MERTECH: INSTRUMENT PLAYING TECHNIQUE DETECTION USING SELF-SUPERVISED PRETRAINED MODEL WITH MULTI-TASK FINETUNING

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ABSTRACT

Instrument playing techniques (IPTs) constitute a pivotal component of musical expression. However, the development of automatic IPT detection methods suffers from limited labeled data and inherent class imbalance issues. In this paper, we propose to apply a self-supervised learning model pre-trained on large-scale unlabeled music data and finetune it on IPT detection tasks. This approach addresses data scarcity and class imbalance challenges. Recognizing the significance of pitch in capturing the nuances of IPTs and the importance of onset in locating IPT events, we investigate multi-task finetuning with pitch and onset detection as auxiliary tasks. Additionally, we apply a post-processing approach for event-level prediction, where an IPT activation initiates an event only if the onset output confirms an onset in that frame. Our method outperforms prior approaches in both frame-level and event-level metrics across multiple IPT benchmark datasets. Further experiments demonstrate the efficacy of multi-task finetuning on each IPT class.

Index Terms— Playing technique detection, self-supervised learning, multi-task learning, transfer learning, music information retrieval

1. INTRODUCTION

Instrument playing techniques (IPTs), such as vibratos and glissandos, play a crucial role in enhancing the expressiveness of musical performances. The goal of IPT detection is to classify IPT types and identify their positions within an audio signal. The modeling and detection of IPTs benefit other tasks in music information retrieval (MIR), such as instrument classification [1], performance analysis [2], and automatic music transcription (AMT) [3, 4].

Early works on IPT detection mostly used machine learning methods, combined with hand-crafted features. Wang et al. [5] employed support vector machines (SVMs) on adaptive scattering features. Chen et al. [6] utilized SVMs on a combination of Melfrequency cepstral coefficients (MFCCs), pitch contour features, and timbre features. Advancements in deep learning have led to the increasing utilization of deep neural networks [7, 8]. Su et al. [3] extended the work of [6] by substituting SVMs with convolutional neural networks (CNNs). Huang et al. [4] introduced U-net models for joint prediction of notes, IPTs, note states, and IPT groups. Li et al. [9] proposed a hybrid model of multi-scale convolution and self-attention mechanism.

However, deep learning approaches often demand extensive datasets comprising high-quality labeled audio tracks. The main challenge in the IPT detection task lies in the scarcity of large-scale datasets. While there exist relatively large datasets for clip-level IPT classification [1], our paper focuses on frame-level and event-level IPT detection in real-world instrumental performance audio sequences. These datasets [4, 5, 9] typically only include around 2 hours of audio each due to the labor-intensive and expert-level manual labeling process. Besides, IPTs serve as embellishments in music performance, resulting in the majority of notes being labeled as 'normal' without any specific IPT assignments. Consequently, the inherent class imbalance issue is present within the IPT detection task. In situations of limited data and class imbalance, supervised learning is susceptible to problems like overfitting, poor performance on minority class samples, and restricted generalization.

To address data scarcity and class imbalance problems in IPT detection, we propose employing self-supervised learning (SSL) models. SSL models are pre-trained on large-scale unlabeled corpora, and the knowledge gained from pre-training can be transferred to downstream tasks either by using the model as a feature extractor or by finetuning the entire model. Previous research has demonstrated the effectiveness of SSL models in low-resource scenarios [10] and their robustness to data imbalance [11]. While initially introduced in natural language processing (NLP), an increasing number of SSL models have recently emerged in the field of acoustic music, such as MULE [12], MapMusic2Vec [13], and MERT [14]. Among these models, MERT excels in sequence labeling tasks where other models encounter difficulties due to the lack of frame-level representations or are too cumbersome to train [15]. Additionally, MERT has been shown to be a particularly promising model for transfer learning [16] and has achieved the best results in performance-level tasks (like vocal technique recognition) [15]. Hence, we opt to finetune MERT for the IPT detection task.

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¹Code: https://github.com/LiDCC/MERTech

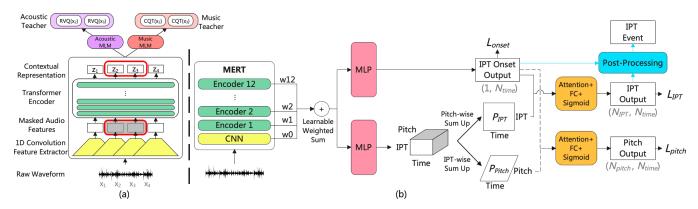


Fig. 1: The overall architecture of MERTech. (a) Stage I: Pre-training MERT-v1-95M. (b) Stage II: Multi-task finetuning for instrument playing technique (IPT) detection, pitch detection, and IPT onset detection. The blue part of (b) denotes Stage III: Post-processing. Characters in parentheses indicate the shapes of the outputs. " N_{IPT} ", " N_{pitch} ", " N_{time} " are the number of IPT classes, pitch classes, and output frames.

To further improve IPT detection performance, we explore multi-task finetuning for IPT detection, where the auxiliary task is pitch detection and IPT onset detection. SSL offers robust feature embeddings that can enhance multi-task finetuning for downstream tasks [17]. Pitch plays a crucial role in capturing IPT nuances while predicting IPT onsets aids in locating IPT events.

The main contributions of this paper are as follows: 1) We propose finetuning a pre-trained SSL model on IPT detection, demonstrating its effectiveness, generalizability, and capability to alleviate class imbalance on three benchmark IPT datasets of Guzheng, guitar, and Chinese bamboo flute (CBF). 2) We further explore multi-task finetuning for IPT detection with pitch detection and IPT onset detection as auxiliary tasks, proving its effectiveness on two IPT datasets with labeled pitch information. 3) We propose a post-processing approach, where an IPT activation initiates an event only if the onset output confirms an onset in that frame, resulting in significant improvement in event-level metrics.

2. METHOD

The overall framework of our proposed model, MERTech, is illustrated in Fig. 1. We first review the structure and the pre-training strategy of MERT. Then we elaborate on the proposed multi-task finetuning method and post-processing strategy.

2.1. Structure and Pre-training Process of MERT-v1-95M

We employ MERT-v1-95M [14], an acoustic music pre-trained model comprising a CNN-based feature extractor coupled with a transformer-based contextual network as shown in Fig. 1(a). When handling the initial 24 kHz audio input, the CNN transforms it into a 75 Hz feature representation. This representation is then processed by a 12-layer Transformer, resulting in a 75 Hz contextual hidden variable with 768 dimensions.

The pre-training approach of MERT-v1 involves segment-wise masking of the feature representation. The model is then tasked with reconstructing two music features using guidance from a musical teacher and an acoustic teacher, following the well-established masked language model (MLM) paradigm. The musical teacher imparts pitch-related knowledge by Constant-Q Transform (CQT), while the acoustic teacher imparts knowledge related to acoustic features, each of which includes 8 embeddings modeled by Residual Vector Quantization (RVQ), generated from EnCodec [18].

The pre-training of MERT-v1 is executed on a dataset comprising roughly 160k hours of unlabeled music data, predominantly of Western origin. In this paper, we employed the base (95M) size models, which are trained with a 1K hours subset.

2.2. Multi-task Finetuning on IPT Detection, Pitch Detection, and IPT Onset Detection

We present the structure of the downstream models in Fig. 1(b). Our downstream model is composed of two branches: the output of the top branch is the IPT onset output (\hat{Y}_{onset}) , while the output of the bottom branch is the raw posteriorgrams of pitch (P_{pitch}) and IPT (P_{IPT}) . Subsequently, two prediction refinement sub-networks, each employing a self-attention layer and a fully connected (FC) layer, combine \hat{Y}_{onset} with P_{pitch} and P_{IPT} , respectively, resulting in frame-level pitch output (\hat{Y}_{pitch}) and IPT output (\hat{Y}_{IPT}) .

The input waveform is trimmed to 5 seconds and resampled to 24k Hz, aligning with the preprocessing step during the pre-training stage. Subsequently, we utilize a weighted sum of CNN and 12 Transformer encoder layer outputs from MERT as the input for the downstream model. The effectiveness of the weighted sum approach lies in its utilization of information from various semantic levels across different layers [19]. We employ 13 learnable weight values, each assigned to the output of its respective layer.

A one-layer 512-unit Multilayer Perceptron (MLP) is applied to each branch. A dropout layer with a rate of 0.2 and a ReLU layer are applied after the first linear layer of each MLP. The last fully-connected (FC) layer is time-distributed (applied to each frame).

IPT onset detection differs from note onset detection. A single note may include multiple consecutive IPTs, and conversely, an IPT event may span multiple notes. For example, a guitar slide technique involves sliding a finger across frets to reach another note. Thus, IPT onset detection identifies the start of each IPT, not individual notes. The last FC layer in the MLP of the top branch has a target size of 1, predicting the presence of IPT onsets of each time frame.

In the bottom branch, the target size of the last FC layer in the MLP is $N_{IPT} \times N_{pitch}$, where N_{IPT} is the number of IPT classes, and N_{pitch} is the number of pitch classes. After that, the output is reshaped to an order-3 tensor D of size $N_{time} \times N_{IPT} \times N_{pitch}$, where N_{time} indicates the number of output frames. Then D is summed up along IPT axis and pitch axis to get P_{pitch} and P_{IPT} , respectively. The multi-task approach of predicting P_{pitch} and P_{IPT}

within a single branch, utilizing the same MLP, is inspired by previous work [20]. We prefer this method to a multi-head architecture commonly used in multi-task learning because it maintains a close alignment between pitch and IPT information throughout the process. For instance, a Guzheng glissando involves discrete pitches within pentatonic scales. Thus, jointly predicting pitch and IPTs is expected to yield superior results compared to separate predictions.

After obtaining \hat{Y}_{onset} , P_{pitch} , and P_{IPT} , we detach \hat{Y}_{onset} firstly to avoid backward propagation, then concatenate it with P_{pitch} and P_{IPT} along the frequency dimension, respectively, to predict \hat{Y}_{pitch} and \hat{Y}_{IPT} . The attention mechanism employed in the refinement modules is self-attention. In terms of the Q-K-V convention used to describe a self-attention block [21], all components-Q, K, and V-are derived from the input of the refinement module.

To address downstream tasks, we finetune the models in a supervised manner. Following the strategy in [10], we freeze the parameters of the CNN-based feature extractor in MERT during finetuning while updating other parts of the model.

The total loss function is a weighted sum of the IPT onset loss (L_{onset}) , IPT loss (L_{IPT}) , and pitch loss (L_{pitch}) . Specifically, L_{pitch} and L_{onset} are computed using frame-level binary cross entropy (BCE) loss between predictions and ground truths. For calculating L_{IPT} , we follow [9], employing the weighted BCE loss as proposed in [22] to further address the class imbalance issue. The final loss is calculated as Eq.1.

$$L = \lambda_1 L_{IPT} + \lambda_2 L_{pitch} + \lambda_3 L_{onset} \tag{1}$$

where λ_1 , λ_2 , and λ_3 are adjustable parameters, set to 1.0, 0.5, and 0.5, respectively, determined via coarse hyperparameter search.

2.3. Post-Processing

The post-processing step is exclusively employed during testing to transform frame-level IPT output into event-level IPT prediction. We use a threshold of 0.5 to binarize the onset output. Similar to [23], an activation from the IPT output is permitted to initiate an IPT event only if the onset output confirms the presence of an onset in that particular frame.

The difference is, in piano transcription [23], the onset output shares the same shape as the pitch output. Thus, when allowing a pitch event to be initiated by an activation from the pitch output, it is essential for the onset output not only to predict an onset in that frame but also for the corresponding pitch. Given that predicting IPT type at the start of a note is more challenging than predicting pitch, our focus is on predicting IPT onsets without specifying the IPT type in the onset output. This minimizes the occurrence of False Negative IPT events after post-processing.

3. EXPERIMENTS

3.1. Datasets

Three different datasets are selected to train and evaluate the proposed models in our experiments.

Guzheng_Tech99 [9] contains 99 polyphonic Guzheng solo pieces recorded by 2 professional Guzheng players, totaling 151.1 minutes. The dataset includes 7 classes of playing techniques, namely vibrato, point note, upward portamento, downward portamento, glissando, tremolo, and plucks.

EG-Solo [4] contains 76 electric guitar solos with polyphonic backing tracks from YouTube, totaling 40 minutes. The dataset

includes 9 classes of playing techniques: normal, slide, bend, vibrato (aka trill), mute, pull (aka pull-off), harmonic, hammer (aka hammer-on), and tap.

CBFdataset [5] comprises 80 monophonic CBF performances recorded by 10 professional performers, totaling 2.6 hours. The dataset includes 7 playing techniques: vibrato, tremolo, trill, fluttertongue, acciaccatura, portamento, and glissando.

3.2. Experimental Setup

The experiments follow the default dataset splits in their original papers. Specifically, the CBFdataset is divided in a 8:2 ratio based on CBF players, and a 5-fold cross-validation is conducted.

We finetune the model using stochastic gradient descend (SGD) with momentum 0.9, an initial learning rate of 0.001, a batch size of 10, a gradient clipping L2-norm of 3, and a cosine learning rate scheduler.

3.3. Metrics

Because the research on IPT detection is still in its early stages, most papers propose new datasets for experimentation, leading to a lack of standardized metrics. In this context, we report four typical metrics to comprehensively evaluate the performance of each model.

We present frame-level and event-level F1-scores with a default 50ms onset tolerance using the mir_eval library [24]. In terms of averaging options for metrics calculation, we provide both micro-averaging and macro-averaging results [25]. Micro-averaging assigns equal weight to individual frame decisions, maintaining consistency with music transcription metrics [23]. Macro-averaging computes the average class-wise performance, placing emphasis on the performance for smaller classes in the problem.

4. RESULTS

In this section, we conduct ablation studies to showcase our design benefits. We then compare our methods with state-of-the-art (SOTA) approaches on three datasets. Finally, we create a histogram of F1-scores for each IPT in Guzheng_Tech99 dataset to analyze the impact of multi-task learning and transfer learning on each IPT.

Firstly, we conduct ablation studies to showcase our design benefits. We consider the following four variant models: (a) IPT+Pitch+Onset eliminates the post-processing step from MERTech, so MERTech can be seen as IPT+Pitch+Onset+pp ("pp" refers to post-processing). (b) IPT+Pitch retains only the bottom branch of MERTech for simultaneous pitch and IPT prediction. (c) IPT_finetune is a single-task version of MERTech, using a one-layer 512-unit MLP in the downstream model for exclusive IPT prediction. (d) IPT_probing shares the model structure of IPT_finetune, but with frozen parameters in MERT and only updates the parameters in the downstream model.

As shown in Table 1, when comparing IPT+Pitch+Onset with MERTech, not using post-processing yields a slight increase in frame-level metrics, while causing a significant 41.4%, 19.1%, 17.6%, and 4.5% decrease in event-level (which better aligns with human judgment [26]) micro-F1 and macro-F1 for Guzheng_Tech99 and EG-Solo, respectively. Similar patterns emerge in other music transcription studies [23]. IPT+Pitch+Onset outperforms IPT+Pitch notably in event-level metrics, especially in the EG-Solo dataset, showing the importance of onset information for identifying the position of IPTs in instrument performance audio with background music interference. IPT+Pitch surpasses

Model	FRAME-LEVEL		EVENT-LEVEL		
	MI-F1 (%)	MA-F1(%)	MI-F1 (%)	MA-F1(%)	
	Guzheng_Tech99				
IPT_probing	81.2	60.3	19.9	16.5	
IPT_finetune	91.0	81.8	49.0	54.7	
IPT+Pitch	91.7	83.4	50.0	54.8	
IPT+Pitch+Onset	91.4	84.5	50.2	57.0	
MERTech	90.0	80.4	91.6	76.1	
	EG-Solo				
IPT_probing	57.3	21.5	12.0	10.5	
IPT_finetune	64.3	29.9	27.6	17.0	
IPT+Pitch	65.2	31.6	23.8	15.6	
IPT+Pitch+Onset	66.1	31.3	36.7	20.1	
MERTech	62.2	28.7	54.3	24.6	
	CBFdataset				
IPT_probing	87.3	73.2	17.1	22.0	
IPT_finetune	92.8	83.5	61.5	60.3	

Table 1: Ablation studies with Frame-level and event-level F1-scores using micro-averaging (MI-F1) and macro-averaging (MA-F1) on three datasets.

IPT_finetune in most cases, evidencing the importance of pitch information. Lastly, IPT_finetune outperforms IPT_probing across all datasets reveals the effectiveness of our finetuning strategy, aligning the SSL model for downstream tasks.

We compare the performance of our proposed methods with previous approaches, as shown in Table 2. We train and evaluate MERTech on the Guzheng_Tech99 and EG-Solo datasets, which include labels for both IPT and pitch. However, due to the absence of pitch labels in the CBFdataset, we present the results of the IPT_finetune model for this dataset. Our method significantly outperforms all previously published results, confirming the effectiveness of our model in IPT detection. Particularly our method improves 52.8% and 37.2% in event-level micro-F1 and macro-F1, respectively, in the Guzheng_Tech99 dataset. Besides, our model excels in both frame-level and event-level macro-F1, showcasing its capability to alleviate class imbalance issues. Furthermore, by comparing IPT_finetune with AST [5] in the CBFdataset, we show the generalizability of our model across a heterogeneous test set and training set (different performers). Lastly, it is vital to note the distributional variance between the Western-centric pre-trained dataset and downstream datasets, including two with Chinese traditional music. This underscores the strong potential of MERT for low-resource music data scenarios of underrepresented styles.

To analyze the multi-task learning and transfer learning impact on each IPT, we create a histogram of frame-level F1-scores for each IPT in Guzheng Tech99 dataset. We exclude event-level results due to the potential interference of onset threshold choice and MERTech outcomes due to rule-based post-processing interference. In Fig. 2, IPT_finetune shows more balanced performance across categories than previous SOTA [9], demonstrating its capability to address class imbalance issues. Besides, IPT+Pitch excels in upward/downward portamento, both involving pitch sliding. It also outperforms IPT_finetune significantly in glissando, as Guzheng glissando relate to pitch, generating discrete pitches within pentatonic scales. IPT+Pitch+Onset yields the best results in glissando, tremolo, and point note (PN). The first two IPTs

Model	FRAME-LEVEL		EVENT-LEVEL			
	MI-F1 (%)	MA-F1(%)	MI-F1 (%)	MA-F1(%)		
	Guzheng_Tech99					
GZFNO [8]	68.7	-	-	-		
Multi-scale [9]	86.5	69.3	38.8	38.9		
MERTech	90.0	80.4	91.6	76.1		
	EG-Solo					
Solola [3]	44.1	-	-	-		
NATSolo [4]	57.9	-	-	-		
MERTech	62.2	28.7	54.3	24.6		
	CBFdataset					
AST [5]	-	79.9	-	- / 63.9*		
IPT_finetune	92.8	83.5	61.5	60.3 / 72.7*		

Table 2: Comparison with state-of-the-art approaches on three datasets. "-" refers to "not reported by the previous papers". Results with "*" were measured with a 200ms onset tolerance for fair comparison with prior studies.

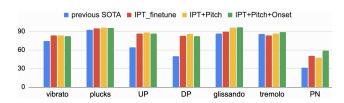


Fig. 2: The frame-level F1-score for each IPT in Guzheng_Tech99 dataset. "UP" is "Upward Portamento", "DP" is "Downward Portamento", and "PN" is "Point Note".

encompass multiple string-plucking onset sounds, while PN resembles a specific type of vibrato with a singular pitch change. Onset information aids in distinguishing PN from vibrato by identifying the IPT boundaries, and the similarity between PN and vibrato is why PN has the lowest F1-score.

5. CONCLUSION

In this paper, we propose to apply an SSL model pre-trained on extensive unlabeled music data and finetune it for IPT detection to address data scarcity and class imbalance challenges. We also explore multi-task finetuning with pitch and IPT onset detection as auxiliary tasks. Additionally, we introduce a post-processing approach for event-level prediction, where an IPT activation initiates an event only if the onset output confirms an onset in that frame. Our method outperforms existing approaches in frame-level and event-level metrics across three IPT benchmark datasets. Further experiments demonstrate the efficacy of multi-task finetuning on each IPT class. In the future, we aim to extend the application of music SSL model to other low-resource conditions and also explore other methods like semi-supervised learning to tackle low-resource challenges in this task.

6. ACKNOWLEDGMENTS

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