ABSTRACT

Singing voice detection is the task to identify the frames which contain the singer’s vocal or not. It has been one of the main components in music information retrieval (MIR), which can be applicable to melody extraction, artist recognition, and music discovery in popular music. Although there are several methods which have been proposed, a more robust and more complete system is desired to improve the detection performance. In this paper, our motivation is to provide an extensive comparison in different stages of singing voice detection. Based on the analysis a novel method was proposed to build a more efficiently singing voice detection system. In the proposed system, there are main three parts. The first is a pre-process of singing voice separation to extract the vocal without the music. The improvements of several singing voice separation methods were compared to decide the best one which is integrated to singing voice detection system. And the second is a deep neural network based classifier to identify the given frames. Different deep models for classification were also compared. The last one is a post-process to filter out the anomaly frame on the prediction result of the classifier. The median filter and Hidden Markov Model (HMM) based filter as the post process were compared. Through the step by step module extension, the different methods were compared and analyzed. Finally, classification performance on two public datasets indicates that the proposed approach which based on the Long-term Recurrent Convolutional Networks (LRCN) model is a promising alternative.

Keywords Long-Term Recurrent Convolutional Networks · Singing Voice Detection · Singing Voice Separation

1 Introduction

Singing voice detection is the task to identify the given mix audio signal frames which are vocal contained. Inspired by the idea that the automatic identification of the segments of a song containing vocals would be a helpful tool in music content processing research and related applications. In the domain of music information retrieval (MIR), singing voice detection is often treated as a pre-process to identify the vocal segments in the original mixed audio signal which can be
exploited in many research topics, such as singer identification [1], singing voice separation [2], singing voice melody transcription [3], query by humming [4], lyrics transcription [5], etc.

In the process of singing voice detection, pattern recognition system based on acoustic features computed from the audio sound mixture can be considered as the standard solution. A significant effort has been put into its improvement by considering different acoustic features and machine learning techniques. In the work of [6, 7, 8, 9, 10, 11, 12, 13] several methods based on machine learning had been proposed and applied to identify the singing voice segments in a song. Results indicate that it seems rather awkward to surpass certain performance bound by variations on this approach.

For this reason, a novel way of addressing the singing voice detection problem was proposed, that involves the separation of harmonic sound sources from the polyphonic audio mixture. This is based on the hypothesis that the sounds could be better characterized after being separated, which would provide an improved classification. Now there are several singing voice separation methods, such as [14, 15, 16, 17, 18, 19] devised for analyzing non-stationary harmonic sound sources such as the singing voice. Within the music less or clean vocal audio, the singing voice detection is nearly the same as the vocal activity detection in speech. Distinguishing of vocal and silence is much easier than that of vocal and the mixed music signal.

Thanks to the continuous development of machine learning and deep learning, there are currently a large number of classifiers available for singing voice detection. Considering the temporal continuity of vocals and silence or noise in a mix audio signal, a time-varying recurrent neural network (RNN) can be easily considered. In this work the basic classifier and the deep models were compared to find the best classifier for the singing voice detection system.

Given the prediction that frame series results may have anomaly points, the post-process of filtering is also needed to improve the singing voice detection system. In the practical application, due to the continuity of music, when finding a very short no-singing voice fragment in continuous singing voice, that novelty fragment was often regarded as the singing voice. Such as the work in [20], a simple smooth filter during 0.5 second to 1 second was added as the post-process.

In our work, the four major parts of the vocal detection were compared including vocal separation, feature selection, classifier selection, and filter smoothing. Finally, the singing voice detection system was proposed with the optimal methods.

The structure of the paper is organized as the following. First, related works of the singing voice detection are introduced in section 2. Section 3 provides an overview of the comparison process on the proposed of our singing voice detection system. Results obtained with this method are presented and compared with state-of-the-art methods in section 4. Section 5 concludes the paper.

2 Related Works

2.1 Acoustic feature

The common procedure followed for partitioning a song into vocal and non-vocal portions is to extract feature parameters from audio signal frames (near a stationary block of samples) at each few tens of milliseconds, and then to classify them to one of each class using a threshold method or a statistical classifier. In the phase of audio representation, many acoustic features had been used on the singing voice detection. With regards to descriptors, research on musical instruments classification has demonstrated the importance of temporal and spectral features, and the speech processing field has contributed to well-known techniques (such as Linear Prediction) to compute voice signal attributes.

In the recent work, mainly used features are Mel-frequency Cepstral coefficients (MFCC), Linear Prediction Coefficients (LPC) and spectral Flux, spectral Centroid and spectral Roll-Off. Delta coefficients of the previous features or variances of them are also used to capture temporal information. The mostly used features come from the speech processing field. In [21] the authors used a simple combination of MFCC, Perceptual Linear Predictive Coefficients (PLP) and Log Frequency Power Coefficients (LFPC) as a feature set. According to [6], MFCC and their derivatives were the most appropriate features. Lehner et al. brought to light in [22] the importance of optimizing the parameters for the MFCC computation, that was the filter bank size, the number of MFCC and the analysis window size. They obtained quite good results only using these features. In [6], to be able to distinguish highly harmonic instruments from singing voice, they designed a set of features that describe temporal characteristics of the signal. It contained fluctogram, spectral flatness, spectral contraction and vocal variance which is the variance of the first five MFCC. And to utilize the music structure in [20], they proposed a novel feature extraction using beat as a unit try to find the boundary between a singing voice and no-singing voice, and introduced a new feature named Chroma to make a comparison with MFCC.
2.2 Singing voice separation

To focus on the vocal part rather than the background music, a pre-process of singing voice separation is necessary. To our best knowledge, there are several singing voice separation methods \[15\] in the area of MIR.

The REPeating Pattern Extraction Technique (REPET) \[14\] was a method, where repeating patterns (background) were identified and used to separate non-repeating (foreground) elements which are often the varying vocals. And it was shown in \[18\], that this technique can be used for music/voice separation.

The FASST toolbox by Ozerov et al. \[22\] allowed to specify prior information and implement arbitrary separation problems. Therefore, it was not merely a method, but more a general framework. However, a baseline implementation was included in the toolbox, which separated a song into the four sources, drums, bass, main melody, and the rest. It came with pre-trained models for several sources. Singing voice, which is in our case used to extract the vocal parts.

The Kernel Additive Modelling (KAM) approach \[18\] used source-dependent proximity kernels to describe local dynamics like periodicity (similar to REPET), smoothness, stability over time or frequency, and more. The different sources were then separated by an algorithm called iterative kernel back fitting.

Huang et al. \[17\] used Robust Principal Component Analysis (RPCA) for the separation of the singing voice. Their basic assumptions were, that singing voice was relatively sparse within songs, and accompaniment was in a low-rank subspace due to its repetitive structure. Their method used solely the spectrogram as input, and neither training nor particular features were required.

In \[19\], Zhu et al. proposed multi-stage non-negative matrix factorization (NMF) for monaural singing voice separation, where NMF was applied to decompose the mixture spectrograms with long and short windows respectively. A spectral discontinuity thresholding method was devised for the long-window NMF to select out NMF components originating from pitched instrumental sounds, and a temporal discontinuity thresholding method was designed for the short-window NMF to pick out NMF components that are from percussive sounds.

In \[16\], based on the U-Net architecture — initially developed for medical imaging — Jansson et al. adapted it on the task of vocal separation. The architecture was built upon the fully convolutional network and the deconvolutional network. The goal of the neural network architecture was to predict the vocal and instrumental components of its input indirectly: the output of the final decoder layer was a soft mask that was multiplied element-wise with the mixed spectrogram to obtain the final estimate.

2.3 Classifier

Existing singing voice detection methods can be categorized into two different classes. First, the early approaches focused on the acoustic similarity between a singing voice and speech, utilizing cepstral coefficients \[6\] and linear predictive coding \[23\]. The second class would be the majority of existing methods, where the systems took advantage of machine learning classifiers such as support vector machines or hidden Markov models, combined with large sets of audio descriptors (e.g., spectral flatness) as well as dedicated new features. There was a recent trend towards feature learning using deep neural networks in which the singing voice detection systems learned optimized features for the task using a convolutional neural network (CNN) \[24\] or a recurrent neural network (RNN) \[11\]. They have achieved state-of-the-art performances on commonly used datasets with over 0.90 of the true positive rate (recall) and accuracy. In an early example, Rocamora and Herrera \[6\] studied the accuracy of identifying those portions of music audio file containing vocals with already used descriptors on a statistical classifier using each kind of them. They found that MFCC is the most appropriate, and the accuracy was around 0.785. Ramona \[17\] used support vector machines (SVM) and a large feature set to do vocal detection on their manually annotated Jamendo datasets. They proposed a temporal smoothing strategy on the output of the predicting sequence. It took into account the temporal structure of the annotated segments. With this post-process, it could improve the system from 0.718 to 0.822 of frame-wise classification accuracy.

To break the bottleneck of tedious and time-consuming manual labelling in singing voice detection, Li \[13\] et al. integrated the active learning mechanism into the conventional SVM-based supervised learning algorithm. By selecting the most informative unlabeled samples and asking for human annotation, active learning substantially reduced the number of training samples to be labelled. With only 1/20 hand-label workload, the active learning system achieved almost the same classification performance as passive learning.

Mauch et al. \[25\] used timbre and melody related features for vocal detection. They used SVM-HMM to try the combination of all the four features. The results showed that the best performance on vocal activity detection was 0.872 achieved by combining all four features. They also released a new set of manually generated reference annotations to 112 full-length pop songs, in which 100 songs were taken from the popular music collection of the RWC Music Database.
Conventional singing voice detection methods ignored the characteristics of the singing signal. Regnier and Peeters [8] presented a method to detect vocal segments within an audio track based on vibrato and tremolo parameters of partials. Using this, a part was said to belong to singing voice or not with a simple threshold method. On a large test set, the best classification result achieves 0.768 in term of F-measure.

In [9], Lehner et al. proposed a towards light-weight and real-time capable singing voice detection system. They used the MFCC feature for feature representation and with the random forest as a classifier. They added post-processing on the temporal frame sequence predictions. Through optimizing MFCC features with the manually tuned MFCC coefficients and the length of frame windows, they achieved 0.823 in term of accuracy. From the observation of Lehner’s work, one of the biggest problems in automatic singing voice detection was the confusion of vocals with other pitch-continuing and pitch-varying instruments.

To overcome the problem of confusion of the pitches between the vocal and instruments, Lehner et al. design a set of three new audio features to reduce the amount of false vocal detection in [10]. The features describe temporal characteristics of the signal. It contains Fluctogram, Vocal Variance, Spectral Flatness and Spectral Contraction. Finally, followed by a post process of median filter, the Random Forest algorithm was used for classification. The experiment result shows that the hand-craft new features could be on par with more complex methods with other common features.

The task vocal detection in music is similar to voice activity detection (VAD) in speech to some extent, Eyben et al. [26] proposed the data-driven approach based on LSTM-RNN trained on standard RASTA-PLP front-end features. The main advantage of the LSTM-RNN model was its ability to model long-range dependencies between the input series. The experiment was tested on their synthesizing data from movies, the final result showed that LSTM-RNN outperformed all other statistical baselines.

With the successful application of LSTM on numerous research areas, [27] introduced the Long Short-Term Memory Recurrent Neural Networks (LSTM-RNN) to singing voice detection. Different from their previous method [10], several audio features were used in the feature representation. It not only contained 30 MFCC and their delta coefficients, but also other three spectral features, totalling up to 111 attributes. With the LSTM-RNN classifier, they achieved state-of-the-art result on the two publicly available datasets (Jamendo and RWC).

Leglaive [11] applied bi-directional LSTM-RNN on vocal detection. It was able to take a past and future temporal context into account to decide on the presence/absence of singing voice. Instead of working on defining a complex feature set, they used neural networks to extract simple representations fitted to singing voice detection from low-level features. Finally, they got the accuracy of 0.915 on Jamendo dataset.

In the work of Schlüter [12], they used the CNN model on Mel spectrograms to design the singing voice detection system. The CNN model had been proven powerful enough to pick up invariances taught by data augmentation in other fields. The CNN model can learn the relation in spatial, it has a high degree of invariance for translation, scaling, tilting, or other forms of spatial deformation. With CNN and data augmentation on the public dataset, they finally got an error rate around 9% which is on par with state-of-the-art ones.

2.4 Temporal Smoothing

The short-term classification of each signal frame considers only local information so it is prone to make errors, and the classification obtained is typically noisy changing from one class to the other. For this reason, usually, long-term information was introduced, by smoothing the classification or by partitioning the song into segments (much longer than frames) and assigning the same class to the whole segment.

Frame-wise classifiers tend to provide noisy results leading to an over-segmentation (short segments). Human annotation tends to provide under-segmentation (long segments ignoring instrumental breaks or singer breathing). For these reasons, post-processing was usually applied to the estimated segmentation. In the practical application, due to the continuity of music, when finding a very short no-singing voice fragment in a continuous singing voice, that novelty fragment was often regard as the singing voice. This post-processing could be achieved using median filtering or an HMM trained on segment duration as suggested in [2]. Ramona et al. proposed the temporal smoothing of the resulting posterior probabilities with a Hidden Markov Model. In [21], a single beat or two beats that are both different from the prior beat and back beat was viewed as a "novelty" peak. For the reason that the short time the difference is hard to be discovered, simple smooth filtering was to pick the novelty peaks away.

3 Proposed singing voice detection system

The architecture of the proposed system is shown in Figure 1 in which singing voice separation (SVS) is used as the pre-process to get the vocal signal, then follows a traditional bag-of-frames approach where a machine learning
Figure 1: Overview of proposed singing voice detection system block.

The technique is applied on a set of features computed on successive frames of the incoming vocal signal. The output of the classifier is then further processed by smooth decision function in order to localize musical segments that contain singing voice. The overview of our singing voice detection system is shown in Figure 1 and the different building blocks of our system are described in detail below.

3.1 Singing Voice Separation

The audio signal is first pre-processed by singing voice separation (SVS), through the SVS the mix music signal can be split into vocal signal and accompaniment signal. A comparison of 6 SVS methods includes REPET, FASST, U-NET, RPCA, KAML, and NMF based method for separating vocals from accompanying instruments.

The comparison results are shown in section 4. The U-net based vocal separation method is selected in the proposed system. The singing voice separation algorithm builds upon the fully convolutional network and the deconvolutional network. In a deconvolutional network, a stack of convolutional layers — where each layer halves the size of the image but doubles the number of channels — encodes the image into a small and deep representation. That encoding is then decoded to the original size of the image with a stack of up-sampling layers. The UNet adds additional skip connection between layers at the same hierarchical level in the encoder and decoder. This allows low-level information to flow directly from the high-resolution input to the high-resolution output.

3.2 Feature Extraction

This section briefly describes the used features in the experiments. There are many features proposed for the singing voice detection problem. Among the features, MFCC [6], (Linear Predictive Cepstral Coefficients (LPCC) [23] and PLP [6] are chosen to examine the performance. The MFCCs have been widely used in many speech and audio recognition problems [9]. The most popular approach for modelling human voice production is LPC which performs well in a clean environment but not so in noise. LPCC are calculated by introducing the cepstrum coefficients in the LPC. Assumed that LPCC, governed by the shape of vocal tract, are the nature of the sound. PLP is originally proposed by Hynek Hermansky as a way of warping spectra to minimize the differences between speakers while preserving important speech information.

Feature vectors from the separated vocal audio are calculated. Three features have been extracted for combining feature vectors concerning the high variability of the singing voice in vocal detection.

The audio signal is first segmented into frames with overlapping. On each frame, an FFT is computed with a Hamming window. Most of the features are selected for their ability to discriminate vocal from music [6].
The features are computed on the short-scale frames stated above. The MFCC with 13 coefficients is extracted. It is important to highlight that while extracting the MFCC feature, the energy coefficient was not contained (e.g., 0-th cepstral coefficient). The LPCC with 12 coefficients is computed from the signal. The PLP with 13 coefficients is calculated. Their different combinations of the three features are compared and the system performances are listed in the section 4. MFCC can achieve the best performance among the other two features and their combinations which is chosen as the audio descriptor in our proposed singing voice detection method.

3.3 Classification

With the comparison experiment in section 4, Long-term Recurrent Convolutional Networks (LRCN) [28] is used as the deep model for classification. The motivation behind the use of LRCN is their ability to learn compositional representations in spatial and temporal. Not only it can model long-range dependencies between the input, but it can also learn more effective features from the convolution to different coefficients of the feature vector.

The networks used for singing voice detection have an input layer which matches the size of the acoustic feature vectors, four hidden layers, and an output layer with a single sigmoid unit. The networks are trained as a classifier to output a voicing score for every frame in the value space of 0 and 1, where 1 indicating singing, 0 indicating nosing. The neural network architecture is shown in Figure 2.

The LRCN model combines a deep hierarchical feature extractor such as a CNN with a model that can learn to recognize and synthesize temporal dynamics for tasks involving sequential data. Figure 2 shows the core of our approach, it works by passing the fusion features of successive audio frames to produce a new vector representation. After the feature representation, the sequence model LSTM then takes over.
In general, the LSTM parametrized by $W$ maps an input and a previous timestep hidden state to output and updates hidden state. So the vector representation after CNN also needs to be sequentialized.

The final step in predicting the audio frame at timestep $t$ is to take a softmax and then do a temporal smoothing over the outputs of the sequential model.

As is customary, our LRCN employs five types of feedforward neural network layers: convolutional layers containing a stack of one dimensional inputs with a set of learned one dimensional kernels, dense layers flattening the input to a vector and through a reshape layer feed to LSTM layer as input, and a max-pooling layer sub-sampling a stack of one dimensional inputs by taking the maximum over small groups of neighbouring frames. On the input layer of the networks, acoustic feature of the successive frames in a fixed duration block are fed. The block duration is set to 600ms which is equal to 29 audio frames, which are proved to provide a best average accuracy.

The input data is concatenated on successive frames. The input vector of successive frames is finally mapped to one label based on the ground truth. In the LRCN layer, 256 convolution filters are used and the convolution kernel with a shape of (1,4) operates a one dimensional convolution along with the feature dimensions. All the input $X(1),...,X(t),cell$ outputs $C(1),...,C(t),hidden states H(1),...,H(t)$, and gates $i(t),f(t),o(t)$ of the LRCN are three dimensional tensors. The LRCN layer determines the future state of a certain cell in the grid of the input and past states of its local neighbours. This can be easily achieved by using a convolution operator in the state to state and input to state transitions. The inner structure is shown in Figure 3. The key equations are shown in Equation (1)-(5).

$$i(t) = \sigma (W_i \cdot [\text{conv}(X(t)), H(t-1), C(t-1)] + b_i)$$

$$f(t) = \sigma (W_f \cdot [\text{conv}(X(t)), H(t-1), C(t-1)] + b_f)$$

$$C(t) = f(t) \cdot C(t-1) + i(t) \cdot \text{tanh} (W_c \cdot [\text{conv}(X(t)), H(t-1)] + b_c)$$

$$o(t) = \sigma (W_o \cdot [\text{conv}(X(t)), H(t-1), C(t)] + b_o)$$

$$H(t) = o(t) \cdot \text{tanh} (C(t))$$

Where \('\cdot'\) represents the element-wise product, and \('\text{conv}'\) represents the convolution operator. $\sigma$ is the sigmoid function, $W$ is the weight matrix, $b$ is the bias vector. The input gate $i(t)$, forget gate $f(t)$ and output gate $o(t)$ of LRCN are separately listed in (1), (2) and (4). The $C(t)$ shown in Equation (3) is the LRCN cell, and $H(t)$ in Equation (5) is the output of the LRCN cell.
3.4 Post Process

Frame-by-frame classifications vary rapidly, with the likelihood ratio varying wildly from frame to frame. This is in stark contrast to the labelling data where the class stays the same for successive frames. Given that the singing voice in music has continuity in a certain period, accumulating the segment likelihood over a longer period is more reliable for decision making. So the audio signal is segmented into a long block. Within the block, the acoustic feature will be calculated from 40ms frames with overlapping of 20ms. Then the audio signal is segmented to sing and non-sing.

Two methods for segmentation smoothing was compared with the raw output label list in the experiment of section 4. One is the median filter which simply smooth the raw classification variable along the time dimension, essentially which can replace the value at each time frame with a kind of weighted average of the values over a wider window. The second method uses the resulting posterior probabilities with a HMM of two states (vocal and non-vocal). The observation of distributions is modelled by a mixture of 45 Gaussians, fitted with the expectation-maximization algorithm. The best path of states is then deduced from the classifier (LRCN et al.) output sequence with the Viterbi algorithm. With the comparison result, the median filter is finally used as the temporal smoothing module.

4 EXPERIMENT AND RESULTS

In the experimental part, the experimental and comparative analysis of the feature representation, singing voice separation method, classifier, and time-domain smooth filtering involved in the proposed singing detection system are performed on the public dataset. In order to speed up the reproduction and comparison of the system, we open source the code in Gitlab.

4.1 Public Datasets

These common databases, provide a fair comparison of our approach with others from literature.

Note that, with the assumption that the signal contains only music, the problem is locating singing within it. Neither distinguishing between vocal and regular speech nor that between music and speech is concerned.

1) Jamendo: a common benchmark dataset

The Jamendo Corpus, a public available dataset, singing voice activity annotations. It contains 93 copyright-free songs, retrieved from the Jamendo website. The database was built and published along with [7]. The corpus is divided into three sets: the training set contains 61 files, the validation set and test set contains 16 songs each.

2) RWC music database

RWC music database contains 100 pop songs released by Goto et al. [29], singing voice annotations was provided by Mauch et al. [25].

3) MIR-1K corpus

MIR-1K corpus, with 1000 song clips taken from 110 karaoke songs, is released by Hsu and Jang in [30]. The songs were recorded in their lab and sung by 8 females and 11 males. They were used for singing voice detection by Hsu et al. in [4].

4) iKala dataset

The iKala dataset [31] contains 352 30-second clips of Chinese popular songs in CD quality. Singers and musicians are professionals. The dataset is human-labelled for pitch contours and timestamped lyrics. Moreover, as the clips are longer, the iKala dataset contains non-vocal regions (e.g., instrumental solos).

4.2 Evaluation

In order to give a comprehensive view of the results four frame-wise evaluation metrics were used for binary classification: accuracy, precision, recall and f1 score. These metrics can be represented in terms of the number of true positives (TP; method says its positive and ground truth agrees), true negatives (TN; method says it’s negative and ground truth agrees), false positives (FP; method says it’s positive, ground truth disagrees) and false negatives (FN; method says it’s negative, ground truth disagrees).

\[
\text{Accuracy} = \frac{TP + TN}{\text{total frames}}
\]

[https://gitlab.com/exp_codes/SVD_system_4_part]
Table 1: Used feature sets and feature dimensions

| feature      | dimension |
|--------------|-----------|
| mfcc         | 13        |
| lpcc         | 13        |
| plp          | 13        |
| mfcc_plp     | 13,13     |
| lpcc_plp     | 13,13     |
| lpcc_mfcc    | 13,13     |
| lpcc_mfcc_plp| 13,13,13  |

Figure 4: The comparison result with SVM and different feature sets on Jamendo dataset.

\[
\text{Precision} = \frac{TP}{TP + FP} \\
\text{Recall} = \frac{TP}{TP + FN} \\
F - \text{measure} = \frac{2 \times \text{precision} \times \text{recall}}{\text{precision} + \text{recall}}
\]

4.3 Acoustic feature extraction and selection

Different features have been explored for singing voice detection. These features included MFCCs [9], LPCs [23], PLPs [32]. MFCCs, LPCs, and PLPs are also widely used for general sound classification tasks and they are the so-called short-term features because they are calculated using short-time frames. There are so many audio features, handcrafting a feature set for vocal detection is a very trivial task. In our work, the feature design is not the key point. In the experiment, three basic acoustic features and their combinations were chosen and compared. They are the MFCCs, LPCCs and PLPs.

As we know, the basic classifier on the singing voice detection is the Support Vector Machine (SVM), so SVM was used as a baseline model to compare the different features and their combinations on the same dataset of Jamendo. As shown in Table 1, we listed the feature sets and the feature dimensions. The frame window size was set as 40ms and without overlap between frames.

As for the setup of the baseline model with the SVM, the LinearSVC from sklearn tools was used. And all the data were normalized with a MinMaxScaler. Different feature sets with SVM classifier comparison results are shown in Figure 4.

Through this experiment, the most valid features were found out. It surprised to find that, with the comparison of the three acoustic features and their combinations, while a lot of effort were investigated into searching for optimal parameter of the features, in the end, simple MFCC always turned out to be at least as good as larger and more complex sets of features. The MFCC feature has been exploited in many tasks such as speech recognition. From the performance of MFCC in singing voice detection, it is clear that it can distinguish between singing and non-singing. Although there
is the influence of accompaniment in singing voice detection, the ability of MFCC to describe the sound in the spectrum reduces the affects of instrument accompaniment.

4.4 Classifier comparison

With the successful application of deep neural networks on the singing voice detection task, now nearly all the types of networks have been used as feature extractors and classifiers trying to improve the performance of the singing voice detection system. As depicted below, several models popularly used in the recent literature were listed and their performance were compared with our proposed new networks architecture.

The SVM model was set as a baseline and compared with DNN, CNN, RNN- (LSTM, GRU), and also with the one of our new imported model LRCN. The DNN was simply setup by two layers, one was input with 13 relu units and the other was output from one sigmoid unit. CNN was used in the experiment with two convolution one dimensional layers both with the 4 convolution kernels and set each filter with the same length as 4. Then, each convolution layer was connected with a max-pooling one dimensional layer with the pool length of 2. Finally, a flatten layer was added and the output layer was constructed with a sigmoid unit. The RNN model was tried for the two models with LSTM and GRU separately. And the LSTM shared the configure with GRU except the GRU unit and the LSTM unit. In the setup of time step the both were set to 29 frames. The two models both had two layers, one for input, the other was the output with one sigmoid unit. The new model of LRCN contains a Convolution LSTM two dimensional layer which was built from the module of Keras and was connected with a max-pooling two dimensional layer then via a flatten layer was linked to three dense layers.

To point out that each network architecture has many different combinations, on the comparison of the models with a simple network structure, each model structure may not be the optimal ones. The comparison results of the different models with the MFCC feature set on the Jamendo dataset are shown in Figure 5.

From the result the DNN model was nearly the worst. This is because the deep network tuned with just two layers and the number of total parameter was small and the recall just achieved 0.36. Except for the DNN model, the other four models (CNN, LSTM, GRU and LRCN) were both better than the baseline SVM model. When comparing the LSTM with GRU in this experiment, the architectures were same, however, GRU got more f1 score than the LSTM, and the LSTM had more parameters to train for the unit gate design. The CNN model also showed better performance but lower recall than the LSTM. The LSTM model had worse performance on the precision, almost achieves 0.63 nearly the same as the SVM. The LRCN model combined the CNN and LSTM in the Convolution LSTM two dimensional layer, and the results showed that its recall was also better with the LSTM and had an improvement of 10% than the CNN. The precision of LRCN was higher than LSTM about 15% and lower than the CNN about 3%. But overall f1 score of LRCN achieves 0.815 and was the best in the comparison with the other models in this experiment.

The LRCN model is a new network architecture for the singing voice detection system. From the comparison result, the LRCN has the ability from both CNN and LSTM, it can learn the time relation frame by frame and also can learn the spatial relation of feature dimensions in one frame.
4.5 Vocal separation pre-process selection

There are six singing voice separation methods collected from the ISMIR-community[^1] and part of them were re-implemented and the others have the open-source codes. REPET, FASST, U-NET, RPCA, KAML, and NMF based method were used in the comparison experiment.

In this experiment, the mix audio signal was first split into a vocal signal and a music signal. Then, the vocal signal would replace the mixed audio signal to extract the MFCC features. Finally the classifying process via the LRCN model was done. And this experiment was also performed on the Jamendo dataset. Figure 6 shows the comparison results with different singing voice separation methods.

Through comparison using different vocal separation method, not all the separation methods worked well on the pre-process of singing voice detection such as FASST and KAML. With the vocal separation, it reduced the music but also affected the vocal part to some extent. Except that the two methods did a negativity effect on the system performance, other four (i.e. REPET, U-net, RPCA, based-NMF) methods as the pre-process on the raw mix audio data improved the final f1 score on the vocal detection system. Especially the U-net compared with the raw mix audio without the vocal separation, it almost achieved 0.871 having an improvement of 6%.

With the comparison results, the pre-process is needed and the more focus on the vocal part will improve the final task of vocal detection.

4.6 Comparison on post process of smoothing

We evaluated, in this work, two novelty detection approaches that used the same framework as the post-processing for the vocal detection system.

The first was a simple median filter with a fix window length of 87 frames (3.48s) which was found to give the best trade-off between complexity and accuracy.

The second was HMM [^7] based method, a temporal smoothing of the posterior probabilities with a hidden Markov model that helped to adapt the segmentation sequence to the manual annotation. The temporal smoothing of the resulting posterior probabilities with a HMM had two states (music and vocal). The observation distributions were modelled by a mixture of 45 Gaussians fitted with the Expectation-Maximization algorithm. The best path of states was then deduced from the SVM output sequence with the Viterbi algorithm.

The two post-process methods were compared on the Jamendo dataset with the previously selected MFCC feature, the U-net pre-process and LRCN architecture for classifier, and the results is shown in the blow Figure 7.

With the comparison of the raw system framework without the post process, using the median filter as the temporal smoothing improve the f1 value from 0.871 to 0.892. As for the HMM-based method, though it achieved the highest

[^1]: https://groups.google.com/a/ismir.net/forum/?utm_medium=email&utm_source=footer#!forum/community
Figure 7: Comparison about different temporal smoothing methods on Jamendo dataset with MFCC feature, U-net for preprocess and LRCN for classifier.

Table 2: The performance of our proposed method on 4 different datasets

| dataset    | accuracy | precision | recall | f1    |
|------------|----------|-----------|--------|-------|
| rwc-mean   | 0.916    | 0.926     | 0.9348 | 0.9302|
| ikala-mean | 0.9498   | 0.9474    | 0.993  | 0.9698|
| mir1k-mean | 0.9582   | 0.9592    | 0.9988 | 0.9786|
| jamendo    | 0.888    | 0.865     | 0.920  | 0.892 |

recall, the accuracy and precision was the lowest. It was caused by a lack of data to train the HMM. With the comparison results, finally, the median filter was chosen for post-processing.

4.7 Proposed system on the public datasets

The optimal components were selected to join in our proposed vocal detection architecture and build our singing voice detection system. The proposed system contains an MFCC feature extraction module, a U-net based vocal separation pre-process module, a new LRCN for classifying module and a median filter for post-process module. Finally, the proposed system was tested on different public datasets.

To get a generalized comparison, four different datasets (i.e. Jamendo dataset, RWC pop dataset, MIR1K dataset and iKala dataset) were used. Table 2 shows out the comparison results on different datasets.

In the module selection phase, the Jamendo dataset was used for development dataset. In this experiment, our proposed system was tested on the other three datasets. Due to no split of the training, testing and valid parts, RWC dataset, iKala dataset and the MIR1K dataset were split into 5 parts by pieces and do a 5-fold validation. The mean value was calculated as the performance for the final result. When applying the system on other datasets, the proposed system can generalize to other common data for singing voice detection.

F1 value was achieved 0.97 on the MIR1K dataset and the iKala dataset. The proposed method also got a 0.93 of F1 value on the RWC dataset. Since iKala and MIR1K were designed for the vocal separation and the vocal label were generated automatically by the vocal parts with energy-based VAD, it could reduce the error segment boundary generated by a human.

4.8 Comparison with related works on vocal detection

Finally, the proposed singing voice detection system was compared with Ramona [7], Schlüter [12], Lehner-1 [10], Lehner-2 [9], Lehner-3 [27], Leglaive [11], on Jamendo corpus, and compare with Mauch [25], Schlüter [12], Lehner-1 [10], Lehner-2 [9], Lehner-3 [27], for RWC pop dataset. The comparison results are shown in the table 3 and table 4. our proposed system is labeled with the model LRCN.
Table 3: The comparison of related methods on jamendo dataset

| Methods   | Accuracy | Precision | Recall | F1    |
|-----------|----------|-----------|--------|-------|
| Ramona[7] | 0.822    | -         | -      | 0.831 |
| Schlüter[12]| 0.923    | -         | 0.903  | -     |
| Lehner-1[10]| 0.882    | 0.88      | 0.862  | 0.871 |
| Lehner-2[9] | 0.848    | -         | -      | 0.846 |
| Lehner-3[27]| 0.894    | 0.898     | 0.906  | 0.902 |
| Leglaive[11]| 0.915    | 0.895     | 0.926  | 0.91  |
| Proposed LRCN | 0.888    | 0.865     | 0.92   | 0.892 |

Table 4: Comparison results on the rwc pop dataset

| Methods   | Accuracy | Precision | Recall | F1    |
|-----------|----------|-----------|--------|-------|
| Schlüter[12]| 0.927    | -         | 0.935  | -     |
| Mauch[25] | 0.872    | 0.887     | 0.921  | 0.904 |
| Lehner-1[10]| 0.875    | 0.875     | 0.926  | 0.9   |
| Lehner-2[9] | 0.868    | 0.879     | 0.906  | 0.892 |
| Lehner-3[27]| 0.923    | 0.938     | 0.934  | 0.936 |
| Proposed LRCN | 0.916    | 0.926     | 0.934  | 0.930 |

Table 3 shows the comparison of the experimental results on Jamendo dataset, the training and testing are split. The LRCN was implemented using the Keras and runned on GPU, the other 6 results were reported in the related reports on the public dataset Jamendo. When compared with shadow models SVM of Ramona, random forest of Lehner-2, our LRCN was better than the both. But the F1 score was lower than the bi-LSTM of Leglaive and LSTM of Lehner-3 with more complex features.

Table 4 gives the comparison results on the dataset of RWC pop. Compared with the SVM-HMM of Mauch, our proposed methods had an improvement of 3% on f1 measure. When compared with the work of Schlüter, CNN was used on the spectrum for a two dimensional convolution, an accuracy of 0.927 and a recall of 0.935 was achieved. They did a data augmentation to increase the training data, the dataset size was changed in their work, and they have no f1 measure and the precision for comparison. With the same size on this dataset, the state-of-the-art method is keeping by Lehner-3 with the LSTM-RNN and their well-design feature sets. The proposed LRCN get an F1 measure of 0.93. It is on par with the state of the art with the value of 0.936.

Our proposed LRCN model is also based on the LSTM to learn the context relation. Although it has not yet reached the best performance of the state of the art, the LRCN is valid to learn the spatial relation and better than the LSTM.

5 CONCLUSIONS

In this paper, our aim is to do an extensive comparison for four different stages during singing voice detection. Based on our analysis, the optimal module combination consists of a novel singing voice detection system based on LRCN. In our singing voice detection system, the vocal is separated from the mix audio signal, and LRCN was used to learn the relationship of different dimensions of the acoustic features in the same frame and also learn the relationship of the successive frames in a temporal context. With a post-processing of temporal smoothing, finally, the proposed system can be on par with state-of-the-art performance on the public dataset of RWC pop.

Future work will investigate the performance of LRCN in more detail, analyzing the context learning behaviour using time-frequency or modulation spectrum features. Furthermore, using the proposed singing voice detection system presented in this paper to specific use cases such as singer identification will be attempted.

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References

[1] Adam Berenzweig, Daniel PW Ellis, and Steve Lawrence. Using voice segments to improve artist classification of music. In *proceedings of the AES 22nd international conference*, 2002.

[2] Shankar Vembu and Stephan Baumann. Separation of vocals from polyphonic audio recordings. In *ISMIR*, pages 337–344. Citeseer, 2005.

[3] Justin Salamon, Emilia Gómez, Daniel PW Ellis, and Gaël Richard. Melody extraction from polyphonic music signals: Approaches, applications, and challenges. *IEEE Signal Processing Magazine*, 31(2):118–134, 2014.

[4] Chao-Ling Hsu, DeLiang Wang, Jyh-Shing Roger Jang, and Ke Hu. A tandem algorithm for singing pitch extraction and voice separation from music accompaniment. *IEEE Transactions on audio, speech, and language processing*, 20(5):1482–1491, 2012.

[5] Annamaria Mesaros. Singing voice identification and lyrics transcription for music information retrieval invited paper. In *2013 7th Conference on Speech Technology and Human-Computer Dialogue (SpeD)*, pages 1–10. IEEE, 2013.

[6] Martín Rocamora and Perfecto Herrera. Comparing audio descriptors for singing voice detection in music audio files. In *Brazilian symposium on computer music, 11th. san pablo, brazil*, volume 26, page 27, 2007.

[7] Mathieu Ramona, Gaël Richard, and Bertrand David. Vocal detection in music with support vector machines. In *2008 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 1885–1888. IEEE, 2008.

[8] Lise Regnier and Geoffroy Peeters. Singing voice detection in music tracks using direct voice vibrato detection. In *2009 IEEE International Conference on Acoustics, Speech and Signal Processing*, pages 1685–1688. IEEE, 2009.

[9] Bernhard Lehner, Reinhard Sonnleitner, and Gerhard Widmer. Towards light-weight, real-time-capable singing voice detection. In *ISMIR*, pages 53–58, 2013.

[10] Bernhard Lehner, Gerhard Widmer, and Reinhard Sonnleitner. On the reduction of false positives in singing voice detection. In *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 7480–7484. IEEE, 2014.

[11] Simon Leglaive, Romain Hennequin, and Roland Badeau. Singing voice detection with deep recurrent neural networks. In *2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 121–125. IEEE, 2015.

[12] Jan Schlüter and Thomas Grill. Exploring data augmentation for improved singing voice detection with neural networks. In *ISMIR*, pages 121–126, 2015.

[13] Wei Li, Xiangyi Feng, and Min Xue. Reducing manual labeling in singing voice detection: An active learning approach. In *2016 IEEE International Conference on Multimedia and Expo (ICME)*, pages 1–5. IEEE, 2016.

[14] Zafar Rafii and Bryan Pardo. Repeating pattern extraction technique (repet): A simple method for music/voice separation. *IEEE transactions on audio, speech, and language processing*, 21(1):73–84, 2012.

[15] Yi-Hsuan Yang. On sparse and low-rank matrix decomposition for singing voice separation. In *Proceedings of the 20th ACM international conference on Multimedia*, pages 757–760, 2012.

[16] Andreas Jansson, Eric Humphrey, Nicola Montecchio, Rachel Bittner, Aparna Kumar, and Tillman Weyde. Singing voice separation with deep u-net convolutional networks. In *18th International Society for Music Information Retrieval Conference*, 2017.

[17] Po-Sen Huang, Scott Deeen Chen, Paris Smaragdis, and Mark Hasegawa-Johnson. Singing-voice separation from monaural recordings using robust principal component analysis. In *2012 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pages 57–60. IEEE, 2012.

[18] Antoine Liutkus, Zafar Rafii, Bryan Pardo, Derry Fitzgerald, and Laurent Daudet. Kernel spectrogram models for source separation. In *2014 4th Joint Workshop on Hands-free Speech Communication and Microphone Arrays (HSCMA)*, pages 6–10. IEEE, 2014.

[19] Bilei Zhu, Wei Li, Ruijiang Li, and Xiangyang Xue. Multi-stage non-negative matrix factorization for monaural singing voice separation. *IEEE Transactions on audio, speech, and language processing*, 21(10):2096–2107, 2013.

[20] Fengyan Wu, Shutao Sun, Jianglong Zhang, and Yongbin Wang. Singing voice detection of popular music using beat tracking and svm classification. In *2015 IEEE/ACIS 14th International Conference on Computer and Information Science (ICIS)*, pages 525–528. IEEE, 2015.
[21] Tin Lay Nwe and Haizhou Li. On fusion of timbre-motivated features for singing voice detection and singer identification. In 2008 IEEE International Conference on Acoustics, Speech and Signal Processing, pages 2225–2228. IEEE, 2008.

[22] Alexey Ozerov, Emmanuel Vincent, and Frédéric Bimbot. Flexible audio source separation toolbox (fasst) version 1.0 user guide, 2011.

[23] Shingchern D You, Yi-Chung Wu, and Shih-Hsien Peng. Comparative study of singing voice detection methods. Multimedia tools and applications, 75(23):15509–15524, 2016.

[24] Jan Schlüter. Learning to pinpoint singing voice from weakly labeled examples. In ISMIR, pages 44–50, 2016.

[25] Matthias Mauch, Hiromasa Fujihara, Kazuyoshi Yoshii, and Masataka Goto. Timbre and melody features for the recognition of vocal activity and instrumental solos in polyphonic music. In ISMIR, pages 233–238, 2011.

[26] Florian Eyben, Felix Weninger, Stefano Squartini, and Björn Schuller. Real-life voice activity detection with lstm recurrent neural networks and an application to hollywood movies. In 2013 IEEE International Conference on Acoustics, Speech and Signal Processing, pages 483–487. IEEE, 2013.

[27] Bernhard Lehner, Gerhard Widmer, and Sebastian Bock. A low-latency, real-time-capable singing voice detection method with lstm recurrent neural networks. In 2015 23rd European Signal Processing Conference (EUSIPCO), pages 21–25. IEEE, 2015.

[28] Jeffrey Donahue, Lisa Anne Hendricks, Sergio Guadarrama, Marcus Rohrbach, Subhashini Venugopalan, Kate Saenko, and Trevor Darrell. Long-term recurrent convolutional networks for visual recognition and description. In Proceedings of the IEEE conference on computer vision and pattern recognition, pages 2625–2634, 2015.

[29] Masataka Goto, Hiroki Hashiguchi, Takuichi Nishimura, and Ryuichi Oka. Rwc music database: Popular, classical and jazz music databases. In Ismir, volume 2, pages 287–288, 2002.

[30] Chao-Ling Hsu and Jyh-Shing Roger Jang. On the improvement of singing voice separation for monaural recordings using the mir-1k dataset. IEEE Transactions on Audio, Speech, and Language Processing, 18(2):310–319, 2009.

[31] Tak-Shing Chan, Tzu-Chun Yeh, Zhe-Cheng Fan, Hung-Wei Chen, Li Su, Yi-Hsuan Yang, and Roger Jang. Vocal activity informed singing voice separation with the ikala dataset. In 2015 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), pages 718–722. IEEE, 2015.

[32] Adam L Berenzweig and Daniel PW Ellis. Locating singing voice segments within music signals. In Proceedings of the 2001 IEEE Workshop on the Applications of Signal Processing to Audio and Acoustics (Cat. No. 01TH8575), pages 119–122. IEEE, 2001.