searching the most similar point ($^\star$) of database $V = \{v_i\}$ for a given query $q$ in $\mathbb{Z}^d$ space can be formulated as maximum inner product search (MIPS), $v_i^\star := \arg \max_i \langle q, v_i \rangle$.

We simulate MIPS in a mini-batch setup that takes into account various acoustic distortions and input frame mismatches occurring in the fingerprint task. MINI-batch with the size of $N/2$ pairs of $\{s^{org}, s^{rep}\}$. $s^{org}$ is the time-frequency representation of sampled audio and $s^{rep}$ is the augmented replica of $s^{org}$, where $s^{rep} = M_\alpha(s^{org})$. $M_\alpha$ is an ordered augmentation chain that consists of multiple augmentors with the random parameter set $\alpha$ for each replica. In this configuration, the indices of original examples are always odd, and that of replicas are even. Therefore, the batch-wise output of $f\circ g(s)$ can be $\{z_{2k-1}^\star, z_{2k}^\star\}_{k=1}^{N/2}$.

We give each $k$-th example a chance to be an anchor (or a query in MIPS) to be compared with all other examples excluding itself in the batch. We calculate the pairwise inner-product matrix between all elements in the batch $\{z_i\}_{i=1}^N$ as $a(i,j) = z_i^T z_j$ for $\forall i, j \in \{1, 2, ..., N\}$ as Figure 2. Then, we define the contrastive prediction task for a positive pair of examples $(i,j)$ as:

$$\ell(i,j) = -log \frac{\exp(a_{i,j}/\tau)}{\sum_{k=1}^{N} I(k \neq i) \exp(a_{i,j}/\tau)}.$$  \hspace{1cm} (1)

$I(.) \in \{0, 1\}$ is an indicator function that returns 1 iff $(.)$ is true, and $\tau > 0$ denotes the temperature \cite{13} parameter for softmax. We employ Equation 1 to replace MIPS from the property: computing the top-$k$ $(k=1$ in our setup) predictions in the softmax function is equivalent to the MIPS. A similar approach is found in \cite{19}. The total loss $L$ averages $l$ across all positive pairs, both $(i,j)$ and $(j,i)$:

$$L = \frac{1}{N} \sum_{k=1}^{N} \ell(2k-1, 2k), \ell(2k, 2k-1).$$  \hspace{1cm} (2)

Updating rules are summarized in Algorithm 1.

It is worth comparing our approach to SimCLR \cite{14} for visual representation. Our approach differs from SimCLR on how to construct positive pairs. We use \{original, replica\}, whereas SimCLR uses \{replica, replica\} from the same original source. In our case, the anchor is already given because the database will always store the clean source, so it can be more important to learn the consistent relation between the original and its replica over all other negatives.

2.2. Sequence search

Our model trained by simulating MIPS is optimized for segment-level search. In the case of searching for a query sequence $\{Q_{l=0}^L\}$ consisting of $L$ consecutive segments: We first gather the top $k$ segment-level search results indices $I_{q_l}$ for each $q_l$ from the DB. The offset is then compensated by $I_{q_l} = I_{q_l} - i$. The set of candidate indices $c_i \in C$ is determined by taking unique elements of $I_{q_l}$. The sequence-level similarity score is the sum of all segment-level similarities from the segment index range $[c, c + L]$, and the index with the highest score is the output of the system.

3. EXPERIMENTAL SETUP

3.1. Dataset

The main experiment in Table 1 is reproducible with the following three data sets, which are isolated from each other.

- Train (10K-30s): A subset of the fma_medium \cite{20} consisting of 30 s audio clips from a total of 10K songs.
- Test-Dummy-DB (100K-full-db): a subset of the fma_full \cite{20} consisting of about 278 s audio clips from a total of 100K songs. We scale the search experiment with this.
- Test-Query/DB (500-30s): Test-DB is another subset of the fma_medium, which is 500 audio clips of 30 s each. Test-Query was synthesized using Test-DB as directed in Section 3.3.

\begin{algorithm}[h]
\caption{Training of neural audio fingerprinter}
\label{alg:training}
\begin{algorithmic}
\STATE \textbf{Input:} $s, z$, representation $z \in \mathbb{R}^d$
\STATE \textbf{Variables:} input $s$, representation $z \in \mathbb{R}^d$
\STATE \textbf{Augmentor:} $M_\alpha(\cdot)$ with parameters $\alpha$
\STATE \textbf{Net:} encoder $f(\cdot)$, $L^2$ projection layer $g(\cdot)$
\STATE \textbf{Algorithm 1:} Training of neural audio fingerprinter
\FOR {each sampled mini-batch $\{s_k\}_{k=1}^{N/2}$}
  \FOR {$\forall k \in \{1, ..., N/2\}$}
    \STATE $z_{org} = g \circ f(s_k)$
    \STATE $z_{rep} = g \circ f(M_\alpha(s_k))$
    \STATE $z = \{z_{org}, z_{rep}, ..., z_{org}, z_{rep}\}$
    \FOR {$\forall i \in \{1, ..., N\}$ and $\forall j \in \{1, ..., N\}$}
      \STATE $a_{i,j} = z_i \cdot z_j$ \textit{/* Pairwise similarity */}
      \STATE $\ell(i,j) = NTXent(a_{i,j}, \tau)$ \textit{/* Eq. (1) */}
    \ENDFOR
  \ENDFOR
  \STATE Update $f, g$ to minimize $L \approx \frac{1}{N} \sum_{i=1}^{N} \ell / \text{Eq. (2) */}
\ENDFOR
\RETURN $f \circ g$ to minimize $L$
\end{algorithmic}
\end{algorithm}
3.2. Data pipeline with augmentation chain

A batch consists of \{x^{\text{org}}, x^{\text{aug}}\} pairs. Each \(x^{\text{org}}\) is generated from its corresponding \(x^{\text{aug}}\) through augmentation steps as following order:

- Time offset modulation: To simulate possible discrepancies in real world search scenarios, we define positive examples as 1 s audio clips with an offset of up to ±200 ms. We first sample 1.2 s of audio and then \{x^{\text{org}}, x^{\text{aug}}\} are chosen by random start positions.

- Background mixing: A randomly selected noise in the SNR range of \([0, 10]\) dB is added to the audio to reflect the actual noise. The noise dataset consists of 4.3 h of a subset of AudioSet \[21\] and 2.3 h of pub and cafe noise recorded by us. The AudioSet was crawled within subway, metro, and underground tags with no music-related tags. Each dataset is split into 8:2 for train/test.

- IR filters: To simulate the effect of diverse spatial and microphone environments, microphone and room impulse response (IR) are sequentially applied by convolution operation. Public microphone and spacial \[22\] IR dataset are split into 8:2 for train/test.

- Cutout \[24\] and Spec-augment \[25\] are applied after extracting log-power Mel-spectrogram features, such that \(\{s^{\text{org}}, s^{\text{aug}}\}\). Like other augmentations, we uniformly apply a batch-wise random mask to all examples in a batch including \(s^{\text{org}}\). The size and position of each rectangle/vertical/horizontal mask is random in the range \([1/10, 1/2]\) the length of each time/frequency axis.

3.3. Network structure

In Table 1, a space-saving notation \(C_{k\times s}^{p, q}\) denotes Conv2d with input channel \(p\), output channel \(q\), kernel size \(k\times k\), and stride \(s\). The \(k'\) and \(s'\) denote input \(k\times k\) and \(s\times s\). \(\text{Split}^{h/d}\) splits input dimension \(h\) into \(d\) parts of each output dimension \(v = h/d\). \(g(<.)\) is \(g(f(<.)\)). The network parameters \(\{d, h, u, v\}\) are in Table 2.

- **Convolutional encoder \(f(<.)\):** \(f(<.)\) takes as input a log-power Mel-spectrogram \(s_t\) with a time step \(t\) representing 1s audio captured by 50% overlapping window. \(f(<.)\) consists of several blocks containing spatially separable convolution \(SC\) \[26\] followed by a layer normalization (LN) \[27\] and a ReLU activation.

- **\(L^2\) projection layer \(g(<.)\):** We take the split-head from the input embeddings and pass it through the separate Linear-ELU-Linear layers for each split as in previous works \[8,28\]. After concatenating the multi-head outputs, we apply \(L^2\)-normalization.

3.4. Implementation details

The replication of Now-playing and our work shared the short-time Fourier transform (STFT) settings listed in in Table 2. Note that, due to ambiguity in the previous study \[8\], the STFT parameters were set by us. We trained Now-playing using online semi-hard triplet loss \[13\] with the margin \(m = 0.4\) and batch size \(N = 320\).

We trained our model using LAMB \[29\] optimizer, which performed 2 pp better than Adam \[30\] with the 3 s query sequence for batch size \(N \geq 320\). In practice, Adam worked better only for \(N \leq 240\). The learning rate had an initial value of 1e-4. N/640 with cosine decay without warmup \[31\] or restarts \[32\], then it reached a minimum value of 1e-7 in 100 epochs. The temperature in Eq. \[1\] was \(\tau = 0.05\), and we did not observe a meaningful performance change in the range \([0.01, 0.1]\). The training finished in about 30 h with a single NVIDIA RTX 6000 GPU or v3-8 Cloud TPUs.

The search algorithm in Section 2.2 was implemented using an open library \[33\]. We used the inverted file (IVF) index structure with product quantizer (PQ) as a non-exhaustive MIPS. The IVF-PQ had 200 centroids with the code size of 2\(k\), and 8-bits per index. In this setting, the loss of recall remained below 0.1% compared to the exhaustive search of 100K songs \((\approx 56\,\text{M segments})\) database.

### Table 1. Fingerprinter (FP) network structure in Section 3.3

| Parameter | Value |
|-----------|-------|
| Sampling rate | 8,000 Hz |
| STFT window function | Hann |
| STFT window length and hop | 1024, 256 |
| STFT spectrogram size \(F_t \times T\) | \(512 \times T(T = 32)\) |
| log-power Mel-spectrogram size \(F_t \times T\) | \(256 \times T(T = 32)\) |
| Dynamic range | 80 dB |
| Frequency \(\{\min, \max\}\) | \((300, 4,000)\) Hz |
| Fingerprint \{window length, hop\} | \(\{1, 0.5s\}\) or \(\{2s, 1s\}\) |
| Fingerprint dimension \(d\) | 64 or 128 |
| Network parameters \(\{h, u, v\}\) | \(\{1024, 32, h/d\}\) |
| Batch size \(N\) | 120 or 320 or 640 |

3.5. Evaluation protocol

- **Evaluation metric:** To measure the performance in segment/song-level search in Section 4, we use Top-1 hit rate (\%) 

\[
100 \times \frac{(n\ of\ hits\ @\ Top-1)}{(n\ of\ hits\ @\ Top-1) + (n\ of\ miss\ @\ Top-1)}
\]

which is equivalent to recall. In Table 3, exact match is the case when the system finds the correct index in database. We further define the tolerance range for near match as ±500 ms.

- **Test-Query generation:** 2K query-sources for each \(\{1, 2, 3, 5, 6, 10\}\) s length are randomly cropped from Test-DB containing 500 clips of 30s each. Each query is synthesized through the random augmentation pipeline as described in Section 3.2. Note that we exclude Cutout and Spec-augment. The default SNR range is \([0, 10]\) dB. We make sure that the data used for background mixing and IR as unseen to our model by isolating them from training set.

4. RESULTS AND DISCUSSION

4.1. Experimental results

The main results are listed in Table 3. Our implementation of the Now-playing \[8\] based on semi-hard triplet \[13\] took 2 s as a unit audio segment. The modified Now-playing with 1 s unit audio segment could be more fairly compared with our works.

**VS. Now-playing (semi-hard triplet)** Modified Now-playing consistently performed better than the replicated Now-playing. While cutting the dimension in half, this trend was maintained. Considering that the DB size was the same when the number of fingerprint dimensions was half, it could be seen that constructing DB with 1
Table 3. Top-1 hit rate (%) of large-scale (total of 100K songs) segment-level search. \textit{d} denotes the dimension of fingerprint embedding. \textit{exact match} means that our system finds the exact index. \textit{near match} means a mismatch within ± 1 index or ± 500 ms.

| Method                      | \textit{d} | \textit{1 s} | \textit{2 s} | \textit{3 s} | \textit{5 s} | \textit{6 s} | \textit{10 s} |
|-----------------------------|-----------|------------|------------|------------|------------|------------|------------|
| Now-playing (replicated)    | 128       | 43.3       | 60.1       | 73.6       | 81.0       | 86.1       |            |
| Now-playing (modified for 1 s unit) | 64       | 25.8       | 58.5       | 69.3       | 78.5       | 81.4       | 87.7       |
| This work (\(N=640\))      | 64       | 26.3       | 58.2       | 69.5       | 78.4       | 81.4       | 87.8       |
| This work (\(N=320\))      | 64       | 30.9       | 61.1       | 71.8       | 79.8       | 83.0       | 89.2       |
| This work (\(N=120\))      | 128      | 62.2       | 83.2       | 87.4       | 92.0       | 93.3       | 95.6       |

The models in Table 3 were trained with about 70 h dataset. This size was less than 1% of the total 5K h DB for test. We assumed that using the entire DB for training would be impractical—a huge number of new songs are produced every day. In additional experiment, we used 10% of the Test-dummy-DB for training a \(d=64\) model. It achieved \(\{58.3, 81.1, 86.5, 92.4, 93.4, 96.0\}\% of Top-1 hit rate for the query sequence of \(\{1, 2, 3, 5, 6, 10\}\) s. This improved \(\{53.6\}\% pp at the 6 s query over the best model with \(d=64\) in Table 3, still lower than the result of \(d=64\). Thus, both \(d\) and the amount of training data were the factors affecting performance.

In our best model with \(d=128\), the final DB size was about 7.5 GB for 56M segments from total of 100K songs. We report about 1.5 s search time for parallel search of 19 segments (= 10 s query) with \(i9-10980XE\) CPU. Expanding beyond 1 M songs would be difficult to handle with in-memory search: we could observe on-disk-search using the latest SSD was only twice as slow as in-memory-search. We reserve the industry-level scalability issues for future work.

4.2. Size of training set, search time and scalability

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4.3. Transfer to down-stream task

We further investigated the generality of the learned embeddings by performing a downstream task, as in the typical SSL \(\{14,17\}\) settings. By fixing \(f(.)\) and fine-tuning a linear classifier, we tried audio genre classification in \textit{GTZAN} dataset with stratified 10-fold cross-validation. Fine-tuning on the pre-trained embeddings for fingerprint achieved 59.2\% accuracy, while training from scratch achieved only 32.0\%. This showed that the features encoded by \(f(.)\) were linearly interpretable, which was consistent with other SSL reports \(\{15,17\}\). However, our result was slightly lower than the baseline of 61.0\% accuracy using \textit{MFCC++GMM} \(\{35\}\). This problem might be due to the limitation of the lightweight networks with the relatively short-time analysis window.

5. CONCLUSIONS AND FUTURE WORK

This study presented a neural audio fingerprinter for high-specific audio retrieval. Our model was trained to maximize the inner-product between positive pairs of fingerprints through a contrastive prediction task. To this end, we explicitly sampled positive pairs to achieve the product between positive pairs of fingerprints through a contrastive loss. This reaffirmed the training benefits of our contrastive learning over conventional methods in both performance and scalability.
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