

DUAL ATTENTION-BASED MULTI-SCALE FEATURE FUSION APPROACH FOR DYNAMIC MUSIC EMOTION RECOGNITION

ISMIR 2:02:3 Milan, Italy

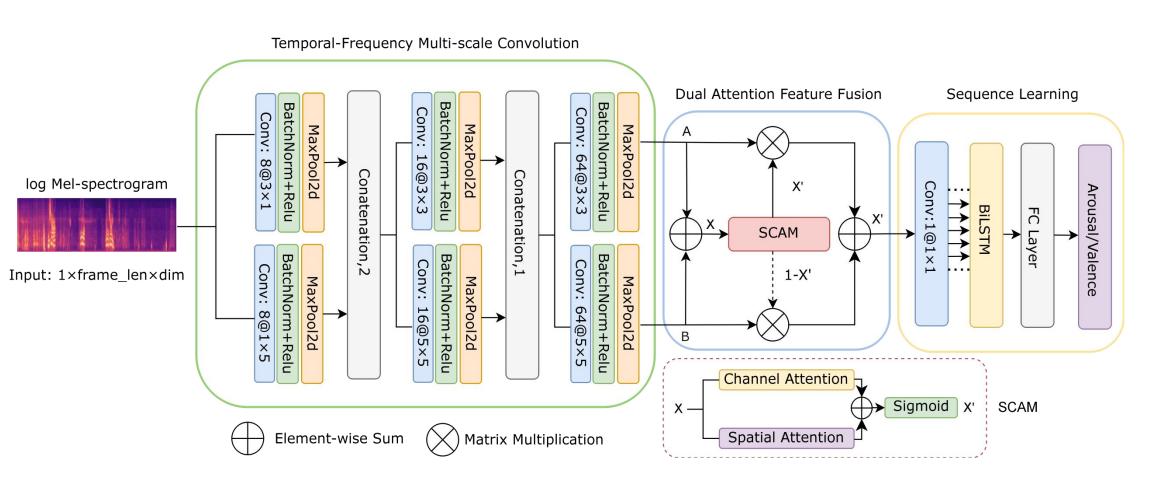
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Motivation & Contributions

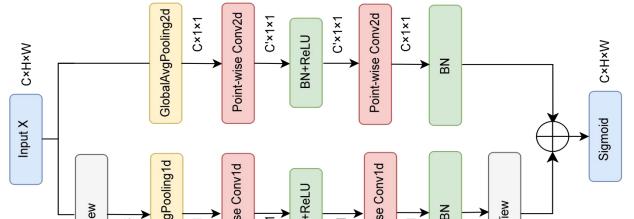
- There are some issues with the current DMER models. LSTM-based \bullet models still use handcrafted features as input, and some widely used handcrafted feature operations will lose high-level features. The CNN-RNN based model mainly uses a fixed-scale CNN. Due to its fixed receptive field, the learned CNN features are limited, and the emotional crucial features of different fields of view are not extracted. Various problems exist in existing music emotion datasets, which also hinder the progress of DMER.
- This paper proposes a novel Dual Attention-based Multi-scale Feature Fusion (DAMFF) network, which extracts multi-scale convolutional features from spectrograms and exploits the dualattention mechanism to capture important channel and spatial information.
- The music emotion dataset MER1101 we developed contains 1101 music audio with 16 genres, 5 languages and a balanced distribution of emotion labels.

Methodology

This paper proposes a novel Dual Attention-based Multi scale Feature Fusion (DAMFF) network.



Dual Attention Feature Fusion



Spatial Channel Attention *Module (SCAM)*

Temporal-Frequency Multi-scale Convolution

We extract features through three layers of parallel convolutional • blocks in the Temporal-Frequency Multi-scale Convolution module.

(H×W)×C GlobalAvg (H×W)×1 (H×W)'×1 (H×W)'×1 (H×W)'×1 (H×W)'×1 (H×W)×1 (H×W)×1

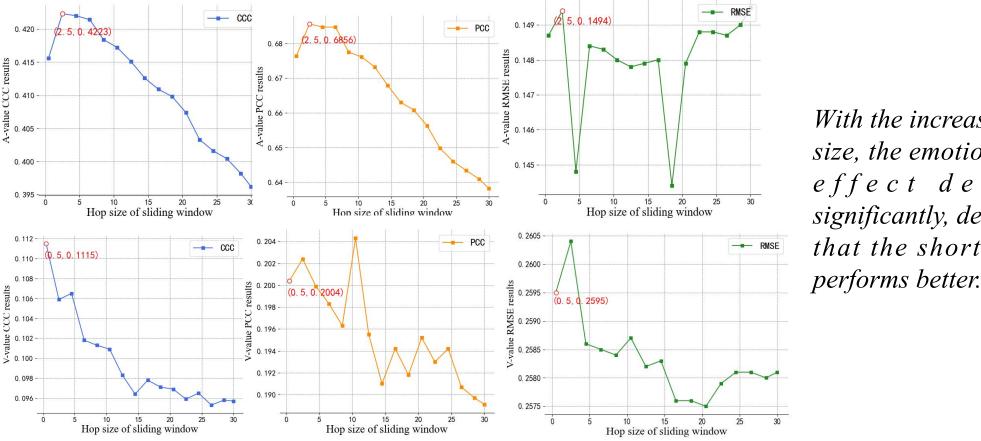
- $C = \beta(Conv2d_2(\delta(\beta(Conv2d_1(Pool2d(X))))))$ Channel Attention Module
- $S = \beta(Conv1d_2(\delta(\beta(Conv1d_1(Pool1d(X))))))$ Spatial Attention Module
- $X' = Sigmoid(S \oplus C)$
- $Z = X' \otimes A + (1 X') \otimes B$ Feature Fusion Strategy
- **Sequence Learning**
- Finally, we employ BiLTSM, building a map from emotion-crucial ulletfeatures to emotional space.

Experiments

> MER1101 dataset

• Compared with the existing publicly available datasets in the MER domain, MER1101 contains 1101 music snippets from 16 genres with richer languages, more extensive size, and more balanced emotion label distribution.

Hop Size Selection of Sliding Window



With the increase of the hop size, the emotion prediction effect decreased significantly, demonstrating that the shorter hop size

•	The proposed method	DMAFF	achieves	state-of-the-an	rt results!
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MER1101 dataset								
Valence								
C↑ PCC↑ RMSE↓								
573 0.1033 0.2721								
660 -0.0647 0.4143								
118 0.0017 0.2734								
155 0.0028 0.2752								
115 0.2004 0.2595								

DEAM2015 dataset									
Madal		Arousal			Valence				
Model	CCC↑	PCC↑	RMSE↓	CCC↑	PCC↑	RMSE↓			
CRNN	0.3488	0.5885	0.2197	0.0053	-0.0292	0.3542			
BCRSN	0.3168	0.5148	0.2397	0.0125	-0.0171	0.2914			
DNN	0.2757	0.4282	0.2483	0.0075	0.0031	0.3353			
MCRNN	0.2700	0.4396	0.2428	0.0137	0.0126	0.3135			
DAMFF	0.4203	0.6866	0.2401	0.0151	0.0366	0.3403			

Impact of CNN filters

Model		Arous	al		Valence			
	CCC↑	PCC*↑	RMSE*↓	CCC↑	PCC↑	RMSE↓		
Hybrid CNN	0.4223	0.6856	0.1494	0.1115	0.2004	0.2595		
T-F CNN	0.4120	0.6787	0.1478	0.0846	0.1363	0.2684		
Square CNN	0.4130	0.6894	0.1439	0.0732	0.1343	0.2703		
T-S CNN	0.4090	0.6881	0.1458	0.1085	0.1959	0.2542		
F-S CNN	0.4150	0.6804	0.1562	0.1046	0.1640	0.2800		

* The result of the significance test (Student's t test) show that there is no significant difference between the results of this metric.

Comparison with the Existing Models

Ablation Study

M 1 . 1	Arousal			Valence		
Model	CCC↑	PCC* ↑	RMSE*↓	CCC↑	PCC↑	RMSE↓
DAMFF	0.4223	0.6856	0.1494	0.1115	0.2004	0.2595
w/o Fusion Strategy	0.4097	0.6869	0.1563	0.0846	0.1363	0.2684
w/o Channel Attention	0.4061	0.6894	0.1439	0.0732	0.1343	0.2703
w/o Spatial Attention	0.4090	0.6881	0.1458	0.1085	0.1959	0.2542
w/o DAFF	0.4150	0.6804	0.1562	0.1046	0.1640	0.2800

* The result of the significance test (Student's t test) show that there is no significant difference between the results of this metric.