ABSTRACT

The human ability to track musical downbeats is robust to changes in tempo, and it extends to tempi never previously encountered. We propose a deterministic time-warping operation that enables this skill in a convolutional neural network (CNN) by allowing the network to learn rhythmic patterns independently of tempo. Unlike conventional deep learning approaches, which learn rhythmic patterns at the tempi present in the training dataset, the patterns learned in our model are tempo-invariant, leading to better tempo generalisation and more efficient usage of the network capacity.

We test the generalisation property on a synthetic dataset created by rendering the Groove MIDI Dataset using FluidSynth, split into a training set containing the original performances and a test set containing tempo-scaled versions rendered with different SoundFonts (test-time augmentation). The proposed model generalises nearly perfectly to unseen tempi (F-measure of 0.89 on both training and test sets), whereas a comparable conventional CNN achieves similar accuracy only for the training set (0.89) and drops to 0.54 on the test set. The generalisation advantage of the proposed model extends to real music, as shown by results on the GTZAN and Ballroom datasets.

1. INTRODUCTION

Human musicians easily identify the downbeat (the first beat of each bar) in a piece of music and will effortlessly adjust to a variety of tempi, even ones never before encountered. This ability is the likely result of patterns and tempi being processed at distinct locations in the human brain [1].

We argue that factorising rhythm into tempo and tempo-invariant rhythmic patterns is desirable for a machine-learned downbeat detection system as much as it is for the human brain. First, factorised representations generally reduce the number of parameters that need to be learned. Second, having disentangled tempo from pattern we can transfer information learned for one tempo to all others, eliminating the need for training datasets to cover all combinations of tempo and pattern.

Identifying invariances to disentangle representations has proven useful in other domains [2]: translation invariance was the main motivation behind CNNs [3] — the identity of a face should not depend on its position in an image. Similarly, voices retain many of their characteristics as pitch and level change, which can be exploited to predict pitch [4] and vocal activity [5]. Crucially, methods exploiting such invariances don’t only generalise better than non-invariant models, they also perform better overall.

Some beat and downbeat trackers first estimate tempo (or make use of a tempo oracle) and use the pre-calculated tempo information in the final tracking step [6–15]. Doing so disentangles tempo and tempo-independent representations at the cost of propagating errors from the tempo estimation step to the final result. It is therefore desirable to estimate tempo and phase simultaneously [16–20], which however leads to a much larger parameter space. Factorising this space to make it amenable for machine learning is the core aim of this paper.

In recent years, many beat and downbeat tracking methods changed their front-end audio processing from hand-engineered onset detection functions towards beat-activation signals generated by neural networks [21–23]. Deep learning architectures such as convolutional and recurrent neural networks are trained to directly classify the beat and downbeat frames, and therefore the resulting signal is usually cleaner.

By extending the receptive field to several seconds, such architectures are able to identify rhythmic patterns at longer time scales, a prerequisite for predicting the downbeat. But conventional CNN implementations learn rhythmic patterns separately for each tempo, which introduces two problems. First, since datasets are biased towards mid-tempo songs, it introduces a tempo-bias that no post-processing stage can correct. Second, it stores similar rhythms redundantly, once for every relevant tempo, i.e. it makes inefficient use of network capacity. Our proposed approach resolves these issues by learning rhythmic patterns that apply to all tempi.

The two technical contributions are as follows:

1. the introduction of a scale-invariant convolutional layer that learns temporal patterns irrespective of their scale.
2. the application of the scale-invariant convolutional layer to CNN-based downbeat tracking to explicitly learn tempo-invariant rhythmic patterns.

Similar approaches to achieve scale-invariant CNNs, have been developed in the field of computer vision [24, 25], while no previous application exists for musical signal analysis, to the best of our knowledge.

We demonstrate that the proposed method generalises better over unseen tempi and requires lower capacity with respect to a standard CNN-based downbeat tracker. The method also achieves good results against academic test sets.

2. MODEL

The proposed downbeat tracking model has two components: a neural network to estimate the joint probability of downbeat presence and tempo for each time frame, using tempo-invariant convolution, and a hidden Markov model (HMM) to infer a globally optimal sequence of downbeat locations from the probability estimate.

We discuss the proposed scale-invariant convolution in Sec. 2.1 and its tempo-invariant application in Sec. 2.2. The entire neural network is described in Sec. 2.3 and the post-processing HMM in Sec. 2.4.

2.1 Scale-invariant convolutional layer

In order to achieve scale invariance we generalise the conventional convolutional neural network layer.

2.1.1 Single-channel

We explain this first in terms of a one-dimensional input tensor \( x \in \mathbb{R}^N \) and only one kernel \( h \in \mathbb{R}^{N'} \), and later generalise the explanation to multiple channels in Sec. 2.1.2. Conventional convolutional layers convolve \( x \) with \( h \) to obtain the output tensor \( y \in \mathbb{R}^{N'-N'+1} \)

\[ y = x \ast h, \tag{1} \]

where \( \ast \) refers to the discrete convolution operation. Here, the kernel \( h \) is updated directly during back-propagation, and there is no concept of scale. Any two patterns that are identical in all but scale (e.g. one is a “stretched” version of the other) cannot be represented by the same kernel.

To address this shortcoming, we factorise the kernel representation into scale and pattern by parametrising the kernel as the dot product \( h_j = \langle \psi_j, k \rangle \) between a fixed scaling tensor \( \psi_j \in \mathbb{R}^{N' \times M} \) and a scale-invariant pattern \( k \in \mathbb{R}^M \). Only the pattern is updated during network training, and the scaling tensor, corresponding to \( S \) scaling matrices, is pre-calculated (Sec. 2.1.3). The operation adds an explicit scale dimension to the convolution output

\[ y_j = x \ast h_j = x \ast \langle \psi_j, k \rangle. \tag{2} \]

The convolution kernel is thus factorised into a constant scaling tensor \( \psi \) and trainable weights \( k \) that learn a scale-invariant pattern. A representation of a scale-invariant convolution is shown in Figure 1.

2.1.2 Multi-channel

Usually the input to the convolutional layer has \( C_x \) input channels and there are \( H > 1 \) kernels. The formulas in Section 2.1 can easily be extended by the channel dimension, as illustrated in Table 1.

2.1.3 Scaling tensor

The scaling tensor \( \psi \) contains \( S \) scaling matrices from size \( M \) to \( s_j M \) where \( s_j \) are the scale factors.

\[ \psi_{n,m,j} = \int_{\tilde{n}} \int_{\tilde{s}} \delta(\tilde{n} - \tilde{n}m)\kappa_n(n - \tilde{n})\kappa_s(s_j - \tilde{s})d\tilde{n}d\tilde{s}, \tag{3} \]

where \( \delta \) is the Dirac delta function and \( \kappa_n, \kappa_s \) are defined as follows:

\[ \kappa_n(d) = \frac{\sin(\pi d)}{\pi d} \]

\[ \kappa_s(d) = \alpha \cos^2(\pi d/2)H(1 - |d|), \]

\[
\begin{array}{c|c|c}
\text{variable} & \text{single-channel} & \text{multi-channel} \\
\# frames & N & N \\
\# pattern frames & M & M \\
\# scales & S & S \\
\# input channels & 1 & \mathbb{C}_x \\
\# kernels & 1 & \mathbb{H} \\
\text{signal } x & \mathbb{R}^N & \mathbb{R}^{N \times \mathbb{C}_x} \\
\text{patterns } k & \mathbb{R}^M & \mathbb{R}^{M \times \mathbb{C}_x \times \mathbb{H}} \\
\text{kernel } h & \mathbb{R}^{N' \times S} & \mathbb{R}^{N' \times \mathbb{C}_x \times S \times \mathbb{H}} \\
\text{output } y & \mathbb{R}^{(N' - N' + 1) \times S} & \mathbb{R}^{(N' - N' + 1) \times \mathbb{C}_x \times S \times \mathbb{H}} \\
\text{scaling tensor } \psi & \mathbb{R}^{N' \times \mathbb{C}_x \times S} & \mathbb{R}^{N' \times \mathbb{C}_x \times S \times \mathbb{H}} \\
\text{scale indices} & j = 0, \ldots, S - 1 & j = 0, \ldots, S - 1 \\
\end{array}
\]

Table 1. Variables and dimensions.
where $\mathcal{H}$ is the Heaviside step function. The inner integral can be interpreted as computing a resampling matrix for a given scale factor and the outer integral as smoothing along the scale dimension, with the parameter $\alpha$ of the function $\kappa_s$ controlling the amount of smoothing applied. The size $N^*$ of the scaling tensor $\psi$ (and the resulting convolutional kernel $h$) is derived from the most stretched version of $k$:

$$N^* = \max_j s_j M.$$  \hspace{1cm} (4)

### 2.1.4 Stacking scale-invariant layers

After the first scale-invariant layer, the tensor has an additional dimension representing scale. In order to add further scale invariant convolutional layers without losing scale invariance, subsequent operations are applied scale-wise:

$$y_j = x_j \ast (\psi_j, k).$$  \hspace{1cm} (5)

The only difference with Eq. (2) is that the input tensor $x$ of Eq. (5) already contains $S$ scales, hence the added subscript $j$.

### 2.2 Tempo invariance

In the context of the downbeat tracking task, tempo behaves as a scale factor and the tempo-invariant patterns are rhythmic patterns. We construct the sequence of scale factors $s$ as

$$s_j = \frac{r \tau_j B}{M}, \quad \tau_j = \tau_0 2^\frac{j}{T}$$  \hspace{1cm} (6)

where $\tau_j$ are the beat periods, $r$ is the frame rate of the input feature, $B$ is the number of beats spanned by the convolution kernel factor $k$, $\tau_0$ is the shortest beat period, and $T$ is the desired number of tempo samples per octave. The matrix $k$ has a simple interpretation as a set of rhythm fragments in musical time with $M$ samples spanning $B$ beats.

To mimic our perception of tempo, the scale factors in Eq. (6) are log-spaced, therefore the integral in Eq. (3) becomes:

$$\psi_{n,m,j} = \int \int \int \delta(n - s_j m) \kappa_n(n - \tilde{n}) \kappa_s(j - \tilde{j}) d\tilde{n} d\tilde{j},$$  \hspace{1cm} (7)

where the parameter $\alpha$ of the function $\kappa_s$ has been set to 1. A representation of the scaling tensor used in the tempo-invariant convolution is shown in Figure 2.

### 2.3 Network

The tempo-invariant network (Fig. 3) is a fully convolutional deep neural network, where the layers are conceptually divided into two groups. The first group of layers are regular convolutional layers and act as onset detectors. The receptive field is constrained in order to preserve the tempo-invariance property of the model: if even short rhythmic fragments are learned at a specific tempo, the invariance assumption would be violated. We limit the maximum size of the receptive field to 0.25 seconds, i.e. the period of a beat at 240 BPM.

The second group is a stack of tempo-invariant convolutional layers (as described in Sec. 2.1, 2.2). The receptive field is measured in musical-time, with each layer spanning $B = 4$ beats. The last layer outputs only one channel, producing a 2-dimensional (frame and tempo) output tensor.

The activations of the last layer represent the scores (logits) of having a downbeat at a specific tempo. An additional constant zero bin $^1$ is concatenated to these activations for each frame to model the score of having no downbeat. After applying the softmax, the output $o$ represents the joint probability of the downbeat presence $D$ and tempo $\tau$.

$$\alpha_j = \begin{cases} p(D, \tau_j) & j = 0, \ldots, S - 1 \\ p(\neg D) & j = S \end{cases}$$  \hspace{1cm} (8)

$^1$ We can keep this constant because the other output values will adapt automatically.
The categorical cross-entropy loss is then applied frame-wise, with a weighting scheme that balances the loss contribution on downbeat versus non-downbeat frames.\(^2\)

The target tensors are generated from the downbeat annotations by spreading the downbeat locations to the neighbouring time frames and tempi using a rectangular window (0.1 seconds wide) for time and a raised cosine window (\(2/T\) octaves wide) for tempo. The network is trained with stochastic gradient descent using RMSProp, early stopping and learning rate reduction when the validation loss reaches a plateau.

### 2.4 Post-processing

In order to transform the output activations of the network into a sequence of downbeat locations, we use a frame-wise HMM with the state-space [26].

In its original form, this post-processing method uses a network activation that only encodes beat probability at each position. In the proposed tempo-invariant neural network the output activation models the joint probability of downbeat presence and tempo, enabling a more explicit connection to the post-processing HMM, via a slightly modified observation model:

\[
P(o_j|q) = \begin{cases} 
 c(\tau_{j}, \tau_{o})o_j & q \in D, \quad j < S \\
 o_S/\sigma_S & q \in \neg D 
\end{cases} \tag{9}
\]

where \(q\) is the state variable having tempo \(\tau_q\), \(D\) is the set of downbeat states, \(c(\tau_{j}, \tau_{o})\) is the interpolation coefficient from the tempi modeled by the network \(\tau_{j}\) to the tempi modeled by the HMM \(\tau_{q}\) and \(\sigma\) approximates the proportion of non-downbeat and downbeat states (\(|\neg D|/|D|\)).

### 3. EXPERIMENTS

In this section we describe the two experiments conducted in order to test the tempo-invariance property of the proposed architecture with respect to a regular CNN. The first experiment, described in Sec. 3.1, uses a synthetic dataset of drum MIDI recordings. The second experiment, outlined in Sec. 3.2, evaluates the potential of the proposed algorithm on real music.

#### 3.1 Tempo-invariance

We test the robustness of our model by training a regular CNN and a tempo-invariant CNN on a tempo-biased training dataset and evaluating on a tempo-unbiased test set. In order to control the tempo distribution of the dataset, we start with a set of MIDI drum patterns from the magenta-grove dataset [27], randomly selecting 4 bars from each of the 40 eval-sessions, resulting in 160 patterns. These rhythms were then synthesised at 27 scaled tempi, with scale factors \(\varepsilon_i = 2^{i/26}\) \((13 \leq i \leq 13)\) with respect to the original tempo of the recording. Each track starts with a short silence, the duration of which is randomly chosen within a bar length, after which the rhythm is repeated 4 times. Audio samples are rendered using FluidSynth\(^3\) with a set of 40 combinations of SoundFonts\(^4\) and instruments, resulting in 172800 audio files. The synthesised audio is pre-processed to obtain a log-amplitude mel-spectrogram with 64 frequency bins and \(r = 50\) frames per second.

The tempo-biased training set contains the original tempi (scale factor: \(\varepsilon_0 = 1\)), while the tempo-unbiased test set contains all scaled versions. The two sets were rendered with different SoundFonts.

We compared a tempo-invariant architecture (inv) with a regular CNN (noinv). The hyper-parameter configurations are shown in Table 2 and were selected maximising the accuracy on the validation set.

The results of the experiment are shown in Fig. 4 in terms of \(F_1\) score, using the standard distance threshold

\(^2\) The loss of non-downbeat frames is reduced to 1/3.

\(^3\) http://www.fluidsynth.org

\(^4\) https://github.com/FluidSynth/fluidsynth/wiki/SoundFont
of 70 ms on both sides of the annotated downbeats [28]. Despite the tempo bias of the training set, the accuracy of the proposed tempo-invariant architecture is approximately constant across the tempo spectrum. Conversely, the non-invariant CNN performs better on the tempi that are present in the training and validation set. Specifically, Fig. 4a shows that the two architectures perform equally well on the training set containing the rhythms at their original tempo (scale equal to 0 in the figure), while the accuracy of the non-invariant network drops for the scaled versions. A different view of the same results on Fig. 4b highlights how the test set accuracy depends on the scaled tempo. The accuracy of the regular CNN peaks around the tempi that are present in the training set. As shown in the figure, data-augmentation improves generalisation, but has similar tempo dependency effects.

### 3.2 Music data

In this section, we used real music recordings. We trained on an internal dataset (1368 excerpts from a variety of genres, summing up to 10 hours of music) and the RWC dataset [29] (Popular, Genre and Jazz subsets) and tested on Ballroom [30,31] and GTZAN [32] datasets. With respect to the previous experiment we used the same input features, but larger networks\(^5\) because of the higher amount of information contained in fully arranged record-

\(^5\) In terms of number of channels, layers and convolution kernel sizes, optimized on the validation set.

---

**Table 2.** Architectures used in the experiment. Groups of layers are expressed as (number of layers \(\times\) output channels). All layers in group 1 have kernel size equal to 3 frames. dil-CNN is a stack of dilated convolution layers with kernel size equal to 7 frames and exponentially increasing dilation factors: 2, 4, 8, 16. The specific hyperparameters of the tempo-invariant network TI-CNN are configured as follows: \(T = 8, \tau_0 = 0.25, S = 25, M = 64, B = 4\). ReLU non-linearities are used on both architectures.

| group | architecture | inv | noinv |
|-------|-------------|-----|-------|
| 1     | CNN         | 3 \(\times\) 32 | 3 \(\times\) 32 |
| 2     | TI-CNN      | 2 \(\times\) 16 | 3 \(\times\) 64 |
|       |             | 1 \(\times\) 1  | 1 \(\times\) 1  |

| #params | 60k | 80k |
|---------|-----|-----|

---

**Figure 5.** Results of the experiment on music data in terms of F-measure. Track scores are used to compute the average and the confidence intervals at 95\% (using bootstrapping). The proposed tempo-invariant architecture is able to better generalise over unseen data with respect to its standard CNN counterpart.

The results in Fig. 5 show that the proposed tempo-invariant architecture is performing worse on the training set, but better on the validation and test set, with the comparisons on train and test set being statistically significant \((p < 0.001)\). Here the tempo-invariant architecture seems to act as a regularisation, allocating the network capacity to learning patterns that better generalise on unseen data, instead of fitting to the training set.

### 4. DISCUSSION

Since musicians are relentlessly creative, previously unseen rhythmic patterns keep being invented, much like “out-of-vocabulary” words in natural language processing [33]. As a result, the generalisation power of tempo-invariant approaches is likely to remain useful. Once tuned for optimal input representation and network capacity we expect tempo-invariant models to have an edge particularly on new, non-public test datasets.

Disentangling timbral pattern and tempo may also be useful to tasks such as auto-tagging: models can learn that some classes have a single precise tempo (e.g. ballroom dances [30]), some have varying tempos within a range (e.g. broader genres or moods), and others still are completely invariant to tempo (e.g. instrumentation).

### 5. CONCLUSIONS

We introduced a scale-invariant convolution layer and used it as the main component of our tempo-invariant neural network architecture for downbeat tracking. We experimented on drum grooves and real music data, showing that the proposed architecture generalises to unseen tempi by design and achieves higher accuracy with lower capacity compared to a standard CNN.

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