

Audio-to-Score Alignment Using Deep Automatic Music Transcription

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Abstract

Audio-to-score alignment (A2SA) is a multimodal task consisting in the alignment of audio signals to music scores. Recent literature confirms the benefits of Automatic Music Transcription (AMT) for A2SA at the frame-level. In this work, we aim to elaborate on the exploitation of AMT Deep Learning (DL) models for achieving alignment at the note-level. We propose a method which benefits from HMM-based score-to-score alignment and AMT, showing a remarkable advancement beyond the state-of-the-art. We design a systematic procedure to take advantage of large datasets which do not offer an aligned score. Finally, we perform a thorough comparison and extensive tests on multiple datasets.

Index Terms

audio-to-score alignment, music information retrieval, automatic-music-transcription

I. INTRODUCTION

Audio-to-score alignment (A2SA) is a Music Information Retrieval (MIR) task which aims at finding correspondences between time instants in a music recording and time instants in the associated music score. Such a technology facilitates various tasks, ranging from cultural heritage applications attempting to ease the fruition of music, to preprocessing stage for various multimodal MIR tasks [1].

A major difference in A2SA methods is set between online and offline alignment. Online methods, often named “score-followers”, try to predict the time instant in which a new note is played and track the change without future information about the performance. Offline methods, instead, try to match time instants by exploiting the knowledge of the full performance. In this work, we will concentrate on offline A2SA.

Similarly to other alignment problems, offline A2SA can be addressed using dynamic programming approaches and, as such, most of the literature focuses on Dynamic Time Warping (DTW) based methods [2]. DTW is an algorithm which is able to find the minimum cost path in a fully connected graph where nodes are the elements of two sequences and branches are weighted according to a given distance function. Even though DTW is effective and versatile, it has a strong requirement: the two input sequences must be sorted with the same element

order. Formally, given any two pairs of corresponding elements (a', b') and (a'', b'') , then $a' \geq a'' \implies b' \geq b''$. This requisite is met by music representations at sample or frame-level, but it hinders the alignment of polyphonic music at the note-level because the sequence of note onsets and offsets in a performance is not always the same as in the score. As consequence, most DTW methods use a sequence of frames as input. Moreover, since DTW is based on a distance function, such methods focus on discovering the optimal function and feature space.

There is a limited number of works that have faced the problem of note-level alignment, mainly with the objective of music performance analysis. Indeed, it is known that subtle asynchronies are generated during a human performance: notes in the same chord are written in musical scores as events having the same onset – and possibly the same offset –, but music players always introduce asynchronies of less than 0.05 seconds among the timings of such notes [3]. Other discrepancies between score and performance note order are related to the phrasing and articulation practices; for instance, the *legato* articulation consists in a slight overlap between two successive notes, even if in the musical score they are notated with no overlap. These almost imperceptible timing effects are considered to be responsible of the incredibly various expressiveness of music performances and are consequently of crucial importance in music performance analysis studies [4]. Methods used for note-level alignment so far include HMM, DTW, NMF and blob recognition in spectrograms [3], [5]–[8]

The rise of Artificial Neural Networks in their Deep Learning (DL) paradigm has led several researchers to exploit DL models for feature learning tailored to DTW. Two methods are particularly noteworthy: one [9] employs Siamese Networks for learning features that can be used for some distance function in DTW; the second method relies on the improvements made in the field of AMT for converting the sequences to a common space — the space of the symbolic notation [10].

In this work, we elaborate on the exploitation of AMT DL-based models for achieving note-level alignment. We propose a method which benefits from HMM-based score-to-score alignment and AMT, showing a remarkable advancement against

the state-of-the-art. We design a systematic procedure to take advantage of large datasets, where aligned scores are unavailable. Last but not least, we perform a thorough comparison and extensive tests on multiple datasets. For reproducibility purposes, the implementation of the proposed method along with the present experiments is available online.¹

II. BASELINE METHOD

DTW requires as input a distance matrix representing every possible matching between sorted sequence elements. If N and M are the number of elements in the input sequences, the distance matrix will have size $N \times M$. DTW finds the shortest path from element $(1, 1)$ to (N, M) according to so-called *local* and *global* constraints. *Local* constraints list all possible moves among which the algorithm can choose during the computation of the path, while *global* constraints limit the computational complexity of the procedure (which in the unconstrained form is dominated by $O(M \times N)$ in both time and memory). As a consequence, DTW is highly expensive for long sequences: for instance, to align sample-to-sample two audio recordings lasting 10 minutes with sample rate 22050 Hz, DTW needs a distance matrix with 1.75×10^{14} elements, meaning 318 Terabytes using 16-bit floating point numbers.

Apart from the *global* constraints, various approximated alternatives for common local constraints have been proposed to relax the high complexity in time and memory, with *FastDTW* [11] being one of the most widely adopted solutions.

Interestingly, one of the most widespread methods for A2SA consists in converting all the data to the audio level (usually by synthesizing the music score) and subsequently extracting some audio-related features (see Figure 1Ⓐ). Notably, one method [12] uses the sum of two distance matrices computed with two different combinations of audio features and distance functions; the main objective is to consider both percussive and harmonic features of musical instrument acoustics. In this paper, we will refer to such method with the name SEBA².

III. THE PROPOSED ALIGNMENT METHODS

A. AMT-based frame-level alignment

AMT consists in the analysis of music audio recordings to discover semantically meaningful events, such as notes, instruments and chords. Two main methodologies for AMT exist, i.e. Non-negative Matrix Factorization (NMF) and Deep Learning (DL) (for a thorough review see [14]). During the last 4 years, DL has tremendously advanced the state-of-art of AMT, especially for piano music recordings [15], [16]. Due to the high variability of timbres, instrumental acoustics, playing practice, and difficulties in collecting data, multi-instrument AMT remains a hard challenge.

To our knowledge, the state-of-art of A2SA for piano music [10] is based on (1) AMT of recorded audio, and, (2) alignment of piano-roll representations of music. This approach can be seen as the opposite of classical DTW

¹<https://github.com/LIMUNIMI/MMSP2021-Audio2ScoreAlignment>

²Here and in the following sections, SEBA, EITA, TAFE and, EIFE refer to the first syllables of the researcher first name who worked at the corresponding method — i.e. SEBAstian [12], EITA [13], TAegyun [10] and FEderico (this paper first author)

methods since it converts data to the symbolic domain instead of the audio domain.

Piano-rolls are 2D boolean matrices with K rows and N columns in which the entry (k, n) is 1 if pitch k at time n is playing, and 0 otherwise. Usually, K is set to 128 so that it is directly related to the MIDI specifications.

In [10], an AMT system is used to infer a MIDI performance; from there, a piano-roll is constructed. Piano-rolls coming from the transcribed audio and from the score can then be aligned using FastDTW to create a mapping between columns (frames) in the score domain and columns in the audio domain. The mapping, so-called “warping path”, can be used to recompute the correct duration of the notes found in the score without relying on the AMT output, which is prone to errors in pitch identification [14].

Following the same line of thought, we used the new state-of-art piano AMT model [16] for the alignment, which by itself has a greater precision than the method previously used. The second improvement we made is the use of 3-valued piano-rolls, that is, we introduced a new value to represent the onset of a note bringing two advantages: (1) in the boolean piano-roll, repeated notes are not distinguishable if the onset is immediately after the offset of the previous note, and, (2) the introduction of a new value works as “anchor” for the DTW algorithm, which tries to find correspondences between the alternations of three values instead of only two. We also attempted to use the same approach for multi-instrument A2SA by using a state-of-art multi-instrument AMT model [17].

Here, we will refer to the specific method with the name TAFE. A schematic representation of the method is depicted in Figure 1Ⓑ.

B. AMT-based note-level alignment

The merit of the above method was to highlight that DL models for piano AMT are tremendously effective in identifying onsets; however, the accuracy with pitch identification is low, due to issues such as false octaves and fifths. Moreover, as we will show in the results, offset time identification is still an unresolved obstacle.

On the other side, the TAFE method relies on DTW algorithm for aligning score and audio at the frame-level. This not only is a high computationally demanding task, but also suffers from the DTW requirements; in other words, it cannot align transcribed notes to score notes because of the discrepancies between score note order and audio note order. As such, it fails in two important tasks:

- it cannot handle correctly the subtle asynchronies that a human performer introduces among onsets of notes in the same chord and that are fundamental for performance analysis [4];
- it cannot correctly align scores that differ from the recorded performance or from the transcribed one — e.g. has some missing/extra note(s).

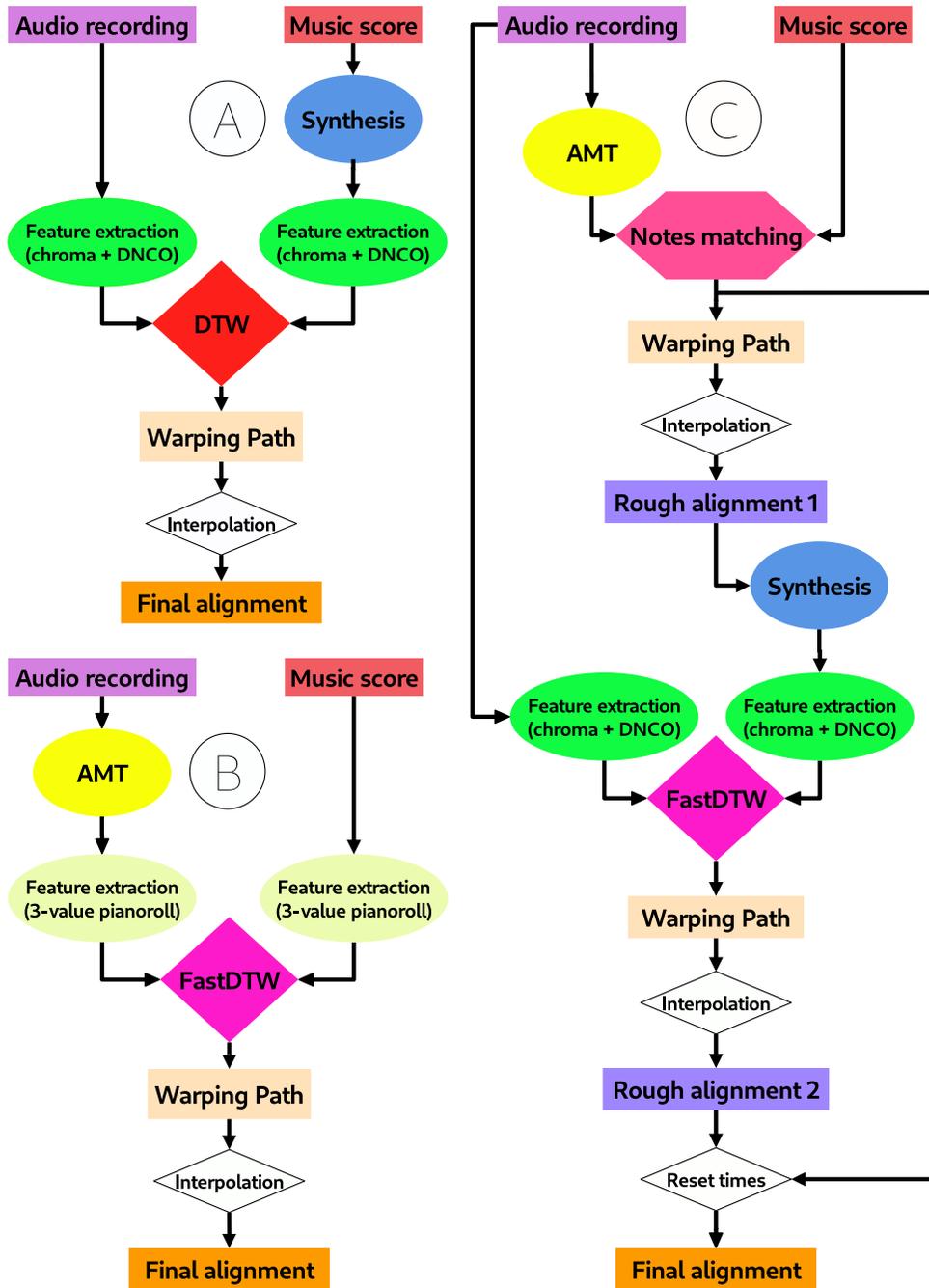


Figure 1. Flow chart of the three methods used here: (A) SEBA method; (B) TAFE method; (C) EIFE method

In the music alignment domain, a few studies have faced the problem of aligning scores and music performances which refer to the same music piece but differ in terms of presence/absence of a few notes — e.g. wrong performances, different score editions, etc. Such methods usually try to classify if a certain note in a score/performance is a *missing* note or an *extra* note compared to another score/performance. Commonly used approaches are DTW and HMM, with the latter being so far the best-performing approach [13].

To overcome the TAFE issues, we propose to use what we

here call *EITA* method [13]. *EITA* uses HMM to create a mapping between two sequences of notes in order to identify missing/extra notes and notes that have different pitches — e.g. wrong pitch inferred by the AMT.

However, after having identified extra notes in the performance/transcription, missing notes remain in the score. Here, we assume that such notes were actually played but not identified by the AMT. In this perspective, we build a warping path from the mapping between notes matched by *EITA* in score and AMT output; then, we use the warping path

to linearly interpolate the onsets and offsets times of the non-matched notes — i.e. notes in the score that are not present in the transcription according to EITA. To align such notes with even higher precision, we apply the standard SEBA method based on the synthesis of the score. Moreover, to reduce the computational cost, we use FastDTW instead of the classic version. Since we expect that the AMT output contains precise onsets, after SEBA processing, we set the EITA matched notes onsets using AMT output and keep SEBA alignment only for non-matched notes. The flow-chart of this method is shown in Figure 1©. In the next, this method is referred to as *EIFE*.

IV. THE EMPLOYED DATASETS

Unfortunately, there is not a great variety of datasets providing exact matches between score and midi performances. Thus, we used a systematic approach to generate misaligned sequences of notes as similar as possible to a musical score. The drawback of our method is that the resulting evaluation will not produce reliable values for real-world applications. However, it ensures that data does not contain manual annotation errors regarding matching notes. Moreover, here we are interested in the comparison of the considered approaches and leave the perceptual assessment of a performance on real-world score for future work.

In our previous work [18], we proposed a simple way for statistically modeling misalignments between scores and performances, and used such models to recreate similar misalignments for datasets not including scores, collecting them in framework called “ASMD”. Here, we improve upon it by using meaningful statistics and inference. This section will also work as scientific reference for the new version of ASMD.

The first improvement we made is the addition of the ASAP [19] dataset to enlarge the number of considered statistics. Second, we used the EITA method to select matching notes against which we compute statistics as well. Third, instead of modeling the misalignment of onsets and offsets, we have now recorded statistics about the onsets and the duration ratio between score and performance. Fourth, statistics are computed with models trained on the “stretched” scores, so that the training data consists of scores at the same average BPM as the performance; as such, the misaligned data consists of times at that average BPM.

More precisely, we create statistical models as follows:

- 1) we compute standardized onset misalignment and duration ratio for each note by subtracting the mean value for that piece and dividing by the standard deviation;
- 2) we collect two histograms, one for the standardized onset misalignments (X_{ons}) and one for the standardized duration ratios (X_{dur});
- 3) we collect each piece-wise mean and standard deviation in four histograms: two for the onset misalignment means and standard deviations (Y_{ons}^m, Y_{ons}^{std}), and two for duration ratio means and standard deviations (Y_{dur}^m, Y_{dur}^{std})

To infer a new misaligned onset or duration, we choose a standardized value for each note from histograms X_{ons} and X_{dur} , and a mean and a standard deviation for each

piece, using the corresponding histograms $Y_{ons}^m, Y_{ons}^{std}, Y_{dur}^m, Y_{dur}^{std}$; with these data, we compute a non-standardized onset misalignment and duration ratio for each note. These two latter values can be used in reference to the ground-truth performance to compute the misaligned timing values.

We actually tested two methods for choosing the standardized value: an HMM with Gaussian mixture emissions (GMM-HMM) and the above-described histogram-based sampling. We hand-tuned the HMMs finding an optimum in 20 states and 30 mixture components for onsets and 2 states and 3 components for duration models. We then compared GMM-HMM and histogram models on the notes matched by the EITA method. During this evaluation, we used the scores provided by ASMD for a total of 875 scores, namely “Vienna Corpus” [20], “Traditional Flute” [21], “MusicNet” [22], “Bach10” [23] and “asap” [19] group from “Maestro” [24] dataset. We divided the data into train and test sets with 70-30 proportion, resulting in 641 pieces for training and 234 for testing. As evaluation measure, we used the L1 macro-average error between matching note onsets and offsets in music score and performance. However, due to EITA’s high computational cost, we removed the scores for which EITA terminates after 20 seconds. This resulted in a total of 347 songs for training and 143 songs for testing — $\sim 54\%$ and $\sim 61\%$ of the corresponding splits. Table ?? shows the results.

Misaligned data are finally created, using the histogram-based method for every dataset provided by ASMD by collecting the histograms corresponding to all 875 scores — 481 considering songs where EITA method took less than 20 sec. Thus, we set up a corpus of 1787 music recordings with misaligned and aligned MIDI data.

Artificially misaligned data is more similar to a different performance than to a symbolic score; however, for most of MIR applications, such misaligned data is enough to cover both training and evaluation needs. To achieve an even more accurate evaluation, in this work we also applied a single-linkage clustering to the onsets of each misaligned score. We stopped the agglomerative procedure when a certain minimum distance t among clusters was reached. We have randomly chosen such threshold in $[0.03, 0.07]$ seconds, representing broad interval around 0.05 seconds that is assumed as upper-bound of usual chord asynchronies [3]. Subsequently, we set the onsets of the notes in each cluster equal to the average onset time of that cluster so that the final misaligned note sequence contains chords made by notes having the same onset. This is a crucial difference between scores and performance data, in which chords are played with light asynchronies between same-onset notes.

In the updated version of ASMD, we provide randomly generated missing and extra notes as well. To this end, we chose the number n of notes to be tagged as “missing” or “extra” as a random variable with uniform distribution in $(0.1 \times L, 0.5 \times L)$, where L is the number of notes in the music piece. Then, we picked random contiguous sequences of notes until the total number n was met and we labeled each

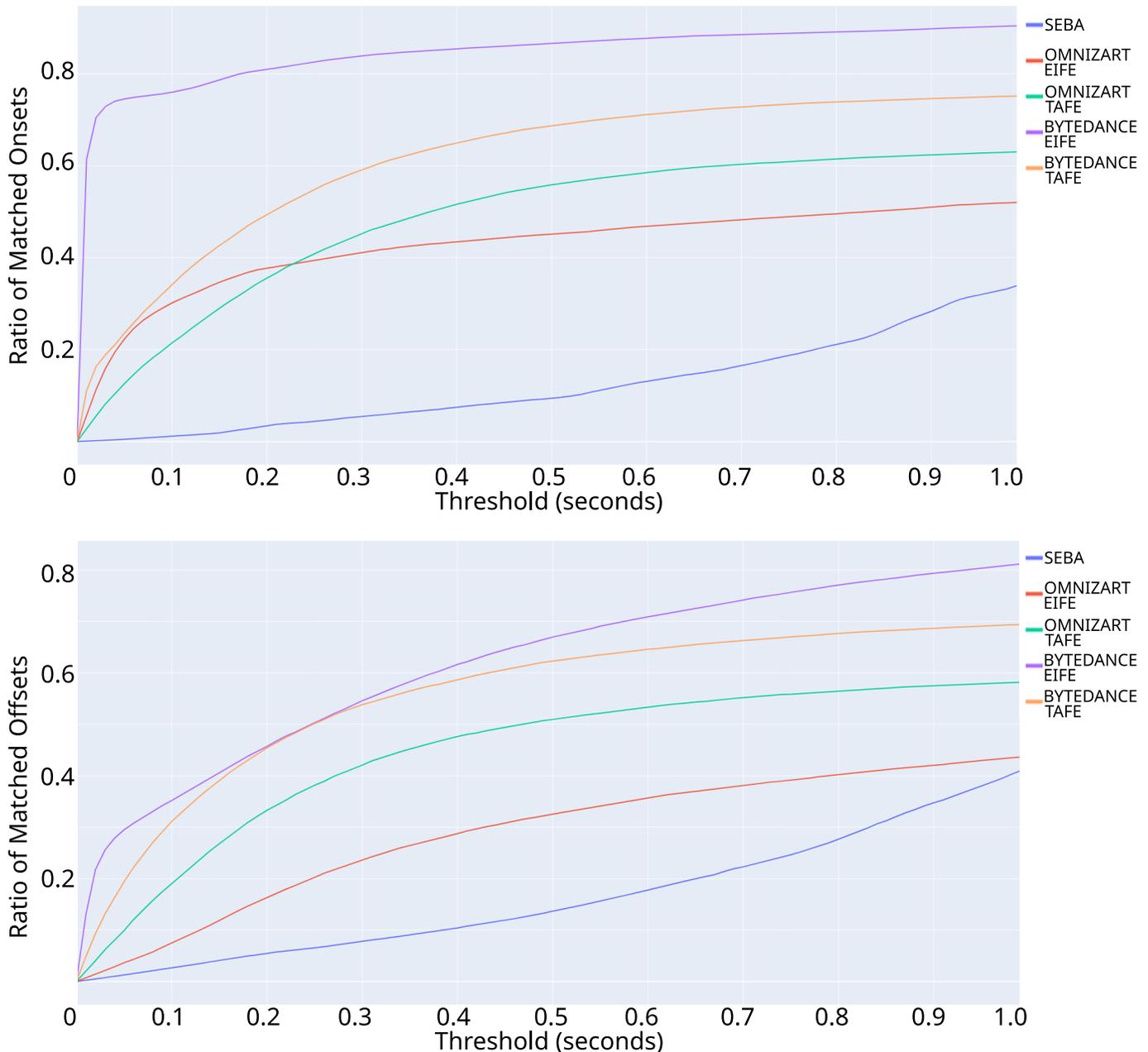


Figure 2. Evaluation on piano-solo music (SMD dataset) without missing/extra note. Curves are the ratio macro-averaged curves of ratios between the number of matched notes at a given threshold and the total number of notes.

of the chosen region as “missing” or “extra” according to two random variables p_1 and p_2 defined by a uniform distribution in $(0.25, 0.75)$ and $p_2 = 1 - p_1$.

V. EXPERIMENTAL SET-UP

We conducted four experiments to cover every aspect of the problem space as generated by the combination of two different conditions. Namely, we observed how alignment methods change in case (1) missing/extra notes between the score and the performance are introduced, and (2) instruments other than piano are present. To ensure a fair comparison of

AMT-based A2SA methods, we used two state-of-art models, namely one trained on Piano solo music [16] (BYTEDANCE) and one trained on ensemble music [17] (OMNIZART).

We used the ASMD Python API to retrieve missing and extra notes computed as explained in section IV. To simulate notes unavailable in the score, we removed the “extra” notes from the artificially misaligned score, while to simulate notes not played in the recording — “missing” —, we generated ad-hoc notes using the same procedure and removed them from the transcribed performance. However, since the SEBA method

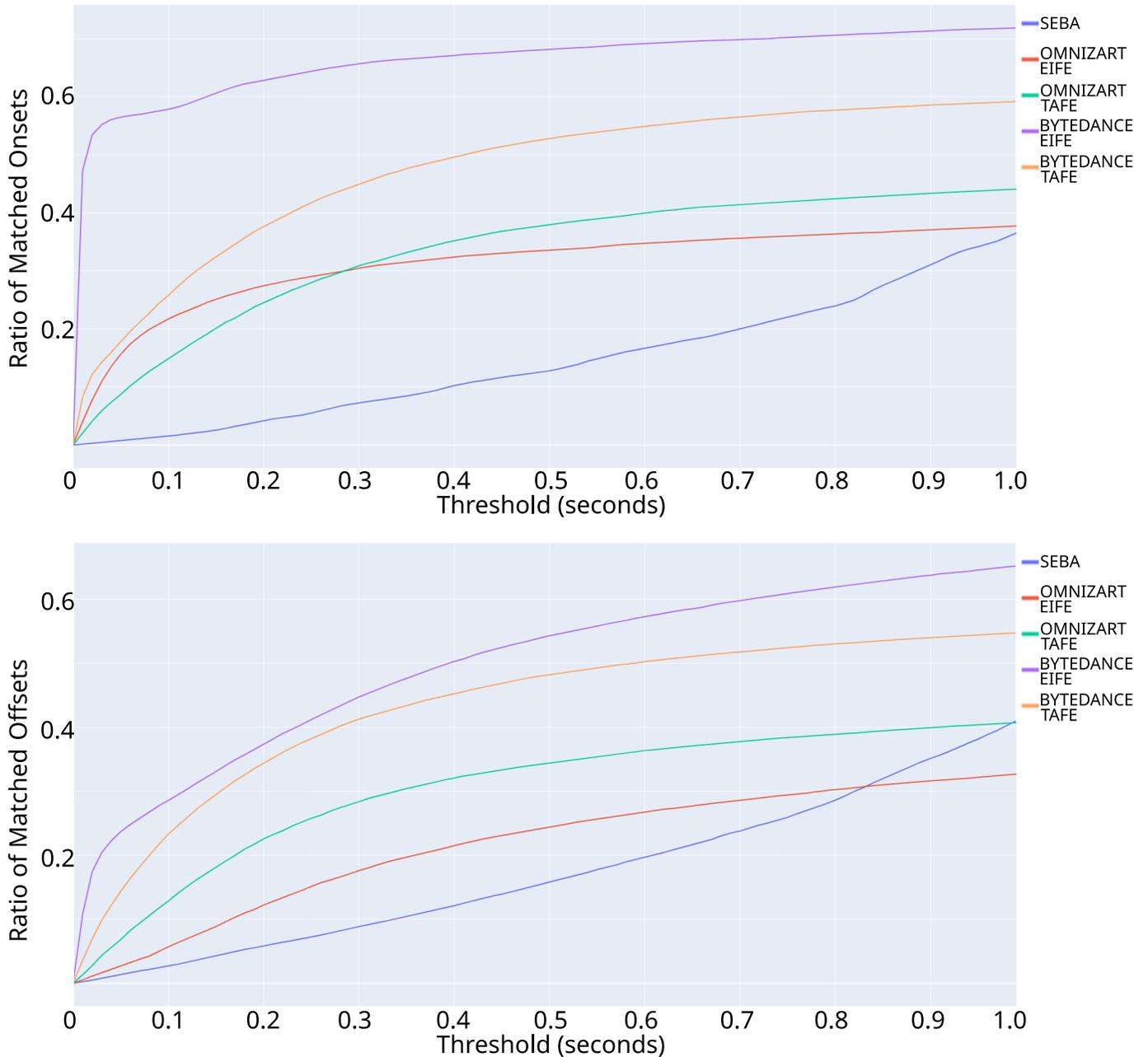


Figure 3. Evaluation on piano-solo music (SMD dataset) with missing/extra note. Curves are the ratio macro-averaged curves of ratios between the number of matched notes at a given threshold and the total number of notes.

does not rely on AMT, it is tested without extra notes. Note that even though we remove notes in the input data, we still have them in the ground-truth, allowing to correctly assess all inferred timing.

We also used the ASMD Python API to select the proper datasets for our experiments. To avoid over-fitting during the evaluation stage, we did not use the Maestro [24] and MusicNet [22] datasets because the AMT models were trained on them. Instead, we used the “Saarland Music Dataset” [25] for evaluating piano A2SA. It consists of 50 piano audio

recordings along with the associated MIDI performances, recorded with high-quality piano equipped with MIDI transducers. As regards to multi-instrument music, we relied on another well known dataset: the “Bach10” [23] dataset, which includes 10 different Bach chorales synthesized with virtual chamber instruments. Even though Bach10 dataset provides non-aligned scores, we used our artificially misaligned data to obtain results comparable with the other datasets.

To reduce the computational cost, we constrained each method inside 32 GB of RAM and 600s. Whenever a method

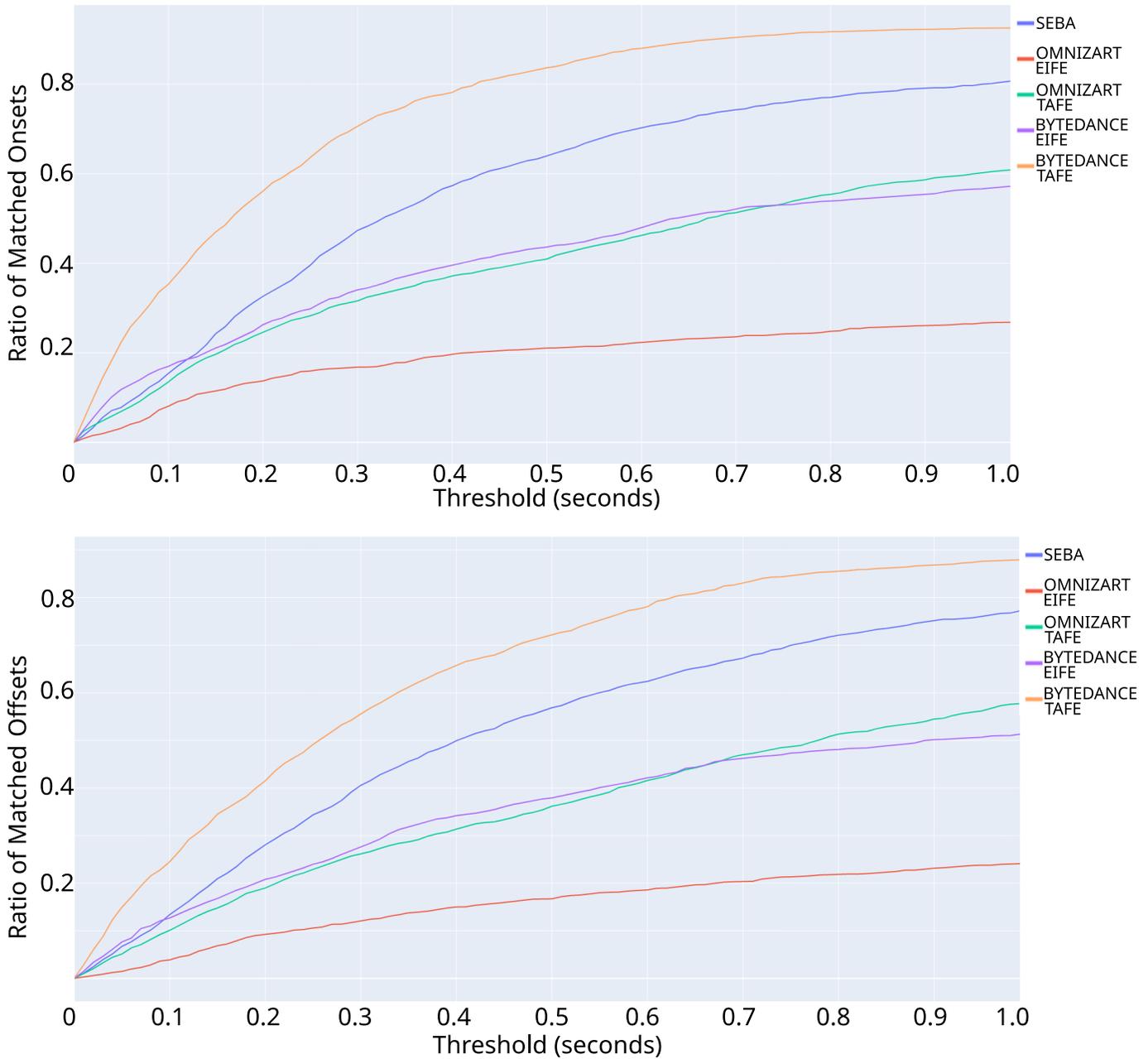


Figure 4. Evaluation on multi-instrument music (Bach10 dataset) without missing/extra note. Curves are the ratio macro-averaged curves of ratios between the number of matched notes at a given threshold and the total number of notes.

failed for an out-of-ram/out-of-time error, the specific piece was removed from the evaluation. In doing so, we also get a rough reliability estimation of the various approaches here tested. Hence, due to the high resources required by EITA, the SMD dataset size is reduced to 26 music pieces when testing without missing/extra notes and 31 music pieces when considering them.

To ease alignment, we preprocessed both score and audio by stretching the note timings so that the score duration was the same as the trimmed audio. This operation corresponds to

enforcing in the music score the performance average BPM.

We tuned the TAFE method by using the 5% of the available pieces sampled with a uniform distribution from the entire ASMD. We ran the TAFE method to find the best parameters for aligning the misaligned data to the ground-truth performance, after having removed missing and extra notes. We adopted a Bayesian Optimization approach with an Extra Trees surrogate model, Expected Improvement acquisition function, and exploitation-exploration factor set to 0.01. We used 180 calls and let the space of parameters being defined

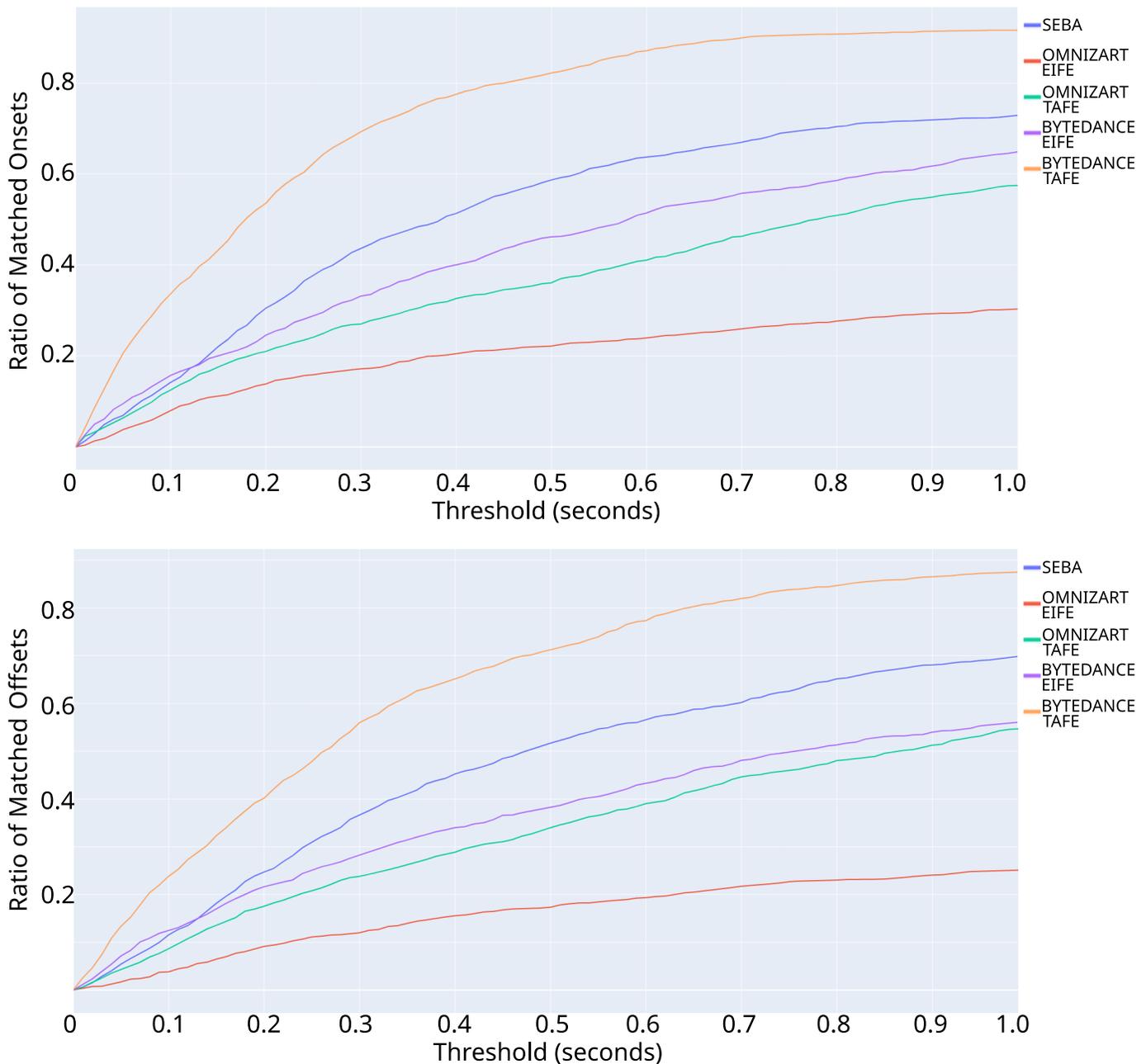


Figure 5. Evaluation on multi-instrument music (Bach10 dataset) with missing/extra plots) and with missing/extra note. Curves are the ratio macro-averaged curves of ratios between the number of matched notes at a given threshold and the total number of notes.

by 7 different distance functions and the *FastDTW* radius in [1, 200]. We found *cosine* distance and radius 178 as optimum parameters. We then used the same radius size for *FastDTW* in the EIFE method, while using the distance defined by SEBA.

For synthesizing MIDI files in the SEBA and EIFE methods, we employed the freely available MuseScore SoundFont³. As evaluation measure, we observed the ratio of matched onsets and offsets under several different thresholds in each music piece; we then averaged the obtained curves to get a macro-

³MuseScore 2.2 SF2 version: <https://musescore.org/en/handbook/3/soundfonts-and-sfz-files>

curve representing the overall performance of each method.

VI. EXPERIMENTAL RESULTS

With regard to piano-solo music, methods based on BYTEDANCE model are outperforming the rest – see Fig. 2 and 3. EIFE manages to exploit the good onset prediction of BYTEDANCE better than TAFE. However, the performance decreases when considering offsets due to the poor inference of onset positions of generic AMT models.

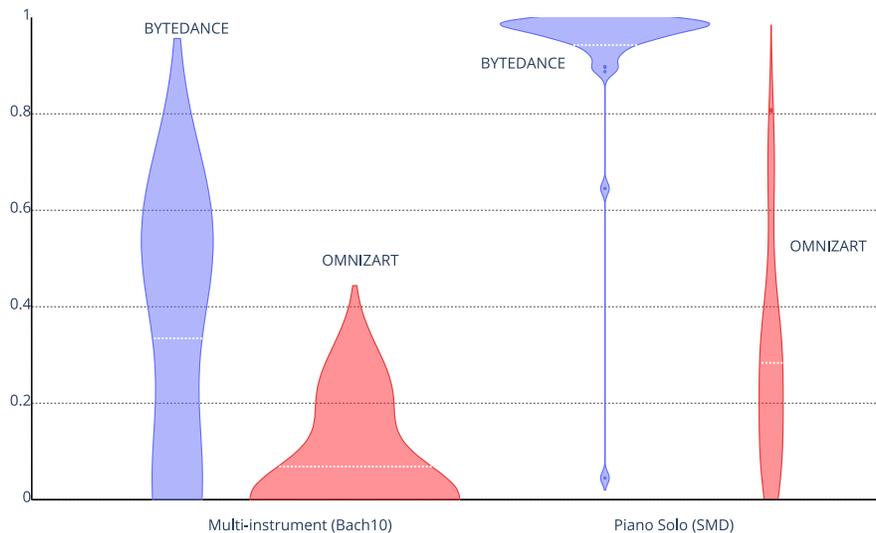


Figure 6. Onsets F1-measure for the two AMT models

OMNIZART does not perform well, as shown in Figure 6, which is expected as it is trained on multi-instrument music. Finally, SEBA method seems more robust in offset prediction and maintains a similar score for both offsets and onsets.

Furthermore, we observe that in non-piano music TAFE method is the best-performing one – see Fig. 4 and 5. Indeed, the good performance of AMT models, makes EIFE and TAFE approaches still reliable, especially for little thresholds – i.e. < 0.1 seconds. Moreover, even though we were expecting a useful input from OMNIZART multi-instrument model, we observed better performance with BYTEDANCE; this could be due to the low generalization ability of OMNIZART — see Fig. 6.

Every considered model suffers in case of missing notes, while retaining a similar curve shape and proportions. As such, we think that the most promising option for increasing the performance of A2SA with missing and extra notes is to increase the overall alignment accuracy.

VII. CONCLUSION

We designed a methodology to compare various alignment systems and proposed two methods for frame and note-level alignment. After extensive experiments, it was shown that the proposed method for note-level alignment brings notable advancement to the state-of-art thanks to the AMT models. Moreover, even if AMT is still not reliable for non-piano solo music, the top-performing approach among those tested is still based on the AMT model trained on piano-solo music. Our intuition is that the size of the training dataset is extremely relevant for the good performance of the model.

Our future studies will focus on the quality of the alignment with perceptual measures to confirm the results obtained through the present assessment.

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