Exploiting Temporal Dependencies for Cross-modal Music Piece Identification

Luís Carvalho[1], Gerhard Widmer[1,2]
[1]*Institute of Computational Perception* & [2]*LIT Artificial Intelligence Lab*
Johannes Kepler University Linz, Austria

***Abstract*—This paper addresses the problem of cross-modal musical piece identification and retrieval: finding the appropriate recording(s) from a database given a sheet music query, and vice versa, working directly with audio and scanned sheet music images. The fundamental approach to this [1] is to learn a cross-modal embedding space with a suitable similarity structure for audio and sheet image snippets, using a deep neural network, and identifying candidate pieces by cross-modal near neighbour search in this space. However, this method is oblivious of temporal aspects of music. In this paper, we introduce two strategies that address this shortcoming. First, we present a strategy that aligns sequences of embeddings learned from sheet music scans and audio snippets. A series of experiments on whole piece and fragment-level retrieval on 24 hours worth of classical piano recordings demonstrates significant improvement. Second, we show that the retrieval can be further improved by introducing an attention mechanism to the embedding learning model that reduces the effects of tempo variations in music. To conclude, we assess the scalability of our method and discuss potential measures to make it suitable for truly large-scale applications.**

***Index Terms*—alignment, piece identification, sheet music, cross-modal, embedding learning**

I. Introduction

Large amounts of music-related contents are available nowadays in the digital realm, in diverse forms, from studio and live audio recordings to scanned sheet music images and video clips. Making such heterogeneous collections searchable and explorable in a content-based way requires efficient techniques for cross-linking between items of different modalities. In *cross-modality document retrieval*, we have a collection of items of a certain modality (e.g., music recordings) and wish to retrieve relevant documents from this by querying with items of a different modality (e.g., scores) – either entire documents or fragments thereof.

In this paper we address the problem of *score-based piece identification*. Our goal is to perform this task in *both search directions*, which means finding a score from a collection given an audio query and, inversely, retrieving an appropriate audio performance given a sheet music input. We attempt to solve this problem in its most extreme setup, in the absence of any metadata or machine-readable information: we work directly with raw material, that is, audio recordings and digitised images of scanned sheet music.

The research is supported by the European Union under the EU's Horizon 2020 research and innovation programme, Marie Skłodowska-Curie grant agreement No. 765068. The LIT AI Lab is supported by the Federal State of Upper Austria.

Previous work [2] has shown how to perform audio-sheet music piece identification with a two-stage procedure, by retrieving short snippets of music and then generating a ranked list by counting the number of retrieved snippets per piece. The audio-to-score correspondences were obtained by learning a cross-modal embedding space for both audio and score snippets by means of a deep neural network [1]. Despite encouraging results, a number of challenges have remained open. Most importantly, the counting-based strategy entirely neglects the inherent temporal dependencies between music snippets, both on the score and audio side. And second, the network architecture is not designed to account for (possibly large) tempo variations in music, where varying speed greatly affects the amount of audio/visual content in fixed-size snippets, making the approach rather brittle.

Our central contribution is a musically more meaningful identification procedure that exploits the strong temporal relations between consecutive audio and score snippets, aiming for more robust and accurate identification. The basic idea will be to compute a matching function by aligning subsequent snippets of a query and corresponding retrieved items, both projected onto a learned embedding space, using a dynamic time warping (DTW) [3] algorithm whose cost is defined over pairwise distances in this multi-modal embedding space.

A first experiment (Section III-A) evaluates our alignment-based procedure against the voting approach in [2], revealing a significant boost in performance, which indicates the positive impact of introducing an alignment method to this task. This latter point is further corroborated by an experimental comparison to an adapted version of the identification algorithm used in the popular *Shazam* system [4], which does not rely on alignment. To make the snippet retrieval step more robust to extreme differences in tempo between score and audio excerpts, we then add a soft-attention mechanism (as described in [5]) to the baseline architecture (Section III-B), permitting the network to decide the appropriate temporal context for a given query snippet. Experimental results show that the compound effect of addressing the two aforementioned problems amounts to 280% and 80% improvement over the baseline method for audio-to-score and score-to-audio retrieval, respectively.

The above experiments aligned entire scores and pieces. To get an understanding of how our system behaves under a more realistic usage scenario, we conduct a set of fragment-level retrieval experiments, systematically varying the lengths of the queries (Section III-C), giving more insight into the

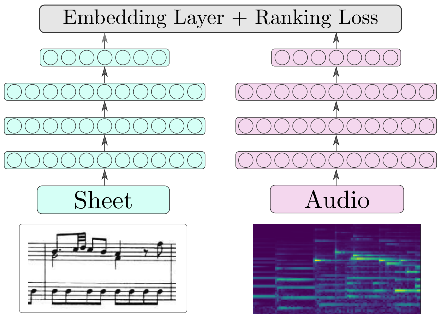


Fig. 1: Architecture of cross-modal embedding network [2].

relation between query length and identification accuracy. Lastly we investigate how our system behaves when increasing the dataset size (Section III-D), and discuss opportunities to make it suitable for very large music collections. All the experiments in this work are conducted with commercial recordings of several hundred complex classical piano pieces (24 hours worth of audio), and their respective sheet music scans.

II. System description

We first explain how to connect audio to sheet music images by learning an embedding space, then introduce our identification procedure that aligns snippets of musical content. The main premise is that the documents of both modalities – audio recordings and score images – have been cut, in a pre-processing step, into a set of fixed-size segments (*snippets*); these are the items for which we wish to learn a joint embedding space that should place related snippets of both modalities in close proximity, to permit distance-based retrieval [2].

A. Learning Audio-to-score Relations

To learn a cross-modal score/audio embedding space, we employ a deep neural network model depicted in Fig.1. It consists of two convolutional pathways, each responsible for embedding one of the music modalities. The canonically correlated (CCA) embedding layer ensures that the outputs of the two pathways are projected into a shared 32-dimensional space [1]. The network is trained by optimising a pairwise ranking loss [6]: the cosine distances between corresponding snippet pairs are minimised, while distances between non-corresponding pairs are maximised. This results in matching pairs being projected close to each other and dissimilar ones falling apart. To train our model, we use the MSMD dataset [2], which contains over 300,000 score-audio snippet pairs from synthesised classical piano music.

One advantage of this approach is that pairs of audio and sheet music snippets are required only during training. At test time, each pathway can embed their corresponding snippets independently. Thus, the network can operate in both retrieval directions: audio-to-score and score-to-audio.

B. Piece Identification via Snippet Voting

The retrieval task now consists in finding a corresponding audio recording when given a score scan, or the correct score when given a recording. The basic method for cross-modal identification works as follows. We outline the steps for the audio-to-score direction (the audio recording is the query), but emphasise that the opposite direction works analogously.

Let $\mathcal{D}$ be a collection of L images of sheet music pages, and Q an audio query. Each document $D_i \in \mathcal{D}$ is processed by a system detector to automatically identify system coordinates in the score and then cut into a set of image snippets as the one shown in Fig.1. The snippets are then embedded by passing them through the score pathway of the trained network, resulting in a set of sheet music embeddings $\{y_1^i, y_2^i, ..., y_{M_i}^i\}$ for each piece. Analogously, the audio query is segmented into short spectrogram excerpts, which are embedded via the audio pathway of the model, resulting in a set of audio embeddings $\{x_1, x_2, ..., x_N\}$ for the query.

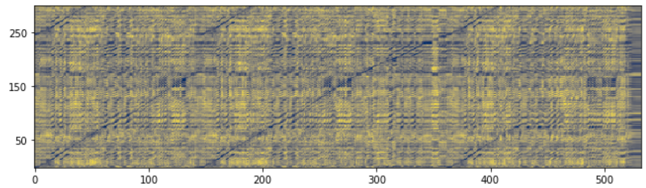
Given this database of sheet music images and an audio query embedded to the same shared space, a two-stage strategy for piece identification was employed in [2] that generates a ranked list via snippet retrieval. First for each audio snippet x_j of the query, its nearest neighbour from the database of all embedded image snippets is selected via cosine distance. Each retrieved snippet then votes for the piece it originated from, resulting in a ranked list of piece candidates. From now on, this will be our *baseline* method.

C. Exploiting Temporal Dependencies

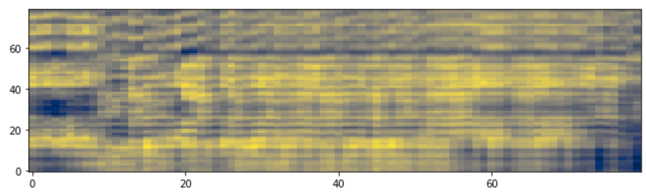
The vote-based procedure completely ignores the temporal relationships between subsequent snippet queries, which are key in music. Since both query and database items are now segmented and projected onto a shared space, a piece (score and audio recording) can be seen as a sequence of snippet embeddings, with a distance metric defined in this space, also between snippets of different modality. Thus, we can use an *alignment procedure* to test how well an audio query (as a sequence of audio snippet embeddings) and a score (as a sequence of score snippet embeddings) 'fit' together, using the embedding space distance as a cost function. A similar approach was adopted in [7], where sheet image scans are converted into chroma features via an optical music recognition system and aligned to audio recordings.

In the following, we first assume that our query is always a full piece (recording or score). This will be relaxed later, in Section III-C. We formalise the matching procedure similarly to [8], but replace the Subsequence Dynamic Warping (SDTW) by its standard DTW algorithm, as we are aligning entire sequences. The sequence of embedded snippets $\{y_1^i, y_2^i, ..., y_{M_i}^i\}$ of each piece $D_i \in \mathcal{D}$ from the database[1] is aligned to the query sequence $\{x_1, x_2, ..., x_N\}$ via DTW, using the cosine distance as a cost function. The DTW alignment cost between query Q and piece D_i is regarded as the matching

[1] For now, we simply go through the entire database of pieces and run a DTW alignment on all of them. Obviously, one could first obtain a subset of k top candidates via voting-based retrieval, which would then be further checked and re-ranked via DTW, but as DTW is so efficient – especially given the low (snippet-level) resolution of our sequences –, it turned out that our simple procedure, which does not require near-neighbour search in embedding space, is basically equally fast.



(a) Mozart KV 280, 1st movement



(b) Chopin Prelude Op.28 No.22

Fig. 2: Distance matrices (x axis: audio; y axis: score) of two cases where standard DTW fails: (a) presence of repeats; (b) when the embedding projections are meaningless.

Method	**R@1**	**R@5**	**R@10**	**MRR**	**MR**
Baseline [2]	43 (0.13)	93 (0.29)	135 (0.42)	0.23	15
Baseline+Att	93 (0.29)	188 (0.59)	231 (0.72)	0.42	4
DTW	195 (0.61)	257 (0.80)	279 (0.87)	0.69	1
DTW+Att	266 (0.83)	292 (0.91)	303 (0.94)	0.87	1
Shazam [4]	129 (0.40)	173 (0.54)	193 (0.60)	0.47	4
Shazam [4]+Att	154 (0.48)	189 (0.59)	210 (0.65)	0.54	2

(a) Audio-to-score (A2S) piece identification results.

Method	**R@1**	**R@5**	**R@10**	**MRR**	**MR**
Baseline [2]	115 (0.36)	183 (0.57)	209 (0.65)	0.46	4
Baseline+Att	185 (0.58)	242 (0.75)	262 (0.82)	0.66	1
DTW	225 (0.70)	266 (0.83)	292 (0.91)	0.76	1
DTW+Att	247 (0.77)	288 (0.90)	298 (0.93)	0.83	1
Shazam [4]	129 (0.40)	172 (0.54)	187 (0.58)	0.46	4
Shazam [4]+Att	140 (0.44)	174 (0.54)	191 (0.60)	0.49	3

(b) Score-to-audio (S2A) piece identification results.

TABLE I: Piece identification results for both query directions. R@k: Recall@k, MRR: Mean Rec. Rank, MR: Median Rank.

cost $c_i = \mathrm{DTW}(Q, D_i)$. Finally we generate a ranked list based on the matching cost of each piece to the query, with the best matching piece having the lowest alignment cost.

III. Experiments

We use a collection of 321 commercial recordings of classical piano pieces and their corresponding sheet music scans, which consists of our private music collection plus scores obtained from the IMSLP online library[2] and recordings retrieved from Youtube[3]. This amounts to over 24 hours of recorded music and 1,696 pages of scores, and comprises complex pieces such as Chopin Ballades and Beethoven and Mozart piano sonatas. The scores were manually scanned, are slightly noisy, and the score grid lines (staff lines, bars, etc) are not perfectly aligned to the scanned document margins, bringing our retrieval scenario closer to real cases.

Moreover, manual inspections revealed that at least 84 of the 321 pieces (26%) manifest some sort of structural mismatch between score and audio recording – mainly due to repeats played in the audio, but not written out in the score.[4] This is rather challenging, as the standard DTW algorithm cannot handle such structural differences. To illustrate, we show in Fig.2(a) the distance matrix of a Mozart piece with repeated sections, which can be seen as the main dark diagonal path jumps to the beginning of the score.

Embeddings are generated as in Section II-A. All score pages are first resized to a width of 835 pixels, and 160×200-pixel snippets are sequentially cut from them with a hop size of 50 pixels. We replaced the CNN-based system detector [9] used in [2] with an open source software [10], resulting in 32% more systems accurately detected. Audio recordings are transformed into 92-bin log-frequency spectrograms, and excerpts of roughly 2 seconds of music are segmented with a hop size of approximately half a second, resulting in audio snippets with dimension 92×42 (bins $\times$ frames).

We evaluate our piece identification procedure on both query directions: audio-to-score and score-to-audio; from now on we refer to these tasks as A2S and S2A, respectively. For evaluation we calculate standard metrics for document-level retrieval from the resulting ranked lists: different recalls $R@K$, looking at the top K matches; mean reciprocal rank (MRR; higher is better) and median rank (lower is better).

A. Experiment 1: Baseline vs. Alignment

In the first experiments, we compare our alignment-based matching procedure to the baseline method. Additionally, we adapted the *Shazam* search method [4] to our task by using the embeddings as the spectral fingerprints from the original formulation, in order to compare our findings with an efficient (non-alignment-based) benchmark framework. We define a search space $\mathcal{D}$ with all 321 pieces in one modality and a query set $\mathcal{Q}$ consisting of their respective counterparts. Then we query each piece $Q_i \in \mathcal{Q}$ in the search collection $\mathcal{D}$ and compute the aforementioned metrics. The results are summarised in Table I (methods without "+Att").

Overall we see that the DTW-based strategy performs better, by a large margin, than the baseline and also the Shazam method for all evaluation metrics, in both search directions. The baseline retrieves around 13% of the queries (43 pieces) correctly as the best match (R@1) in the A2S task, whereas the DTW method correctly retrieves 61% (195 pieces). Similar improvements can be seen in the S2A direction. At higher k, the recall values reach 90% levels. Also noteworthy is the median rank of 1, indicating that in the majority of cases, the correct answer indeed appears at the top of the list. Generally,

[2]https://imslp.org
[3]https://www.youtube.com/
[4]We currently do not have a reliable method for identifying and correctly interpreting repeat signs, *da capo / dal segno* indications, etc.

the Shazam search method performed better than the baseline, but not as well as the alignment-based strategy.

A few observations can be derived from this. First, the considerable improvements of our method indicate that the learned representations can support meaningful DTW synchronisation paths. The baseline vote-based strategy relies solely on snippet-wise distance computations, which may not exhibit the expected projection characteristics (see II-A) for all excerpts, whereas the DTW-based method can overcome local projection mismatches by computing an overall alignment path. Second, we noticed a trend that if a piece creates problems in one query direction, it also performs poorly in the opposite direction. Manual inspection revealed that such pieces failed to generate meaningful embedding vectors, therefore producing a poor alignment path for the audio-score piece pair. To illustrate, Figure 2(b) shows the distance matrix of Chopin's Prelude No. 22, which gives the worst retrieval results (ranked at 28 and 179 for A2S and S2A, respectively). No evident alignment path is visible from the matrix, and the DTW algorithm appears to have found less costly warping paths by synchronising the query to other pieces.

B. Experiment 2: Attention Mechanism

In a second experiment, we modify the snippet embedding model by introducing a soft-attention mechanism [5] to the audio input. Since in the original approach the snippet dimensions are fixed, tempo variations will inevitably affect the amount of musical content that audio excerpts will accommodate. This leads to discrepancies between what the network sees during training, and the test data. As a solution, [5] proposes to increase the audio field of view and let the network decide on the appropriate temporal context for the given audio snippet, by adding an attention branch to the audio pathway of the network. When comparing different audio snippet lengths, we achieve the best identification results using an audio context of 4 seconds (84 frames). The same context window is applied to all methods indicated by *+Att* in Table I.

We observe additional improvement on both A2S and S2A tasks, for both baseline and DTW-based methods. In both directions, now at least 93% of the sought pieces are correctly returned among the top 10 ranks. More generally, the experiment supports several interesting observations. First we note that learning better representations, which produced superior audio-to-score snippet retrieval results [5], also leads to better piece identification. By simply adding the attention model to the baseline vote-based strategy, the MRR improves by approximately 83% and 43% for tasks A2S and S2A, respectively. Moreover, we observe that, while in [5] the attention models were evaluated only for the audio-to-score snippet retrieval direction, the updated models also show positive impact on sheet-to-audio direction tasks, for all methods. Modifying the network architecture and adopting an alignment-based matching strategy revealed the most substantial improvement over the baseline: 280% and 80% better for the MRR, on the A2S and S2A task, respectively.

Length (s)	10	20	30	40	50	60	70	80
MRR	0.41	0.51	0.56	0.59	0.61	0.62	0.63	0.64

(a) Audio-to-score direction.

Systems	1	2	3	4	5	6	7	8
MRR	0.45	0.54	0.59	0.63	0.63	0.63	0.63	0.64

(b) Score-to-audio direction.

TABLE II: Fragment-level retrieval results by varying the length of the query (MRR = Mean Reciprocal Rank).

C. Experiment 3: Fragment-level Retrieval

In this set of experiments, we test our method on incomplete queries, modelling a realistic scenario where one may not have the entire piece for a search, but a fragment of an unknown audio recording or an unlabelled page of sheet music, and wishes to identify its originating piece. A similar study on MIDI-to-score retrieval was recently described in [11].

First, we replace the DTW by its variant SDTW [3], to permit synchronisation of short sequences to longer ones. We follow the pipeline described in [8]. For the audio queries, we vary the fragment context from 10 to 80 seconds, in increments of 10. On the score side, we vary the query sizes in system units (rows in the score), from one to eight. For each fragment size, 1,500 queries are randomly selected from our database and the search is performed and evaluated as before.

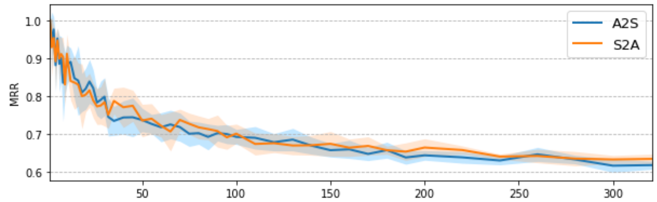
The main observation (see Table II) is the upward trend of the MRR values as queries get longer. The biggest jumps in performance were obtained when going from 10 to 20 seconds in the A2S retrieval direction, and from one to two systems on the S2A task. Interestingly, in both directions, the performance increase rate tends to decrease as the queries get bigger. A possible explanation is the number of pieces with structural differences in our collection (see above): a longer query is more likely to contain such deviations, and increasing its length appears to be not as meaningful as expected.

D. Experiment 4: Scalability

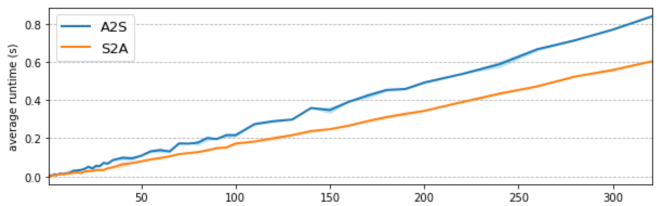
The last set of experiments evaluates the scalability of our method. As digitisation of music content rises and online music/score archives can reach the order of tens of thousands of items, retrieval systems are expected to scale to larger collections. Our current music collection is limited in size; however, we can use it to experimentally investigate how well our method scaled to our current data volume.

We randomly select smaller subsets of the main collection and perform short queries in both directions, as in Section III-C. For each subset we randomly select 1,000 fixed-size query fragments, the sizes being 50 seconds and four lines in the score for the audio and score queries, respectively. Then we measure the final MRR value and the average search time per query. We repeat this procedure 10 times for each subset size and use the average of the results, similarly to [11].

Figure 3 shows the MRR and average search time for both search directions as the dataset size increases. Regarding the



(a) Mean reciprocal rank across different dataset sizes



(b) Average search time across different dataset sizes

Fig. 3: (a) MRR and (b) average search time for many dataset sizes, which are indicated by the horizontal axis (given in terms of number of entire pieces. Note that, on average, a single piece is represented by around 523 audio excerpts and 422 score snippets; a dataset size of 300 pieces thus corresponds to roughly 160,000 excerpts and 130,000 snippets)

MRR, we consider that the system scaled moderately up to our current collection size. For instance, the MRR value dropped less than 0.1 as the dataset size increased from 100 to 321, for both A2S and S2A.

Regarding the average search time, as expected the system scaled roughly linearly, since the time complexity of DTW is $O(MN)$ [3], with M and N the size of the database and the query length (fixed), respectively. It is clear that without any efficiency improvement measures, this would not be practicable for huge music repositories. There are fairly obvious solutions to this. One way to improve the numbers in absolute terms is to adopt the re-ranking strategy described in Footnote 1 and accelerate the voting process via faster indexing techniques. In [12] we showed how to achieve speedups of up to 40 times compared to an exhaustive linear scan, by using a filter-and-refine approach, which made it possible to efficiently answer nearest neighbour queries in a collection of 2.5 million songs. An analogous approach, adapted to our distance measure, would also be applicable in our present system.

IV. Conclusion and Future Work

We have presented an audio-score piece identification procedure that aligns sequences of embeddings learned from sheet music and audio snippets, and confirmed experimentally, on complex piano music, that our DTW-based matching strategy performs better than existing alternative methods, for all experiment setups and in both search directions. The implementation of all evaluated methods is publicly available.[5]

A central problem of our approach is that the DTW algorithm does not handle substantial structural differences between performances and scores, caused by, e.g., jumps and repeats. A number of works [13]–[15] have explored this theme, however we do not consider the proposed solutions practical for our applications. Moreover, the scalability experiment uncovered some serious issues regarding the execution time. There are ideas for addressing the linear growth issues, but they will require some fundamental changes to the model. As an example, a potential strategy to overcome the two aforementioned problems at once is to replace the DTW strategy with fingerprints computed over the embeddings. This approach could result in features that are robust to jumps and repeats in scores, as well as permit a more time-efficient search engine.

[5] https://github.com/CPJKU/audio_sheet_retrieval/tree/eusipco-2021

References

[1] M. Dorfer, J. Schlüter, A. Vall, F. Korzeniowski, and G. Widmer, "End-to-end cross-modality retrieval with CCA projections and pairwise ranking loss," *International Journal of Multimedia Information Retrieval*, vol. 7, no. 2, pp. 117–128, Jun 2018.

[2] M. Dorfer, J. Hajič jr., A. Arzt, H. Frostel, and G. Widmer, "Learning audio–sheet music correspondences for cross-modal retrieval and piece identification," *Transactions of the International Society for Music Information Retrieval*, vol. 1, no. 1, 2018.

[3] M. Müller, *Fundamentals of Music Processing*. Springer Verlag, 2015.

[4] A. Wang, "An industrial strength audio search algorithm," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Baltimore, Maryland, USA, 2003, pp. 7–13.

[5] S. Balke, M. Dorfer, L. Carvalho, A. Arzt, and G. Widmer, "Learning soft-attention models for tempo-invariant audio-sheet music retrieval," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Delft, Netherlands, 2019, pp. 216–222.

[6] R. Kiros, R. Salakhutdinov, and R. S. Zemel, "Unifying visual-semantic embeddings with multimodal neural language models," *arXiv preprint (arXiv:1411.2539)*, 2014.

[7] C. Fremerey, M. Müller, F. Kurth, and M. Clausen, "Automatic mapping of scanned sheet music to audio recordings," in *Proceedings of the International Conference on Music Information Retrieval (ISMIR)*, Philadelphia, USA, Sep. 2008, pp. 413–418.

[8] S. Balke, V. Arifi-Müller, L. Lamprecht, and M. Müller, "Retrieving audio recordings using musical themes," in *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Shanghai, China, 2016, pp. 281–285.

[9] A.-J. Gallego and J. Calvo-Zaragoza, "Staff-line removal with selectional auto-encoders," *Expert Systems With Applications*, vol. 89, pp. 138–148, 2017.

[10] H. Bitteur, "Audiveris optical music recognition (OMR)," Website: https://github.com/audiveris, last accessed 19/02/2021, 2004.

[11] T. J. Tsai, "Towards linking the Lakh and IMSLP datasets," in *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, 2020, pp. 546–550.

[12] D. Schnitzer, A. Flexer, and G. Widmer, "A filter-and-refine indexing method for fast similarity search in millions of music tracks," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Kobe, Japan, 2009, pp. 537–542.

[13] C. Fremerey, M. Müller, and M. Clausen, "Handling repeats and jumps in score-performance synchronization," in *Proceedings of the International Conference on Music Information Retrieval (ISMIR)*, Utrecht, The Netherlands, 2010, pp. 243–248.

[14] M. Grachten, M. Gasser, A. Arzt, and G. Widmer, "Automatic alignment of music performances with structural differences," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Curitiba, Brazil, 2013, pp. 607–612.

[15] M. Shan and T. J. Tsai, "Improved handling of repeats and jumps in audio-sheet image synchronization," in *Proceedings of the International Society for Music Information Retrieval Conference (ISMIR)*, Montreal, Canada, 2020, pp. 62–69.