Melody extraction in polyphonic musical audio is important for music signal processing. In this paper, we propose a novel streamlined encoder/decoder network that is designed for the task. We make two technical contributions. First, drawing inspiration from a state-of-the-art model for semantic pixel-wise segmentation, we pass through the pooling indices between pooling and un-pooling layers to localize the melody in frequency. We can achieve result close to the state-of-the-art with much fewer convolutional layers and simpler convolution modules. Second, we propose a way to use the bottleneck layer of the network to estimate the existence of a melody line for each time frame, and make it possible to use a simple argmax function instead of ad-hoc thresholding to get the final estimation of the melody line. Our experiments on both vocal melody extraction and general melody extraction validate the effectiveness of the proposed model.

Index Terms— Melody extraction, encoder/decoder

1. INTRODUCTION

Melody extraction is the task that aims to estimate the fundamental frequency (F0) of the dominant melody. Automatic melody extraction has been an active topic of research in the literature, since it has many important downstream applications in music analysis and retrieval [1-4].

Lately, many deep neural network architectures have been proposed for melody extraction. [5-9] The basic idea of such neural network based methods is to use the neural nets to learn the mapping between a matrix that represents the input audio and another matrix that represents the melody line. For the input, it is usually a time-frequency representation such as the spectrogram, which can be viewed as an $F \times T$ real-valued matrix, where $F$ and $T$ denote the number of frequency bins and time frames, respectively. For the output, it is another $F \times T$ matrix but this time it is a binary matrix indicating the F0 of the melody line for each frame. We only consider music with a single melody line in the music, so at most one frequency bin would be active per frame. It is also possible that there is no melody for some frames. From the training data, we have a number of such input and output pairs. We can use the difference between the target output and the predicted one to train the neural net in a supervised way.

Existing work has shown that using neural nets to learn the nonlinear mapping between audio and melody leads to promising result. However, we find two glaring issues that require further research. First, because it is easier for neural nets to deal with continuous values, the output of most existing models (if not all) is actually an $F \times T$ real-valued matrix, not a binary one. This is fine for the training stage, since we can still use cost functions such as cross entropy to measure the difference between a real-valued matrix (the estimated one) and a binary matrix (the groundtruth). However, for the testing stage, we still need to binarize the output of the neural net. This binarization cannot be easily achieved simply by picking the frequency bin with the maximal activation per frame, because this would lead to false positives for frames that do not have melody. Therefore, most existing methods have to use a threshold whose value is empirically determined in a rather ad-hoc way for binarization.

The second issue is that existing models that lead to state-of-the-art result in melody extraction benchmark datasets usually have a complicated design. It is hard to understand what the model learns. For example, the model presented by Lu and Su [9] uses in total 45 convolution or up-convolution layers, using residual blocks for the convolution modules and a sophisticated spatial pyramid pooling layer. The goal of this paper is to propose a streamlined network architecture that has much simpler structure, and that does not need additional post-processing to binarize the model output. With a simple structure, we can better interpret the function of each layer of the network in generating the final result. We hope that the network can have accuracy that is comparable with, if not superior to, the state-of-the-art models.

We make two technical contributions to realize this. First, following Lu and Su [9], we use an encoder/decoder architecture to learn the audio-to-melody mapping. But, while they use the skip connections to pass the output of the convolution layers of the encoder to the up-convolution layers of the decoder, we propose to add links between the pooling layers of

**A STREAMLINED ENCODER/DECODER ARCHITECTURE FOR MELODY EXTRACTION**

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ABSTRACT

Melody extraction in polyphonic musical audio is important for music signal processing. In this paper, we propose a novel streamlined encoder/decoder network that is designed for the task. We make two technical contributions. First, drawing inspiration from a state-of-the-art model for semantic pixel-wise segmentation, we pass through the pooling indices between pooling and un-pooling layers to localize the melody in frequency. We can achieve result close to the state-of-the-art with much fewer convolutional layers and simpler convolution modules. Second, we propose a way to use the bottleneck layer of the network to estimate the existence of a melody line for each time frame, and make it possible to use a simple argmax function instead of ad-hoc thresholding to get the final estimation of the melody line. Our experiments on both vocal melody extraction and general melody extraction validate the effectiveness of the proposed model.

Index Terms— Melody extraction, encoder/decoder
the encoder and the un-pooling layers of the decoder, and pass along the “pooling indices” [10]. While the skip connections they use will be short paths for gradient propagation, there is no trainable weights in pooling and un-pooling layers. We argue from a functional point of view that our method makes it easier for the model to localize the melody. Second, we propose to use the bottleneck layer of the network to estimate the existence of melody per time frame, and design a way such that we can simply use argmax to binarize the output.

3. PROPOSED MODEL

The system overview is given in Fig. 2. It has a simple encoder/decoder architecture. For the encoder, we use three convolution layers and three max pooling layers. The output of the encoder is taken as the input by two separate branches of layers. The first branch is simply the decoder that uses three up-convolution layers and three un-pooling layers to estimate the salience frequency map. The second branch uses one convolution layer to estimate the existence of melody per frame. Finally, the salience map and the non-melody estimate are then concatenated, after which we get a binary-valued estimate of the melody line with a simple softmax layer. Our model has in total 7 convolution or up-convolution layers. We give more details of the network below.

3.1. Model Input

While the model can take any audio representation as the input, we choose to use the Combined Frequency and Periodicity (CFP) representation [16]. It contains three parts: the power-scaled spectrogram, generalized cepstrum (GC) [17, 18] and generalized cepstrum of spectrum (GCoS) [19]. The latter two are periodicity representations, which have been shown to carry information complementary to frequency representations for multi-pitch estimation (MPE) [20]. Given $X$, the magnitude of the short-time Fourier transform (STFT) of an input signal, GC and GCoS can be computed as:

$$Z_S[k, n] := \sigma_0 (W_f X)$$  \hspace{1cm} (1)

$$Z_{GC}[q, n] := \sigma_1 \left( W_f F^{-1} Z_S \right)$$  \hspace{1cm} (2)

$$Z_{GCoS}[k, n] := \sigma_2 \left( W_f Z_{GC} \right)$$  \hspace{1cm} (3)

where $W_f$ and $W_r$ are high-pass filters for eliminating the DC terms and $\sigma_i$ are activation functions [16].
we use simple convolution/up-convolution and pooling/un-pooling layers in our model. Moreover, we pass the pooling indices between the pooling and un-pooling layers.

The design is motivated by SegNet [10], a state-of-the-art model for semantic pixel-wise segmentation of images. We found that melody extraction is similar to image segmentation in that both tasks require learning the mapping between a real-valued, dense matrix and a binary-valued, sparse matrix. For melody extraction, the target output is indeed sparse—we only have at most one active entry per column (i.e. per time frame). Therefore, we can follow the idea of SegNet and use pooling indices to inform the un-pooling layers the exact entries picked by the pooling layers in the encoding process. This makes it easier for the decoder to localize the melody in frequency. This is illustrated in Fig. 3.

In each convolution block, we use only one convolution layer with batch normalization and scaled exponential linear units (SELU) [21] as the activation function. The convolution kernel size is (5,5) with padding size (2,2) and stride size (1,1). For the max-pooling layer, we use kernel size (4,1) and pool only along the frequency dimension. The feature map at the bottleneck of the network is a \(128 \times T\) matrix.

### 3.3. Non-melody Detector and ArgMax Layer

The design of the non-melody detector represents the second technical contribution of this work. As depicted in Fig. 2, we learn one additional convolution layer that converts the \(128 \times T\) matrix into a \(1 \times T\) vector. This vector is then concatenated with the salience map to make an \((F + 1) \times T\) matrix, where the last row corresponds to this vector (see Fig. 3 for an illustration). We then use the argmax function to pick the entries with the maximal value per time frame and return the melody line with the following rule—if the argmax is the \(F + 1\) entry for a frame, we consider that there is no melody for that frame. In this way, the output of the model is an \(F \times T\) binary matrix with only one or no active entry per frame.

In the model training process, the model output would be compared with the groundtruth output to calculate the loss and to update the network parameters. Therefore, according to our design, the convolution layer we just mentioned would be “forced” to learn whether there is a melody for each frame. Moreover, the frames without melody would tend to have high activation (close to ‘1’), whereas the frames with melody would have low activation (close to ‘0’). This is why we call this branch the non-melody detector.

We can view the non-melody detector as a singing voice detector [22, 24] when the task is to detect the vocal melody. However, there are three points to be made here. First, we do not need extra data for training our non-melody detector. Second, while most existing work on vocal detection treats vocal as ‘1’ and non-vocal as ‘0’, our model treats non-vocal as ‘1’ instead. Finally, our design is for general melody extraction, no only for vocal melody extraction.

The argmax layer is significant in that we do not need a separate, postprocessing step to discern melody/non-melody frames and to binarize the model output. The non-melody detection and binarization are built-in and trained together with the rest of the network to optimize the accuracy of melody extraction. To our best knowledge (also see Section 2), there is no such a model in the literature.

The argmax layer is not a general solution for any music-related tasks that require binarization. For example, in MPE [16, 20] there are usually multiple active entries per frame.

### 3.4. Model Update

While Lu and Su [9] use the focal loss [25] to deal with the sparsity of melody entries, we find our model works well with a simple loss function—the binary cross entropy between the estimated melody and the groundtruth one. Model update is done with mini-batch stochastic gradient descent (SGD) and the Adam optimizer. The model is implemented using PyTorch. For reproducibility, we will share the source code at https://github.com/bill317996/Melody-extraction-with-melodic-segnet.

4. EXPERIMENT

#### 4.1. Experimental Setup

We evaluate the proposed method on general melody extraction for one dataset, and on vocal melody extraction for three datasets. For general melody extraction, we use the MedleyDB dataset [26]. Specifically, we use the “melody2” annotation, which is the F0 contours of the melody line drawn from multiple sound sources. Following [11], among the 108 annotated songs in the dataset, we use 67 songs for training, 14 songs for validation and 27 songs for testing.

For vocal melody extraction, we use the MIR-1K dataset and a subset of MedleyDB for training. The former contains

\[1\]https://sites.google.com/site/unvoicedsoundseparation/mir-1k
1,000 Chinese karaoke clips, whereas the latter contains 48 songs where the vocal track represents the melody. The testing data are from three datasets: 12 clips from ADC2004, 9 clips from MIREX05\(^2\) and 12 songs from MedleyDB. We set the training and testing splits of MedleyDB according to \([9]\). There is no overlap between the two splits.

We compare the performance of our model with the three state-of-the-art deep learning based methods \([9, 11, 12]\), described in Section\(^2\). Moreover, to validate the effectiveness of the non-melody detector branch, we implement an ablated version of our model that removes the non-melody detector. For binarization of this method, we run a grid search to find the optimal threshold value using the validation set.

Following the convention in the literature, we use the following metrics for performance evaluation: overall accuracy (OA), raw pitch accuracy (RPA), raw chroma accuracy (RCA), voicing recall (VR) and voicing false alarm (VFA). These metrics are computed by the \textit{mir_eval}\(^2\) library with the default setting—e.g., a pitch estimate is considered correct if it is within 50 cents of the groundtruth one. Among the metrics, OA is often considered more important.

To adapt to different pitch ranges required in vocal and general melody extraction, we use different hyperparameters in computing the CFP for our model. For vocal melody extraction, the number of frequency bins is set to 320, with 60 bins per octave, and the frequency range is from 31 Hz (B0) to 1250 Hz (D\#6). For general melody extraction, the number of frequency bins is set to 400, with 60 bins per octave, and the frequency range is from 20 Hz (E0) to 2048 Hz (C7). Moreover, since we use more frequency bins for general melody extraction, we increase the filter size of the third pooling layer of the encoder from (4,1) to (5,1) for this task.

We use 44,100 Hz sampling rate, 2,048-sample window size, and 256-sample hop size for computing the STFT. Moreover, to facilitate training the model with mini-batches, we divide the training clips into fixed-length segments of \(T = 256\) frames, which is nearly 1.5 seconds.

### 4.2. Result

Table\(^1\) first lists the performance of vocal melody extraction for three datasets. We see that the proposed model compares favorably with DSM \([12]\) and Lu & Su’s model \([9]\), leading to the highest OA for the ADC 2004 and MedleyDB datasets. In particular, the proposed model outperforms the two prior arts greatly for MedleyDB, the most challenging dataset among the three. We also see that the proposed method outperforms DSM in VFA consistently across the three datasets, meaning that our model leads to fewer false alarms. This may be attributed to the built-in non-vocal detector.

The bottom of Table\(^1\) shows the result of general melody extraction. The proposed method outperforms DSM \([12]\) and compares favorably with CRNN \([11]\). In general, this suggests that our simple model is effective for both vocal melody and general melody extraction.

A closer examination of the results reveals that, compared to existing methods, our model is relatively weaker in the two pitch-related metrics, RPA and RCA, especially for MedleyDB. We conjecture this can be improved by adding the skip connections between the convolution and up-convolution layers as did in \([9]\), to improve the communication between the encoder and decoder. We leave this as a future research topic.

Table\(^1\) also shows that our model outperforms its ablated version almost consistently across the five metrics and the four datasets, validating the effectiveness of the non-melody detector. Although not shown in the table, we have implemented another ablated version of our model that replaces CFP with the constant-Q transform (CQT). This would decrease the OA by about 10% for vocal melody extraction.

### 5. Conclusion

We have introduced a streamlined encoder/decoder architecture that is designed for melody extraction. It employs only 7 convolution or up-convolution layers, and the model training can converge within 20 minutes with a single GTX1080ti GPU. Due to the use of a built-in non-melody detector, we do not need further post-processing of the result. The code is public and we hope it contributes to other music tasks.

| Method          | VRA | VRB | PCA | OA  |
|-----------------|-----|-----|-----|-----|
| DSM \([12]\)    | 92.9| 50.5| 77.1| 78.8| 70.8|
| Lu & Su’s \([9]\)| 73.8| 3.0 | 71.7| 74.8| 74.9|
| ours            | 91.1| 19.2|**84.7**|**86.2**|**83.7**|
| ours (ablated)  | 74.3| 6.1 | 72.0| 75.6| 75.1|

| Method          | VRA | VRB | PCA | OA  |
|-----------------|-----|-----|-----|-----|
| DSM \([12]\)    | 93.6| 42.8| 76.3| 77.3| 69.6|
| Lu & Su’s \([9]\)| 87.3| 7.9 | 82.2| 82.9|**85.8**|
| ours            | 84.9| 13.3| 75.4| 76.6| 79.5|
| ours (ablated)  | 71.9| 12.6| 66.3| 67.8| 73.8|

| Method          | VRA | VRB | PCA | OA  |
|-----------------|-----|-----|-----|-----|
| DSM \([12]\)    | 88.4| 48.7| 72.0| 74.8| 66.2|
| Lu & Su’s \([9]\)| 77.9| 22.4| 68.3| 70.0| 70.0|
| ours            | 73.7| 13.3| 65.5| 68.9|**79.7**|
| ours (ablated)  | 62.1| 14.1| 53.1| 58.8| 68.4|

| Method          | VRA | VRB | PCA | OA  |
|-----------------|-----|-----|-----|-----|
| DSM \([12]\)    | 60.9| 24.3| 75.1| 69.2| 61.7|
| CRNN \([11]\)   | 69.8| 31.0| 71.4| 76.5| 64.3|
| ours            | 70.9| 26.2| 57.2| 62.5|**64.3**|
| ours (ablated)  | 66.5| 27.1| 53.3| 58.6| 59.8|

\(^2\)https://labrosa.ee.columbia.edu/projects/melody/
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