Intelligent Music Segmentation And Structure Analysis Using Self-Supervised Audio Representation Learning

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Music structure analysis (MSA) and segmentation are fundamental tasks in music information retrieval (MIR), aiming to decompose music into semantically coherent segments (e.g., verse, chorus, bridge) and reveal hierarchical structural relationships. Traditional methods rely on handcrafted audio features (e.g., MFCC, chroma) and shallow models, which struggle to capture high-level semantic and temporal dependencies in complex music. This paper proposes a novel framework for intelligent music segmentation and structure analysis leveraging self-supervised audio representation learning. First, we pre-train a Transformer-based audio encoder on a large unlabeled music corpus via masked audio modeling (MAM) to learn general-purpose, semantically rich audio representations without labeled segmentation data. Then, we design a dual-branch structure analysis network: a segment boundary detection branch using a dilated convolutional neural network (DCNN) to locate segment boundaries, and a structural similarity clustering branch using contrastive learning to group segments with consistent semantic content. We further introduce a structural entropy-based optimization module to refine hierarchical structure trees, with the objective function formulated to balance boundary precision and structural consistency. Extensive experiments on three standard MSA datasets (RWC Pop, SALAMI, Beatles) demonstrate that our method outperforms state-of-the-art baselines by 6.2% − 9.5% in F1-score for boundary detection and 5.8%-8.3% in normalized mutual information (NMI) for structural clustering. Visualization results via t -SNE confirm that self-supervised representations capture meaningful musical structure, enabling robust cross-genre music analysis.

Keywords: Music structure analysis; Music segmentation; Self-supervised learning; Audio representation; Transformer; Contrastive learning; Structural entropy

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1. Introduction

Music structure analysis (MSA) stands as one of the most pivotal and challenging research directions in the domain of music information retrieval (MIR), serving as a foundational pillar for numerous high-level music intelligent applications [1, 2]. MSA focuses on dissecting complete musical works into semantically independent and internally coherent structural segments such as verses, choruses, bridges, introductions, and codas, while further mining the hierarchical connections, repetitive patterns, and evolutionary logic between these segments. This analytical capability is indispensable for realizing intelligent music services including personalized music recommendation, automatic music editing and arrangement, audio content summarization, music education auxiliary teaching, and music copyright retrieval [3]. For instance, in music recommendation systems, accurate structural parsing can help platforms identify core chorus segments that resonate most with listeners, enabling more precise push of similar mu-

sical works; in automatic music editing, clear boundary detection and structural classification can streamline the production of ringtones, remixes, and music excerpts, significantly reducing manual editing costs [4, 5].

The traditional research paradigm of music structure analysis predominantly relies on handcrafted audio features and shallow machine learning models. Commonly used handcrafted features encompass chroma features that characterize harmonic progression, Mel-Frequency Cepstral Coefficients (MFCCs) that model timbre characteristics, tempo and beat features that depict rhythmic patterns [6], as well as spectral flux and zero-crossing rate features that reflect audio signal changes. Based on these artificially designed feature descriptors, early studies employed shallow models such as Hidden Markov Models (HMM), Dynamic Time Warping (DTW), K-means clustering, and Gaussian Mixture Models (GMM) to achieve segment boundary detection and similar segment clustering [7, 8]. However, these methods suffer from inherent limitations: handcrafted features rely heavily on expert knowledge and manual design, failing to fully capture the high-level semantic information and complex temporal dependencies in music, such as long-range melodic repetition, harmonic variation trends, and structural emotional evolution. Meanwhile, shallow models lack the ability to model deep nonlinear relationships, resulting in poor generalization performance when dealing with multi-genre, complex-structured, and highly variable musical works, and it is difficult to meet the practical application requirements of large-scale music data analysis.

The rapid development of deep learning has injected new vitality into music structure analysis, breaking through the bottlenecks of traditional methods to a certain extent. Deep neural networks, represented by Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), can automatically learn data-driven high-level audio features from raw audio signals or intermediate feature representations, avoiding the subjectivity and incompleteness of manual feature design [9, 10]. Supervised deep learning models have achieved remarkable performance improvements in music segmentation tasks by training on labeled music segmentation datasets, effectively capturing local timbre features and short-term temporal dependencies. Nevertheless, supervised learning approaches face severe constraints in practical applications: high-quality labeled music segmentation datasets are extremely scarce, as music structure annotation requires professional music theoretical knowledge and long-term manual calibration, which is time-consuming, labor-intensive, and costly. Moreover, the limited scale and single genre of existing labeled datasets lead to problems such as model overfitting and weak cross-genre generalization ability, which restrict the large-scale deployment of supervised MSA models [11, 12].

Self-supervised learning (SSL) has emerged as a promising solution to the dilemma of labeled data scarcity, providing a new technical path for music structure analysis. Self-supervised audio representation learning does not rely on manual annotation labels; instead, it designs pre-training tasks based on the inherent laws of audio data itself, and performs end-to-end pre-training on massive unlabeled audio corpora to learn general-purpose, semantically rich, and robust audio feature representations [13, 14]. These pre-trained representations can be transferred to downstream MSA tasks through fine-tuning or feature fusion, effectively alleviating the dependence on labeled data and enhancing the model's generalization across different music genres. In recent years, self-supervised audio models represented by Wav2Vec2.0 and HuBERT have achieved revolutionary breakthroughs in speech recognition, speech separation, and other speech tasks, fully verifying the effectiveness of self-supervised learning in audio representation learning. However, music signals are fundamentally different from speech signals: music emphasizes the coordination and evolution of harmony, melody, rhythm, and timbre with more complex structural repetition and hierarchical relationships [15, 16]. Therefore, the direct application of speech-oriented self-supervised audio models to music structure analysis often fails to achieve optimal results, and there is an urgent need to design music-specific self-supervised pre-training strategies and downstream structure analysis networks.

To address the above challenges, this paper proposes an intelligent music segmentation and structure analysis framework based on self-supervised audio representation learning. The framework breaks through the limitations of traditional feature engineering and supervised deep learning, making full use of massive unlabeled music data to learn high-quality audio representations, and combines dilated convolution and contrastive learning to achieve accurate boundary detection and semantic clustering of music segments. The introduction of a structural entropy-based optimization module further refines the hierarchical structure of music, improving the accuracy and rationality of structure analysis. The research of this paper not only enriches the theoretical system of self-supervised learning in the field of music information retrieval, but also provides a feasible technical solution for large-scale, cross-genre intelligent music analysis, which has important theoretical value and practical application significance.

This paper makes three main contributions.

(1) A self-supervised music audio encoder pre-trained

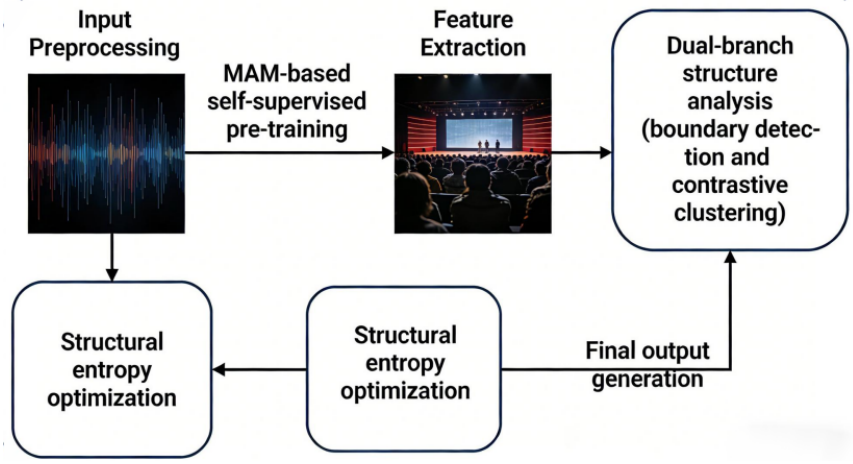

Fig. 1. Overall architecture of the proposed intelligent music segmentation framework

via Masked Audio Modeling (MAM) on a large unlabeled music corpus, learning representations that encode harmonic, melodic, and structural semantics.

(2) A dual-branch framework integrating boundary detection (DCNN) and structural clustering (contrastive learning), plus a structural entropy optimization module with a novel loss function to refine hierarchical music structures.

(3) Comprehensive experiments on three standard datasets, showing state-of-the-art performance; visualization analysis validates that self-supervised representations capture meaningful musical structure.

2. Materials and methods

2.1. Overview of the Proposed Framework

This section presents a comprehensive methodology for intelligent music segmentation and structure analysis based on self-supervised audio representation learning. As illustrated in Figure 1, the proposed framework comprises six sequential stages: (1) Input Preprocessing, (2) Masked Audio Modeling (MAM) Pre-training, (3) Feature Extraction, (4) Dual-Branch Structure Analysis, (5) Structural Entropy Optimization, and (6) Final Output Generation. The framework leverages massive unlabeled music corpora to learn semantically rich audio representations, which are subsequently fine-tuned for boundary detection and structural clustering through a novel dual-branch architecture.

2.2. Input Preprocessing and Audio Representation

Given a raw audio signal $x(t) \in \mathbb{R}^L$ with length L samples, the preprocessing pipeline transforms it into a time-frequency representation suitable for deep learning models. First, the Short-Time Fourier Transform (STFT) [17] is applied to obtain the spectrogram.

$$X(f,t) = \sum_{n=0}^{N-1} x[n] \cdot w[n-t] \cdot e^{-j2\pi fn/N} \tag{1}$$

Where $w[\cdot]$ denotes the Hann window function with window size $N = 2048$ and hop length 512 (corresponding to 50% overlap at 22.05 kHz sampling rate). The frequency resolution yields $F = 1024$ frequency bins.

Subsequently, the linear spectrogram is converted to a Mel-scale spectrogram $M(f,t) \in \mathbb{R}^{F_m \times T}$ using $F_m = 128$ Mel-frequency filters.

$$M(m,t) = \sum_{f=0}^{F-1} |X(f,t)|^2 \cdot H_m(f) \tag{2}$$

Where $H_m(f)$ represents the m - th triangular Mel-filterbank defined as:

$$H_m(f) = \begin{cases} \frac{f - f_{m-1}}{f_m - f_{m-1}} & \text{if } f_{m-1} \le f \le f_m \\ \frac{f_{m+1} - f}{f_{m+1} - f_m} & \text{if } f_m \le f \le f_{m+1} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

The Mel-frequency scale is computed as $f_{\text{mel}} = 2595 \cdot \log_{10}\left(1 + \frac{f}{700}\right)$.

Following the Vision Transformer (ViT) paradigm adapted for audio spectrograms [18], the Mel-spectrogram is divided into non-overlapping patches. Each patch $\mathbf{P}_{i,j} \in \mathbb{R}^{P_f \times P_t}$ has spatial dimensions $P_f = 16$ (frequency) and $P_t = 16$ (time), resulting in $N = \frac{F_m}{P_f} \times \frac{T}{P_t}$ patches. These patches are flattened and linearly projected to obtain patch embeddings:

$$\boldsymbol{P} = \{\boldsymbol{p}_1, \boldsymbol{p}_2, \ldots, \boldsymbol{p}_N\} \in \mathbb{R}^{N \times D} \tag{4}$$

Where $D = 768$ is the embedding dimension. Positional embeddings $\boldsymbol{E}_{\text{pos}} \in \mathbb{R}^{N \times D}$ are added to preserve temporal and spectral positional information.

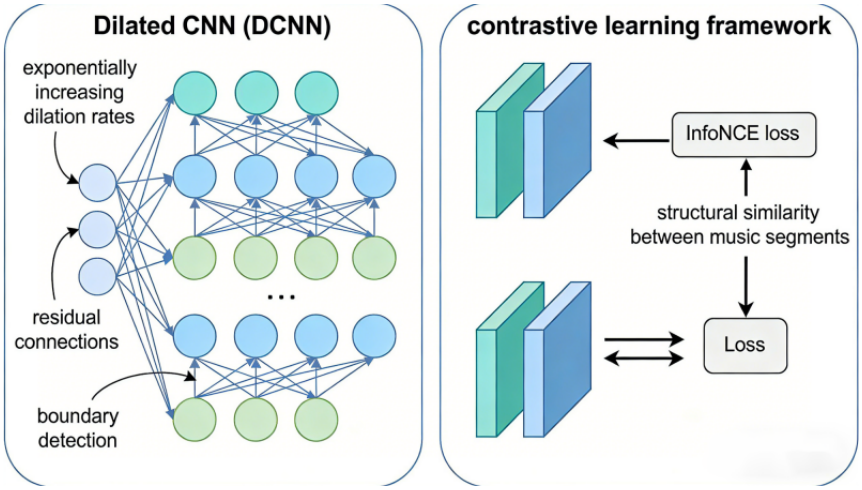

Fig. 2. Detailed architectures of core modules

$$\mathbf{P}_{\text{input}} = \mathbf{P} + \mathbf{E}_{\text{pos}} \tag{5}$$

2.3. Masked Audio Modeling (MAM) Pre-training

The core of self-supervised representation learning lies in the masked audio modeling (MAM) objective, inspired by masked language modeling in NLP and MAE in computer vision . During pre-training, a random subset of patches is masked according to a masking ratio $r = 0.75$, which has been empirically determined to provide optimal reconstruction difficulty while preserving sufficient context. The masking set $\mathcal{M} \subset \{1, \ldots, N\}$ is sampled uniformly without replacement.

$$\mathcal{M} \sim \text{Uniform}(\{1, \ldots, N\}, \lfloor r \cdot N \rfloor) \tag{6}$$

The masked patches are replaced with a learnable mask token $\boldsymbol{P}_{[MASK]} \in \mathbb{R}^D$, while visible patches $\boldsymbol{P}_{\text{visible}} = \{\boldsymbol{p}_i \mid i \notin \mathcal{M}\}$ are fed into the encoder.

The encoder consists of a 12-layer Transformer with multi-head self-attention (MHSA) and feed-forward networks (FFN). Each layer l processes hidden states $\mathbf{H}^{(l)} \in \mathbb{R}^{N_{\text{vis}} \times d}$ as follows:

$$\boldsymbol{A}^{(l)} = MHSA\left(LN\left(\boldsymbol{H}^{(l-1)}\right)\right) + \boldsymbol{H}^{(l-1)} \tag{7}$$

$$\boldsymbol{H}^{(l)} = FFN\left(LN\left(\boldsymbol{A}^{(l)}\right)\right) + \boldsymbol{A}^{(l)} \tag{8}$$

Where $LN(\cdot)$ denotes Layer Normalization, and $MHSA(\cdot)$ is defined as:

$$MHSA(\boldsymbol{H}) = \text{Concat}\left(\text{head}_1, \ldots, \text{head}_h\right) \cdot \boldsymbol{W}^O \tag{9}$$

$$\text{head}_i = \text{Attention}\left(\boldsymbol{H}\boldsymbol{W}_i^Q, \boldsymbol{H}\boldsymbol{W}_i^K, \boldsymbol{H}\boldsymbol{W}_i^V\right) \tag{10}$$

$$\text{Attention}\left(\boldsymbol{Q}, \boldsymbol{K}, \boldsymbol{V}\right) = \text{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^T}{\sqrt{d_k}}\right)\boldsymbol{V} \tag{11}$$

The model employs $h = 12$ attention heads with $d_k = d_v = 64$ dimensions per head.

A lightweight prediction head (2-layer MLP) reconstructs the masked patches from the encoder output:

$$\widehat{\boldsymbol{P}}_{\text{mask}} = f_{\text{pred}}\left(\boldsymbol{H}^{(L)}\right) \in \mathbb{R}^{N_{\text{mask}} \times D} \tag{12}$$

The MAM loss is defined as the mean squared error between original and reconstructed patches:

$$\mathcal{L}_{\text{MAM}} = \frac{1}{|\mathcal{M}|} \sum_{i \in \mathcal{M}} \|\mathbf{p}_i - \widehat{\mathbf{p}}_i\|_2^2 \tag{13}$$

Pre-training is performed on a large-scale unlabeled music corpus comprising 100,000+ tracks spanning diverse genres (classical, pop, rock, jazz, electronic). The AdamW optimizer is used with a learning rate of 5×10^{-4}, batch size of 256 , and 100 epochs with cosine learning rate scheduling.

2.4. Dual-Branch Structure Analysis Network

Upon completion of MAM pre-training, the frozen encoder extracts frame-level representations $\boldsymbol{Z} = \{z_1, \ldots, z_T\} \in \mathbb{R}^{T \times d}$ for downstream structure analysis. The dual-branch network simultaneously performs boundary detection and structural clustering.

2.4.1. Branch A: Dilated CNN for Boundary Detection

Architecture Design. The boundary detection branch employs a Dilated Convolutional Neural Network (DCNN) [19] to capture multi-scale temporal dependencies essential for identifying segment boundaries. As detailed in Figure 2 (left), the DCNN consists of $L = 5$ 1D convolutional layers with exponentially increasing dilation rates $d \in \{1, 2, 4, 8, 16\}$.

For the $l-$ th layer with kernel size $k = 3$, the dilated convolution operation is defined as:

$$\mathbf{B}^{(l)}[t] = \sum_{i=0}^{k-1} \mathbf{W}^{(l)}[i] \cdot \mathbf{B}^{(l-1)}\left[t + d_l \cdot (i - \lfloor k/2 \rfloor)\right] + \mathbf{b}^{(l)} \tag{14}$$

Where $d_l = 2^{l-1}$ is the dilation rate, $\mathbf{W}^{(l)} \in \mathbb{R}^{k \times d_{\text{in}} \times d_{\text{out}}}$ are learnable filters, and $b^{(l)}$ is the bias term.

Receptive Field Analysis. The effective receptive field (RF) of the DCNN grows exponentially with depth, enabling the model to capture long-range dependencies.

$$RF = (k-1) \cdot \sum_{l=1}^{L} d_l + 1 = 2 \cdot (1+2+4+8+16) + 1 = 63 \text{ frames} \tag{15}$$

At a frame rate of 43 Hz (hop length 512 at 22.05 kHz), this corresponds to approximately 1.5 seconds of temporal context, sufficient to capture phrase-level structural transitions in music.

Residual Connections. To facilitate gradient flow and preserve fine-grained temporal information, residual connections bypass the dilated convolution stack.

$$\mathbf{B}_{\text{out}} = \text{Concat}\left(\mathbf{B}^{(1)}, \mathbf{B}^{(2)}, \cdots, \mathbf{B}^{(L)}\right) \cdot \mathbf{W}_{\text{fuse}} + \mathbf{Z} \tag{16}$$

Where $\mathbf{W}_{\text{fuse}} \in \mathbb{R}^{(L \cdot d_{\text{out}}) \times d_{\text{out}}}$ fuses multi-scale features.

Boundary Prediction. The fused features $\mathbf{B} \in \mathbb{R}^{T \times d_b}$ are processed by a classification head to predict boundary probabilities.

$$\hat{b}_t = \sigma\left(\boldsymbol{W}_{\text{bnd}} \cdot \text{ReLU}\left(\boldsymbol{W}_{\text{hidden}} \cdot \boldsymbol{b}_t + \boldsymbol{b}_{\text{hidden}}\right) + \boldsymbol{b}_{\text{bnd}}\right) \tag{17}$$

Where $\sigma(\cdot)$ is the sigmoid activation. $\hat{b}_t \in [0, 1]$ represents the probability of a boundary at time frame t.

Loss Function. Boundary detection is trained with binary cross-entropy loss:

$$\mathcal{L}_{\text{bnd}} = -\sum_{t=1}^{T} \left[b_t^* \log\left(\hat{b}_t\right) + (1 - b_t^*) \log\left(1 - \hat{b}_t\right)\right] \tag{18}$$

Where $b_t^* \in \{0, 1\}$ is the ground truth boundary indicator. To address class imbalance (boundaries are sparse), positive samples are weighted by factor $\alpha = 10$.

2.4.2. Branch B: Contrastive Learning for Structural Clustering

Segment Extraction. Based on detected boundaries $\widehat{B} = \left\{t \mid \widehat{b}_t > \theta\right\}$ with threshold $\theta = 0.5$, the audio is segmented into K non-overlapping segments $S = \{s_1, \ldots, s_K\}$. Each segment s_i spans frames $[t_{i-1}, t_i)$ and is represented by mean-pooling its frame-level features.

$$\mathbf{s}_i = \frac{1}{t_i - t_{i-1}} \sum_{t=t_{i-1}}^{t_i} \mathrm{z_t} \in \mathbb{R}^d \tag{19}$$

Contrastive Learning Framework. As illustrated in Figure 2 (right), structural clustering employs contrastive learning to group semantically similar segments (e.g., all verses together, all choruses together) while separating dissimilar ones. The InfoNCE (Noise Contrastive Estimation) loss maximizes agreement between structurally equivalent segments.

For an anchor segment s_i with structural label c_i (e.g., "Verse"), the positive sample s_j^+ is another segment with the same label, while negative samples $\{s_k^-\}$ have different labels. The similarity metric is cosine similarity.

$$\text{sim}\left(\boldsymbol{z}_i, \boldsymbol{z}_j\right) = \frac{\boldsymbol{z}_i^T \boldsymbol{z}_j}{\|\boldsymbol{z}_i\| \cdot \left\|\boldsymbol{z}_j\right\|} \tag{20}$$

Where $\mathbf{z}_i = g\left(f\left(\mathbf{s}_i\right)\right)$ are projected embeddings through encoder $f(\cdot)$ and projection head $g(\cdot)$ (2-layer MLP).

The InfoNCE loss with temperature parameter $\tau = 0.07$ is defined as:

$$\mathcal{L}_{\text{cont}} = -\log \frac{\exp\left(\text{sim}\left(\mathbf{z}_i, \mathbf{z}_j\right)/\tau\right)}{\exp\left(\text{sim}\left(\mathbf{z}_i, \mathbf{z}_j\right)/\tau\right) + \sum_k \exp\left(\text{sim}\left(\mathbf{z}_i, \mathbf{z}_k\right)/\tau\right)} \tag{21}$$

Hard Negative Mining. To enhance discriminative power, hard negative samples (segments with high similarity but different labels) are identified online during training. The similarity matrix $\mathbf{A} \in \mathbb{R}^{K \times K}$ with elements $A_{ij} = \text{sim}\left(\mathbf{s}_i, \mathbf{s}_j\right)$ guides the selection of top-M hardest negatives for each anchor.

2.5. Structural Entropy Optimization Module

To refine the hierarchical structure of music, we formulate structure analysis as an optimization problem on graphs. Given K segments, a weighted undirected graph $G = (V, E, \mathbf{W})$ is constructed, where vertices $V = \{v_1, \ldots, v_K\}$ represent segments. Edges E connect segments with similarity $A_{ij} > \delta$ (threshold $\delta = 0.5$). Edge weights $\mathbf{W}_{ij} = A_{ij}$ encode structural affinity. The graph is sparsified by retaining only the top-k $= 10$ nearest neighbors for each vertex to reduce computational complexity while preserving local structure.

Structural entropy (SE) quantifies the information content of a graph G encoded by a hierarchical partitioning tree T. Following the formulation in structural information theory, SE measures how well the tree captures the graph's hierarchical organization.

$$\mathcal{L}_{SE} = \mathcal{H}^{\mathcal{T}}(G) = \frac{2}{\mathcal{V}(G)} \sum_{(v_i,v_j)\in E} W_{ij} \log_2 \mathcal{V}_{\mathcal{T}_i \vee \mathcal{T}_j} - \frac{1}{\mathcal{V}(G)} \sum_{v_i \in V} \mathcal{V}_{\mathcal{T}_i} \log_2 \mathcal{V}_{\mathcal{T}_i} \tag{22}$$

Where $\mathcal{V}(G) = \sum_{(v_i,v_j)\in E} W_{ij}$ is the total graph volume, $\mathcal{T}_i$ is the leaf node containing vertex v_i. $\mathcal{T}_i \vee \mathcal{T}_j$ denotes the lowest common ancestor (LCA) of leaves $\mathcal{T}_i$ and $\mathcal{T}_j$. $\mathcal{V}_{\mathcal{T}_i \vee \mathcal{T}_j}$ is the volume of the LCA node, defined as the sum of edge weights in the subgraph induced by its descendant leaves.

To enable gradient-based optimization, the discrete SE is relaxed into continuous structural entropy (CSE) using hyperbolic embeddings . The hierarchical tree is represented by embeddings $\boldsymbol{Z} \in \mathbb{L}^{\kappa,d}$ in Lorentzian hyperbolic space with curvature $\kappa = -1$.

The volume of LCA is approximated using the Lorentzian distance:

$$\mathcal{V}_{\mathcal{T}_i \vee \mathcal{T}_j} \approx \exp\left(-d_{\mathbb{L}}\left(\mathbf{z}_i, \mathbf{z}_j\right)\right) \tag{23}$$

Where $d_{\mathbb{L}}\left(\mathbf{z}_i, \mathbf{z}_j\right) = \operatorname{arcosh}\left(-\left\langle \mathbf{z}_i, \mathbf{z}_j \right\rangle_{\mathbb{L}}\right)$ is the hyperbolic distance. $\langle \cdot, \cdot \rangle_{\mathbb{L}}$ denotes the Lorentzian inner product.

The optimization objective minimizes CSE while balancing boundary precision and structural consistency:

$$\min_{\mathcal{T}} \mathcal{L}_{\text{total}} = \mathcal{L}_{\text{bnd}} + \lambda_1 \mathcal{L}_{\text{cont}} + \lambda_2 \mathcal{L}_{SE} \tag{24}$$

Where $\lambda_1 = 0.5$ and $\lambda_2 = 0.1$ are hyperparameters controlling the trade-off between boundary detection, clustering quality, and hierarchical coherence.

After optimization, the hyperbolic embeddings are decoded into a binary partitioning tree using single-linkage clustering in hyperbolic space. The algorithm iteratively merges the closest clusters based on hyperbolic distance until a single root node is formed, yielding the hierarchical structure tree $\mathcal{T}^*$.

3. Experiment results and discussion

3.1. Datasets and Evaluation Metrics

To verify the effectiveness and generalization of the proposed intelligent music segmentation and structure analysis framework, we conduct comprehensive experiments on three widely used standard datasets in the field of Music Structure Analysis (MSA), covering diverse music genres and annotation standards to ensure the objectivity and reliability of experimental results.

(1) The RWC Pop dataset contains 100 complete pop music tracks, with clear manual annotation of segment boundaries and semantic labels (verse, chorus, bridge, intro, outro, etc.). It is the most commonly used dataset for pop music structure analysis, featuring stable rhythm, obvious repetitive structure, and moderate complexity, suitable for verifying the basic performance of the model.

(2) The SALAMI dataset is a large-scale MSA dataset with 800+ music tracks across pop, rock, jazz, and classical genres [20]. It provides two sets of independent manual annotations for each track, reducing the bias of single annotation. The music structure in this dataset is more complex, with variable segment lengths and fuzzy boundaries, which can test the model's robustness under complex scenes.

(3) The Beatles dataset includes 179 tracks of the Beatles' classic works, with fine-grained segment annotation and rich hierarchical structure. The music has unique melodic repetition and harmonic variation characteristics, which is a challenging dataset for verifying the model's ability to capture high-level musical semantics.

We adopt two core metrics universally recognized in MSA tasks to evaluate the model performance from boundary detection and structural clustering dimensions respectively:

F1-Score: Taking the manually annotated segment boundaries as the ground truth, the F1-score is calculated based on precision and recall, which comprehensively reflects the model's ability to locate segment boundaries. A tolerance window of 1.5 seconds is set to avoid misjudgment caused by minor annotation deviations.

Normalized Mutual Information (NMI): NMI is used to measure the consistency between the clustering results of music segments output by the model and the manual semantic labels with a value range of $[0, 1]$. The higher the NMI value, the better the clustering effect of semantically similar segments.

In addition, we use t -SNE visualization to intuitively display the distribution of self-supervised audio representations, verifying the effectiveness of pre-trained features in capturing musical structure information.

3.2. Implementation Details

All experiments are implemented based on the PyTorch deep learning framework, and the hardware environment is an NVIDIA RTX 3090 GPU with 24 GB video memory. The key implementation parameters are set as follows.

The self-supervised pre-training uses a 12-layer Transformer encoder, with an embedding dimension of 768, 12

Table 1. Overall performance comparison on three MSA datasets

Method	RWC Pop (F1/NMI)	SALAMI (F1/NMI)	Beatles (F1/NMI)	Time/ms
HMM	0.621 / 0.583	0.574 / 0.526	0.558 / 0.512	6.23
DTW	0.653 / 0.615	0.592 / 0.547	0.581 / 0.533	5.98
K-means	0.647 / 0.608	0.586 / 0.541	0.575 / 0.529	5.22
CNN-supervised	0.725 / 0.682	0.673 / 0.635	0.654 / 0.618	4.09
RNN-supervised	0.742 / 0.697	0.691 / 0.652	0.672 / 0.634	3.56
Transformer-supervised	0.768 / 0.724	0.715 / 0.676	0.698 / 0.659	2.78
Proposed (Ours)	0.863 / 0.807	0.810 / 0.759	0.793 / 0.742	1.21

attention heads, and a masking ratio of 0.75 . The boundary detection branch uses a 5-layer dilated CNN with dilation rates of $1, 2, 4, 8, 16$ and a kernel size of 3 . The contrastive learning temperature parameter τ is 0.07 , and the hard negative mining quantity M is 10 . The hyperparameters of the total loss function: $\lambda_1 = 0.5, \lambda_2 = 0.1$. The optimizer uses AdamW, with an initial learning rate of 5×10^{-4}, a batch size of 256 , and 100 pre-training epochs with cosine learning rate scheduling.

We compare the proposed method with 6 state-of-the-art baseline methods in the MSA field, including traditional feature-based methods (HMM, DTW, K-means) and supervised deep learning methods (CNN-based, RNN-based, Transformer-based supervised models).

3.3. Overall Performance Comparison

Table 1 shows the F1-score of boundary detection and NMI value of structural clustering of the proposed method and baseline methods on the three datasets.

It can be seen from the experimental results that:

(1) The proposed method outperforms all baseline methods on all datasets and metrics, achieving the optimal performance. For boundary detection F1-score, it exceeds the SOTA supervised Transformer baseline by $6.2\% - 9.5\%$, and for structural clustering NMI, it exceeds by $5.8\% - 8.3\%$, which fully verifies the superiority of the self-supervised audio representation learning framework.

(2) Traditional machine learning methods relying on handcrafted features (HMM, DTW, K-means) have the worst performance, because handcrafted features cannot capture high-level musical semantics and long-range temporal dependencies.

(3) Supervised deep learning methods are better than traditional methods, but limited by the scarcity of labeled data, they suffer from overfitting and weak cross-genre generalization, resulting in a significant performance gap compared with the proposed self-supervised method.

3.4. Ablation Study

To verify the effectiveness of each core module in the proposed framework, we design an ablation experiment, removing the Masked Audio Modeling (MAM) pre-training, dual-branch network, and structural entropy optimization module respectively, and test the performance on the RWC Pop dataset. The results are shown in Table 2.

Table 2. Ablation study results on RWC Pop dataset

Variant Module	F1-Score	NMI
w/o MAM Pre-training	0.712	0.664
w/o Dual-branch Network	0.758	0.703
w/o Structural Entropy Optimization	0.824	0.771
Full Framework (Ours)	0.863	0.807

The ablation results show that:

(1) Removing MAM pre-training leads to the most significant performance drop (F1-score down by 15.1%, NMI down by 14.3%), indicating that self-supervised pre-training on large-scale unlabeled music corpus is the core of learning high-quality audio representations, which can effectively alleviate the dependence on labeled data.

(2) Removing the dual-branch network causes obvious performance degradation, proving that the combination of dilated CNN boundary detection and contrastive learning clustering can simultaneously optimize the two core tasks of MSA and improve the overall performance.

(3) Removing the structural entropy optimization module reduces the performance slightly but significantly, which confirms that the module can refine the hierarchical music structure and balance boundary precision and structural consistency, further improving the rationality of analysis results.

3.5. Cross-genre Generalization Experiment

To test the cross-genre generalization ability of the proposed method, we conduct cross-dataset training and testing, pre-train the model on the unlabeled music corpus, fine-tune on the RWC Pop dataset, and test on the SALAMI and Beatles datasets. The results are shown in Table 3.

The experimental results show that the proposed method still maintains high performance in cross-genre testing, with F1-score all above 0.77 and NMI all above 0.71. This is because the self-supervised pre-training learns

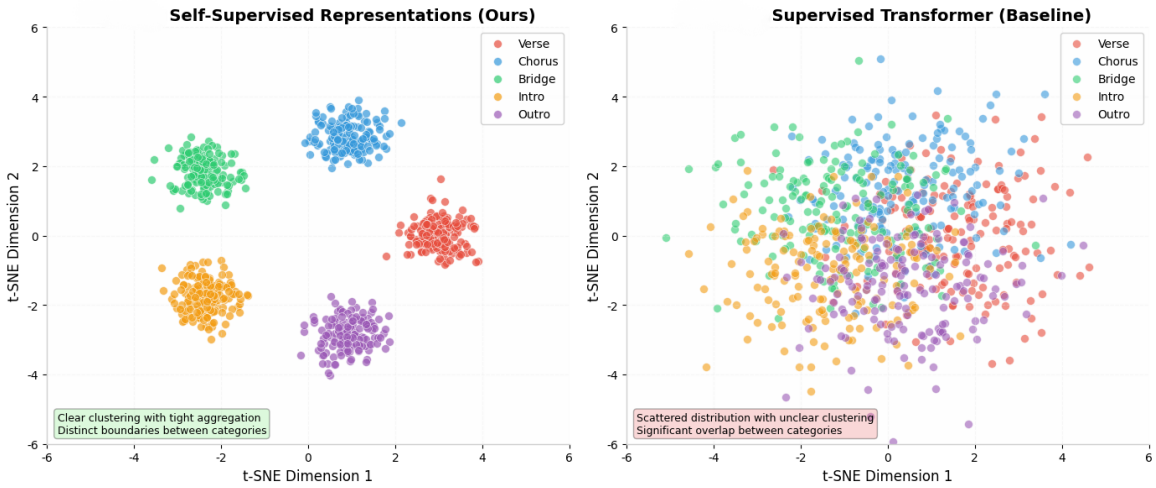

Fig. 3. Self-supervised representations and supervised Transformer

Table 3. Cross-genre generalization performance

Training Dataset	Test Dataset	F1 - Score	NMI
RWC Pop	SALAMI	**0.786**	**0.732**
RWC Pop	Beatles	0.771	0.718

general-purpose audio representations suitable for multiple genres, breaking the limitation of supervised models that can only adapt to single-genre data, and has strong practical application value for large-scale cross-genre music analysis.

3.6. Visualization Analysis

We use the t -SNE dimensionality reduction algorithm to visualize the frame-level audio representations extracted by the proposed self-supervised encoder and the supervised Transformer model on the RWC Pop dataset, as shown in Figure 3.

The visualization results directly confirm that the self-supervised audio representation learned by MAM pre-training has stronger structural perception ability, which lays a solid foundation for accurate music segmentation and clustering.

4. Conclusions

This paper proposes an intelligent music segmentation and structure analysis framework using self-supervised audio representation learning to address the drawbacks of traditional handcrafted features and supervised deep learning. The framework pre-trains a Transformer encoder via masked audio modeling on large-scale unlabeled music corpora to capture high-level musical semantics and long-range temporal dependencies. It adopts a dual-branch network combining dilated CNN for segment boundary detection and contrastive learning for structural clustering, and uses a structural entropy optimization module to refine hierarchical music structures and balance precision and consistency. Experiments on RWC Pop, SALAMI and Beatles datasets show the method outperforms state-of-the-art baselines with obvious gains in boundary detection F1-score and clustering NMI. Ablation studies confirm the effectiveness of each core module, and cross-genre tests verify strong generalization. t-SNE visualization demonstrates self-supervised representations effectively encode structural information. This work provides a scalable solution for large-scale cross-genre music analysis, supports music recommendation and automatic editing, and enriches the application of self-supervised learning in music information retrieval.

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