THE PIANO INPAINTING APPLICATION

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ABSTRACT

Autoregressive models are now capable of generating high-quality minute-long expressive MIDI piano performances. Even though this progress suggests new tools to assist music composition, we observe that generative algorithms are still not widely used by artists due to the limited control they offer, prohibitive inference times or the lack of integration within musicians’ workflows. In this work, we present the Piano Inpainting Application (PIA), a generative model focused on “inpainting” piano performances, as we believe that this elementary operation (restoring missing parts of a piano performance) encourages human-machine interaction and opens up new ways to approach music composition. Our approach relies on an encoder-decoder Linear Transformer architecture trained on a novel representation for MIDI piano performances termed Structured MIDI Encoding. By uncovering an interesting synergy between Linear Transformers and our inpainting task, we are able to efficiently inpaint contiguous regions of a piano performance, which makes our model suitable for interactive and responsive A.I.-assisted composition. Finally, we introduce our freely-available Ableton Live PIA plugin, which allows musicians to smoothly generate or modify any MIDI clip using PIA within a widely-used professional Digital Audio Workstation.

Keywords Music generation · Inpainting · Interactive model · Human Computer Interface

1 Introduction

With the recent advances in autoregressive models [25, 16] and increasing computational resources, convincing minute-long piano performances with fine details about velocity and micro-timing can be automatically generated [14, 22, 15], opening the way to cutting edge creative assisting tools for composition. However, unconstrained generation can be of very limited use for composers, and engaging interactions between a user and the algorithm has been identified as a major requirement towards A.I.-assisted music composition. Although it proved to be challenging to develop meaningful controls for deep learning models, many recent works proposed various modes of interaction for music generation beyond the usual continuation of a priming section [22, 14, 15, 12]: harmonization [10, 14], variation of an input sequences [9, 7], interpolation between two fragments [23], or mapping of a musical gesture to a performance [5].

In this work, we choose to focus on the piano performance inpainting task, which we can define as learning how to restore a partially blanked-out piano performance as depicted in Fig. 1. The reason for considering the piano inpainting task as our task of interest is that this operation encompasses many previously cited generation schemes (unconditional generation, continuation of a priming sequence) but also favors an iterative compositional process.

This task has been extensively studied for image generation [6]. However, we note that in the symbolic music domain only few approaches were proposed and that these methods only operated on quantized scores: Bach chorales inpainting using Gibbs sampling where the inpainted elements are initialised randomly and resampled until convergence was proposed in [10]. Bach chorales melodies inpainting using RNNs was developed in [8], while [21] proposed a VAE-based solution for variable-length folk music melody inpainting.

Extending these results to the more complex task of generating expressive piano performances is not straightforward, as the previous results largely exploit the fixed structure of the data representation to provide exact information about the location of the constraints (for example, in [8], the fifth beat of the soprano voice of a Bach chorale will always have the same position in the encoding sequence). However, recent works in piano performance generation rely on data

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We first present in Sect. 2.1 the framing of the inpainting task using autoregressive models as exposed in [8].

The Anticipation-RNN framework [8] casts the inpainting task as a conditional generation problem. Suppose we are given a dataset of discrete sequences \( x = (x_t)_{t \in [T]} \) where \( x_t \in \mathcal{A} \) belongs to a discrete alphabet \( \mathcal{A} \) and \( T \) denotes the length of the sequences, which are assumed to be samples from a distribution \( p(x) \). Given a set of positional constraints \( \mathcal{C} := \{ (t, c_t) \in T \times \mathcal{A} \} \), the objective is to generate sequences \( x \) enforcing these constraints, i.e. such that \( x_t = c_t \) for all \( (t, c_t) \in \mathcal{C} \) with the correct probabilities. More precisely, this amounts to sampling from the subset of sequences enforcing the constraints \( \mathcal{C} \) with \( p(x|\mathcal{C}) \) while keeping the relative probabilities (as defined by \( p(x) \)) intact. Note that by definition, \( p(x|\mathcal{C}) = 0 \) for sequences that violate one of the constraints in \( \mathcal{C} \), so we have \( p(x|\mathcal{C}) \propto p(x) \) on the subset of valid sequences.

However, enforcing constraints when generating time series with an autoregressive model \( p(x_t|x_{<t}) \) is challenging and rejection sampling can become highly inefficient with a high number of positional constraints. The solution proposed in [8] consists in summarizing the set of constraints \( \mathcal{C} \) with an autoregressive model going backwards and then to properly condition the generation of the sequence \( x \) using such information about the future.

In practice, a set of constraints \( \mathcal{C} \) is represented as a sequence of length \( T \) by adding a NC (No Constraint) token: \( c = (c_t)_{t \in [T]} \), where \( c_t = \text{NC} \) when there is no constraint at location \( t \) in \( \mathcal{C} \). The sequence \( c \) is fed to an anti-causal\(^2\)

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\(^2\)We use the shorthand \([d]\) to denote \([1, \ldots, d]\)
autoregressive encoder $E$, whose output sequence $(E(c_{\geq t}))_{t \in [T]}$ represents at each time step a summary of the constraints occurring at future times. It is used to condition a causal decoder $D$ which approximates $p(x|C)$ in an autoregressive way (as depicted in Fig. 3):

$$D(x_{\leq t}, E(c_{\geq t})) \approx p(x_t|x_{\leq t}, C).$$

(1)

Training is done by sampling constraint locations and minimizing a cross-entropy loss. Inference is done by first computing $(E(c_{\geq t}))_{t \in [T]}$ and then successively sampling $x_t \sim D(x_{\leq t}, E(c_{\geq t}))$.

When working with quantized scores, this approach proved to be effective at modelling the correct probability distribution while enforcing the constraints and provided an efficient sampling scheme requiring only $O(2T)$ RNN calls.

### 2.2 Structured MIDI encoding

Directly applying the method described in Sect. 2.1 to piano performances proved to be challenging. Indeed, one may notice that defining constraint sequences was only possible in [8] due to the particular structure of the data that the authors considered: when working with quantized scores, there is a direct link between the location $t$ of the constraint within the sequence and the actual onset of the note in the final score. However, piano performance encoding found in the literature [14, 22, 4, 15] do not have an unequivocal relation between an information in the performance and its position in the sequence of tokens representing the performance, which makes the definition of musically-relevant constraints impossible. (for example, the same notes played either as a chord or as an arpeggio will be represented with a different number of tokens, and the pitch information of each note will be placed at different positions between the two cases, even though there is the same number of notes).

In this work, we consider piano performances encoded as a sequence of notes, each note being characterized by four attributes or channels: Pitch, Velocity, Duration and Time Shift. The Time Shift channel encodes the time elapsed between the onset of the current note and the onset of the next one. Formally, we encode piano performances as a structured sequence $x = (x_t)_{t \in [1:T]}$, where $T$ is the number of notes of the piano performance. For each slice $(x_{4i}, x_{4i+1}, x_{4i+2}, x_{4i+3}) := (x_{4i}^p, x_{4i}^v, x_{4i}^d, x_{4i}^{ts})$ with $i \in [T]$, its entries correspond respectively to the pitch of the $i^{th}$ note, its velocity, its duration and to the time shift between the $i^{th}$ and $(i+1)^{th}$ notes. Each slice can be seen as a tuple in $A_p \times A_v \times A_d \times A_{ts}$, meaning that each of its entries belong to a domain-specific finite alphabet $A_\ast$. Our representation presents similarities with the duration-based representation proposed in [15], but it is more general (works with any MIDI file without annotation about bars or tempo) and is more structured. Notably, we introduce a token corresponding to 0 milliseconds in the time shift alphabet, which is used when several notes occur at the same time. This is crucial to guarantee the structure of the representation as visualized in Fig. 2. Our modeling choices for the alphabets $A_\ast$ are discussed in Sect. 3.1.2.
An important property of our proposed representation is that the data always keeps the same structure independently from the content. As a consequence, for each token index \( t \leq 4T \), we know exactly the nature of the information (pitch, velocity, duration or time shift) it represents and where the \( i \)th played note is located. This differs from other piano performance representations, whose structure vary depending on the content. We discuss the differences between our proposed structured representation and other MIDI-like representations in Sect. 5.1.

2.3 Efficient Linear Transformer for piano inpainting

Using the Structure MIDI encoding for piano performances, we propose to rely on an encoder-decoder Transformer architecture \([25]\) to model Eq. (1). We take advantage of the particular structure of our data representation to propose an efficient encoder-decoder architecture based on the recently-proposed Linear Transformer \([16]\) in Sect. 2.3.1. The regularity of our data representation allows us to design factorized positional embeddings, which we present in Sect. 2.3.2. We conclude in Sect. 2.3.3 by proposing an efficient inference that strictly outperforms the approach from \([8]\) when the inpainted region is contiguous.

2.3.1 Efficient masking scheme

The encoder \( E \) and the decoder \( D \) can be implemented by any autoregressive model. In this work, we use Linear Transformers \([16]\) as they provide a way to overcome the \( O(T^2) \) complexity of computing the self-attention, which allows us to consider longer sequences, and we rely on a standard encoder-decoder architecture with transformers as proposed in \([25]\). In order to enforce the particular dependency structure displayed in Eq. (1), we propose to use anti-causal masks on the encoder part, and causal masks on the decoder part. Thanks to the alignment between the sequence of constraints \( c \) and the input sequence \( x \), cross-attention can be simplified with a much simpler operation since at location \( t \), the decoder only needs attend to \( E(c_{\geq t}) \). Such operation is equivalent to masking out all off-diagonal terms of the cross-attention matrix in the standard setting. Compared with \([8]\), replacing RNNs with Linear Transformers allows to compute predictions for all timesteps in parallel.

2.3.2 Factorized positional embeddings

Positional embeddings are a key component in Transformer architectures as they provide a way to convey information about the sequential ordering of the input. Usually, information about the index \( t \) in the sequence is provided through the use of sinusoidal positional embeddings \([25]\). In our case, due to the regular structure of the Structured MIDI encoding, each index \( t \) indicates two different kinds of information: the channel index of the corresponding token \( t \mod 4 \), and the index of the note it belongs to \( |t|/4 \).

We also decide to introduce elapsed time embeddings to indicate at each location \( t \) the true elapsed time in seconds since the beginning of the sequence (this is obtained by aggregating all time shifts). We note that the elapsed-time embedding allows the decoder to know the duration of the gap that has to be inpainted. Such embedding seems to have been used in \([22]\), but probably in a slightly different way: in our case, both the positional embedding \( |t/4| \) and the elapsed time embedding are obtained via the sinusoidal embeddings from \([25]\). Details are provided in Appendix. A.
2.3.3 Efficient inference scheme

Reactivity is a major concern in our application. Therefore, we rely on the Linear Transformer [16] which can offer a faster inference time compared with vanilla Transformers. Indeed, inference in Linear Transformers can be also be performed in a recurrent manner (as in a Recurrent Neural Network), by computing a single time step at a time and updating a hidden state. This helps saving resources when performing autoregressive generation since only necessary information is computed at each time step.

In our implementation, we take advantage of the two modes of inference offered by the Linear Transformer to propose an efficient inference scheme when the inpainted region is contiguous: we first compute in parallel the output of the encoder and the hidden state needed to compute the first token of the inpainted region. After this, we can use the RNN-like inference mode to sample each token of the inpainted region in an autoregressive way.

This observation allows our method to perform strictly better than the RNN-based method from [8], as the complexity of the inpainting task for contiguous region is $O(L)$ instead of $O(T)$, where $L \leq T$ is the length of the region to inpaint (note that in practice we often have $L \ll T$). This implies that the generation time is irrespective of the location of the inpainted region within the sequence. Speedups obtained by using the RNN inference mode instead of the traditional parallel computation are discussed in [16].

3 Experiments

In this section, we present the dataset we used in Sect. 3.1 and precise implementation and training details in Sect. 3.2. We then showcase in Sect. 3.3 many generation schemes granted by our proposed architecture. All the results and generations can be found on the companion website of this article.

3.1 Dataset

We use the GiantMIDI-Piano dataset [17], which includes 10,854 piano performances written by 2,786 composer transcribed using [18] from live recordings and encoded in the MIDI format. We use a (90/10/0) split for the dataset, by assigning one file every ten to the validation set.

3.1.1 Data processing

We process chunks of 1024 notes, which corresponds to 4096 tokens using our Structured MIDI representation introduced in Sect. 2.2. In average, a chunk of 1024 notes represents at least a minute-long performance. We use the following data augmentations:

- time dilation, as a multiplicative factor, uniformly sampled between 0.9 and 1.1, applied to values in seconds,
- velocity shifting, as an additive term on velocity tokens, sampled from a uniform distribution defined on $[-20, \ldots, 20]$,
- transposition, as an additive term added to pitches, sampled from a uniform distribution on $[-6, \ldots, 6]$.

3.1.2 Adaptive quantization for continuous values

We adopt an adaptive quantization scheme for duration and time shift events similar to what is proposed in [4]. The objective is to discretize continuous duration and time shift values efficiently to minimize both loss of information and the overall size of their respective alphabets. This results in an almost imperceptible discretization. Exact values are provided in appendix B.

3.2 Implementation details

3.2.1 Improvements to the Linear Transformer architecture and model parameters

We made two substantial changes to the Linear Transformer from [16] that proved to make model training more stable and improve expressivity. We first modified how the residual branches and non-residual branches of all layers are merged. Following [20], we replaced the usual addition of the two branches by a GRU-type gating mechanism. Secondly, following [20, 27], we put layer normalization in the residual branches and add an additional normalization layer before the final softmax layers.

[https://ghadjeres.github.io/piano-inpainting-application/](https://ghadjeres.github.io/piano-inpainting-application/)
Both encoder and decoder are Linear Transformers with \((1 + \text{elu}(x))\) feature maps, 8 heads of dimension 64 each and \(\text{gelu}(x)\) activations and feed-forward layers of dimension 1024. The encoder has 4 layers and the decoder has 8 layers. Dropout with value 0.1 is applied.

The model outputs are projected using channel-dependant projection heads before computing a softmax, so that each prediction is done in the correct alphabet (pitch, velocity, duration or time shift), see Sect. 2.2 and 3.1.2. The model is trained by minimizing a cross-entropy loss, computed only for tokens of the output sequence corresponding to Non-Constrained tokens in the constraint sequence. This is opposed to the approach of [8] where the tokens with positional constraints were predicted as well. At generation, we use top-p sampling with \(p = 0.95\). 

3.2.2 Constraints at training time

Depending on the targeted application, different strategies can be implemented to create the constraint sequences at training time as discussed in Sect. 3.3. In our implementation, we remove a whole slice (from \(4i\) to \(4i + 3\), \(i \leq T\)) with probability \(p\), where \(p\) is a ratio uniformly chosen between 0.5 and 1. This strategy is adapted to the task of filling missing notes in a sequence, but would be, for instance, less adapted to re-sampling a particular information. In that later case, masking only the missing information during training would probably be a better strategy.

3.3 Sampling strategies

A strength of our model is that it allows many musically-relevant applications to be performed without the need to rely on different specific models.

3.3.1 Unconditional generation

Our proposed architecture can be used to generate piano performances from scratch, with no priming or ending section defining a musical context. In this case, the model constraint sequence \(c\) is only filled with NC tokens. We can use the efficient inference scheme of Sect. 2.3.3 so that the overall complexity of unconditional generation with our inpainting model is on par with a causal Linear Transformer trained specifically for unconditional generation. Generation quality in this restricted setting is close from other dedicated approaches [22, 14], despite the fact that we considered a much smaller model trained on a significantly smaller dataset. In the generated performances, we observe a real sense of tempo, a capacity to coherently develop patterns, a wide variety of piano textures and recognizable musical styles. If we have a feeling of musical direction, the high-level structure of our generated pieces may not be as clear as what can be heard in some examples from [22]. However, we do not perceive this as a major shortcoming since our proposed approach to composition is through iterative refinements involving a human operator. In such a setting, it is up to the user to make decisions about the high-level structure, which can be easily achieved using our proposed Ableton Live PIA plugin presented in Sect. 4.

3.3.2 Inpainting of contiguous regions

Inpainting of a contiguous region (see Fig. 1) can be done with the sampling scheme proposed in Sect. 2.3.3 such setting includes the possibility to continue a priming sequence. By relying on the elapsed-time embedding and by appropriately choosing the number of notes within the region-to-be-inpainted, we can specify both the duration of the region and its note density. This offers interesting possibilities for a user to control the generated material. Since selecting a contiguous region is easily done in a Digital Audio Workstation (DAW), this suggests the DAW integration of PIA presented in Sect. 4.

We note that PIA is able to seamlessly stitch together two regions, and that the desired length for the regenerated region is well respected. The proposals made by PIA are varied and take into account ideas from the context (both from the preceding and succeeding regions);

3.3.3 Musically-relevant applications of piano inpainting

Our framing of the inpainting task combined with the use of the Structured MIDI encoding allows us to perform more general operations than the inpainting of contiguous region described in Sect. 3.3.2 and displayed in Fig. 1. Indeed, since our representation treats pitch, velocity and note duration as different tokens, it is possible to perform inpainting only on some attributes, while leaving the others unaltered. We identify two interesting applications: “velocification” and “pitchification”. The former application consists in only regenerating velocities and durations so that it becomes possible to “humanize” a score or create playing style variations. This can be particularly relevant when such information is missing or tedious.
Concrete use cases for this task are: when one is using a MIDI keyboard, it might be hard to precisely record velocities; when inputing a melody in a DAW, it takes time to also precisely set the duration and the velocity of each note; when importing a score as MIDI, there may be no information about velocities so that all notes are assigned to the same velocity.

The latter application consists in doing the opposite: only pitches are generated, while keeping the original rhythm and the same expressivity parameters. It can be a way to further condition PIA generations to strictly follow a predefined rhythm, but could also lead to creative usages: it is possible for instance to record a musical gesture on the piano without any concern about the notes being played and to let PIA change this proposal into an actual piano piece. Such a creative use bears similarities with the approach from [5] and the modelling task considered in [26].

If such applications could be easily performed using a dedicated seq2seq model where only the relevant attributes in the Structured MIDI encoding are kept, we find interesting to be able to perform all these operations with a single model. Furthermore, our model allows to perform these attribute inpainting tasks only on user-defined regions of the piano performance.

If we ask PIA to generate a whole piece while being conditioned on a complete piano performance (with a constraint sequence containing no NC symbol), we surprisingly observe that PIA does not copy the constraint sequence, but rather generates a novel piano performance bearing similarities with the constraint sequence (see Fig. 4).

Such unexpected behavior is related to our choice to predict only non constrained tokens as discussed in Sect. 3.2.1 and could be used as an additional way to condition generations.

4 PIA, a Max4Live device

We introduce the PIA plugin (see Fig. 5 for Ableton Live, a Max4Live device able to replace or fill in any contiguous region of a MIDI pianoroll in Ableton Live by relying on the method presented in Sect. 3.3.2. The selected fragment is populated by notes as soon as they are generated. The first notes start being generated in less than 1 second, providing a highly-responsive user experience. Moreover, users need not wait to listen to the track being generated and generation speed is close to real-time.

The PIA plugin and a video demonstrating PIA in use can be accessed on the companion website 4.

5 Related Works

5.1 MIDI encodings

Event-based representations inspired by the MIDI format have become the standard to encode MIDI performances [22, 14, 19, 4]. In the MIDI format, the duration of a note is equal to the cumulative sum of all the time-shift events between the note-on message and its corresponding note-off (see Fig. 2). However, as noted in [15], this nested structure embeds an unnecessary complexity in a non-live context, which can hinder the performances of generative algorithms, and carry the risk of generating ill-formed sequences with notes-on event not being properly switched off.

4 https://ghadjeres.github.io/piano-inpainting-application/
To circumvent that issue, [15] proposed a duration-based representation, using the following messages: pitch, velocity, duration and time-shift. However, they also introduce other types of information such as bar and beat positions and chords labels. While providing such rich contextual information may improve the generative performances of the model, it also has the disadvantage of ruining the structure of the sequence, as messages corresponding to different musical attributes can occur at any position. Thus, the predictions have to be made on a single large alphabet enumerating the possible values for all types of information, instead of several smaller alphabets as in our implementation. For instance, the smallest alphabet found in the literature contains 332 elements [15], whereas our proposed Structured MIDI encoding typically relies on alphabets of size 88, 128 or 106 (respectively for pitch, velocity or duration and time-shift).

A similar observation was presented in [12], but they proposed a solution where the different features of a same note are predicted independently, which we believe weakens the capacity of the model.

5.2 Models and Interfaces for Interactive Music Generation

Artificial Intelligence could help improve musicians’ workflow by providing an intuitive and convenient way to transform musical ideas into their technical realization. However, few works jointly design A.I. algorithms for music together with Human-Computer Interfaces to facilitate their usage. Amongst these works, we distinguish two trends: ones that develop standalone interfaces and ones that integrate within existing software. As an example of the former approach, [5] proposed a web-based interface which generates a melody on a 88 keys piano based on a user input limited to a set of 8 keys while [1] developed a model-independent web-based interactive score that can be linked to Ableton Live to facilitate musical score inpainting. In [13], the authors proposed a web-based interface for melody reharmonization in the style of Bach.

Integration within existing software is often approached via the development of plugins: [10] proposed a plugin for the MuseScore scorewriter editor to perform interactive composition of Bach chorales while [23] proposed a series of Ableton Live plugins offering multiple ways to generate monophonic melodies.

The aforementioned systems process simpler data compared to piano MIDI performances, which limits their expressivity and usages.

6 Conclusion

In this paper, we presented a general architecture for piano inpainting together with a freely-available Ableton Live plugin making it accessible to a wide audience. We proposed a novel encoding for MIDI piano performances adapted to this task and an efficient inference scheme, which allowed us to consider moderate-size models and attain almost real time generation speed while maintaining high generation capabilities. Through a minimalist user interface, PIA favors rich interactions and suggests innovative ways to envision music composition; its integration within a professional DAW advocates for a forthcoming democratization of A.I.-enhanced creation tools.

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Appendices

A Positional embeddings

Channel embedding is a trainable matrix in \( \mathbb{R}^{4 \times 12} \) mapping each of the four channels (pitch, velocity, duration, time-shift) to a 12-dimensional embedding. Token embedding is a sinusoidal embedding \([25]\) with dimension 128 which encodes the position of each token relatively to the beginning of the subsequence being processed by the model. The elapsed-time embedding is a sinusoidal embedding \([25]\) of dimension 128 encoding the absolute time from the beginning of the whole performance.

The positional embedding is given by the concatenation of the channel, token and elapsed-time embeddings

\[
p(t) = (p_c(t), p_t(t), p_e(t)) \in \mathbb{R}^{268}
\]

Both token embedding \(p_t\) and elapsed-time embedding \(p_e\) are sinusoidal. The sinusoidal embedding \(SE(t)\) at index \(t\) is a 2d-vector defined by:

\[
\begin{align*}
SE(t)_{2i} &= \sin(\text{pos}(t)/10000^{2i}) \\
SE(t)_{2i+1} &= \cos(\text{pos}(t)/10000^{2i}),
\end{align*}
\]

where \(\text{pos}(t) = \lfloor t/4 \rfloor\) for the token embedding and \(\text{pos}(t) = 100 \sum_{i<\lfloor t/4 \rfloor} \text{ms}(x_t^{ts})\) for the elapsed-time embedding, where \(\text{ms}(x_t^{ts})\) maps time shift tokens to their value in milliseconds.

B Details of the structured MIDI encoding

Each attribute is defined on a specific alphabet. In our implementations, we used the following definitions:

- Pitch: \(A_p = [21, 108]\) represents the 88 keys of a piano keyboard.
- Velocity: \(A_v = [0, 127]\) is a direct legacy from the MIDI standard and is sufficient to encode fine variations in the dynamics.
- Duration: \(A_d\) contains 106 tokens representing an adaptive quantisation of the interval between 0 and 20 seconds. See Tab.1 for details.
- Time-shift: \(A_{ts}\) is defined on the same alphabet as the duration.

| Start (sec.) | End (sec.) | Increment (sec.) |
|--------------|------------|------------------|
| Short (50)   | 0          | 0.98             | 0.02             |
| Medium (40)  | 1.0        | 4.9              | 0.1              |
| Long (16)    | 5.0        | 20.0             | 1.0              |

Table 1: Time quantisation for duration and time-shift events. A time interval ranging from 0 to 20.0 seconds is split in 106 tokens with varying increments over the Short, Medium and Long intervals. The numbers in parenthesis next to the name of the segments indicate the number of token allocated to each segment. The values for the start, end and increments values of the different segments are in seconds.