Recurrent Neural Network-based Music Language Models for Improving Automatic Music Transcription

Abstract

In this paper, we investigate the use of Music Language Models (MLMs) for improving Automatic Music Transcription (AMT) performance. AMT is the process of converting an acoustic music signal into a symbolic notation, and is considered to be a fundamental problem in music signal processing. The MLMs are trained on sequences of symbolic polyphonic music. We train RNN-based models, as they are capable of capturing complex temporal structure present in the symbolic music data. Similar to the function of language models in automatic speech recognition, we use the MLMs to generate a prior probability for the occurrence of a sequence. The acoustic AMT model is based on probabilistic latent component analysis (PLCA), and prior information from the MLM is incorporated into the transcription framework using Dirichlet priors. We test our hybrid models on a dataset of multiple-instrument polyphonic music and report a significant 2.5% improvement in terms of F-measure, when compared to using an acoustic-only model.

1. Introduction

Automatic Music Transcription (AMT) involves automatically generating a symbolic representation of an acoustic musical signal (Benetos et al., 2013a). AMT has is considered to be a fundamental topic in the field of music information retrieval (MIR) and has noumerous applications in related fields in music technology, such as interactive music applications and computational musicology. Typically, the output of an AMT systemis a *pianoroll* representation, which is a two-dimensional matrix representation of a musical piece where the X-axis represents time quantized into regular intervals, and the Y-axis represents the 88 keys of a piano in increasing pitch. A cell in this matrix is 1 if the key represented by its X-coordinate is sounded at the time instant represented by its Y-coordinate.

The majority of recent transcription papers utilise and expand *spectrogram factorisation* techniques, such as non-negative matrix factorisation (NMF) (Li & Seung, 1999) and its probabilistic counterpart, probabilistic latent component analysis (PLCA) (Smaragdis et al., 2006). Spectrogram factorisation techniques decompose an input two-dimensional spectrogram of the audio signal into a product of spectral templates (that typically correspond to musical notes) and component activations (that indicate when each note is active at a given time frame). Spectrogram factorisation-based AMT systems include the work by Bertin et al. (Bertin et al., 2010), who proposed a Bayesian framework for NMF, which considers each pitch as a model of Gaussian components in harmonic positions. Benetos and Dixon (Benetos & Dixon, 2012) proposed a convolutive model based on PLCA, which supports the transcription of multiple-instrument music and supports tuning changes and frequency modulations (modelled as shifts across log-frequency). An alternative approach for AMT was proposed in (Nam et al., 2011), where features suitable for transcribing music are learned using a deep belief network consisting of stacked restricted Boltzmann machines (RBMs). The model performed classification using support vector machines and was applied to piano music.

There is no doubt that a reliable acoustic model is important for generating accurate symbolic transcriptions of a given music signal. However, since music exhibits a fair amount of structural regularity much like language, it is natural for one to think of the possibility of improving transcription accuracy using a *music language model* (MLM) in a manner akin to the use of a language model to improve the performance of a speech recognizer (Rabiner & Juang, 1993). In (Boulanger-Lewandowski et al., 2012), the predictions of a polyphonic MLM were used to this end. More generally, *score informed* approaches have been found to benefit the performance of purely acoustic models in music research tasks such as source separation (Ewert & Müller, 2012), voice separation (Ewert & Müller, 2011) and tonic identification (Sentürk et al., 2013).

In the present work, we make use of the predictions made by a Recurrent Neural Network-Neural Autoregressive Distribution Estimator (RNN-NADE) based polyphonic

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MLM proposed in (Boulanger-Lewandowski et al., 2012) to refine the transcriptions of a PLCA based AMT system (Benetos & Dixon, 2012; Benetos et al., 2013b). *NOTE: Summary of the combination strategy using Dirichlet priors, etc. could go here*. It was observed that combining the two models in this way boosts transcription accuracy to 100.00% on the Bach-10 dataset, where the existing state-of-the-art accuracy is 99.00%.

The outline of this paper is as follows. The PLCA-based transcription system is presented in Section 2. The RNN-RBM-based polyphonic music prediction system that is used as a music language model is described in Section 3. The combination of the two aforementioned systems is presented in Section 4. The employed dataset, evaluation metrics, and experimental results are shown in Section 5; finally, conclusions are drawn and future directions are indicated in Section 6.

2. Automatic Music Transcription System

For combining acoustic and music language information in an automatic transcription context, we employ the transcription model of (Benetos & Dixon, 2012), which supports the transcription of multiple-instrument polyphonic music and also supports pitch deviations or frequency modulations. The model of (Benetos & Dixon, 2012) is based on probabilistic latent component analysis (PLCA), which is a latent variable analysis method which has been used for decomposing spectrograms (Shashanka et al., 2008) and can be viewed as a probabilistic version of non-negative matrix factorization (Li & Seung, 1999). For computational efficiency purposes, we employ the fast implementation from (Benetos et al., 2013b), which utilized pre-extracted note templates that are also pre-shifted across log-frequency, in order to account for frequency modulations or tuning changes. In addition, as was shown in (Smaragdis & Mysore, 2009), PLCA-based models can utilise priors for estimating unknown model parameters, which will be useful in this paper for informing the acoustic transcription system with symbolic information.

The transcription model takes as input a normalised log-frequency spectrogram $V_{\omega,t}$ (ω is the log-frequency index and t is the time index) and approximates it as a bivariate probability distribution $P(\omega,t)$. $P(\omega,t)$ is decomposed into a series of log-frequency spectral templates per pitch, instrument, and log-frequency shifting (which indicates deviation with respect to the ideal tuning), as well as probability distributions for pitch, instrument, and tuning.

The model is formulated as:

$$P(\omega,t) = P(t)\sum_{p,f,s} P(\omega|s,p,f)P_t(f|p)P_t(s|p)P_t(p) \quad (1)$$

where p denotes pitch, s denotes the musical instrument source, and f denotes log-frequency shifting (which indicates tuning/pitch deviations). $P(t)$ is the energy of the log-spectrogram, which is a known quantity. $P(\omega|s,p,f)$ denote pre-extracted log-spectral templates per pitch p and instrument s, which are also pre-shifted across log-frequency. The pre-shifting operation is made in order to account for pitch deviations, without needing to formulate a convolutive model across log-frequency. $P_t(f|p)$ is the time-varying log-frequency shifting distribution per pitch, $P_t(s|p)$ is the time-varying source contribution per pitch, and finally, $P_t(p)$ is the pitch activation, which essentially is the resulting music transcription. As a time-frequency representation in the log-frequency domain we use the constant-Q transform (CQT) with a log-spectral resolution of 60 bins/octave (Schörkhuber & Klapuri, 2010).

The unknown model parameters ($P_t(f|p)$, $P_t(s|p)$, $P_t(p)$) can be iteratively estimated using the expectation-maximisation (EM) algorithm (Dempster et al., 1977). For the *Expectation* step, the following posterior is computed:

$$P_t(p,f,s|\omega) = \frac{P(\omega|s,p,f)P_t(f|p)P_t(s|p)P_t(p)}{\sum_{p,f,s} P(\omega|s,p,f)P_t(f|p)P_t(s|p)P_t(p)} \quad (2)$$

For the *Maximization* step (without using any priors) unknown model parameters are updated using the posterior computed from the Expectation step:

$$P_t(f|p) = \frac{\sum_{\omega,s} P_t(p,f,s|\omega)V_{\omega,t}}{\sum_{f,\omega,s} P_t(p,f,s|\omega)V_{\omega,t}} \quad (3)$$

$$P_t(s|p) = \frac{\sum_{\omega,f} P_t(p,f,s|\omega)V_{\omega,t}}{\sum_{s,\omega,f} P_t(p,f,s|\omega)V_{\omega,t}} \quad (4)$$

$$P_t(p) = \frac{\sum_{\omega,f,s} P_t(p,f,s|\omega)V_{\omega,t}}{\sum_{p,\omega,f,s} P_t(p,f,s|\omega)V_{\omega,t}} \quad (5)$$

We consider the sound state templates to be fixed, so no update rule for $P(\omega|s,p,f)$ is applied. Using fixed templates, 20-30 iterations using the update rules presented in the present section are sufficient for convergence. The output of the system is a pitch activation which is scaled by the energy of the log-spectrogram:

$$P_t(p)\sum_{\omega} V_{\omega,t} \quad (6)$$

After performing 5-sample median filtering for note smoothing, thresholding is performed on $P(p,t)$ followed by minimum note duration pruning set to 40ms (corresponding to the length of one time frame) in order to convert $P(p,t)$ into a binary piano-roll representation, which is the output of the transcription system, and is also used for evaluation purposes.

3. Polyphonic Music Prediction System

It was demonstrated in (Boulanger-Lewandowski et al., 2012) how a music language model (MLM) can be used to improve the transcription performance of a purely acoustic model. The MLM employed there was based on the recurrent neural network-restricted Boltzmann machine (RNN-RBM). A related model — the recurrent neural network-neural autoregressive distribution estimator (RNN-NADE) was also used for the same purpose with comparable results. In the present work, we employ both the standard RNN, and the RNN-NADE as MLMs for boosting the transcription accuracy of the PLCA based model described in the previous section. In this section, we briefly describe the RNN-NADE which we used in our work as the MLM, and the necessary background for understanding this model.

3.1. Recurrent Neural Network

A recurrent neural network (RNN) is a powerful model for time-series data which is known to account for long-term temporal dependencies when trained effectively. Given a sequence of inputs $v_1, v_2, \ldots, v_T$ each in $\mathbb{R}^n$, the network computes a sequence of hidden states $\hat{h}_1, \hat{h}_2, \ldots, \hat{h}_T$ each in $\mathbb{R}^m$, and a sequence of predictions $\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_T$ each in $\mathbb{R}^k$ by iterating the equations

$$h_t = e(W_{\hat{h}x} v_t + W_{\hat{h}\hat{h}} \hat{h}_{t-1} + b_{\hat{h}}) \quad (7)$$

$$\hat{y}_t = g(W_{y\hat{h}}) \quad (8)$$

where $W_{y\hat{h}}$, $W_{\hat{h}x}$, $W_{\hat{h}\hat{h}}$ are the weight matrices and $b_{\hat{h}}$, b_y are the biases and e and g are pre-defined vector valued functions which are typically non-linear and applied element-wise. The RNN also has a special initial bias $b_{\hat{h}}^{init}$ which replaces the formally undefined expression $W_{\hat{h}\hat{h}}\hat{h}_0$ at time $t = 1$.

In theory, a recurrent neural network can be easily trained using the gradient-based Back-Propagation Through Time algorithm (Werbos, 1990) using the exactly computable error gradients in the network. However, 1^{st} order gradient methods fail to correctly train RNNs in certain cases. This difficulty has been associated with what is known as the *vanishing/exploding gradients* phenomenon (Bengio et al., 1994), where the errors exhibit exponential decay/growth as they are back-propagated through time. Several proposals have been made to overcome this difficulty while retaining the predictive power of the RNN (Hochreiter & Schmidhuber, 1997; Jaeger, 2002; Martens & Sutskever, 2011).

3.2. Neural Autoregressive Distribution Estimator

The neural autoregressive distribution estimator (NADE) (Larochelle & Murray, 2011) is a graphical model inspired by the Restricted Boltzmann Machine (Smolensky, 1986; Hinton, 2002). It shares the structural properties of the RBM in that it has a visible layer v (with biases b_v), a hidden layer h (with biases b_h), with these two layers connected by a weight-matrix W. It facilitates the exact inference $p(v)$ given an input vector v, which is not possible in RBMs since there one has to compute the intractable *partition function* (Larochelle & Murray, 2011). This wass made possible by thinking of the RBM as a *fully visible sigmoid belief network* (FVSBN) (Neal, 1992). The FVSBN is a special case of a family of models known as fully visible Bayesian networks (Frey, 1998) with the property

$$p(v) = \prod_{i=1}^{D} p(v_i | v_{parents(i)}) \quad (9)$$

where all observation variables v_i are arranged into a directed acyclic graph and $v_{parents(i)}$ corresponds to all the variables in v that are parents of v_i. In an FVSBN, the acyclic graph is obtained by defining the parents of v_i as all variables that are to its left, or $v_{parents(i)} = v_{<i}$ where $v_{<i}$ refers to the subvector containing all variables v_j such that $j < i$. In the case of the NADE, $p(v_i|v_{parents(i)})$ can be computed as follows

$$p(v_i = 1 | v_{parents(i)}) = \sigma(b_v^{(i)}) + (W^T)_{i,\cdot} h_i) \quad (10)$$

$$h_i = \sigma(b_h + W_{\cdot,<i} v_{<i}) \quad (11)$$

Untying the weights W and W^T results in a more powerful model. In the NADE, the cost of computing $p(v)$ is $O(HD)$, where H is the number of hidden units and D is the dimensionality of the vector v.

3.3. Recurrent Neural Network-Neural Autoregressive Distribution Estimator

Putting together the models described in Sections 3.1 and 3.2, we obtain the RNN-NADE, which is a model proposed for high-dimensional time-series.

4. Combining Transcription and Prediction

In this section, we describe the process for combining the acoustic model with the music language model for deriving an improved transcription. Firstly, the input music signal is transcribed using the process described in Section 2. The resulting piano-roll representation of the transcription system is considered to be a sequence $v_1, v_2, \ldots, v_T$ that is placed as input to the MLM presented in Section 3. We compute the probability $p(v_i = 1|v_{parents(i)})$ for all time frames, and use that as prior information for the combined model (the prior information will be denoted as $P_{MLM}(p, t)$).

As shown in (Smaragdis & Mysore, 2009), PLCA-based models use multinomial distributions; since the Dirichlet distribution is conjugate to the multinomial, a Dirichlet prior can be used to enforce structure on the pitch activation distribution $P_t(p)$. Following the procedure of (Smaragdis & Mysore, 2009), we define the Dirichlet hyperparameter for the pitch activation as:

$$\alpha(p|t) = \frac{P(p|t)P_{MLM}(p,t)}{\sum_p P(p|t)P_{MLM}(p,t)} \quad (12)$$

where $\alpha(p|t)$ essentially is a pitch activation probability which is filtered through a pitch indicator function computed from the symbolic prediction step (the denominator is simply for normalisation purposes).

The recording is then re-transcribed, using as aditional information the prior computed from the transcription step. The modified update for the pitch activation which replaces (5) is given by:

$$P_t(p) = \frac{\sum_{\omega,f,s} P_t(p,f,s|\omega)V_{\omega,t} + \kappa\alpha(p|t)}{\sum_{p,\omega,f,s} P_t(p,f,s|\omega)V_{\omega,t} + \kappa\alpha(p|t)} \quad (13)$$

where κ is a weight parameter expressing how much the prior should be imposed (in (Smaragdis & Mysore, 2009) it decreases from 1 to 0 throughout the iterations). In a larger context, the transcription creates a symbolic prediction, which in turn improves the subsequent re-transcription of the music signal.

5. Evaluation

5.1. Dataset

For testing the transcription system, we employ the Bach10 dataset (Duan et al., 2010), which is a freely available multi-track collection of multiple-instrument polyphonic music, suitable for multi-pitch detection experiments. It consists of ten recordings of J.S. Bach chorales, performed by violin, clarinet, saxophone, and bassoon. Pitch ground truth for each instrument is also provided. Due to the tonal and homogenous content of the dataset, it is suitable for testing the incorporation of music language models in a transcription system. For training the transcription system, pre-extracted and pre-shifted spectral templates are extracted for the instruments present in the dataset, using isolated note samples from the RWC database (Goto et al., 2003).

5.2. Metrics

For evaluating the performance of the proposed system for multi-pitch detection, we employ the precision, recall, and F-measure metrics, which are commonly used in transcription evaluations (MIR):

$$Pre = \frac{N_{tp}}{N_{sys}}, \quad Rec = \frac{N_{tp}}{N_{ref}}, \quad F = \frac{2 \cdot Rec \cdot Pre}{Rec + Pre} \quad (14)$$

where N_{tp} is the number of correctly detected pitches, N_{sys} is the number of detected pitches, and N_{ref} is the number of ground-truth pitches. As in the public evaluations on multi-pitch detection carried out through the MIREX framework (MIR), a detected note is considered correct is if its pitch is the same as the ground truth pitch and its onset is within a 50ms tolerance interval of the ground-truth onset.

5.3. Results

6. Conclusions

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