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Preface

Dear colleagues!

We are very pleased to present to you the proceedings of the 4th International Workshop on Reading Music Systems (WoRMS). Following the success of last year's edition in a hybrid format, we decided to have this years edition as an online-only workshop to allow people around the world to easily participate while still being as interactive as possible. We hope that in the next couple of years we will be able to return to an in-person workshop, while maintaining the online option.

When we started the workshop series five years ago we did not now how it would be perceived by the community. Therefore, we are very happy that WoRMS has established a fixed place in the community and is seeing great interest from people all around the world that share a common interest in music reading systems, allowing them to exchange ideas and form relationships with one another.

We would also like to use the opportunity here to mention and promote our public YouTube channel https://www.youtube.com/OpticalMusicRecognition, which has recordings for last year's sessions and we plan on adding this year's presentations as well. If you have interesting content that you want to share through this channel, please get in touch with us.

This year's edition features 9 contributions, reaching from topics like dataset generation, via new attempts to tackle music notation assembly to measure detection and drum transcription. We are looking forward to very interesting discussions. We also want to thank the TU Wien for providing Zoom conferencing facilities.

Jorge Calvo-Zaragoza, Alexander Pacha, and Elona Shatri

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Challenging sources: a new dataset for OMR of diverse 19th-century music theory examples

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Abstract—A major limitation of current Optical Music Recognition (OMR) systems is that their performance strongly depends on the variability in the input images. What for human readers seems almost trivial—e.g., reading music in a range of different font types in different contexts—can drastically reduce the output quality of OMR models. This paper introduces the 19MT-OMR corpus that can be used to test OMR models on a diverse set of sources. We illustrate this challenge by discussing several examples from this dataset.

Index Terms—optical music recognition, historical sources, diversity, music theory, digital humanities

I. INTRODUCTION

While Optical Music Recognition (OMR) techniques have advanced in recent years, several challenges remain, and the current state-of-the-art does not always provide satisfactory solutions [1]–[5]. In this report we want to draw the attention of the OMR community to one particular issue, namely the case that the sources themselves are challenging by their inherent diversity. The datasets to which OMR models are applied or on which they are trained are frequently *homogeneous* in the sense that they stem from a single source or collection of more or less uniform sources. This often entails that the images are stylistically similar [7] and that the presence of text is largely limited to lyrics or annotations.

If it is the goal of OMR to perform (at least) at humanlevel music transcription, it must be able to deal with scores printed with different font types, be capable of understanding which parts of a page contain music and which do not, and distinguish between raw text, lyrics and other textual information such as chords or harmonic analysis indications.

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This is particularly relevant for research applications with a historical focus, where font types may be less standardized.

In this report, we introduce the 19MT-OMR corpus, a multilayered dataset of heterogeneous and multimodal data that may aid researchers in progressing towards this goal, and illustrate the failure of current OMR approaches with a handful of salient examples.

II. DESCRIPTION OF THE DATA

The 19MT-OMR corpus was created within the context of the digital-humanities project "Digitizing the dualism debate: a case study in the computational analysis of historical music theory sources" [8]. It consists of scans and transcriptions of 19th-century German music theory textbooks in TEI and MEI formats (see Fig. 1). Common to all books is their music-theoretical content and *not* their typeface and graphical layout. We provide the corpus in three versions of increasing specificity with respect to OMR:

- 19MT-OMR-A: complete segmentations and transcriptions of all sources in the corpus
- 19MT-OMR-B: only pages containing music examples
- 19MT-OMR-C: only the music examples

The dataset is hosted within the *Open Science Framework*¹ [9] under a CC-By Attribution 4.0 International license. To create the corpus, publicly available scans of the books were segmented and transcribed using the *Transkribus* software [10] for segmentation and Optical Character Recognition (OCR), using the ONB_NEWSEYE_GT_M1+ model and TRAINDATALAN-GUAGEMODEL dictionary [11].

During segment markup and transcription, we made several editorial decisions. For instance, some sources contained purely rhythmic notation [12], which we decided to ignore. As a short-hand rule, only music examples with five lines

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¹https://osf.io/qm9z5/



Fig. 1: Crop of page extracted from the corpus.

were encoded. However, if they were embedded in complex diagrams or annotated with lines and arrows, we likewise excluded them from our transcription. Since the examples were taken from segmented page elements, the dataset excludes the small number of in-line music examples.

The music examples are encoded in the Humdrum (**kern) symbolic music representation The choice of this format is due to its simplicity, unambiguity, and its capability to encode all the desired features of the notation. Thanks to the *Verovio Humdrum Viewer* tool,² engraving was fairly simple. Additionally, we have described each image with some features that will be relevant for the OMR process and provide them in an accompanying CSV file (see Section IV for a detailed description).

The transcribed data spans 9 textbooks and a total of 368 musical excerpts. Most of the examples contain between 1 and 32 measures of music. Some examples include single-line-staff rhythmic patterns, however, most examples feature multiple voices per staff with unconventional engravings as described below in Section IV. Musically, many of them feature basic scales and cadences, while others contain short excerpts from known compositions. In all the examples, the



Fig. 2: Particularly challenging cases. Example A) shows an encoding where the original source is missing an augmentation dot (m. 4, first eighth note), which is added to the digital encoding. Example B) shows an unconventional form of the time signature $\frac{3}{4}$ in the original source. Example C) shows a case with more than one voice. In the latter example, the note colors in the encoding highlight the notes that are encoded as the first (blue) and second (green) voices.

direction of stems, number of voices, time signatures, slurs, ties, and accidentals have been meticulously encoded. Other features, such as musical fonts or some special symbols were not taken into consideration. The text in the examples was initially encoded separately from the music notation. Later, in order to have a TEI file that describes both the text and the music, **kern files will be converted into MEI to be linked from the TEI files by using the <music> TEI element [13].

III. CHALLENGING EXAMPLES AND ENCODING DECISIONS

As a corpus of music theory books illustrating specific situations, the dataset contains several unusual musical notations that are difficult to encode. Figure 2 shows three examples from the corpus. The first example, Fig. 2-A, shows a situation where the encoding requires the inclusion of a symbol (augmentation dot) in the last bar that is missing in the source image. This is rare, but it occurs throughout the corpus for some symbols, such as, augmentation dots and triplets. The second example, Fig. 2-B, shows an unconventional notation of the time signature in the source image. Other unconventional notations found in the 19MT-OMR corpus include: music fonts that are hard to read, double augmentation dots that are widely separated from their corresponding note, whole notes located at the center of a measure instead of at

²https://verovio.humdrum.org/

the beginning, etc. The third example, Fig. 2-C, showcases the strategy followed for encoding multiple voices. To ensure consistent encoding, a single voice was used whenever possible. However, when two notes have differing stem directions and/or note durations, an additional voice was encoded. The order of the voices was always encoded from top to bottom. That is, the first voice is always the upper voice. Additional (lower) voices were encoded below as needed. The examples in the corpus span up to four voices in one staff.

IV. OMR CHALLENGES

In order to understand the possible difficulties that OMR systems may encounter when approaching the corpus, we have created a set of features to qualitatively describe the source images that may also be used to filter subsets of our corpus (see Section II).

The first feature is the *polyphonic or monodic nature* of the individual staves in the image. For instance, the image in Fig. 3a is not tagged as polyphonic because both staves are monodic. As mentioned above, some music examples contain purely *rhythmic notation*, see Fig. 3b.

One of the most challenging features of the dataset is the presence of *harmonic indications* that are difficult for an OMR system to distinguish from lyrics or other text annotations (see Fig. 3a (figures bass), 3c) (reference labels), and 3d (groupings).

The corpus contains different *layouts*, from single staves containing just one voice such as in Fig. 2-A and -B, grand staff examples containing multiple voices (Fig. 2-C), as well as small ensemble scores or several staves that should be read aligned (Fig. 3a). Consequently, those images that contain more than one staff are tagged using either the "grand staff" or "several staves" feature. A feature has also been created for those images containing several *systems*, such as Fig. 3d.

As the musical excerpts are meant to illustrate the content of the treatises, a single image may in many cases contain several separate examples (Fig. 3e), or have numbers or section labels naming the different examples in the image (see staff above footnote in page shown in Fig. 1, or Fig. 3c).

The corpus contains a range of symbols and engravings for which there are no standard encodings, such as dots indicating metrical strength (top staff in Figure 3b), braces around chords (Fig. 3d), duplicate note heads, bar lines broken by slurs, movable types (Fig. 3h), or whole note horizontally displaced (Fig. 3h, fourth measure), to name just a few.

Finally, the corpus contains several cases of unusual fonts or engravings such as elliptical note heads (Figs. 2-B and 3), beams, slurs and stems made of movable types that are visible (Fig. 3f), overlapping notes (see last measure in Fig. 3h), and notes that seem to be printed over other contents (Fig. 3e).

V. EVALUATION

Having described the type of content to be handled by OMR, it was *a priori* expected that no current system approach would be able to correctly handle the entire corpus. No rule-based system is built with the nature of this corpus in mind. Given the



(c) Two examples, i on the first bar and k on the third one. Inversions shown below notes.



(d) Braces enclosing chords. See also black note heads.



(e) Images containing two separated examples. Note the messy artifacts below symbols.



(f) Visible movable types used to engrave slurs, beams, and stems.



(g) Cue-sized notes along with whole notes not following at all any metric relationship.



(h) Bar lines cut by slurs. Double note heads and overlapped ones (see last measure).

Fig. 3: Examples of special cases found in the corpus.

small size of the dataset, on the other hand, machine learning algorithms do not have sufficient samples to build a model capable of recognizing the diversity of situations found.

To qualitatively evaluate this 'bad-performance' hypothesis for current OMR systems with the 19MT-OMR corpus, we have chosen some salient examples that we consider representative of the different characteristics introduced above. We used trial or demo versions of the most popular commercial systems PhotoScore by Neuratron,³ SmartScore by Musitek,⁴ Maestria by Newzik that claims to use state-of-the-art neuralnetwork techniques,⁵ Capella-Scan, Version 9.0-10,⁶, FORTE 12 Premium Edition that contains ScanScore 2 Ensemble,⁷ and finally the open-source system Audiveris.⁸

Each of the systems has different requirements for the input images in terms of file formats and resolutions that have been met in all cases by using an image processing program, in some cases by resampling the source images. As mentioned in the introduction, most OMR systems have been designed with a different type of repertoire in mind, with content and image size requirements that are, in most cases, far from 19MT-OMR. This may be the main reason why the recognition accuracy is extremely low in all tested systems.

This is illustrated in Fig. 4. A score example that is easily recognized by a human reader (Fig. 4a) comes with a single symbol that can confuse the OMR: the portamentolike lines showing where the semitones are. The remaining sub-figures show the output of the used OMR software (the output from Newzik is missing because it just generated an empty MusicXML file). In addition to the 'garbage' obtained regarding the scale in the original, none of the approaches is able to recognize the harmonic annotation as such.

The results for the examples in Fig.3 are similar. For Fig. 3f, PhotoScore does not detect anything but a list of whole rests, warning us in a dialog box that the image contains a high number of reading errors. SmartScore fails in the operation and Newzik just generates an empty MusicXML file. Audiveris detects some notes and strange symbols, and both Capella-Scan and Forte 12 just output noise. For Fig. 3e the situation is not better. Photoscore and Newzil identify one example with many errors. Smartscore crashes and Forte 12 does not export anything. Both Audiveris and Capella-Scan correctly detect two separated regions, but these contain just clusters of unrelated symbols. The output for all other examples is similarly problematic.

VI. DISCUSSION

Most efforts of the OMR community are now focused on whole scores containing predominantly music notation with only few text elements. In this work, we have introduced a different kind of purpose that likewise needs the improvement

⁴https://www.musitek.com/ (Accessed Sept. 20, 2022).



Fig. 4: Music recognized by different systems from a single image.

to render OMR technologies that we illustrated by introducing the 19MT-OMR corpus and discussing a number of salient examples of where current OMR approaches and encoding formats fail. We believe that progress is particularly needed in order to exploit the full potential of OMR techniques also for traditional musicologists and digital humanists.

We consider 19MT-OMR and the discussed examples to be a valuable contribution to OMR research. What may look like odd idiosyncrasies from a modern engraving perspective were actually common historical engraving techniques. Elliptical white note heads, for instance, also feature in several important eighteenth century treatises [14]. Recognizing an object, such as a half note, across various historical printing conventions is a significant long-term challenge, comparable to what has recently been achieved in OCR models handling black letter as well as Roman fonts. Finally, the correct identification of different harmonic annotations is a pending feature that should be addressed in the future by the music encoding and OMR communities.

³https://www.neuratron.com/photoscore.htm (Accessed Sept. 20, 2022).

⁵https://newzik.com/en/maestria/ (Accessed Sept. 20, 2022).

⁶https://www.capella-software.com (Accessed Sept. 20, 2022).

⁷https://www.fortenotation.com (Accessed Sept. 20, 2022).

⁸https://audiveris.github.io/audiveris/ (Accessed Sept. 20, 2022).

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CompIdNet: Sheet Music Composer Identification using Deep Neural Network

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Abstract—There have been significant breakthroughs in computer vision research in many subfields, including composer identification from images of sheet music. Previous work in composer identification depends on a specific digital semantic representation of music and various evaluation criteria, making it difficult to quantify their relative merits. We present a novel approach using an end-to-end deep neural network model for music composer identification with images of sheet music as inputs. Hence, this method is not dependent on the conversion of the sheet music to any other intermediate digital semantic format. Additionally, we compare results from classification applied to sheet music and the respective bootleg representation. Identifying the composer can lead to more inferred data, which is helpful in archiving historical pieces digitally. Based on our experimental results, it can be concluded that the composer identification in sheet music images with deep neural models shows promising results. With the proposed model, we achieved 83% accuracy for composer identification on sheet music images compared to 76% accuracy when applied to the bootleg representations on our newly collected dataset.

Index Terms—Deep Learning, Composer Identification, Musicology, Sheet Music

I. INTRODUCTION

Music notations have been used as a visual representation of music for a long time. In Music Information Retrieval (MIR) and musicology, there is an interest in recognising the composer from different music representations such as audio, MIDI [29] and recently from sheet music [23]. This would assist in archiving, searching and analysing different composers, eras and genres [3, 34]. Identifying the composer from images or scans of sheet music is the most challenging of the approaches. This approach is particularly helpful for sheets that do not have an accompanying digital representation such as MIDI or MusicXML [12].

This paper addresses the composer identification problem in three phases. First, we create a balanced dataset containing scans of works from a variety of composers. Second, we create a bootleg representation of the score. Finally, we create a system that can distinguish between these composers based on the sheet music scans and the bootleg representation of these scores.

Most of the composer identification work focuses on using machine-readable representations of sheet music such as Musical Instrument Digital Interface (MIDI), MusicXML, Kern [13], or MEI [14]. However, such representations are often not available. To retrieve these digital representations of sheet $_{\Omega}$

music we need to use Optical Music Recognition (OMR) systems. The objective of an OMR system is to transform scanned images of sheet music into symbolic representations, and these systems are not robust [1]. Hence, this work examines the possibility of using the sheet music itself, avoiding the need of an OMR system. To enable quantitative comparison we also use a bootleg representation extracted with object detection from the score. For these two main purposes, we collected a dataset from the Int. Music Score Library Project (IMSLP)¹.

II. RELATED WORK

Composer identification using only the means of visual representations of music scores is not an easy task for humans. In many cases, human experts have difficulty classifying similar composers, achieving 48% accuracy on four composers [5] and 57% on two composers [2]. So far, composer classification has mostly focused on the digital semantic representation of music and limited to a relatively small number of composers [16, 22]. The three main approaches in composer identification, also given in Table I, include: (i) solutions based on digital semantic representation of music and audio signals, (ii) solutions using OMR and sequence-based models, and (iii) solutions using visual representation of music score, i.e., music sheets directly.

 TABLE I

 Composer Identification Related Work

Research W	Vork Dataset Type	Intermediate Conversion
[4]	Music Audio	Mel-spectrogram
[6]	Audio Songs	30Sec Audio Clip
[7]	MIDI	Rhythm, melody, texture, tempo
[11].	Handwritten Music Sheet	Feature words Embeddings
[15]	Music Sheets	Bootleg Score and N-Gram
[17]	Music Audio	Spectrogram
[24]	Sheet Music Images	Bootleg Score and N-Gram
[25]	MIDI and Mxl.	Tonality and Harmonic Interval
[26]	Piano Sheet Music	Bootleg Score and N-Gram
[27]	MIDI	N-Gram Features
[28]	MIDI	Text file format

¹http://imslp.org

A. Identifying composers using a digital semantic representation of sheet music.

Jain et al. use MIDI for input for the composer identification tasks [7]. Features such as melody, rhythm, texture, melody and tempo are well represented and can be learnt by the models used. They achieve an accuracy of 79% across a dataset of six composers. Features that contributes the most were intervals and textures. Another approach includes using a 20-second audio extract from a music composition [4] which produces an accuracy of 70%. However, when stylistic similarities are found across composers, that is when the accuracy drops.

Maximos et al. [27] examine the information capacity of the proposed Dodecaphonic Trace Vector (DTV) for composer classification and identification. DTV is analogous to Pitch Chroma Profile [36] and represents densities of degrees in a diatonic major scale. The authors proposed Probabilistic Neural Nets to construct a similarity matrix between composers by using trained Feedforward Neural Networks, and analyses the DTV's ability to identify a composer. MIDI files were converted to a simple text file format using the MSQ tool [28, 30], where each note is represented using a text symbol, which preserves information about its duration, onset time, pitch, and velocity.

B. Composer identification or classification through Optical Music Recognition

This approach is a more challenging one given that it depends on the advancements of OMR. Composer identification work that falls into this approach utilise Convolutional Neural Networks (CNNs) to project either audio or the sheet music into an embedding space to calculate similarity [8]. This approach is also applied in the audio-music sheet alignment [9]. Extracting a bootleg representation from sheet music has been one of the more sought approaches. A bootleg representation is a sequence of "musical words" of the sheet music. Merity et al. [31] and Liu et al. [32] use AWD-LSTM and RoBERTa respectively and achieve a 70% test accuracy on 9-way classification task [24]. The composer identification task was adversely impacted by bootleg scores conversion and object recognition, resulting in increased complexity and decreased accuracy. Another approach is to perform OMR on the sheet music and then perform n-gram lookups, string matching, or keyword spotting to find matches with symbolic queries [11].

C. Composer Identification using Sheet Music Image data

More recently, the approach is shifting to using raw images/prints of sheet music rather than digital representations of the score. The complexity of music notations and its respective theoretical challenging feature representation posed limitation to this approach. However, with the advancements of deep neural networks such limitations and challenges have been reduced.

III. DATASET DESCRIPTION

In this section, we present our composer dataset, which contains more than 32,000 score images from nine different $_{10}$

TABLE II Overview of Composer Dataset

Composer	Themes	Images
Bach	176	3841
Beethoven	120	3665
Chopin	92	4492
Haydn	91	2751
Liszt	169	3326
Mozart	94	3301
Schubert	95	3623
Schumann	92	3208
Scriabin	88	3576

composers. Images are of similar scale and the resolution varies between 6887x9275 and 2550x3299. Then, we perform bootleg extraction using the images of scores. These two sets, the original images of sheet music and the bootleg representations are both designed to be fed into deep neural networks for end-to-end composer identification and to serve as a reference for further research. Half of the scores were collected from IMSLP, one third score images were created by directly converting MIDI files to score images using Dorico² and 20% were generated using a data augmentation technique. A combination of low-resolution images from very old composition styles and augmented data with very high-resolution musical score images (generated using Dorico) make up the dataset. The dataset content by composer is shown in Table II. A partition of the dataset will be made available as part of the DoReMi dataset $[35]^3$.

We used a proportion of 80%-20% for each composer for training and testing.

IV. PROPOSED METHOD

We propose three different Composer Identification Networks (CompIdNet) to create a baseline for composer identification on images of sheet music and compare to the same networks applied in the bootleg representation of the same scores. In the bootleg representation of sheet music, there are $62 \times M$ binary matrices, where 62 represents the total number of staff line positions in the left and right hands, and M represents the number of note event groups after simultaneous note events are collapsed into groups. An overview of how to compute a bootleg score from sheet music can be seen in Figure 1. Each image is first analysed to detect noteheads, bar lines, and staff lines. Object detection models can detect these objects relatively efficiently and robustly since they are all simple geometrical shapes (filled elliptical blobs and straight lines). Third, we encode the resultant information into a bootleg score by estimating the location of filled noteheads relative to the staff lines. A large number of important aspects of sheet music are discarded by this representation, including duration, key signature, accidentals, clef changes, and octaves. More details can be found in [21].

²https://new.steinberg.net/dorico

³https://github.com/steinbergmedia/DoReMi



Fig. 1. Bootleg Score Conversion

Deep Convolutional Neural Network architecture GoogLeNet with its three different versions Inceptionv1, Inception-v2 [18, 19] and Inception-v4 [20] are utilised as backbone support for building CompIdNet. The main hallmark of this architecture is the improved utilisation of computing resources inside the network. The network's depth and width were increased while maintaining the computational budget through a carefully crafted design. Using a fixed kernel size makes it difficult to capture appropriate information in music score sheet images with different features of large or small scales. This issue is handled very tactfully with the Inception network architecture. A large kernel size filter captures the information that is distributed over the whole image.

V. TRAINING METHODOLOGY

To reduce computational complexity, over-fitting, and to cover dense and sparse feature representations on different music score sheets, we propose the use of different versions of the inception blocks in CompIdNet, which increases performance both in terms of speed and accuracy. Due to its depth, we assume CompIdNet is likely to suffer from the vanishing gradient problem, which we prevent by adding an "auxiliary classifier" in the middle of the architecture. Auxiliary classifiers apply the softmax function to the outputs of the inception module and compute auxiliary loss. Total loss is calculated based on the summation of real loss and the weighted sum of auxiliary loss. The auxiliary weight is usually between 0.1 to 0.4, chosen empirically .

$$total_loss = real_loss + weight \times aux_loss$$
 (1)

Our proposed approach, consists of three stages: prepossessing, training, and inference. As part of the prepossessing stage, all sheet music images were converted to grayscale to maintain uniformity throughout the dataset. Background subtraction was applied to minimise the effect of lighting conditions, by subtracting the resultant image where a gaussian blur filter was applied and foreground mask from the original image. The CompIdNet-V1, CompIdNet-V2 and CompIdNet-V3 models based on different version of Inception nets, given below, are trained on composer dataset with batch sizes of 128, 11 architecture is given in Figure 2.

with an early stopping callback. When the model is no longer improving, ReduceLROnPlateau is used to reduce the learning rate based on a threshold. The learning rate is scheduled using poly decay. The validation accuracy for callbacks is used to track the update and improve the hyper-parameters. We use 50 epochs as the patience value to achieve an accuracy threshold of 90% trained with 500 epochs. The dataset was split into 75% for training, 15% for validating, and 10% for testing.

A. CompIdNet-v1 – Based on Inception V1

The first proposed architecture is CompIdNet-v1, which has seven inception layers with a depth of 22 layers and another five pooling layers. The last inception module is topped with a global average pooling layer. We use an auxiliary classifier to improve convergence of the network that might be caused by the network depth. This is a CNN inserted between layers during training, and its loss is then added to the main network loss, as shown in Equation 1.

We use three different filter sizes starting with a 1x1 convolution to reduce the number of parameters, which is then followed by a 3x3 and a 5x5 filters on same level with max pooling.

B. CompIdNet-v2 – Based on Inception V2

Using carefully factorised convolutions and aggressive regularisation we propose CompIdNet-v2 based on Inception-v2, with improved efficiency [19]. This improved efficiency is a result of combining nxn convolutions with 1xn and nx1 convolutions. However, such dimensionality reduction can introduce loss of information, also knows as representational bottleneck. In CompIdNet-v2 the filters are expanded in parallel. Due to this, excessive dimension reduction can be prevented, thus reducing the representational bottleneck.

C. CompIdNet-v3 – Based on Inception V4

In this model we use a combination of *1xn* and *nx1* instead of the nxn for a lower computation cost [20]. By using filter banks we avoid the representational bottleneck. The



Fig. 2. CompIdNet-v3 Architecture based on Inception-v4, with more inception modules

 TABLE III

 MODEL PERFORMANCE ON MUSIC SHEET IMAGES - F1 SCORES

Composer	CompIdNet-v	l CompIdNet-v2	CompIdNet-w	3 AlexNet	ResNet5	0 VGG
Bach	0.84	0.83	0.85	0.73	0.65	0.38
Beethoven	0.78	0.74	0.81	0.63	0.52	0.32
Chopin	0.91	0.76	0.84	0.69	0.55	0.32
Haydn	0.87	0.75	0.85	0.65	0.53	0.29
Liszt	0.80	0.73	0.82	0.55	0.47	0.30
Mozart	0.87	0.78	0.88	0.56	0.56	0.32
Schubert	0.80	0.76	0.85	0.63	0.55	0.29
Schumann	0.84	0.75	0.86	0.65	0.55	0.32
Scriabin	0.85	0.78	0.88	0.67	0.56	0.35

VI. EXPERIMENTS AND RESULTS

In this study, we evaluate the performance of six different models for estimating the composer identification task based on music sheet images and their respective bootleg representation: CompIdNet-v1, CompIdNet-v2, CompIdNet-v3, VGG [37], AlexNet [38] and ResNet [33].

A. Sheet Music as Input

The evidence suggest that success rates are generally quite high for CompIdNet-v1 and CompIdNet-v3. There is greater ease in categorising composers such as Mozart and Chopin with 87-89% of scores being correctly identified. There is a lower degree of identification accuracy for Liszt compared to any other composer. In addition, there was a trade-off between accuracy and computation time. To reduce computation time and to increase accuracy, we modified the architecture of the CompIdNet in different versions. As a result of that attempt, CompIdNet-v2 takes 10-13 seconds per image, 10% less time than CompIdNet-v1 and 20% less than CompIdNetv3 to achieve its best results, but its results are poorer than those of CompIdNet-v1 and v3. In comparison with all other models, CompIdNet-v3 shows the best results, but it also has the longest computation time. For the same computation time VGG and ResNet are not able to achieve similar good results on composer identification.

B. Bootleg Representation of Sheet Music as Input

The number of images used from the main dataset decreased of pixel resolutions and during the conversion of music sheet images to bootleg scores, $_{12}$ on sheet music images.

due to the poor quality of the score representation on historical music sheets. A total of 17,111 training images, 2,789 validation images, and 2,421 test images were used for the study of composer identification. The distribution of data allows us to estimate the degree of generalisation of our training models.

Based on the results shown in Table IV, some composers are more easily categorised than others. For instance, Mozart and Chopin are often identified with some 85/90% of success rates.

 TABLE IV

 MODEL PERFORMANCE ON BOOTLEG REPRESENTATION - F1 SCORES

Composer	CompIdNet-v	1 CompIdNet-v2	CompIdNet-v	3 AlexNet	ResNet5	0 VGG
Bach	0.81	0.77	0.82	0.63	0.53	0.37
Beethoven	0.64	0.57	0.67	0.56	0.45	0.31
Chopin	0.72	0.68	0.75	0.58	0.37	0.28
Haydn	0.78	0.81	0.77	0.64	0.43	0.29
Liszt	0.68	0.66	0.72	0.53	0.47	0.33
Mozart	0.84	0.85	0.84	0.56	0.39	0.30
Schubert	0.65	0.59	0.69	0.55	0.45	0.27
Schumann	0.78	0.74	0.81	0.54	0.46	0.31
Scriabin	0.85	0.84	0.83	0.57	0.40	0.35

VII. CONCLUSION AND FUTURE WORK

In this study, we propose reducing the dependence of composer identification task on intermediate representations. As a result, we reduce the likelihood of information loss during the conversion process.

To create the music sheet image dataset, a variety of composers' scores were collected. In the following step, we extracted the bootleg representation of the score. In parallel, we perform two different sets of experiments. The first set explores the performance of deep neural networks in identifying composers based on the scans/prints of sheet music, the second set uses the bootleg representations of the score as input to the models.

As a result of our comparative analysis, we found that visual representations of sheet music are more effective for identifying composer than correspondence bootleg scores visual representation.

According to our results, neural network architectures that contain a combination of larger and smaller kernels perform better on music sheet images. CompIdNet-v3, a model based on the Inception V4 architecture, provides the best results of all models, as it uses the most extensive and deep network. Proposed data distribution methods are able to minimise biases while training. The evidence suggests that sheet music images that were not exposed to a model during training had a good chance of being identified with correct composer. Results show that our model is able to learn some specific patterns that could indicate the musical styles of composers. In order to generalise model performance to new composers a larger more diverse dataset should be collected.

The models presented can be further scaled to take advantage of larger sets of sheet music images with diverse quality of pixel resolutions and different angles of alignment of score on sheet music images.

VIII. ACKNOWLEDGEMENT

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Obstacles with Synthesizing Training Data for OMR

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Abstract—Training with synthetic data has been successfully used in many domains of deep learning where authentic training data is scarce. Optical Music Recognition (OMR), especially recognition of handwritten music, greatly benefits from training on synthetic data too. In this paper, we explore the challenges of synthesizing images of sheets of music for training deep learning OMR models and compare such synthesis to the process of digital music engraving. We also contrast that with the architecture of our synthesizer prototype, which was used to achieve state-ofthe-art results by training on the synthetic images only.

Index Terms—Optical Music Recognition, Synthetic Training Data, Data Augmentation, Deep Learning

I. INTRODUCTION

Most recent advances in Optical Music Recognition (OMR) have been possible thanks to the use of deep learning models [1], [4]–[6]. These models, however, require large amounts of annotated training data, which are difficult to obtain for this task. Manual annotations in complex schemes, such as *Music Notation Graph* (MuNG) [3], are very costly to be produced in amounts required by supervised deep learning models [2].

In other domains, the exploitation of synthetic training data has greatly helped with this problem, covering various areas of computer vision, such as handwritten text recognition, natural scene text recognition, or optical-flow estimation [10]–[16]. Synthetic data is generated by a computer simulation of a real-world process. It can be used in situations where the datagenerating process can be accurately simulated.

This paper outlines the challenges of synthesizing training data for OMR, both printed and handwritten. The second part of this paper describes the inner workings of our handwritten music synthesizer prototype *Mashcima* (Figure 1, top). We evaluated suitability of our synthetic images for OMR model training in our previous paper [24], where a model trained on our synthetic data was compared to other previously published state-of-the-art models, and the results indicated superior performance of our approach.

II. SYNTHESIS OF MUSIC SCORES

The idea of using synthetic training data for OMR is not completely new. Calvo-Zaragoza and Rizo [6] published the



Fig. 1. A sample image created by the Mashcima synthesizer using symbols from single writer (41) from the MUSCIMA++ dataset (top) and a sample image from the Camera-PrIMuS synthetic dataset (bottom).

PrIMuS dataset containing images of printed monophonic music that were created digitally using the engraving tool Verovio¹. An augmentation of this dataset was introduced later, called Camera-PrIMuS (Figure 1, bottom). It contains the same music as PrIMuS but the images are distorted and blurred to simulate the process of taking pictures of physical sheets of music under various conditions [7]. A similar approach was also used by Baró et al. [4] to produce images of historical music documents. The DeepScores dataset of printed music [8] was created in a similar way to the PrIMuS dataset but was not constrained to monophonic music. DoReMi [9] is a new synthetic dataset that also contains printed music and it provides multiple annotation schemes, each best suitable to a different stage of OMR.

In all of the above-mentioned works, the synthetic data was produced using some music engraving tool – a software for producing *printed* sheet music. There are no well-used datasets of synthetic handwritten music, but efforts in such direction exist. Baró et al. [5] introduced a data augmentation method based on measure shuffling where a staff of handwritten music from the MUSCIMA++ dataset [2] was sliced into individual measures and those were then shuffled and joined again. Our synthesizer prototype is based on the same idea taken further – shuffling individual symbols [24].

The production of printed music is called *engraving* and there is a variety of software tools available for this task (MuseScore, Verovio, and Lilypond, to name a few). Using them to produce synthetic training data is possible but requires certain modifications. Training data should be diverse in style

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¹https://www.verovio.org/



Fig. 2. Demonstration of various challenges of music engraving process.

so that the trained model learns to generalize to unseen music. Such diversity can be increased e.g. by using multiple music fonts [6], [8] or by distorting and blurring the produced images to simulate imperfections introduced by scanning and paper degradation [4], [7], [23].

While these modifications let us better synthesize printed music, synthesis of handwritten music requires much more control over the process. There are music fonts that mimic a handwritten style, such as the Petaluma font family², but the resulting image still contains the same symbol shape in all of its occurrences. Similarly, the layout system will not introduce any variability to symbol placement. This is what motivated us to build a dedicated handwritten music synthesizer, instead of modifying an existing engraving tool [24].

Straightforward candidates for data synthesis are generative deep learning models, such as Generative Adversarial Networks (GANs) [17] that were successfully used to generate synthetic images of faces, text, or even cuneiforms [11], [18], [19]. While GANs are typically suitable for generating individual symbols, synthesizing entire sheets of music is very difficult. They also have limited control over their output and require large amounts of training data. For all these reasons, GANs seem as not a solution for synthesizing OMR data.

A. Complexities of Digital Music Engraving

This section provides a brief overview of music engraving, because engravers are currently used for printed music synthesis and we believe most of their architecture will likely be reused in a handwritten music synthesizer.

The defining problem of music engraving is the positioning of musical symbols on a blank page. An empty music document contains only stafflines and these also define the spatial unit – the staff space (Figure 3).



Fig. 3. Definition of the staff space (sp) unit (image from CVC-MUSCIMA).

There are many ways to draw a graph-like structure, for example, a force-directed layout could in-theory be used [20]. In practise, though, a more bottom-up approach is typical.

²https://www.smufl.org/fonts/

MuseScore places objects called *segments* from left to right onto the staff. The horizontal size of each segment is computed based on its type and content, e.g. a chord, rest, barline, clef. While this segment approach solves the high-level horizontal placement, there are lots of specialized systems and rules that handle various edge-cases within and in-between segments. The complexity of music engraving stems from the unexpected interactions of these systems, resulting in awkward spacing or symbol collisions. Below, we provide a list of some of the challenges and illustrate them in Figure 2.

- Horizontal spacing: more space for longer notes and distributing evenly the remaining staff space³
- Note clusters: placing notes in a chord to not overlap
- Stem orientation: note orientation in general (pointing up or down)
- Accidentals and ornaments: allocating additional space for accidentals, preventing multiple accidentals from overlapping, placing dots in spaces and not on stafflines
- Beam placement: stretching stems to meet the beam, tilting the beam
- Slurs and ties: shaping a slur to not intersect notes, yet stay close to them
- **Multiple voices:** simultaneous notes from all voices should be horizontally aligned, two nearby voices must have stems pointing away from each other
- Lyrics: width of lyrics may influence note positioning
- **Tuplets:** tuplet markings and numbers interact with beams and slurs
- Grace notes: share features of notes and ornaments
- Dynamics: hairpins, dynamics, piano pedal marking
- **Text:** other text around the music, chord names, chord fingering diagrams, etc.

The precise documentation of how these subsystems are implemented by the existing tools is usually not available. However, most of the engraving systems we mentioned are open-source and the technical details can be inferred from their code. Some of them feature active forums and communities willing to answer questions (e.g., MuseScore, see *Engraving improvements in MuseScore 4.0*⁴).

The vector shapes of the symbols come from a *Music Font* where the very basic musical symbols (noteheads, stems, flags) are mapped onto Unicode characters and stored in a font file,

³https://musescore.org/en/node/299741 at 13th of October 2022

⁴https://musescore.org/en/node/330793 at 13th of October 2022

such as OTF⁵. The mapping from musical symbols to Unicode characters is standardized as SMuFL (Standard Music Font Layout)⁶.

B. Technical Differences in Handwritten Synthesis

Most existing handwritten music datasets contain images in raster form because they come from scanned physical documents. It is therefore convenient to have the synthesizer use and produce images in raster form as well. This is in opposition to engraving systems which work with vector images only. The consequence of this is that we need to harmonize the data resolution throughout the synthesis process.

We should mention that some datasets of music symbols contain richer information. For instance, HOMUS [22] contains symbols that are stored as a path, traced by a stylus or a finger, as it was drawn. This opens doors for sophisticated pen models that could learn specific handwriting styles. However, to the best of our knowledge, no such attempts have been published so far and we will focus on raster-based generation pipelines.

C. Understanding the Style of Handwriting

The most important difference between printed and handwritten music synthesis is the need to model the diverse visual style of handwritten music. We identify three areas that together compose the handwritten style:

- Layout style
- Symbol style
- Environment style

Layout style is the way in which the writer positions musical symbols relative to each other. In the previous section we described how engraving systems focus heavily on achieving the perfect layout. Such level of precision is not necessary for handwritten music synthesis because the hand is not as precise as a printer. While the layout style can, and should, be modeled, Figure 4 shows that our synthesizer with fixed layout rules still preserves most of the overall style of the source writer. To learn the layout style for future synthesizers, we can leverage the dataset MUSCIMA++ [2].



Fig. 4. A synthetic image with the sloppy handwriting style of writer 49 of the MUSCIMA++ dataset.

Engraving systems usually justify the staff to fit the width of the paper. Some human writers do this as well, first laying out measures and then filling them in, while others just write eagerly from left to right and leave empty space at the end of the staff when no more measures fit.

TABLE I Synthesis Stages in Mashcima

Phase	Tasks
1. Input parsing	Building internal representation,
	adding cross-references (beams, slurs)
2. Symbol synthesis	Selecting symbol images
3. Layout synthesis	Placing notes (with ornaments),
	orienting stems, placing beams,
	placing slurs
4. Render	Building the final image

Symbol style describes shapes of individual symbols, such as noteheads, stems, accidentals. A music font cannot be used, because each instance of the same symbol has slightly different appearance. This is probably the most interesting area of handwritten music synthesis and a lot of research can be performed here. Smaller symbols like noteheads and accidentals can be synthesized by convolutional models, elongated symbols like stems, slurs, and beams could benefit from sequential models. These sequential models could be trained on online symbol datasets, such as HOMUS [22]. We would argue that a pen model also belongs to this category, as certain pens affect the way a music symbol is drawn.

We define the *environment style* as all the influences that turn an ideal binarized image to the actual scanned or photographed image. This includes paper degradation, camera distortions, blur, noise, stains, etc. Erosion and dilation can also be used to alter the pen style. These methods have been used before in printed music recognition and more general document recognition [4], [7], [23]. We can call this environment simulation process *postprocessing*.

III. PROTOTYPING A HANDWRITTEN MUSIC SYNTHESIZER

In this section, we present a prototype implementation of a handwritten music synthesizer that can be used to generate training data for OMR. It is called *Mashcima* and is available on GitHub⁷. Initially, we tried to modify existing tools to produce handwritten-like music scores, however the particularities of handwritten music described in the previous section lead us to build a new tool. Our experiments show that training with synthetic data produced by Mashcima lead to the state-of-theart model for handwritten OMR [24].

A. Synthesizer Pipeline

The synthesizer accepts as input a sequential encoding containing some monophonic music. This encoding is very similar to the *PrIMuS Agnostic Encoding* [6]. Agnostic means the encoding contains note positions, rather than note pitches, making the recognition task slightly easier. Then, four stages shown in Table I process this input and build the resulting image. This image contains only one staff, as seen in all examples in this paper. Mashcima was designed for monophonic music because it simplified the synthesis and allowed us to use the PrIMuS dataset as a source of input sequences [6].

⁵http://www.microsoft.com/en-us/Typography/OpenTypeSpecification.aspx

⁶https://www.smufl.org/

⁷https://github.com/Jirka-Mayer/Mashcima

The first stage converts the input encoding into the internal representation. The core object is the *Canvas*, which acts as a container for *Canvas Items* and implements the layout synthesis logic. *Canvas Items* are larger groups of symbols that take up horizontal space on the staff, for example a quarter note with accidental and a duration dot; a clef; or a key signature. A staff is represented as a sequence of *Canvas Items* that are placed next to each other, similar to how text characters are arranged by a word processor (Figure 5). In this phase we also construct representations of beams and slurs, which break the sequential nature of the representation.



Fig. 5. *Canvas Items* (the red boxes) form the basis of horizontal spacing. The red crosses denote key positioning points, such as notehead centers and stem tops.

The second stage performs symbol synthesis. In the previous section of this paper we described various symbol synthesis approaches, but our synthesizer uses the simplest approach possible – printing symbol bitmaps from symbol datasets with no modifications. Specifically, we use symbol masks from the MUSCIMA++ dataset [2], including the empty staff image onto which other symbols are placed. This makes the synthesized images have similar style as the datasets. In the future we plan to utilize additional symbol datasets [22], [25], [26].

The bitmap sampling can be restricted to a subset of writers, giving us control over the handwriting style. The only modification we do to the sampled bitmaps is the vertical stretching of stems so that they meet the beam. Also, beams and slurs are not sampled due to their varied appearance and complex shape (they should align well with other symbols). Instead, they are rendered as straight lines and parabolic arcs, respectively. They are the least believable parts of the synthetic score, but a dedicated synthesizer would be too costly for a prototype.

The third synthesis stage is responsible for positioning symbols relative to each other. It is performed eagerly from left to right, where each *Canvas Item* requires some space and variable padding is added in between. Before a *Canvas Item* is placed, we first calculate its internal layout depending on its content, for example, accidentals and dots around notes make the *Canvas Item* wider.

Most of the layout rules determining a symbol position have the form of a fixed offset plus a random offset drawn from a uniform distribution. This introduces variability into the final score, however, this variability has the same hardcoded distribution for all writers. We do not perform any layout style learning.

In the final rendering phase, bitmaps are copied onto the output image. These bitmaps are binarized, but their position



Fig. 6. A synthetic image with staves above and below the main staff mimicking the looks of a cropped image.

is non-integer, causing interpolation, so the resulting image is grayscale.

In the previous section of this paper we defined the *environment style* and called *postprocessing* the stage that simulates it. Our synthesizer can perform only minor affine transformations of the image. We plan to add a more capable postprocessing stage in the future.

B. Miscelaneous

In our experiments [24], we noticed that our model did not learn to output *empty sequence* when it was given an empty staff. For this reason, we started inserting random gaps in the synthetic music, which our model has to learn to ignore. This spacing algorithm modification was however disabled for images shown in this paper.

The synthesizer can also render three staves into one image (possibly using tall barlines), thus further improving the feel of a cropped image (Figure 6). It also helps the trained model to learn to ignore the surroundings.

A major assumption we made is the separation of symbol synthesis from layout synthesis into two stages. When a human creates a score, they interleave these two stages constantly – they can, for example, draw notes smaller and tighter when not enough space is available because of symbols already drawn. This would require feeding the spatial constraints into the symbol synthesizer, which makes it only more complicated.

IV. CONCLUSION

A sheet music image synthesizer consists of many smaller, semi-independent subsystems (notehead synthesis, slur synthesis, beam placement, horizontal spacing). For this reason, developing a synthesizer is very costly. However, contrasting that with the cost of annotating enough music sheets in the MuNG scheme, it becomes a viable alternative, especially given the promising results shown by our relatively simple synthesizer. While professional music engraving is, in certain situations, needlessly complex, we can focus our efforts on the average case. In such settings, synthetic data becomes a viable way of building OMR systems. We believe that training data synthesis will play a crucial role in solving the task of optical music recognition.

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End-To-End Full-Page Optical Music Recognition of Monophonic Documents via Score Unfolding

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Abstract—Full Page Optical Music Recognition (OMR) systems typically consist of multi-step workflows. However, the fine-tuning of these systems tends to be costly. We present the first layout analysis-free full-page OMR model that receives a page image and directly outputs its transcription in a single step. This model requires only the annotations of full score pages during training. The model has been tested with early-notation monophonic music scores, for which the presented approach is especially beneficial. Results show that this methodology provides a solution with promising results and establishes a new line of research for endto-end music transcription.

Index Terms—Optical Music Recognition, Full Page, Monophonic Documents, Score Unfolding.

I. INTRODUCTION

Optical Music Recognition (OMR) is the research field that studies how to computationally read music scores [1] that still has open problems, especially in the most complex contexts.

With the advent of machine learning technologies, namely those related to deep neural networks, OMR systems have evolved from complex multi-stage workflows [2]–[4] towards alternatives where complete results are attainable. One of them is holistic music transcription, where the system directly outputs the symbolic sequence—typically text—that represents an input image [5], [6].

Although significant advances have been brought, these systems still rely on pipeline-based solutions to transcribe full page documents. In the case of end-to-end approaches, proposed solutions are limited single music staves transcription, relying on previous staff detection algorithms to work [7], [8].

This transcription approach is inconvenient for practical scenarios. Firstly, the solution relies on a composition of two models that are trained specifically on independent tasks–layout analysis and music transcription. This requires, first, labeling the bounding boxes and region classes present in the document. Then, the corresponding music representation must be written for each staff. Therefore, labeling a corpus to train a production-ready full-page OMR system can be tedious and time-consuming [9]. Another issue is that there has to be assumed an accumulated error from one step to the next [7],

where the performance of one step is highly correlated to its previous ones, creating a snowball effect.

In this paper, we propose an alternative full-page layout analysis-free transcription solution that tackles these problems.

II. EXTENDING OMR TRANSCRIPTION SYSTEMS

A. End-to-end staff transcription systems

The state-of-the-art end-to-end music staff transcription systems consist in neural models that directly output the music notation sequence of a given staff image. These networks are based on two main blocks: first, there is an encoder that filters an input image to learn and establish its relevant features, which is typically established with Convolutional Neural Networks (CNN). Then, the output of this module is processed by a decoder block, which learns temporal dependencies in the data to enhance results. This is commonly implemented with Recurrent Neural Networks (RNN). The whole model, referred to as a Convolutional Recurrent Neural Network (CRNN), is trained using the Connectionist Temporal Classification (CTC) [10] loss strategy, which forces the network to align the output sequence to the available information extracted from the image. One key step in this model is how the output of the encoder is adapted to be processed as a sequence in the decoder. State-of-the-art implementations [5], [11] reshape this feature map—which is a 3D structure of size (h, w, c), where h is its height, w is its width, and c is the number of filters (channels) obtained from the last convolutional layer-, by concatenating all the consecutive frames on the height axis of the image. That is, we obtain a sequence-like structure that now has a shape of $(w, c \times h)$.

B. The issue with full-page images

The methodology described in the previous section is ideal for single-staff images, as each frame (image column) is understood to contain information about the same symbol. This way, transcription can be done by reading the input image from left to right. However, full-page transcription cannot follow this formulation. In this case, a single frame contains more than one symbol. This leads to the CTC method to maximize the probability of non-consecutive symbols in consecutive time steps. That is, the network has to classify symbols from different staves in close image columns, failing at retrieving a symbolic sequence that respects the reading order of the music score, which hinders its transcription performance.

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C. From one staff to full page

In this paper, we reinterpret the feature map reshape by applying a score unfolding method. Instead of concatenating frame-wise elements along the height axis, we reshape the map by concatenating all of its rows, obtaining then a $(h \times w, c)$ sequence. From a high-level perspective, this method can be understood as a staff concatenation process, as shown in Fig. 1. This operation has to be done from top to bottom of the page, as it is crucial to respect the reading order of the music score during transcription.

Processing the feature maps this way prevents the aforementioned issue, as the CTC method will not face the problem of non-consecutive timestep collision—and will be able to produce symbolic sequences that respect the music score reading order.

This methodology, although theoretically valid, presents some points that should be discussed. The adaptation of the current state-of-the-art models only needs the symbolic representation of the full page for training, as the model directly outputs the music sequence from the input image. By avoiding the previously required layout analysis step from the pipeline, now the model has to face two main challenges: (i) identifying all the staves in the score and (ii) transcribing them into an ordered sequence. The second challenge is solved by the reshape method. In this case, the CTC blank token-which is an element introduced in the notation vocabulary to indicate time step separations-denotes both music element separations and staff breaks, since the single-staff-like produced sequence by the reshape method identifies the first symbol of the next staff as a consecutive timestep to the last symbol of the previous one. Challenge (i), is relegated to learning, whose effectiveness should be validated by experimental results.

D. Further considerations

The proposed method in this paper is still a single-staff transcription system, as all the staves of the pages are understood as a single long staff divided by the physical constraints of music pages. This methodology implicitly learns to reconstruct this original interpretation to transcribe the resulting long single-staff image in one step.

It is important to note that, at this point, the proposed method is suitable only for monophonic staves, as polyphony requires additional information and processing to be transcribed holistically. Vocal music scores—such as those written in mensural notation—can benefit from this approach. For this reason, the experiments are carried out with early music scores written in mensural notation.

III. EXPERIMENTAL SETUP

A. Models

As mentioned throughout this paper, we are adapting stateof-the-art OMR models to perform full-page transcription. All the presented solutions contain a fully convolutional block, which acts as an encoder of the input image features. This network is composed of stacked convolutional layers, which end up producing a feature map of size (h/32, w/8, c, b), h and w being the height and the width of the input image, c the filters in the last convolutional layer, and b the batch size. Then, the following decoding architectures are proposed:

1) Recurrent Neural Network: We follow the implementation of the original CRNN-CTC staff transcription model from [5], where the reshaped feature map is fed into a Bidirectional LSTM (BLSTM) and linearly projected onto the music notation dictionary. Specifically, we implemented a BLSTM with 512 units.

2) The Transformer: As we have observed in the reshape step, the model would have to process long sequences in one step, something that can have a negative impact on the performance of RNNs. For this reason, we propose an alternative encoder based on the Transformer [12] (referred to as CNNT). In particular, we implemented one encoder layer with an embedding size of 512, a feed-forward dimension of 1024, and 8 attention heads.

3) Sequence-processing-free module: In Sec. II-C, we hypothesize that the encoder would be able to learn to perform staff alignment in order to be read by the decoder module after reshaping. We implemented an analogous text model [13] that does not use sequence processing in the decoding stage, leaving all the data processing to the CNN. With this model, we intend to prove this hypothesis without the influence of sequence processing methods.

B. Corpora

Two mensural-notation music datasets with different characteristics in engraving style were used, in order to represent the different challenges that the model can face in these real-case scenarios.

The first corpus is "Il Lauro Secco" [14] (denoted as SEILS), which corresponds to an anthology of 150 typeset printed images of the 16th-century Italian madrigals.

The second corpus is the CAPITAN dataset [5], which contains a complete ninety-six pages manuscript from the 17th-century containing a handwritten *missa*. Fig. 2 depicts examples of these documents.

TABLE I: Details of the corpora regarding the pages' features, such as sizes in pixels, number of samples and staves per page, number of symbols present and unique symbols per dataset (*vocabulary*).

	SEILS	CAPITAN
Num pages	150	123
Max page size	1200×813	1593×2126
Min page size	1200×813	1100×780
Avg staves per page	4	10
Max staves per page	9	12
Min staves per page	1	2
Avg symbols per page	222	136
Max symbols per page	331	220
Min symbols per page	110	23
Unique symbols	183	321



Fig. 1: Graphic visualization of the reshape method to adapt current systems to full-page transcription. The reshape module learns how to separate and concatenate the staves on a page in a single line. Note that the original image has been used in the reshape for clarity of explanation, but the alignment is done in the *feature space* extracted by the encoder.



Fig. 2: Music page examples from the used corpora.

C. Metrics

To carry the evaluation of the models performance, we used the Sequence Error Rate (SER) metric [15], as it represents accurately the performance of the model in recognition tasks and correlates with the effort a user would have to expend to manually correct the results.

IV. RESULTS

Table II shows the results obtained by the studied methodology on the test set for each corpus. Results reported by Castellanos et al. [16] are included to establish a reference value from a state-of-the-art algorithm based on a standard OMR pipeline. Note that this reference model is trained under more favorable conditions, as it addresses the fullpage transcription in two separate tasks. Therefore, it should be understood only as a reference and not as a competing approach.

The results obtained show that the extended models were able to transcribe full-page scores with fair SER values, below TABLE II: Test SER (%) obtained for the studied models. Castellanos et al.'s work is included in the last row as a reference value to observe how current OMR pipelines work to transcribe the used corpora in this paper.

Model	Augmentation	SEILS	CAPITAN
CPNN	-	6.3	26.6
CRININ	\checkmark	4.3	15.5
CNNT		12.9	28.4
	\checkmark	7.2	18.2
FCN		23.3	89.5
FUN	\checkmark	13.3	22.5
Staff-based [16]	-	3.6	10.8

30% except for the FCN without data augmentation in the CAPITAN dataset. These error values also scale depending on the engraving complexity of each corpus. The model that reported the best results was the combination of the CNN with the RNN decoder (CRNN), which reported an error rate of 4.3% in the SEILS corpus and 15.5% in CAPITAN.

The models that use sequence processing decoders (CRNN and CNNT) performed better than the single FCN network. This was expected to some extent, as these architectures exploit and optimize sequential information to improve performance. In fact, they also seem to bring some robustness to the model against the scarcity of training data, something observed comparing the performance of the FCN when no data augmentation was applied to the CAPITAN corpus.

It can also be observed that applying data augmentation, significantly improved the overall performance of all models. The produced SER was reduced by approximately 30%–40% and, in the case of the FCN in the CAPITAN corpus, produced



(a) Original page.

(b) Transcribed prediction with CRNN, rendered with the Verovio toolkit [17].

Fig. 3: Visualization of the transcription produced by the CRNN model in a music page from the SEILS dataset. Errors are highlighted. Note that the output is actually produced on a single line, but a multi-line representation of the score has been reconstructed to facilitate comparison with the original document. In this particular case, the obtained SER is 6.1% (higher than the average on this corpus).

competitive results. In other words, the models are able to work with few samples, but they require a considerable amount of data to obtain their best performance.

Comparing the two sequence processing decoders, we observe that RNNs performed better than CNN Transformers in all cases. The reason for this is aligned with the results obtained in works that explore the use of these models on document transcription [18], where RNNs are, in an advantageous situation where sequences with less than 512 tokens have to be processed, which also happens in this case (see Table I).

For the sake of visualization, Fig. 3 presents the results obtained in a test set page from the SEILS dataset by the best model (CRNN). As can be seen, the system produces a good transcription, in which most of the symbols are correctly labeled and aligned within their corresponding staves. If we analyze the produced errors, most of them are subtle—such as vertical position misplacement— and can be easily corrected with score editing software. This happens often with narrow symbols—such as rests—whose manual annotation would also have been difficult to perform.

V. CONCLUSION

In this paper, we present a first layout analysis-free end-toend approach for full-page OMR. This method is trained with weakly-annotated data: it only requires a set of page images with their corresponding transcription, in contrast to current state-of-the-art full-page OMR pipelines that require spatial information. Our methodology extends the current staff-level end-to-end systems to full-page transcription by applying an unfolding step that enables the network to process full pages as single staves. The reported results showed that the proposed system produces competitive results for full-page transcription. Although precision is slightly lower than a multi-stage OMR pipeline, the proposed approach stands as an interesting alternative for those models. The model provides a favorable trade-off between the cost of labeling and the system's accuracy.

Future research research arises from this work. First, this work only covers monophonic music documents. However, in modern music, the coverage is more restricted, since polyphony is much more common. This scenario could be an interesting case to analyze alternative architectures for OMR, such as attention-based systems [19] or non-CTC-based image-to-sequence architectures [20].

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End-to-End Graph Prediction for Optical Music Recognition

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Abstract—Modern advances in computer reading technologies have found excellent results using end-to-end neural approaches. In addition to reducing the number of steps required, these formulations force the neural network to learn to take into account the contextual nature of visual languages to boost recognition. So far, however, such approaches are only feasible when the output can be represented as a sequence. This works for many old music notations, or even for modern monophonic scores, but it is insufficient for the highest degrees of complexity of music notation. Furthermore, music notation can be nicely represented using a graph structure. In this paper, we present a first attempt at an end-to-end approach to predict graphs from images, taking complex music-notation symbols as input.

Index Terms—Optical Music Recognition, Graph Representation, Deep Learning.

I. INTRODUCTION

Music notation can intuitively be interpreted as a visual language whose primitives—the graphic elements of which a music symbol is composed—can be modeled using pairwise relationships [1]. Therefore, the field of Optical Music Recognition (OMR) [2] might benefit from neural approaches that are capable of generating graphs from images in an end-to-end fashion.

In this work, we summarize the novel neural architecture proposed in the work of Garrido-Munoz et al. [3], that retrieves a certain representation of a graph—identified by a specific order of its vertices—in an end-to-end manner. This architecture works by means of a double output: it sequentially predicts the possible categories of the vertices, along with the edges between each of their pairs. We will also overview the experiments carried out to retrieve a graph from images depicting complex music-notation symbols from the MuSCIMA++ [1].

II. METHODOLOGY

In order to retrieve a graph representation, we conceptually divide the problem into two tasks: node and edge prediction. In the first task, the nodes of a specific representation of a graph are retrieved by means of a sequential prediction of node categories. In the second task, the network predicts whether a pair of nodes are connected, which can be seen as predicting the adjacency matrix of that graph representation. We propose a multi-output architecture that performs the two tasks simultaneously. Figure 1 provides a general overview of the proposed neural network.

The first stage involves an image-to-sequence neural model. This is done using an encoder-decoder architecture that retrieves image features by employing a Convolutional Neural Network (CNN). These images are then fed to a Recurrent Neural Network (RNN), which decodes a series of primitives and their representations. The RNN activations are also used for node classification and, by grouping them by pairs, the model predicts whether there is an edge between them.

This neural network can be trained without any specific geometric information concerning where the vertices are located in the input image. This might represent a competitive advantage when creating training sets, as it is much less expensive to annotate music scores in this way and the process could also be automated from existing encoded sheet music.

III. EXPERIMENTS

A. Data

The experiments were carried out using the MUSCIMA++ dataset [1]. This dataset provides a great variety of handwritten music scores, which consist of musical symbols—primitives and the annotated relationships between them, presented in the form of graphs. For our task, we isolated some musical structures and eventually obtained a dataset of independent annotated image-graphs pairs containing the nodes—musicnotation primitives—and the relationships between them as an adjacency matrix.

B. Metrics

Computing a graph edit distance is known to be an NPhard problem [4]. This fact leads us to discard a single metric that encompasses all the differences between the predicted and ground-truth graphs. Alternative metrics that could correlate with the performance are, therefore, required in this task. Here, we measure two factors for the graph prediction task in hand: (i) the accuracy of the node sequences predicted and (ii) how accurately the edges between these nodes are predicted. For the former, we consider the Symbol Accuracy (Acc), whereas the latter is measured using the F_1 .

Symbol Accuracy is a metric based on the Symbol Error Rate (SER). This is a common metric in tasks related to sequences, such as Handwritten Text Recognition. This value measures the error of the model in the recognition task and

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Fig. 1: General schema of the image-to-graph neural network (from [3]).

correlates to the effort that a user would have to make in order to manually correct the results. When measuring accuracy, it is possible to resort to symbol accuracy (Acc), which is computed as 1 - SER. We resort to this metric for the sake of readability so that both metrics (F1 and Acc) stick to "the higher the better".

The F_1 metric is defined as

$$F_1 = \frac{2 \cdot TP}{2 \cdot TP + FP + FN} \tag{1}$$

where TP, FP, and FN are the true positives, false positives, and false negatives, respectively. As we wish to measure the accuracy in the predicted edges, we use actual edge connections as the positive class to compute the F_1 .

C. Evaluation scenarios

In this work, we have considered the following scenarios for evaluation:

- Function Choice of graph representation. We must consider a function that consistently converts a graph into a specific representation in which its nodes are expressed as a sequence for the RNN to retrieve. We shall analyze how the choice of this function by considering two possibilities:
 - Topologic: sorting nodes according to the image topology, ordered from left to right and top to bottom.
 - Alphabetic: sorting the nodes alphabetically, according to the vocabulary of primitives.
- 2) **Visual-attention**. We implemented two neural models with and without a visual-attention mechanism.
- Scarcity of data. In order to simulate different conditions, we restrict the data used for training to the following percentages: 5 %, 25 %, 50 %, and 100 %.

D. Results

Fig. 2 shows the average results in the test set, following a 5-fold cross-validation strategy.

First note that the proposed approaches are successful in carrying out their tasks, obtaining satisfactory results in almost any scenario. Note also that the symbol accuracy and F_1 score are closely related. This high correlation denotes that, although these tasks are measured independently, their performances are linked.

Concerning the choice of the ordering function, there are significant differences in the performance. Sorting the symbols alphabetically increases both symbol accuracy and F_1 by approximately 20%. The reason for this difference might be the sensitivity to image variations of the topological order and its impact during training. When presented with two similar images that have displaced elements, it is likely that their graph representations will be topologically different, as the nodes appear in a different order and this alters the adjacency matrix. This is problematic in neural network training, since very similar inputs might have completely different outputs.

With regard to the use of the visual-attention mechanism, there were no significant differences. Nevertheless, in scenarios where data scarcity becomes more prominent, we find that models that use the visual attention mechanism clearly outperform models that do not. This is because attention mechanisms are able to obtain filtered information from specific feature representations, which enable the model to converge with fewer training samples.

In relation to data scarcity, the performance is also strongly linked to the choice of the nodes' ordering. With the proper ordering function, the model behaves well even when data scarcity is extreme, as in the case of only 5% of the available data. The models with alphabetical sorting and only 25 %



Fig. 2: Barplot visualization (mean and standard deviation) of the results.

of the available data perform better than the best model with topological sorting using the complete dataset.

In order to illustrate the performance, Fig. 3 depicts two predictions in the test set from the best configuration. As Fig. 3a shows, the model labels all the nodes correctly and successfully retrieves their corresponding edges. Nevertheless, there are some errors in Fig. 3b: one node is wrongly labeled it predicts an 8th flag rather than a beam, which can be considered a reasonable mistake from the graphics recognition point of view, and the edge between the bottom-left notehead and the top beam is missed. Note that, since the graphs are inferred without specific indications about the positions of the nodes in the input image, these visualizations are simply a possible interpretation of the relationships that the neural network could have established.

In general, results showed that the proposed methodology and formulation are successful in solving the image-to-graph task within the specific context of music-notation structures. Our method is able to retrieve the graph from the image without the need for spatial information regarding the elements in the input source.



(a) Example of a correct prediction in which nodes and edges are retrieved successfully.



(b) Example of prediction with errors. The red box represents the fact that the node has been wrongly labeled, while the dashed red line indicates that the edge between the corresponding nodes has not been predicted.

Fig. 3: Examples of test set predictions. Images on the left represent the input image given to the model, while those on the right represent the graphs retrieved by our best model. Note that the bounding boxes depicted are simply a visual aid, as our approach does not retrieve them specifically. Green indicates correct predictions and red indicates errors, which are described in each example.

IV. CONCLUSION

We describe a new holistic image-to-graph model with which to retrieve a graph representation of the elements present in an input image. We propose a formulation based on sequential node classification and pairwise edge reconstruction. This formulation has been devised for use in the Optical Music Recognition (OMR) field.

The results showed that the proposed methodology and formulation are successful in solving the image-to-graph task within the specific context of music-notation structures. Our method is able to retrieve the graph from the image without the need for spatial information regarding the elements in the input source.

The primary objective of our future work is to retrieve graphs from full pages, since the state-of-the-art models are limited as regards the task of retrieving the sequence representation of these document types. This will open up an interesting scenario for the use of graph representation in order to approach the complete OMR problem.

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Efficient Approaches for Notation Assembly in Optical Music Recognition

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Abstract-Optical Music Recognition (OMR) is the field of research that studies how to computationally read music notation from written documents. Thanks to recent advances in computer vision and deep learning, there are successful approaches that are able to locate the notation elements out of a given image. However, the stage of notation assembly, in which these elements must be related to reconstructing the musical notation itself, has received little attention in the last years. Furthermore, given the large number of elements in a music score, this stage must be efficient enough to be useful in practice. In this work, a couple of neural approaches that perform this stage efficiently are studied. Our experiments using the MUSCIMA++ handwritten sheet music corpus show that there exists an underlying trade-off between effectiveness and efficiency, since each approach shows very good results in only one of these two aspects. We hope that this work represents a starting point for further research in this important stage of the OMR.

Index Terms—Optical Music Recognitionm Notation Assembly, Neural Networks.

I. INTRODUCTION

Building upon previous work, this paper proposes a series of methods for the automatic inference of relationships between isolated music-notation elements, which are assumed to be detected from the image in previous steps of the Optical Music Recognition (OMR) pipeline. It should be noted that this inference must be made between each pair of elements, which implies a high computational complexity because of the density of elements within music score images. Therefore, in addition to accuracy, one must carefully take into account the efficiency of the inference. That is why our methodology considers two efficient neural approaches: one that is based on classifying each pair of elements by means of a series of simple numerical features, while the other uses asymmetric kernels [1], which can be computed with high parallelization and provide results very fast. In our experiments, using the well-known MUSCIMA++ corpus, we will compare the tradeoff between effectiveness and efficiency that these methods provide and discuss the experimental outcomes.

II. BACKGROUND

To our knowledge, the only existing work that focuses on the retrieval of relationships using machine learning techniques is that of Pacha et al. [2]. In this work, for each pair of nodes detected, a single image is built with different channels: one that depicts the area of the image that contains both nodes, another that depicts the same region but only showing the first node, and another that depicts also the region of interest but only showing the second node. A Convolutional Neural Network (CNN) is then trained to recognize whether or not there is a relationship between the nodes involved in this threechannel image. Despite the reported good results, the approach is tremendously inefficient, since it requires the independent construction of an image for each pair of nodes, which must be also processed by a CNN. As we will see below, this scheme entails a computational complexity that is infeasible in practice. Therefore, in our paper, we focus on providing a solution to the same problem based also on machine learning but with a level of efficiency that enables its use in a real system.

III. METHODOLOGY

This paper follows the formulation proposed in previous works [2]–[4], where it is assumed that the computational reading of a music score, in the context of OMR, can be described by retrieving a graph structure from the image. In this graph, the notation elements (referred to as "primitives") represent nodes, while the relationships between them are the edges. In this work, we are particularly interested in the retrieval of the edges, once the nodes have been detected somehow (as for instance, with the existing approaches mentioned in the previous section).

We assume that for a given music score s there exist a graph g_s that represents its content. The graph is defined as a pair (V, E), where V represents in terms of P and R as wellsents the set of nodes and E the set of edges. Two nodes $v_i, v_j \in V$ are connected if there exists and edge $e_{i,j} = (v_i, v_j) \in E$.

In the context of OMR, information about the set of symbols V can be obtained through existing techniques. This corresponds to the *music symbol detection* stage of the pipeline. Therefore, we here assume that exists a function that maps s onto a set V. Typically, each symbol $v_i \in V$ is further represented as a set of features with, at least, the following information: class label and coordinates within the image score. The problem we address here is how to get a E given V, which corresponds to the *notation assembly* stage of the OMR pipeline.

The problem can be considered from two points of view: (i) as a binary classification task in which a model predicts the class of each pair of nodes v_i, v_j present in each score and (ii) as an adjacency matrix reconstruction A of a given

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Fig. 1: General schema of the methodology for retrieving the edges of the music notation graph.

graph, which represents all the possible relationships between a set of nodes. For the sake of simplicity, the objective of our approach is to solve problem (i), since it is straightforward to convert the set of retrieved relationships to an adjacency matrix.

In this binary classification, $e_{i,j}$ is labeled as a 1 if there is relationship between v_i and v_j , and 0 otherwise. The prediction of the relationship class can be represented as a function $\varphi(v_i, v_j)$ that takes the two nodes' features as input and computes the probability of connection. Figure 1 depicts a general outline of the methodology adopted in this work.

A. Approaches

From the formulation given above, it is important to emphasize that the cost of predicting each possible edge entails a complexity $O(|V|^2)$. Therefore, the approaches to φ must take into account the computational cost in order to make the task feasible in practice.

We here propose two shallow neural architectures that take a pair of nodes and predict the class of the relationship. These two neural architectures are (i) a Multilayer Perceptron (MLP) architecture that takes the input of each node's features concatenated and (ii) an asymmetric kernel model.

1) MLP architecture.: In this method, the features attributes—of the nodes are first concatenated, forming a single feature vector that contains the entire information from the pair of nodes. Then, this vector is passed through a series of layers of an MLP. The final layer implements a function σ that models the probability of the two input nodes being connected:

$$\hat{e}_{i,j} = \sigma(\varphi_{MLP}([v_i, v_j]))$$

2) Asymmetric kernels.: In this second scheme, our proposed neural architecture learns an asymmetric kernel function [1]. This function is defined by $k(v_1, v_2) = (\langle \phi_{k_1}(v_1), \phi_{k_2}(v_2) \rangle)$, where $\langle \cdot, \cdot \rangle$ is the dot product of two N-dimensional points in two Hilbert spaces—features spaces.

In this work, we use this asymmetric kernel as a similarity function between the two mapped features to distinct Hilbert spaces.

$$\hat{e}_{i,j} = \sigma(\langle \phi_{k_1}(v_i), \phi_{k_2}(v_j) \rangle) \tag{1}$$

In this approach, $\phi_{k_1}(v_1)$, $\phi_{k_2}(v_2)$ are kernels implemented as MLPs that map the initial node features onto two different (asymmetric) embedding spaces. This space is supposed to represent the appropriate features for the task at hand. After computing the similarity score, a σ function is applied to obtain probabilities between 0 and 1.

What is really interesting about this approach is its computational efficiency: the embeddings are calculated independently for each node. Then, for each possible relationship, it is only necessary to compute the dot product between node embeddings and apply the σ function. That is why the complexity is much lower than the previous approach, as there is hardly any specific computation in the order $O(|V|^2)$.

IV. EXPERIMENTS

The experiments were carried out using the MUSCIMA++ dataset [3], which consists of handwritten scores with different levels of complexity. Given that we we are interested in obtaining the edges of the graphs that represent the music scores, we will use the well-known F_1 metric.

A. Results

In this section, we present and discuss the results obtained. Specifically, we study performance at two levels: effectiveness and efficiency. For this study, we include the two proposed approaches, further disaggregated by the node features considered: only the node label, only the node coordinates, or both features. This will give us an idea of what features are important for edge retrieval. In addition, to establish a reference in the effectiveness that can be obtained for this task, we include the results of Pacha et al. [2], measured under comparable conditions. However, its time cost is so high (it



Fig. 2: Average results (5-fold cross validation) in terms of F_1 with respect to the model and features considered. The dotted line represents the result from Pacha et al. [2] (upper bound).

TABLE I: Average results (5-fold cross validation) in terms of precision (P), recall (R) and F_1 , with respect to the approach and features considered.

Features		Asymm. Kernels	MLP
Class	Box coordinates	<i>F</i> ₁	F_1
✓ ✓	×	1.0	0.4
×	\checkmark	61.4	79.6

will be shown later) that makes it unfeasible to be integrated into a real system. Therefore, it should only be considered as an upper bound of the performance for the task of retrieving relationships.

First, Fig. IV-A show the average performance of the 5-fold cross-validation in terms of F_1 . The first thing to note is that the features play a fundamental role in both approaches. The class label, as one might expect, is hardly informative by itself. In such a case, the results are tremendously poor (1.0 % of F_1 , at most). However, it does manage to remarkably complement the performance obtained by using only the geometric features of the nodes (i.e., position in the image). In the case with both types of features, the MLP method attains 91.9 % of F_1 , very close to the upper bound established by the work of Pacha et al. [2]. The asymmetric kernel method, on the other hand, offers fair but much poorer performance (76.8 % of F_1).

To complement these results, we depict a representative visualization of what these results imply in musical scores in Fig. 3. Note the very large number of relationships to be computed (despite not highlighting the correctly ignored edges), which demonstrates the computational complexity of the task. Precisely due to this issue, below we study the time it takes for the different methods to achieve these results.

B. Time comparison

In this section, we analyze the time performance at inference time for each considered method. Table II shows the average

TABLE II: Time performance of each method proposed according to the number of nodes in a score.

No. nodes	Method	Time (s)	Nodes/s
500	Asymmetric kernels	3.5×10^{-4}	1,417,313.0
	MLP	9.5×10^{-2}	5,234.4
	CNN [2]	336.2	1.5
1,000	Asymmetric kernels	3.01×10^{-4}	3,325,810.0
	MLP	1.7×10^{-1}	5,922.4
	CNN [2]	1,346.0	0.7

processing time and the node's relationships (one vs. all) that can be analyzed per second depending on the number of nodes of the score.¹ For this comparison, we consider two music scores with 500 and 1,000 symbols, from which we have to compute all the possible relationships.

As can be observed, the CNN proposed by Pacha et al. [2] takes several minutes to complete a score (5 in the case of 500 elements and 22 in the case of 1000 elements). This means that it could not be integrated in a friendly way in any system that requires user interaction. The MLP does achieve a rather acceptable efficiency, with just a few milliseconds per score. Furthermore, the asymmetric kernel approach is extremely efficient.

Note that the asymmetric kernel method exploits the parallelization of the dot product operation and the independent node processing. The same does not occur with the other methods, which, due to the way they perform the classification, require more computation. In the case of MLP, the approach has to first generate all possible pairs of combinations between symbols and then predict with the concatenation of their features. In the case of Pacha et al. [2], an image needs to be built first and then processed by a CNN for each pair of nodes. Although there are 5 blocks of convolutions, pooling, and batch normalization, the input images are very large (256×512) , which makes the method excessively slow.

These results demonstrate that there is no single method that beats the rest in both accuracy and efficiency. However, we could postulate the proposed MLP method as the best candidate to date, given that it obtains a very good F_1 (very close to the upper bound provided by CNN) while its efficiency is sufficient for a system that requires interaction with users

V. CONCLUSION

In this work, we study the retrieval of relationships between symbols from music scores, referred to as *notation assembly* in the OMR literature. We approached the problem as a binary classification task where the goal is to predict if there is a relationship between each pair of the nodes that have been previously detected.

We proposed two methods that have been empirically proven to be feasible to solve the task at hand: an MLP

¹Only for comparing execution times, we implemented the CNN architecture proposed in Pacha et al. [2] with the details provided in the paper.



(a) Edge retrieval by the MLP approach.



(b) Edge retrieval by the Assymetric Kernels approach.

Fig. 3: Visualization of the performance of the approaches. Green lines represent TP, while blue and red lines represent FP and FN, respectively. Turquoise boxes represent the nodes.

architecture that works very precisely to the expense of a (little) higher computational cost and an asymmetric kernel model which works extremely fast, with a noticeable loss of accuracy. Also, we empirically demonstrated that all features considered (class labels and bounding box coordinates) are relevant for the performance.

We consider that this work demonstrates the need to pay attention to the notation assembly stage in OMR, given that it is not trivial to solve the task by attending to both precision and efficiency issues. In addition, several avenues of future research are opened: on the one hand, it would be important to estimate the relevance of each error produced. So far, it has not been studied what errors (losing positive relationships or making relationships that do not exist) and what type of elements involved cause the most impact on the OMR system. On the other hand, this work has considered the labeling of the MUSCIMA++. However, it has not been explored in depth whether the way of annotating relationships is more or less appropriate for the learning algorithms. More consistent annotations may be possible, as long as the goal of correctly encoding music notation is still met.

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Computer-Assisted Measure Detection in a Music Score-Following Application

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Abstract—ConcertCue is a web application that synchronizes content delivery with live music. During a concert, a human operator supervises a score-following process to ensure it stays in sync. To aid the operator, the system displays a scanned copy of the score and highlights the current estimated measure, which requires the system to know the visual location of each measure on each page.

In this paper, we present a fast, accurate OMR algorithm for identifying systems and barlines in a musical score and an integrated user interface that allows for quick OMR verification and correction. The use of this system as a part of ConcertCue has accumulated over 1,000 pages of human-verified annotations, which we plan to release as a dataset in the near future.

Index Terms—Real-time Score Following, Optical Music Recognition, Measure Detection, User Interface

I. INTRODUCTION AND RELATED WORK

Score following is the task of continuously estimating the position of a live musical performance relative to a predetermined reference track. The musical performance is typically captured as a live audio signal, while the reference track might be a preexisting audio recording of the same music [1] or a symbolic representation such as a MIDI file or digital score [2]. Applications of score following include automatic accompaniment [3], automatic page turning [4], and synchronized content delivery to audiences during live music [5].

ConcertCue,¹ a web application that we have developed over the past several years, is an example of the latter. A timeline of events (snippets of content including text, images, and animations) is authored to align with important musical moments in a particular piece. When the piece is performed, these events are displayed on target devices such as personal mobile devices or screens in the concert hall at exactly the right musical times. While this real-time alignment may happen automatically, in practice, a musically-literate human operator must be present during the performance to ensure that the system is working properly and to correct any synchronization errors that might occur.

As shown in Fig. 1, the ideal environment for the operator is an application that displays the music score of the piece being performed while also indicating the estimated real-time position of the live music overlaid on top of the score. In

¹See https://concertcue.org and https://concertcue.com

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Fig. 1. ConcertCue System Overview. Audio of a performing orchestra (a) is sent to a human operator (b) who ensures that score following behaves correctly. A score is displayed with the current measure highlighted in red (c), which can be adjusted by the operator as needed. Timing data is streamed to a server (d) which in turn synchronizes content on the audience display device (e) during the performance.

this way, the operator has a full understanding of "where the system is" relative to the music and can make adjustments as needed via a suitable user interface.

To enable this functionality, a digitized score of the piece must be properly annotated so that the application can create a mapping between musical time (the measure and beat of the music) and its 2D location in the digitized score. Optical Music Recognition (OMR) makes this annotation task feasible and much faster than manual annotation. While the full complement of OMR tasks includes a complete understanding of the music score (such as notes, rests, dynamic markings, and articulations [6]), we are only interested in the early stages of an OMR system: identifying the locations of the systems of a score and the measures within each system (such as [7]).

II. IMPLEMENTATION

An overarching goal in implementing ConcertCue is to develop powerful and easy-to-use tools for content creators. As such, the entire platform is a web-based client-server app with all its inherent advantages (e.g., works anywhere on any computer browser, zero installation, easy deployment and software updates). Much work went into user interface (UI) and user experience design in the two primary usage domains: pre-concert content authoring, and real-time operation. In both cases, the most important UI element is the digital representation of the score and its associated annotations.

A. Score Annotation Tool

Fig. 2 shows the score annotation tool. A user begins by uploading a PDF of the entire score for a piece of music. The server initiates an automatic OMR process that estimates the locations of all system bars on every page. An overview of the algorithm is described below in section II-B.

Processing a single page may take anywhere from 2-20 seconds, largely depending on the CPU resources available to the server. As soon as the first page has been processed, it is displayed in the editor so that the user can verify the system and measure positions and make corrections if necessary. Thus, the user can immediately start working while the server continues to process subsequent pages.

Our UI supports multiple systems per page and assumes that all barlines belonging to a single system share the same y coordinates.² This enables the user to easily add, delete, or move a barline by dragging it to adjust its x coordinate, rather than specifying a rectangle for each measure separately.

Ideally, the OMR process correctly identifies all systems of a page and the barlines within each system. To aid the user in quickly assessing the automated estimation process, we employ a pseudo-random coloring scheme for displaying measures. Measure colors are chosen such that adjacent measures are tinted with highly contrasting hues. Barlines are displayed as blue lines (see Fig. 2). Both measure tinting and barlines can be toggled on or off. Typically, a page can be verified by a musician within a few seconds.

If the OMR process incorrectly identifies the systems of a page (for example, by accidentally combining two separate systems into one), the barlines of these incorrect groupings will likely be incorrect as well. At this point, the user can correct an erroneous system's y coordinates using the drag handles and then initiate a partial OMR task that only reestimates barlines within the selected system. This feature makes quick work of fixing an early error (system misidentification) which would otherwise render the whole page incorrect. After correcting the system annotations, barlines can be re-estimated, producing the correct result much more quickly than by manually correcting every barline.

In addition, the user can easily number the measures of a score by setting a number for a particular measure. The editor automatically numbers the following measures sequentially until the end of the piece, or until a new measure number is entered. This case is useful, for example, if a multimovement score begins renumbering measures at the start of each movement.

B. OMR Implementation

Our OMR implementation uses a statistical image processing approach based on assessing the probability of long,



Fig. 2. Screenshot of the score annotation tool. Measure tinting is guaranteed to have high visual contrast between adjacent measures. Barlines are overlaid as blue lines. Shown above, the first system is selected. The system grab handles (a, b) let the user modify a system's vertical bounds, which also dictate the vertical extents of the barlines. A single button click (c) re-estimates barlines of the currently selected system, or of the entire page if no system is selected.

mostly-continuous horizontal lines (staff lines) at a given y coordinate and of mostly-continuous vertical lines (barlines) at a given x coordinate. This approach is similar to the strategy taken by [8] though it was developed independently. The algorithm happens in three phases.

First, the full image is rotated so as to maximize the likelihood of perfectly horizontal and vertical lines. This process removes whatever slight rotation may exist if the original score was scanned by hand. Removing rotation greatly improves accuracy in the rest of the process.

Next, staff lines are detected. The image is processed with a median filter to enhance horizontal lines and then averaged across the x-axis to produce a staff-line likelihood curve, where peaks correspond to staff line locations along the y-axis. See Fig. 3. Then, intra-staff-line spacing is measured. Small gaps are likely to be spaces between lines of a single staff while large gaps are likely to be spaces between distinct staves. Once staves are identified, they are grouped into systems. In a typical multi-system score, the left-most edge of the score has a vertical line connecting staves into a single system. Therefore, undisturbed white space between staves usually

²While this assumption may not be strictly true due to page skew or other scanning artifacts, it works well enough for this application and simplifies the UI, as barline y coordinates are inferred from the containing system.



Fig. 3. Staff line identification. The original image (a) is passed through a median filter (b). Averaging across the filtered image produces a staff line likelihood curve (c). Peaks in this curve correspond to staff line locations.

indicates the beginning of a new system.

Finally, each system is analyzed for the likelihood of barlines within its vertical bounds. Since all barlines of a single system are vertically aligned, they tend to reinforce each other. A similar median-filtering approach along the y-axis is used to create a barline likelihood curve. Once the x-coordinates of barlines are estimated, they are used in combination with the system bounds to generate a listing of system measures.

C. Other Tools

The rest of the application comprises basic content management (e.g., creating concerts, pieces, movements), and other editors needed to complete data entry. For example, the cue editor is used to attach cues (HTML snippets with text and images) to a location in the score. A score location is defined as a measure number and a fractional position within that measure in the range [0, 1]. The cue editor is shown in Fig. 4. Cues are easily added, modified, or deleted from the score with mouse clicks and drags.

During a live performance, the score is displayed and its pages are automatically scrolled into view based on the estimated current location in the piece. The current measure is highlighted in red (see Fig. 1) using the annotations created by the user (section II-A) with the aid of our OMR algorithm (section II-B). The operator monitors the progress of the estimated location and make manual adjustments as needed.

III. EVALUATION

The measure detection task was evaluated against a corpus of fourteen typeset scores totalling 1,117 pages of music. Eleven scores were scanned from printed copies, while the other three were exported from engraving software and thus have no scanning artifacts. There are no hand-written scores. This ground-truth set was created and human-verified using the score annotation tool described above. The data for system barlines are stored as normalized page coordinates. In other words, x-coordinates are in the range [0, 1] relative to page width, and y-coordinates are similarly relative to page height.

 TABLE I

 Barline estimation results. Type S is hand-scanned score. Type

 E is exported directly from engraving software

Score	Туре	Pages	Barlines	F-Score
Beethoven Rondino	S	8	142	0.996
Adams Doctor Atomic	S	97	826	0.987
Debussy La Mer	S	137	845	0.987
Debussy Nocturnes	S	120	666	0.977
Haydn 49	S	23	503	0.983
Liszt Prometheus	S	66	516	0.976
Maskats My River	Е	66	387	0.996
Mozart Piano Concerto 24	S	64	1049	0.980
Prokofiev Violin Concerto 2	S	85	981	0.931
Ruehr Cosmic Cowboy	Е	41	320	1.000
Ruehr Lucy	Е	42	406	1.000
Schumann 3	S	67	1290	1.000
Thomas Prayer Bells	S	44	234	0.998
R-Korsakov Scheherazade	S	257	1888	0.952
Total		1117	10053	0.976

Our evaluation considers an estimated barline to match a ground-truth barline if all normalized coordinates fall within a threshold of 0.01. This metric produces an F-score of 0.976 for the entire corpus. See Table I for details.

IV. DISCUSSION AND FUTURE DIRECTIONS

The innovation of displaying the music score with overlaid annotations seems simple enough, but it has proven to be incredibly effective for running live concerts. We recently used ConcertCue to display supertitles in opera productions. Typical production workflows without ConcertCue involve an operator looking at a printed score on a desk while also operating a computer with a PowerPoint-style presentation to advance the displayed text at the right musical time. This method is awkward and stressful. Using ConcertCue, the operator looks only at the computer screen and sees all pertinent information in one place.

We have had several users (staff at symphony orchestras and regional opera houses) use the full system to upload scores and verify and correct OMR results. Universally, the sentiment is that the score annotation tools are easy to use, even in cases with long (100+ page) scores. Some even report the task being fun. We believe this is due to the OMR system performing quite accurately in the vast majority of cases, and the visualization and editing tools being user-friendly.

As we continue to use ConcertCue, we will accumulate more human-verified scores with system and measure annotations and hope to release this growing dataset in the near future. Importantly, the majority of these scores are orchestral scores, whereas a number of existing datasets tend to focus on piano pieces or non-orchestral works.

We plan to continue refining the OMR algorithm and report results against this and other datasets (see [7]). An additional area of interest is to automate the measure numbering system using numeric OMR, specifically targeting measure numbers, as motivated by [9].



Fig. 4. Screenshot of the cue editor, showing three cues attached to various locations in the score (a, b, c), with (b) currently selected. Cue content is authored in (d).

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Automated Transcription of Electronic Drumkits

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Abstract—We present a new approach for the transcription of drum performances captured on a MIDI drum kit into scores in conventional Western notation. It works by parsing an input MIDI sequence into a tree-structured intermediate representation, using formal language techniques, post-processing using term rewriting, and finally exporting into an XML score file in the MEI encoding. An experimentation was conducted on the Groove MIDI Dataset.

Index Terms—Drum notation, Automated Music Transcription.

I. INTRODUCTION

Born in the twentieth century, drums have long gone without music scores; Drummers were initially expected to improvise rhythmic accompaniments based from their fellow musician's scores (e.g. from music style, chord progressions and melodic themes). Later, with the emergence of drum schools such as Dante Agostini Drum School in Europe¹, a drum notation was settled as a vector for the preservation of performances for future references, and the transmission of different styles to the apprentice or professional drummers.

Automatic Music Transcription is the problem of converting a musical performance into a music score. The particular case of drums has given rise to many studies recently, with a focus mostly on transcription of audio signals to unquantized MIDI files [14]. However, to our knowledge, fewer works, if any, consider the problem of drum score production.

In this work, we study the problem of parsing drum performances captured in MIDI into music scores conforming to notation standards for drums, that are easy to read. Our transcription procedure ought to *align* the input MIDI events to discrete time values expressible with musical notation. Moreover, simultaneously, the musical events obtained are grouped into hierarchies of *rhythmic structures*. These two tasks are performed jointly thanks to the use of a prior formal language model, Section III-A. Since several input events might be aligned to the same time position, an additional difficulty is to determine whether such *vertical grouping* is possible or not, Section III-B. Then (Section IV), we perform *voice separation*, and some post-processing by *term rewriting* before score typesetting. We experimented this approach on MIDI recordings of the GMD, Section V.

¹https://www.danteagostini.com

II. PRINCIPLES OF DRUM NOTATION

We present in this section a notation for drum sheet music in Conventional Western Notation (CWN). There is actually no official standard, and we follow here the notation in the drum lessons of the the Agostini Drum School (the first European drum school) [1] and the collection of drum pieces by Juskowiak [10]. Other variants, like the one used in the US, called universal, only differ by minor details described below (see Figure 2). Other notation systems not based on CWN are left out of the scope of this work.

A. Elements of Drum Kit and Modes



Fig. 1. The elements of a drum kits

In a typical drum kit (Figure 1), the central part is the Bass Drum (BD, also called kick), that produces the lowest pitch of the kit, and is struck when stepping on a pedal with the right foot. On its left (from a right-handed drummer's point of view) is the Snare Drum (SD), and 3 toms: from left to right, High (HT), Medium (MT) and Floor (FT). The BD, HT and FT might be doubled (it is not the case in Figure 1). The SD and toms are played with drum sticks, in different modes: the stick can either hit the *head* (i.e. the skin, the most common case) or the *rim* of the SD or tom. These two modes can be combined in particular SD techniques: in a rimshot the rim and the head of the SD are hit simultaneously in order to obtain a brighter and sharper sound; in a cross-stick (also denoted *X-stick*), the tip of one stick is maintained against the head, in order to attenuate resonance, while the other end of the stick hits the rim. The detection of rimshots and cross-sticks by a MIDI drum kit can be source of difficulties in the context of transcription, see Section III-B.

The Hi-Hat (HH), on the left of the SD, is made of two cymbals that can be joined (*closed*) or disjoined (*open*) using a

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Fig. 2. Pitches and note heads denoting the drum kit elements and modes.

pedal activated with the left foot. Each configuration produces a different sound when the HH is hit with drum sticks. Closing the HH with the pedal also produces a distinguished sound by itself, with a specific notation (see below). There are different kinds of cymbals: *ride* (RC), for steady beats and patterns played either on the *bow* (the body) or the *bell* (the top part) of the cymbal, and *crash* (CC) or *splash* (SC), generally struck along the *edge* to produce an explosive sound (the drum kit in Figure 1 has two CC). The RC can also be hit on the edge to produce a crash sound. The SC are generally smaller than the CC, and produce a higher tone.

In drum notation, every part of a drum kit is associated with a specific pitch (Figure 2). The height of the pitch corresponds roughly to the position in space of the instrument: the pedals (BD and HH) have the lowest pitches, and cymbals the highest, and the SD and toms are in the middle. Moreover, the shape of the note head indicates the mode (rimshot, X-stick, bow, edge or bell for cymbals...).

B. Dynamics

Notes with louder dynamics are marked with standard *accent* symbols (see Figure 3). According to the related pitch, it may indicate that a particular technique ought to be used. On the opposite, the so called *ghost notes*, denoted within parentheses, are played with low dynamics, although firmly.

C. Ornaments

A *flam* is a figure made of one grace note, played with a significantly lower intensity and slightly ahead of one normal or accented note (main note). It is denoted like an *acciaccatura* (Figure 3). It is executed with two hands, using a particular drum technique producing a sound described by the onomatopoeic term of *flam*. A flam can either be played on one single element of the drum kit, or two distinct elements, e.g. SD and a tom.

Most of the time, in drum notation, the *rolls* are quantified. More common for the orchestral snare drum, the tremolo notation should be denoted literally for drums.

D. Timings

Drum events are *transients*: they have no duration. Therefore, the usual symbols of CWN (flags, beams, ties, dots and rest symbols) represent, in drum notation, the temporal distance between one event's start date (onset) and next event's



Fig. 3. Accents, ghost notes, and flams.



Fig. 4. Examples of voicing in drum scores

start date. Also, notehead cannot be used for scoring these distances because of their variety of use in drum notation. For examples, \downarrow is preferred over \downarrow .

To improve the readability of the score, as few symbols as possible are used. For instance, the simple \checkmark will be preferred over \checkmark ? Moreover, in order for the score to reflect the drummer's way of thinking, the notation is segmented by pulse, for example, \checkmark ? \checkmark is preferred over \checkmark .

Although hi-hat openings are not considered as notes with duration, the fact that they sound until they are closed is taken into account in the scoring. Consequently, ties will sometimes be used for HH notation (but not for the other elements).

E. Voices

As for most polyphonic instruments [8], the notes in a drum score can be grouped into voices, denoted by the stem directions. In drum notation, voices are useful either to separate note played with hands, on the staff top, from those played with feet on staff bottom (Figure 4, left), or to distinguish between repeated rhythmic patterns (played e.g. on HH or RC), and other elements played independently, in a more sporadic way (Figure 4, right).

The voicing is generally defined a priori: every element is assigned a fixed voice number and does not change voice throughout the score.

III. PARSING MIDI DRUM PERFORMANCES

Our transcription process takes place in several steps. In the first, and most important step, an unstructured MIDI input is structured into a tree using parsing techniques. The input is a sequence of timestamped note-on events in a MIDI file. Note-off MIDI events are ignored in the case of drums.

A. Prior Weighted Rhythm Tree Language

The parsing is based on a prior language model whose aim is to define the time positions in a score where the input MIDI events can be aligned. In many quantization algorithms in commercial software, such as Digital Audio Workstations (DAW) or score editors, these positions are equidistant, defined by a regular *grid*. Here, we define those time positions with a generative Regular Tree Grammar (RTG) that reflects a metrical hierarchy [15]. Intuitively, in such a model, the higher the metrical weight of a time position, the more likely it is going to *attract* an input event.

The RTG generates labeled trees by mean of non-terminal (NT) remplacement, following *production rules* of one of the forms: $q_0 \rightarrow a$, where q_0 is a NT and a is a symbol representing one or several output symbols in score (e.g. one note or one flam), or $q_0 \rightarrow b(q_1, \ldots, q_k)$, where q_0, \ldots, q_k are NTs and b is a symbol representing an operation on time intervals. We consider in particular two such operations:

- time division, partitioning a given closed time interval $I = [\tau, \tau']$, into $k \ge 2$ sub-intervals I_1, \ldots, I_k of same duration $\frac{\tau' \tau}{k}$ (symbol b_k beamed and u_k , unbeamed),
- *new bar*, partitioning a given open time interval $I = [\tau, +\infty]$ into two sub-intervals $I_1 = [\tau, \tau+1]$, of duration 1 bar and $I_2 = [\tau+1] + \infty$ (symbol m₂)

1 bar and $I_2 = [\tau + 1, +\infty[$ (symbol m₂).

Every tree t generated by the RTG defines nested time intervals and the bounds of these intervals are the time positions where input events can be aligned. Moreover, t defines hierarchical event grouping, represented by beams in the output score.

Some weight values, in a specific cost domain (*min-plus* algebra S [12]), are associated to the RTG's production rules, in order to evaluate, for every generated tree *t*, a *cost* (in S) *of readability* for the corresponding notation. The RTGs used for our experimental can be found in a repository², and Figure 6.

B. Vertical Alignements

Several input events might be aligned to the same time position defined by a tree. However, not every combination of notes and flams can be played simultaneously by a drummer with only 2 hands and 2 feet. Therefore, we define a language of appropriate combinations of input events, using a Finite State Machine (FSM) that cannot be described here because of space constraints. Moreover, we have noticed some errors in the captation of MIDI events in some modes. For instance, it happens sometimes that a SD *rimshot* is captured, by the MIDI sensors, as a *X-stick* closely followed by a standard (head) SD. Such an unlikely combo is detected by our FSM and corrected as a rimshot.

Like the RTG of Section III-A, the above FSM is weighted, and its computation returns a value, in S, representing the *cost of alignment*, of input events to a unique time point.

Finally, we select a tree t that minimizes, in S, the combined costs of readability, as defined by the RTG of Section III-A and of cost of alignment, defined by the FSM of this section. The selection is done by k-best parsing [9], in polynomial time, using Dynamic Programming techniques.

IV. SCORE ENGRAVING

The tree t obtained from a MIDI input in Section III is converted straightforwardly into a tree-structured abstract Intermediate Score Representation called *Score Model* (SM), used for further post-processing, before exporting to XML.

A score model for drums is a sequence of *measures*, where every measure is a set of *voices*, and every voice is a sequence



Fig. 5. Mapping of MIDI key numbers for the Roland TD-11 electronic drum kit (source: Groove MIDI Dataset).

of events, described by a *rhythm tree* (RT). The internal nodes of a RT are labeled by a time division symbols as above, and each of its leaves is labeled either by \emptyset , representing a tie or a dot in the score, or by one note, one flam, or by a set of notes, representing a chord in the score.

A. Score model construction and Voice separation

The estimation of note names and note heads is easy, since there is a 1-1 mapping (Figure 5) between MIDI key values, in 0..127, and pairs of pitches and note-heads of Figure 2.

The extraction of dynamics and accents, is based on the velocity value of MIDI events, in 0..127.

The voice of every note is estimated, following the previous principle, according to a prior partition of the elements of the drum kit into voices. Hence, the subtask of voice separation, is straightforward for drums, as opposed to the case of other polyphonic instruments like piano [13]. From the tree t, we extract one RT per voice, by projection, see Figure 7.

B. Term Rewriting

The last step consists in post processing the resulted rhythm trees. Each tree goes through transformations which are defined by term rewriting rules [3], which do not change pitches and durations. A term rewriting rule is an oriented equation that defines how one pattern will be rewritten to another. For example, with the rule: $b_2(x, \emptyset) \rightarrow x$, the last tree $b_2(BD, b_2(HHP, \emptyset))$ in Figure 7 (second voice) is rewritten into $b_2(BD, HHP)$, and $\Re_{\pi\pi}$ is rewritten, in two steps, into \square Note that we are using term rewriting and not string rewriting: rules are applied to tree structures. For instance, \square_{π} , \Im will not rewrite into $\Im \square \Im$ because the second 8-th note and the rest do not belong to the same subtree.

The purpose of this post processing step is to fix details of rhythm notation [11]. Drum notation particularly needs attention since although notes do not really have a duration, it is easier to read a score without too many rests. Fixing such details during the parsing would significantly increase the execution time, since rewriting is only applied on one score model, instead of on each candidate parse tree.

V. EVALUATION

A. Implementation

Our parsing approach to drum transcription has been implemented in a C++ library³. We have developped a k-best parsing algorithm with dynamic programming and tabulation techniques, for finding efficiency the parse tree that best corresponds to the input performance.

²https://gitlab.inria.fr/transcription/gmdscores

³https://gitlab.inria.fr/qparse/qparselib/

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Fig. 6. Prior language model as a wRTG. q_1 represents the level of a 4/4 measure, that can contain either one whole rest (c), one whole note (a), or one flam (f), or can be divided into 2 halves or 3 thirds (triplet of half-notes); q_2 represents the level of a half measure, q_4 of a quarter note (beat level), and so on. Finally, q_0 represents the level over the bar, with a first rule to create one measure, in NT q_1 , and a second one to finish the score (m₀ is a double bar).

B. Dataset for Experiments

For our experiment, we used the Groove MIDI Dataset [7] (GMD). Originally created with machine learning tasks in mind, the dataset proposes 1,150 MIDI files, captured by professional or semi-professional drummers, on an electronic drum kit ROLAND T-11, performing with a metronome. The performances are either short rhythmic fills, or full-length rhythm sequences, according to a specific style (rock, funk, jazz...). Overall, the GMD gathers over 22,000 measures of drumming. A unique mapping assigns a MIDI pitch to each of the parts of the drum kit, for all the MIDI file.

We used our code to transcript a selection of around 30 files from the GMD, ranging through as many styles as possible, and the shortest being only 4 bars, and the longest 261 bars.

The tempo, the style, and the time signature are given in the file names of the GMD, and used for parsing. The audio files of the dataset, synthesized from the MIDI files are not used in our experiments.

C. Prior languages for evaluation

We have used essentially the same RTG (and one variant) for all the transcriptions performed during our experiments. These RTGs specify possible drum notations, by restricting metrical divisions, for measures in 4/4, as drum score are often written in this time signature. Figure 6 presents a simplified version of these RTGs. Each NT replacement rule of this RTG defines either a time division, or the creation of a terminal symbol, representing output events.

The RTGs used for conducting our experiments were not trained specifically for the GMD. In particular, the weight values are chosen arbitrarily, following roughly the principles that: every symbol like c or a induces a weight value of 1 (see the 2 first rules of every column of Figure 6), and that triplets are penalized compared to binary divisions (see rules 5 and 6 in the first and second column of Figure 6). Moreover, flams are more penalized for short notes than for longer ones (rule 4 in the first and second column of Figure 6). By lack of the digital drum scores corresponding to the MIDI performances in the GMD, we were not able to train a RTG model with grammatical inference techniques similar to, e.g. [2], [6].



Fig. 7. On the left, the tree corresponding to the first beat in Figure 4. On the right, the trees for each voice (\emptyset represents a rest).

D. Evaluation

A quantitative evaluation of our transcription results would require, for each MIDI file, one corresponding reference score. Such ground truth does not exists for the GMD. Ideally, it would be prepared by professional drummers, but transcribing by hand each of the 1,150 MIDI files of the GMD seems unrealistic, considering in particular the size of files. Moreover, in our case, evaluation cannot by conducted by comparing MIDI files, like e.g. in [14], but would require a tool to diff XML score files, like [5].

To propose a qualitative evaluation, we used other common softwares for music score edition, with the same MIDI files, and visually compared the results. Overall, we found that our algorithm produces scores that are easier to read and closer to expectation. We have gathered all these results on GitLab repository², with all the MIDI files and the corresponding transcription in MEI, and a table of all the parsing times.

VI. CONCLUSION

We presented our first experiments for the automatic transcription of drum performances, by parsing a MIDI input into a structured score model, which can be exported to XML/MEI. Our first results are already promising, although the output scores have some errors, sometimes because of sensor bugs from the drum kit, and sometimes because of the parsing.

Our future objective is to create a complete dataset of drum scores from the GMD, initially transcribed by our parsing technique, then manually corrected by a professional drummer. This dataset could be a companion for the Groove MIDI dataset to use as a base to evaluate drum transcriptions, as well as for OMR for written drum contents.

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Improving Handwritten Music Recognition through Language Model Integration

Based on the ISMIR 2021 publication On the Integration of Language Models into Sequence to Sequence Architectures for Handwritten Music Recognition

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Abstract—Handwritten Music Recognition, especially in the historical domain, is an inherently challenging endeavour; paper degradation artefacts and the ambiguous nature of handwriting make recognising such scores an error-prone process, even for the current state-of-the-art Sequence to Sequence models. In this work we propose a way of reducing the production of statistically implausible output sequences by fusing a Language Model into a recognition Sequence to Sequence model. The idea is leveraging visually-conditioned and context-conditioned output distributions in order to automatically find and correct any mistakes that would otherwise break context significantly. We have found this approach to improve recognition results to 25.15 SER (%) from a previous best of 31.79 SER (%) in the literature.

Index Terms—Handwritten Music Recognition, Historical Music, Sequence to Sequence, Language Models

I. INTRODUCTION

Optical Music Recognition (OMR) [1] is a research field aimed at the production of computer-processable representations of music score images. Research efforts have been made into the field since as early as the 1980s, when carefully handcrafted recognition pipelines were the norm. These pipelines usually involve variations of the following set of steps [2]: image pre-processing in order to lower the effect of paper imperfections and remove staves, symbol extraction and classification, music notation reconstruction and final output format production. Most steps in these pipelines involved a considerable amount of both human knowledge and established assumptions on the nature of the input. Machine Learning techniques were usually reserved to specific steps (symbol classification, global binarisation) with well-defined .

With the advent of Deep Learning, new forms of recognition were developed that allowed OMR to be addressed *end to end*; models such as Connectionist Temporal Classification (CTC) loss Recurrent Neural Networks (RNN) [3] or Sequence to Sequence (Seq2Seq) [4] can be trained holistically by having transcripts of the input images. This has the advantage of allowing recognition for scenarios where obtaining a reliable ground truth for each step in the pipeline is out of reach. One of such scenarios is Handwritten Music Recognition (HMR), especially when applied to historical scores.

Current state-of-the-art techniques for end-to-end historical HMR in western notation are still quite immature, with the lowest symbol error rate at around 30% using the bestperforming Seq2Seq model [5]. This is mostly due to the inherent ambiguity found in these scores, a result of the degradation of the medium that contains them and the irregularity of handwriting. Following recent trends in Optical Character Recognition (OCR), we propose the addition of a Language Model (LM) into the transcription model in order to avoid context-breaking mistakes on ambiguous symbols. The idea is joining the recognition architecture with a LM in various manners (Deep, Shallow [6] and Candidate [7] Fusion) such that the final output is a leverage of the visually plausible tokens produced by the former and the most statistically significant ones accounting only for the context.

II. STATE OF THE ART

Most current attempts at performing the full OMR pipeline using a single neural-based end-to-end architecture are based on image-to-sequence encoder-decoders. Their general structure is composed of a feature extractor, usually implemented by a Convolutional Neural Network, followed by one or more RNN blocks that produce a sequential output.

The first family of models that are currently in use for this context are RNNs with CTC loss [8] at their output. Calvo-Zaragoza *et al.* have performed extensive research on these kinds of models, both for Common Western Notation (CWN) in typeset scores [9] and Mensural Notation in historical handwritten scores [3]. In the latter case, an *n*-gram language model is placed alongside the main recogniser to improve performance. A baseline in handwritten CWN using this RNN + CTC loss is provided by Baró *et al.* [5].

Another established family of models is the Seq2Seq. The first such model for OMR is the result of the work of van der Wel *et al.* [4] exclusively on typeset scores. A variation of the model using an attention mechanism for the decoder is explored in Baró *et al.* [10], which is applied on both typeset and historical handwritten scores in common western notation. This is also the current state-of-the-art for historical OMR.

While LMs have been applied to music recognition through *n*-grams [3], no precedents of RNN-based LMs along with Seq2Seq OMR architectures exist. Examples of domains that deploy RNN-based LMs fused with Seq2Seq models include neural machine translation as in Gulcehre *et al.* [6], handwritten text recognition [7], or speech recognition [11], although the core idea is equally valid whenever the final target is any ordered sequence of tokens. We hypothesise that such integration has the potential to improve the current state-of-the-art results in OMR, as it has already been observed in other related fields [6], [7].

III. DATA AND MODELS

The main recognition architecture in this work is based on prior Seq2Seq OMR architectures from [4], [10]. The whole architecture is depicted in Figure 1, with a reference to the LM integration step (see the dashed lines).

A. Sequence to Sequence model

Seq2Seq models [12] are based on the idea of *translating* an arbitrary input sequence into an arbitrary output sequence. If one considers an input image as a sequence of column vectors, then this "translation" process becomes a transcription task.

An image of a musical measure is fed into a Convolutional Neural Network, a VGG19 [13] with the last max pooling layer removed. The Encoder, a bidirectional stack of Gated Recurrent Units (GRU) [14], generates an intermediate representation comprised of as many feature vectors as the convolutional output. The Decoder then iteratively computes an attention-weighted summary of the resulting hidden state (Chorowsky *et al.* [15]) and then produces an output token with an RNN stack using the summary, the last prediction and the last final state as inputs. The full architecture is trained using a Cross-Entropy loss function, essentially performing token classification at each output time step.

B. Language Model Integration

Recognition architectures based on Seq2Seq models can be thought of as computing the probability distribution of tokens at time step t conditioned by encoder visual features and predictions at time steps 1 to t - 1. On the other hand, LMs estimate the probability distribution of a set of tokens at time step t conditioned by predictions at time steps 1 to t-1 without any visual input. Integration techniques consist of designing an arbitrary function f that takes both distributions as input and produce a final distribution that accounts for them.

Many language modelling techniques exist throughout such as n-grams [3], but RNNs are known to be a superior choice overall [16], thus this work focuses on a single LM architecture consisting on four stacked GRUs.

LM integration with Seq2Seq models has been explored through various approaches aiming at improving recognition performance. Three of such approaches have been explored in this work: Shallow, Deep [6], which are among the most used methods, and Candidate Fusion [7], which showed good performance on handwritten text recognition. Figure 2 shows a graphical summary of each method.

- Shallow Fusion ([6]): The output distribution is obtained by computing the logarithm of the logits for both models and adding them together. There is a scaling value λ for the LM.
- **Deep Fusion** ([6]): A more sophisticated version of the former technique. The scaling value σ is reminiscent of the λ of Shallow Fusion, the main difference being that this value is obtained using a fully connected layer from the logit output of the LM. The final output is produced by passing the concatenated output from the gated LM, the recogniser and the decoder context through a fully connected layer.
- Candidate Fusion (Kang *et al.* [7]): The idea of this technique is to allow the decoder to leverage the LM output distribution freely. The LM logit output is provided as an input to the decoder by concatenating it to the last hidden state and the previous timestep prediction.

All these methods require both the classifier and the LM to be properly pretrained for successful integration. More detail is provided in section IV.

C. Datasets

The output for this recognition task is a sequence of tokens representing the elements within the score found in a predefined reading order (top-bottom, left right). Musical note components are separated into primitives (including but not restricted to: noteheads, stems, flags, or beams), and elements pertaining to the same vertical group are separated through a special ϵ token. An example of this notation may be found in Figure 3.

As the amount of data for handwritten music recognition is very limited, three different datasets are used: (a) a typesetlooking synthetic dataset (Synthetic Modern: SM), (b) a second synthetic dataset which contains typical paper degradation artifacts (Synthetic Old; SO) and (c) the target handwritten dataset (Handwritten: HW). The latter is an extract of a piece from Pau Llinás, a local composer from Barcelona in the early 18th century. Figure 4 shows some example images for each dataset.

IV. EXPERIMENTS

The evaluation of the proposed LM integration methods is performed using two training strategies depending on the data used to pretrain the LM. For the sake of reproducibility, Table I summarises the hyperparameters used in both cases.

All integration methods require a pre-trained LM. We first trained a LM with an unmodified version of the SM dataset. Since this dataset has many tokens not present in HW, we created a version of the SM dataset comprised of the 66% of samples which contained a higher ratio of tokens also present in HW, which we will refer to as ASM, and we trained another LM with it. The idea was trying to "de-noise" the output of the LM in HW scores so that its predictions had a higher level of confidence.



Fig. 1. Summary of the Seq2Seq model used in this work.

Fig. 2. Dataflow graph depicting every integration method that was implemented

barline_light.noNote, epsilon, sharp.S4, epsilon, noteheadBlack.S4, steamQuarterHalf-Down.noNote, epsilon, dot.noNote, epsilon, noteheadBlack.S4, flag8thDown.noNote, epsilon, noteheadBlack.S3, steamQuarterHalfDown.noNote epsilon, noteheadBlack.S3, steamQuarterHalfDown.noNote, epsilon, barline_light.noNote



Fig. 3. Sample measure from the HW dataset with its ground truth annotation. Bounding boxes indicate the boundaries of what a token is, dotted arrows indicate ϵ tokens and small vertical arrows indicate symbols placed together between two ϵ .

 TABLE I

 Reproducibility table. The first segment is devoted to training hyperparameters. The second one to showing relevant information about the various datasets that have been employed.

Parameters	All Training	Data	SM	SO	HW
Optimiser	Adam	Train Samples	18,900	17,872	147
Learning Rate (LR)	$3 \cdot 10^{-4}$	Valid Samples	6,300	5,957	49
LR Checkpoints	@ 20, 40, 60, 80, 100 epoch	Test Samples	6,300	5,957	49
LR Sigma	0.5	Avg. Line Length	22	15	17
Loss Function	Cross-Entropy	Classes	109	123	62

In both cases, the Seq2Seq classifier was first trained alone with the unmodified SM dataset until the model did not improve for 30 epochs. We then fused it with the LM through the 3 previously stated techniques and trained them using a Curriculum Learning strategy: initially, 90% of samples in the training mix were from the SO dataset and the remaining 10% from the HW dataset. Every 10 epochs the proportion of SO scores decreased by 10% over the total, down to 10%. Since the number of samples from SO is considerably higher than those in HW, we randomly duplicated HW samples to match the number of measures in the SO split. The incorporated image augmentation system for training was used to prevent overfitting on input images. Note also that experiments with homogeneous datasets were avoided since they were seen to decrease performance in earlier tests.

Validation and test were performed using HW dataset samples. Lastly, for Shallow Fusion we used a $\lambda = 0.1$ after testing three instances of the full architecture on the SM dataset and keeping the value that gave better output results.

Numerical results are provided using the Symbol Error Rate (SER(%)) metric, which is defined as

$$SER(\%) = \frac{I+R+S}{T} \cdot 100 \tag{1}$$

where I, R and S are the number of token insertions, removals

and substitutions in order to obtain the ground truth sequence from the predicted sequence and T is the length of the ground truth sequence. Lower values mean better results.

A. Quantitative Results

Table II shows numerical SER(%) results obtained from all of our experiments. Since the Seq2Seq model pre-training on the SM dataset alone gave results well below 1% SER(%), we believe it is not worth experimenting with the addition of a LM when transcribing typeset samples. Instead, we show test results using the training strategy stated above compared against two baseline models: the BLSTM + CTC model and the LM-less Seq2Seq model [10]. All results are obtained using the HW test partition as input.

Best baseline results are 56.20% and 31.79% of SER(%) for BLSTM + CTC and Seq2Seq respectively. However, authors mention in their paper that there might be overfitting in the best result of the former model because training was done on handwritten samples alone. Instead, when training with a mixture of both synthetic and real data, the authors state a considerable increase to 74.40 SER(%) from 56.20 SER(%).

Our proposed models obtained better results than those from the Baseline. Candidate and Deep Fusion are the better performing architectures, with highest-scoring results (in bold in Table II) between 5 and 6 SER(%) points below the

TABLE II

Summary of performed experiments and results in SER(%) (Lower is better). The table header indicates the proportion of Synthetic scores against Handwritten scores. The "Pre" column indicates the LM pretraining dataset.

Model	Pre	90-10	80-20	70-30	60-40	50-50	40-60	30-70	20-80	10-90	0-100
CNN + BLSTM [10] Seq2Seq Baseline [10]	-	- 60.03	-	-	- 66.20	-	- 43.38	-	- 37.86	- 34.56	56.20 31.79
Seq2Seq + Deep LM	SM	31.30	28.52	29.87	29.37	28.05	26.11	27.74	27.37	28.32	-
Seq2Seq + Shallow LM	SM	36.79	32.91	33.27	33.36	31.76	32.75	30.87	30.72	30.58	-
Seq2Seq + Cand. LM	SM	33.50	28.93	28.64	28.08	27.48	26.82	27.23	26.61	25.80	-
Seq2Seq + Deep LM	ASM	28.24	29.53	27.82	27.36	25.95	27.21	25.63	25.15	25.54	-
Seq2Seq + Shallow LM	ASM	35.34	34.75	36.67	32.42	34.23	34.52	33.76	33.79	35.13	-
Seq2Seq + Cand. LM	ASM	32.07	28.61	28.71	27.55	27.71	27.20	27.77	28.04	25.73	-

established baseline. Shallow Fusion obtained best results on par with the baseline.

The general pattern is that earlier training iterations perform worse than latter ones, as expected by the lack of HW samples. There are a few exceptions, which are the SM version of Deep Fusion and the ASM version of Shallow Fusion. We suspect this might be caused by the model entering local minima, which it may leave after further epochs.

Another general remark is that models pretrained with the ASM dataset seem to perform slightly better, with a 0.96 SER(%) improvement in Deep Fusion and a 0.07 one in Candidate Fusion, although the relevance of this difference is debatable.

B. Discussion

Numerical proof is indeed found that a LM helps improve recognition results in historical handwritten music scores, especially when using Candidate or Deep Fusion. However, we agree that it is not easy to assess their differences outside of a somewhat subjective qualitative study.

Expectedly, LM lowers the presence of certain syntactic mistakes (for instance, tokens that require a specific successor) or provides information on tokens that appear frequently. There is, however, a set of possible recognition mistakes that the LM was initially presumed to be able to correct which we found it unable to. The most relevant was enforcing the beat of the bar that is being recognised. It can be argued that at no point in the measures that comprise the dataset the



Fig. 4. Sample measures from the SM, SO and HW datasets respectively.

time signature is indicated aside from its very beginning, but since the training dataset is written exclusively in a 4/4 time signature, the LM might have adapted to measures adding up to a beat value. Perhaps this is due to the purely statistical approach taken with the LM, so some postprocessing (based on music notation rules) may be needed for approaching such consistency checks.

Other "artistic" aspects of music - e.g. pitch and duration - cannot be corrected with the LM. This was expected from a statistical point of view, as the only prior knowledge assumed for the LM is the co-occurence of elements in the output sequence and, unsurprisingly, most noteheads have been predicted on the most common ranges within the original score.

A final remark is that we have observed that the adjustment strategy attempted with the ASM dataset showed no significant improvement. Instead, in order to better align training and test datasets without overfitting, more data should be used for training. A common issue when trying to collect data for this purpose is that most common transcriptions of old music adapt their notation style to current trends, which defeats the purpose of using such data for recognition.

V. CONCLUSIONS

This work successfully explored the integration of LMs into a Seq2Seq OMR architecture for recognising historical handwritten scores. An improvement of around 6 SER(%) points from the baseline was obtained when using a Deep Fusion mechanism, lowering it to 25.15 SER(%). This was achieved by reinforcing the model's capacity to keep consistency on predicted sequences. Thus, we can conclude that the integration of language models into OMR Seq2Seq architectures is a promising research direction worth exploring.

From the results we obtained, we propose some future work avenues. Since language models do not seem to enforce key global aspects like beat, a grammar-based parser might be implemented on top of the neural model in order to correct syntactical mistakes. This could use the probability distribution produced by the neural model to weight all possible corrections. Another improvement could be to use the extra information the LM provides in order to reinforce specific steps within the model, such as the attention mechanism. Perhaps this preemptive information might point the model where to look at in the score image.

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