BOTTLENECKS AND SOLUTIONS FOR AUDIO TO SCORE ALIGNMENT RESEARCH

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ABSTRACT

Although audio to score alignment is a classic Music Information Retrieval problem, it has not been defined uniquely with the scope of musical scenarios representing its core. The absence of a unified vision makes it difficult to pinpoint its state-of-the-art and determine directions for improvement. To get past this bottleneck, it is necessary to consolidate datasets and evaluation methodologies to allow comprehensive benchmarking. In our review of prior work, we demonstrate the extent of variation in problem scope, datasets, and evaluation practices across audio to score alignment research. To circumvent the high cost of creating large-scale datasets with various instruments, styles, performance conditions, and musician proficiency levels from scratch, the research community could generate ground truth approximations from non-audio to score alignment datasets which include a temporal mapping between a music score and its corresponding audio. We show a methodology for adapting the Aligned Scores and Performances dataset, created originally for beat tracking and music transcription. We filter the dataset semi-automatically by applying a set of Dynamic Time Warping based Audio to Score Alignment methods using out-of-the-box Chroma and Constant-Q Transform extraction algorithms, suitable for the characteristics of the piano performances of the dataset. We use the results to discuss the limitations of the generated ground truths and data adaptation method. While the adapted dataset does not provide the necessary diversity for solving the initial problem, we conclude with ideas for expansion, and identify future directions for curating more comprehensive datasets through data adaptation, or synthesis.

1. INTRODUCTION

Audio to Score Alignment (ASA) is a longstanding Music Information Retrieval (MIR) problem which aims to synchronize a musical score with its audio performance to map between each instant in a recording and a position in the score. When conducted in an online (real-time) fashion, it is often referred to as Score Following, in which the music stream to be aligned (MIDI or audio) must be processed as it is received. When conducted in an offline (non-realtime) fashion, it is often referred to as simply ASA, in which the music stream can be processed after it is fully received. This allows the advantage of looking forward and backward into the input stream [1] before returning the alignment result of each fragment.

Often, ASA problems are solved with methods previously used in audio to audio alignment problems, where the task becomes aligning the performance audio to a synthesized version of the music score [2–5]. In such methods, the alignment is conducted by comparing the same features computed from the synthesized score and the performance audio. Nevertheless, alignment is sometimes performed in the symbolic modality by first transcribing the audio then aligning it with the MIDI score [6–8], and recently alignments were conducted between audio and sheet music images directly through devising intermediate representations allowing both modalities to be compared [9, 10]. The most prevalent approaches through which ASA has been addressed are Dynamic Time Warping (DTW) [1, 2, 4, 7], and Hidden Markov Models (HMM) [6, 8, 11–13], with the former being a popular choice for alignments conducted audio to audio.

ASA research usually begins by defining the scope of the problem and accordingly proposing a system. The characteristics of the target music (i.e. the instruments, recording conditions, musician proficiency, and performance conventions) affect the scope, so ideally, researchers should find annotated data representative of such music. Very often this is not possible, as the datasets available are small and do not cover a variety of musical scenarios. This complicates benchmarking and evaluation because as a result, researchers tend to vary in their choice of data, which we believe hinders the movement of ASA research beyond the typical use-cases. Researchers have sometimes relied on synthetic data as a low-cost and practical way to generate relevant alignment data with properties not found in other datasets. This was done to curate evaluation data [2, 10], to create ground truth for HMM training [8], or to induce temporal mismatches and file corruptions [14].

In our review of prior research (Section 2), we cover several variants of the family of ASA methods comprised of audio representation plus DTW, thus showing how each

alignment scenario is often addressed in an isolated manner. We believe it would be useful to unify such scenarios under one vision, allowing us to expand the definition of ASA and set clear benchmarking and evaluation strategies representing each of the scenarios formerly addressed in isolation. This would enable researchers to compare between systems and identify directions for improvement, but cannot be achieved without enough varied data to support the development and evaluation of such ASA systems. Since creating datasets is costly, especially at a larger scale, we believe that first we must exhaust the ability to leverage datasets created for tasks other than ASA whenever possible and then synthesize more data as a compliment. This paper demonstrates an example by reusing the Aligned Scores and Performances (ASAP) dataset [15] to generate approximated ground truths for ASA, since it provides 520 classical solo piano performances (audio and MIDI) beat aligned with their symbolic MIDI scores. We thoroughly describe this process in Section 3. In Section 4, we describe the methodology for validating the generated data and discuss their potential problems and aptness for ASA, which involves the application of several DTW-based systems to conduct offline ASA (which, from now onward, we refer to as just ASA). In Section 5, we explain how we use the obtained results to filter data for problems and highlight some limitations of our methods. Although the adapted dataset alone is not a solution to the aforementioned bottleneck, especially since it does not possess the necessary diversity to cover a variety of ASA scenarios, we conclude in Section 6 with ideas for expansion, to support the creation of a unified benchmark and the development of new ideas for ASA research.

2. RELATED WORK

Although this paper concerns ASA, contextualizing its developments requires references to Score Following, which has received more attention over the years. Dixon [16] and Arzt et al. [17] use online versions of DTW suitable for the real-time nature of Score Following. In later years we find the work of Duan et al. [11] and Nakamura et al. [8], both of which propose HMM systems for the same task. Henkel [27] et al. introduce a different paradigm for Score Following, where audio is aligned to score images end-to-end using reinforcement learning. For ASA, recent DTW-based approaches include [2–4, 7]. Table 1 summarizes the datasets used in some of the works above, highlighting the variation among researchers in their choices. The same datasets can be used for the training and evaluation of Score Following and ASA. Although currently inactive, there was a Music Information Retrieval Exchange (MIREX) [1] entry for Score Following which can be used for benchmarking, and it includes several of the datasets shown in Table 1. But the MIREX datasets are small and do not represent a wide variety of scenarios. Moreover, there is no MIREX challenge for ASA.

[1] https://www.music-ir.org/mirex/wiki/2021:Real-time_Audio_to_Score_Alignment_(a.k.a_Score_Following)

2.1 DTW-based Methods

Given two time series $U = u_1, ..., u_n$ and $V = v_1, ..., v_m$, the goal of DTW is to find a minimum cost path $W = w_1, ..., w_n$ where every element in W is an ordered pair (i, j) indicating that the elements u_i and v_j have been aligned. Over the years, researchers have introduced different variants of DTW depending on the specifics of their target problem. For example, FastDTW [28] is a popular, more efficient variant of the algorithm. Moreover, there is the Memory Restricted Multi-Scale DTW (mrmsDTW) [29], which caps the memory requirements of the DTW algorithms for large audio files, for which a python implementation was recently made available in [30]. To the best of our knowledge, there has not been a thorough comparison of all the DTW methods for ASA, although Agrawal et al. [3] compare the results of their proposed system with JumpDTW [31], NWTW [32], and MATCH [16] based on their ability to handle structural variations in the audio compared to the score it is to be aligned with. Moreover, Shan and Tsai [10] compare the alignment results of their proposed Hierarchical DTW with those of JumpDTW and subsequenceDTW [33], where they use intermediate representations [9, 10] allowing the computation of distances between audio and score images. In addition to the variants described above, it is important to note that even within single DTW variant, performance can vary based on system choices such as normalization, the chosen time scales of the feature sequences, and the use of penalties and path constraints [14].

2.2 Audio to Score Alignment Features

Classic features used for ASA are Semitone Energy based features such as Constant-Q Transforms (CQTs) and Pitch Class Profile based features, more commonly known as Chroma representations. In a parameter search by Raffel and Ellis [14] the best alignments were attained with a log-magnitude based CQT. Ewert et al. [21] develop the DLNCO representation, which balances the tradeoff between chroma robustness and time resolution. More recent approaches explore the realm of using learned features [2, 9], or learned distance measures [3]. In [2], the authors explore the use of transposition invariant features learned in an unsupervised way on ASA, thus diverging from pitch based features. They conduct their experiments on piano and orchestral data, and report a result improvement in both. However, in [4], the authors claim that such pitch invariant features underperform in conditions of large tempo variations. So, in their approach, they use features learnt directly from music at the frame level by using a twin Siamese network each containing a Convolutional Neural Network (CNN), and in addition explore the use of salience representations proposed by [34]. In recent work, Automatic Music Transcription (AMT) has been used to first transcribe the target audio before aligning it to the score notes [6, 7].

Source	Datasets	Instruments
[16], [17], [2]	The Vienna 4x22 Piano Corpus [18]	Piano
[11], [8], [1]	Bach10 Dataset [19]	Violin, Clarinet, Tenor Sax, Bassoon
[8], [20], [21]	RWC Database [22]	Polyphonic Multi Instrument
[8]	28 mins of Amateur practice	Clarinet
[7], [2], [4]	MUS Subset of MAPS Database [23]	Piano
[2]	Mozart Sonatas [24], Rachnmaninoff Prelude Op. 23 No. 5 [25]	Piano
[3]	Synthetic dataset based on MSMD [26] and private data	Piano

Table 1: Datasets used across audio to score alignment research

2.3 Evaluation

Cont et al. [35] formalize the quantitative performance metrics of Score Following, forming the basis of the MIREX challenge for the task. Only a subset of their metrics are relevant for ASA since there is no expectation of real-time execution. They define the error as $\mathrm{e}_i = \mathrm{t}_i^e - \mathrm{t}_i^r$, where t_i^e is the estimated time in the score for event i, and t_i^r is the actual time of event i in the reference. The alignment corresponding to an event is considered misaligned only if it exceeds a time threshold θ_e, which we call the misalignment threshold, noting that events could be notes or other time references (See Thickstun et al. [5] for a discussion on the difference between temporal and note based metrics). Accordingly, the following metrics are proposed: the Standard Deviation of the e_i of non misaligned events, the Misalignment Rate (MR) (percentage of events with $|\mathrm{e}_i| \geq \theta_e$, and the Average Imprecision (average absolute error of non misaligned events). For system-wide metrics, they propose the Piece-wise Precision Rate (PPR) over a related subset of scores, calculated as the percentage of non misaligned notes, and the overall precision rate (OPR) calculated similarly to the PPR but over the whole database instead. In practice, researchers slightly vary in their evaluation metrics. They mostly capture the Alignment Rate (AR), according to a set of θ_e usually between 50 ms to 300 ms, sometimes using it as an analogue for PPR.

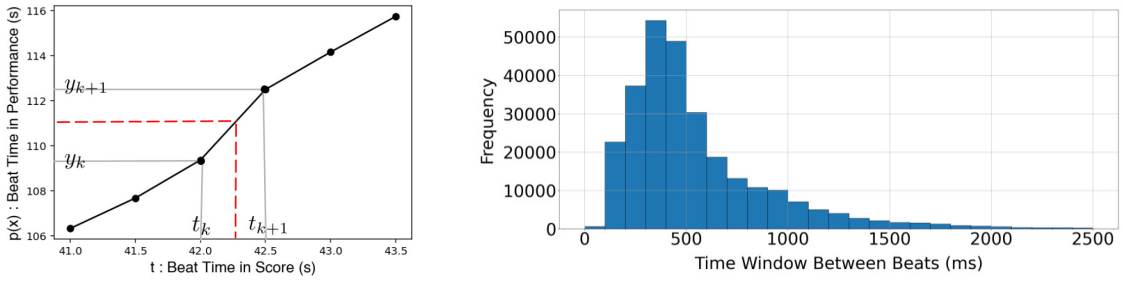
Another commonly used metric is the Average Alignment Error (AAE) defined in [11], which is the average absolute error for each audio frame, distinguishing it from Average Imprecision, which is calculated for non misaligned events only. AAE can be reported in milliseconds or in beats, depending on the end goal in mind [11]. Without using AAE explicitly, Jiang et al. [12] calculate the proportion of misaligned frames by units expressed in beats per measure. A metric with the same essence as AAE is used in [2], where they additionally report the median, 1st, and 3rd quartiles of this difference. In addition to the aforementioned metrics, some authors conduct an extent of qualitative analysis in order to make useful insights about their systems with respect to the scope in which the problem is defined. This has been done to test robustness to performance mistakes [8], for error prone scores [20], to understand the impact of polyphony [11, 19, 20], or the presence of percussion [20], tempo variations [2, 19], or skips [8, 10, 12].

3. GENERATING GROUND TRUTHS FROM ASAP

Reusing the ASAP dataset [15] is a reasonable step to expand the data available for ASA research. First, it offers beat-level aligned audio and music scores for 520 piano performances over various composers and styles. Some pieces are performed by several pianists, and we observe temporal variation in the different interpretations of one piece. In addition, we believe that these alignments could help us create more data by introducing structural variations within a single piece or across different pieces, depending on the scope of the alignment problem we want to consider, which we highlight in Section 6 along with other augmentation ideas to cover a variety of ASA problems. The rest of this section describes how we create ASA ground truth approximations from the beat annotations of ASAP, along with the potential implications and pitfalls of doing so.

3.1 From beat annotations to full alignments

We use the aligned beat annotations of the performance MIDIs and score MIDIs provided by the ASAP dataset to obtain approximated ground truth alignments (performance-aligned scores) for score-performance pairs at a low cost through Piecewise Linear interpolation. Every beat in the score is mapped to a specific time in the performance, yielding an alignment function with which we map each onset time of the MIDI score file to a time in the performance audio. A schematic is shown in Fig 1a. This approach does not give an alignment with a note-to-note resolution. However, we believe it is still usable for evaluating methods outputting temporal alignments that inherently do not provide this level of precision, such as warping paths obtained by DTW alignments, or for training audio to score alignment systems with methods that tolerate weakness in the reference alignments. To understand the extent of the error, we investigate the temporal resolution of the beat annotations (the time distances between consecutive beats) over the chosen subset of the ASAP dataset. As shown in Fig. 1b), the majority of such distances fall between 200 and 1100 ms. Clearly, the faster the tempo of the performance, the less spaced in time consecutive beat annotations are. For context, the distance between two quarter notes in a 120 BPM score is 500 ms.



(a) (b)

Figure 1: (a) Illustrative snippet of the ground truth alignment from the GuoE01M Prelude BMV883 performance. (b) Distributions of the time in between consecutive beats for all files in our chosen subset of the ASAP dataset.

3.2 Error Limits

To understand the limits of the error between the ideal ground truth and the approximated ground truth (ϵ_{gt}) we resort to the definition of Piecewise Linear Interpolation, shown as follows:

$$p(x) = y_k + \frac{y_{k+1} - y_k}{t_{k+1} - t_k}(x - t_k), \text{for } x \in [t_k, t_{k+1}], \quad (1)$$

where x is the time point in the score for which we need to approximate a corresponding time in the performance, t are reference points in the score annotation (in the context of the ASAP dataset, these would be beat times), and y are time reference points in the corresponding performance annotation. This is demonstrated in Fig 1a. In reality, the path between (t_k, y_k) and (t_{k+1}, y_{k+1}) can take any shape as long as it is monotonic (an assumption we can make due to our data). Taking the extreme unrealistic case where $p(x)$ takes on either y_{k+1} or y_k, the ground truth approximation error ϵ_{gt} must be:

$$\epsilon_{gt} = \max(|p(x) - y_k|, |p(x) - y_{k+1}|), x \in [t_k, t_{k+1}]. \quad (2)$$

If x falls on the midpoint of t_k and t_{k+1}, then ϵ_{gt} cannot surpass $\frac{1}{2}(y_k, y_{k+1})$, meaning that even for beats highly spaced apart (1000 ms) the error would be 500ms. Moreover, we would argue that in practice the error would be even less, because of the musical flow. However, the potential of error is a limitation due to which a decision needs to be made on which files to discard. Although not much detail is provided, it is worth noting that Duan and Pardo [19] mention their use of beat annotations to create ground truths, meaning that this process has been accepted in past studies, although it was not discussed elaborately.

4. DATA VALIDATION

The approximated ground truths of our interpolated dataset can have two problem sources: 1) misalignments within the generated annotations due to the low resolution of the score or performance beat annotations (as discussed in Section 3.2), and 2) annotation problems from the original dataset. These need investigation before using the dataset, whether for evaluation or training. We create test audio for every generated annotation file, where the left channel includes the performance-aligned score (the approximated ground truth) and the performance audio on the right channel. Therefore, by listening to all such test audios, it is possible to get a sense of both problems above. However, due to the size of the ASAP subset we reuse, it was not feasible to listen to all the hours of audio. So, we conduct a typical ASA experiment to help give clues as to which files most likely could contain errors and therefore would need to be examined. The rationale of this selective investigation is that files with low misalignment rates have passed an implicit check. Suppose a music score has been aligned with the performance audio using a process different from that with which the ASAP dataset was created. If this result matched the interpolated ground truth, then it is improbable that there is a problem with its beat alignment. Otherwise, there would have been a difference between the alignment result and the ground truth. Moreover, to determine whether we should discard files with large time windows between beats, we listened to a selection of the files with intra-beat annotation time differences of $\approx$ 1500 ms. They sounded correct for several performances, especially for files performed without much temporal variation (such as the Fugue BMV 874 and Prelude BMV 863 performances by Kurz and Shyc, respectively). We decided to keep all such files and only discard them based on the results of the alignment experiment.

4.1 Alignment Experiment

To align a performance and its symbolic score, we sonify the latter using the fluidsynth [2] and conduct DTW-based audio to audio alignment between the synthesized score and the audio performance. We use the librosa [3] [36] DTW implementation, and the distance matrix is computed by applying the Euclidean distance between the feature vectors.

[2] https://www.fluidsynth.org/
[3] https://librosa.org/doc/main/generated/librosa.sequence.dtw.html

4.1.1 Features

We use the CQT and 5 of the chroma representations compared in [37], which are: a Connectionist Temporal Classification loss trained chroma extractor (CTC-Chroma) explained in [38]; Non Negative Least Squares (NNLS) chroma [39]; the Harmonic Pitch Class Profile (HPCP) [40]; the Deep Chroma Extractor (DCE) [41]; and the classic Chroma algorithm implemented in [36]. All these algorithms are easily usable out of the box, and we believe are appropriate to use for piano data. Details on the parameters of each algorithm can be found in the accompanying repository [4] .

4.1.2 Quantitative Results

Since our focus is on filtering files, we report file-based metrics rather than global metrics for each DTW system. Therefore we omit reporting the Overall Alignment Rate (OAR), the system-wide AR considering the notes over all scores (or all temporal units). We use the Average Absolute Error (AAE) for each file in the dataset, shown in the box and whisker plots of Fig. 2 indicating the 1st, median, and 3rd quartiles per each DTW system. We also maintain the AR and the Absolute Errors (AE) for each file. We use these metrics to identify 1) suspects of files with beat alignments that are not highly accurate, which should be discarded, or 2) files for which our ground truth approximation approach yielded a high ϵ_{gt} for annotations within the beats. Those might still be relevant to keep depending on how they will be used. We explain this process in Section 5. However, we must be careful before discarding any files based on performance metrics to avoid cherry-picking only the files for which our ASA systems perform well. This is why we use a variety of audio representations, knowing that some might not be perfectly suitable for audio to score alignment, and no files are discarded unless they performed badly using all DTW systems.

5. RESULT INFORMED DATA FILTERING

Although not the core of our work, we observe that the DTW systems using CQT, HPCP, and Chroma perform better than the rest. This can be seen from Fig. 2 from the lower AAE time windows and the compactness of their distribution, and although we do not show a plot for OAR, these three systems reach very high OARs within the 0 - 60ms error thresholds. In fairness, the CQT system with the best performance is the gold standard obtained by the Bayesian Optimization of [14], suggesting that before making any absolute statements about the superiority of any of the DTW systems, their parameters should be optimized similarly. Besides, comparing such systems or finding the best performing ASA system is not the goal of this paper, and as we argue earlier, ASA is still missing a clear methodology and varied data with which qualitative evaluation can be conducted. This hinders the ability to compare between systems. The ASA results shown are just a means to an end, which is validating the interpolated dataset as described in Section 4, and helping us pinpoint problems and the potential need to filter some files, as shown in Sections 5.1 and 5.2.

5.1 AAE based investigation

Without discarding any generated alignments yet, we start by observing the box-and-whisker plots showing the AAE for all the 520 usable files of ASAP evaluated over the interpolated ground truth references, shown in Fig. 2a. We observe files with very high AAEs, most likely signalling either an annotation or calculation error since they represent alignment error values that are unreasonably high. Drawing a threshold at an AAE of 6000 ms (the red line) allows us to filter those clear outliers, thus arriving at the second plot shown in Fig. 2b. Then, we decide to conduct further filtering at a threshold at an AAE of 1000, arriving at Fig. 2c. We can keep setting lower AAE threshold and filtering more files for as long as needed. But the idea is to listen to the test audio described in Section 4 and to observe the annotations before discarding a file, to make sure that we are not filtering good ground truth approximations.

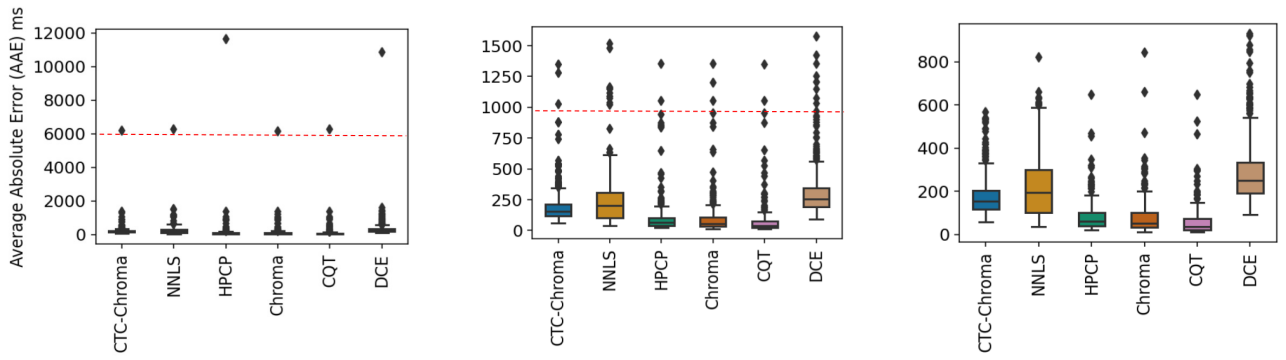
5.2 AR based investigation

Files for which the AR is very low (approx 10%) at θ_e thresholds between 50 and 100 ms signal the need for further investigation. In Section 4 we referred to two problems: 1) the possibility of a temporal offset in the ground truth annotation of the original ASAP dataset, and 2) the possibility of the generated labels being misaligned due to large temporal distances between consecutive beat annotations. If for a file we observe that the 1st quartile, median, and 3rd quartiles do not progress ascendingly as expected a (eg. if the 3 values are nearly equal) and are higher than usual, then this could indicate a temporal offset in the ground truth annotation. Through the listening verification we describe in Section 3, we found that this is the case for at least 6 score-performance pairs. As for the latter problem, if we find that if a file has a low AR, and the 1st, median, and 3rd quartiles of the AE move ascendingly (as expected), then it is a suspect of the low resolution problem. Examples of such files are the 2 performances of Prelude BMV 846, and Prelude BMV 867, where it is clear upon listening that there is a high temporal variation at a phrase level. When coupled with an insufficient resolution of the beat annotations, this would certainly cause ground truth errors. Files of the first category should always be discarded, but files of the second category could be kept, depending on the extent of the misalignment introduced through the ground truth approximation, and the tolerance allowable by the expected use.

5.3 Limitations

A legitimate criticism of our work would be that ground truths generated from the ASAP dataset do not live up to the ambition driving the paper, which is to create a large benchmark for ASA research covering a variety of musical use-cases. Although we do not fully dispute this because

[4] https://github.com/Alia-morsi/asa_benchmarks



(a) Alignment results for all MIDI score-audio pairs. Next cutoff threshold = AAE 6000 ms.

(b) Alignment results for MIDI score-audio pairs with AAE < 6000 ms. Next cutoff threshold = 1000 ms.

(c) Alignment results for MIDI score-audio pairs with AAE < 1000 ms. We do not apply further filtering

Figure 2: Box and Whisker plots showing the Average Alignment Error (AAE) results of the DTW systems using each of the chroma extraction algorithms, calculated using the approximated ground truths. Lower results are better. The red horizontal line of a figure indicates the cutoff threshold to be applied for generating the figure to its right.

all the scores of the ASAP dataset are monotonically increasing classical solo piano performances which highly adhere to their music scores in the performance, our point is that neither the ASAP dataset nor any other single accessible dataset would possess the level of diversity needed to move past the bottleneck. The goal is to start accumulating adapted datasets to eventually arrive at a bigger benchmark. For example, a similar process could be applied to the MazurkaBL dataset [42], and perhaps several others too, although the data preparation methodology and corresponding discussion are coupled with the specifics of the chosen dataset. Moreover, as we better explain in Section 6, even with the generated ground truth approximations from ASAP alone, there is room to create interesting data extensions with the approximated beat alignments. Another drawback of our work could be that the results informed data investigation described in Section 5 is not enough, and there should be a more rigorous manual verification process of the derived ground truths. We agree that manual verification of the whole datatset would be ideal, but we also defend that finding compromises for practical benefit should not be disregarded while being very clear on where these datasets fail. Moreover, perhaps a confidence measure can be created based on comparing the correlation of onsets between the left and right channels of the test audio described in Section 4. Further limitations of this work are that we do not discuss the computational complexity of most ASA methods, and rather constrain the use of the term bottleneck to conceptual hindrances facing ASA.

6. CONCLUSIONS AND FUTURE WORK

In this paper, we argue that ASA research has reached glass ceiling, and a crucial way to get past it is to unify what would be considered core to the problem definition in terms of musical scenarios. For example, what kinds of structural variations between the audio and score should be considered, what kinds of instruments should be supported, what recording quality is expected, etc. We believe this would not be possible without developing benchmarks covering such scenarios, which would support a paradigm shift in how ASA is approached, and would allow us to compare between the performance of ASA systems developed by different researchers. To take a first step towards increasing the size and variety of data, we demonstrate the reuse of the 520 scores of ASAP dataset for which beat aligned scores and performance audio pairs are available. We argue that despite its creation with other MIR research topics in mind, it still can be a very useful resource for researchers interested in ASA for classical piano music. We conduct several data validation steps informed by the AAE and AR from results from a classic DTW pipeline, allowing a selective investigation and filtering of the dataset.

6.1 Future Directions

In addition to adapting more related datasets, we would like to build on this work by artificially extending the data to improve its balance. We need to include cases where the audio performance does not adhere well to the music score, whether through skips, repeats, or performance mistakes. Starting from the generated alignment ground truths (or alignment references from other datasets) we could create semi-artificial data where we shuffle parts of the score, and concatenate the audio from the real performance to match this modified score. To avoid these modifications sounding unnatural, we could try and choose realistic parts of the piece, referring to works on music structure analysis to introduce structural repetitions with more musical sense. Datasets with structural variations would be interesting especially to improve the ability of ASA systems to recover when lost, which is relevant for real-time audio to score alignment. Nevertheless, covering a wider range of instruments still poses a challenge, but this is expected to become easier as synthesis technologies develop further. Finally, we conclude with our hope that ASA approaches would find more inspiration from recent advances in Cover Song Detection and Natural Language Processing.

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