Sheet Music Statistical Layout Analysis

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Abstract-In order to provide access to the contents of ancient music scores to researchers, the transcripts of both the lyrics and the musical notation is required. Before attempting any type of automatic or semi-automatic transcription of sheet music, an adequate layout analysis (LA) is needed. This LA must provide not only the locations of the different image regions, but also adequate region labels to distinguish between different region types such as staff, lyric, etc. To this end, we adapt a stochastic framework for LA based on Hidden Markov Models that we had previously introduced for detection and classification of text lines in typical handwritten text images. The proposed approach takes a scanned music score image as input and, after basic preprocessing, simultaneously performs region detection and region classification in an integrated way. To assess this statistical LA approach several experiments were carried out on a representative sample of a historical music archive, under different difficulty settings. The results show that our approach is able to tackle these structured documents providing good results not only for region detection but also for classification of the different regions.

Keywords-Document Layout Analysis, text region detection and classification, Hidden Markov Models

I. INTRODUCTION

Music constitutes one of the main vehicles for cultural transmission. That is why musical documents have been preserved over the centuries, scattered across cathedrals, museums and archives. To prevent deterioration, access to these sources is often restricted, which hinders the accessibility to these historical heritage remains for musicological study.

This work is part of a larger project aimed at studying a historical archive of Hispanic Early music documents, handwritten in the variant of the Hispanic notation at that time [1]. The archive is particularly interesting because the music was composed between the 16th and 18th centuries, a period of musical diversity and expansion from which we pretend to understand the cultural and social evolution through the musical productions of the time.

We plan to carry out this musicological study by means of computational methods in order to go beyond what humans can achieve by themselves after years of study. Given that the manual transcription of these documents is a long, tedious task, automatic transcription tools become an important need. The technology underlying these tools is referred to as Optical Music Recognition (OMR) or, more precisely in our case, Handwritten Music Recognition (HMR).

Most of the manuscripts of the archive under study correspond to scores of Gregorian chant. In addition to the music content, lyrics (sung text) also represent relevant information to extract. Additionally manuscripts may contain the name of the piece and the author. Before attempting to recognize the content depicted in a musical document, it is important to properly divide the page image into the relevant regions, each of which must be processed with specific methods.

Therefore, we are interested in developing automatic layout analysis methods. Our proposal, based on machine learning, allows not only separating the document into its physical parts but also provides a category label for each of these blocks.

The rest of the paper is organized as follows: first in Section II we present the current state of the art regarding music layout analysis. Section III provides an overview of the preprocessing and layout analysis technologies used. Section IV shows the specific modelling performed in order to apply the framework to sheet music. In Section V we present in detail the corpus used in the experiments, the evaluation measures, the system set-up, and the empirical results. Section VI closes the paper with the conclusions.

II. RELATED WORK

Developments in the field of OMR or HMR have paid little attention so far to the recognition of the lyrics that may accompany music. This is mostly due to the fact that lyrics seldom appear in most modern notation works, unlike what happens with Early manuscripts.

Only the work of Burgoyne et al. [2] has focused on separating music and lyrics sections. Typical layout analysis on musical documents focuses on extracting only the set of staves; that is, the sections that contain a single staff composed of typically five parallel lines (staff lines). Most systems rely on estimating the staff-line thickness and the staff-space that separates the different staves (vertical blank space between two consecutive staff lines). From these estimates, it can be detected where each staff section begins and ends [3], [4], [5]. Other methods used to separate staff

sections include horizontal projection profile analysis [6], or the use of morphological operators [7].

To our knowledge, no previous work has properly addressed the automatic layout analysis of music manuscripts from a machine learning perspective. We adopt this perspective and propose an approach which learns Hidden Markov Models (HHMs) from a few labelled page images. It follows the ideas we had previously introduced for detection and classification of text lines in typical handwritten text images [8]. This approach only accounts for the vertical organization of regions of interest within a handwritten page image; but this is exactly what is needed to detect the regions of interest in our layout analysis task. Once the HMMs have been trained, the proposed method automatically finds optimal vertical boundaries between interesting regions and, at the same time, the optimal class label for each region. It is important to stress that detection and classification is not restricted only to staff and lyrics sections. Different classes within each category can also be distinguished, which may become helpful for the ensuing automatic music and lyrics recognition processes.

III. SYSTEM ARCHITECTURE

The sheet music statistical layout analysis (hereafter referred to as SMSLA) approach used in this work is based on HMMs and a kind of "language models" which we refer to as "Vertical Layout Models". It is an innovative use of the successful statistical framework which is nowadays firmly established for automatic speech and handwritten text recognition. SMSLA follows the ideas successfully used in basic document layout analysis [8], [9]. Here we show its adequateness for tackling the more complex task (due to the varied regions types) of music scores. Furthermore this task clearly showcases the utility of the region classification this framework provides.

A diagram of the proposed SMSLA system is presented in Fig. 1. It encompasses four main steps: image preprocessing, feature extraction, training and decoding.



Figure 1: A system diagram of the proposed SMSLA approach. Note that no line geometric position information is needed in the training labelling.

A. Preprocessing

Before SMSLA proper, the page images are preprocessed in order to reduce the noise, remove the variance in the background and enhance the contrast (see Fig. 2).

First, each image is converted to grey scale and the foreground is enhanced [10]. This process also enhances stains, bleed through, guidelines and other artefacts, and therefore it is necessary to create a binary mask to select the actual foreground image regions. In order to create this mask a three-step process is performed. Initially, a bi-dimensional median filter [11] is applied to remove background and reduce the noise. Next, Otsu's binarization [12] is applied to enhance whatever is left of the foreground. Finally a basic run-length smearing algorithm (RLSA) [13] is used to obtain the required extraction mask. At this step, basic image processing techniques [14], [15] are used in order to calculate the global skew angle. Finally the skew correction angle and the text extraction mask are applied to the previously enhanced image to obtain a de-skewed and cleaned-up page image (Fig. 2(b)).



(b) Cleaned & golbal-skew corrected

Figure 2: A segment of an original musical document and the result after preprocessing.

B. Feature Extraction

Due to the single sequential structure of the relevant information in the pages of the corpus considered, there is no need for any high level block detection. We directly consider the whole page image as a single block and proceed to detection and classification of the relevant document regions.

SMSLA requires a page image to be described in terms of a *feature vector sequence* which represents the vertical concatenation of the "shapes" of the regions of interest which appear in the image. To this end, the cleaned and de-skewed image (Fig. 2(b)) is first passed through an RLSA filter, in order to enhance the text regions, and then horizontally divided into a certain number, m of non-overlapping rectangular slabs (5 in Fig. 3(a)), all with the same height, as that of the image.

We then compute the *horizontal projection profile* (HPP) [16] for each of the m slabs and smooth it by means of a rolling average filter [17]. For each horizontal raw of image pixels, an m-dimensional vector is obtained with the corresponding m HPP values. Finally, these feature vectors are augmented by including HPP first derivatives as in [18].

For a page image of height L, this result in a sequence of L M-dimensional vectors, where M=2m (M=10 in the example of Fig. 3(a)). Figure 3(a) illustrates both the HPPs and their derivatives overlayed over the RLSA image from which it was calculated. It can observed that these feature vectors properly represent (and help to distinguish between) staff and lyric regions.



(b) Baseline detection and region classification results

Figure 3: Feature extraction, line detection and region classification, for the image segment of Fig. 2(b).

C. Vertical Layout Analysis by Viterbi Decoding

Let a page image be represented as a sequence of feature vectors, mow called "observations", $\mathbf{o} = \vec{o}_1^L = \vec{o}_1, \vec{o}_2, \dots, \vec{o}_L$. SMSLA is formulated as the problem of finding the most likely region label sequence hypothesis $\hat{\mathbf{h}} = \hat{h}_1, \hat{h}_2, \dots, \hat{h}_n$ that describes these feature vectors. Thus we must solve:

$$\hat{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{arg\,max}} P(\mathbf{h} \mid \mathbf{o}) = \underset{\mathbf{h}}{\operatorname{arg\,max}} P(\mathbf{h}) P(\mathbf{o} \mid \mathbf{h}) \qquad (1)$$

where $P(\mathbf{o} \mid \mathbf{h})$ is a region shape model and $P(\mathbf{h})$ is a vertical layout model (VLM).

 $P(\mathbf{o} \mid \mathbf{h})$ is approximated by HMMs, while $P(\mathbf{h})$ is modelled by a finite-state model that enforces the a priori restrictions of how the different horizontal regions types (called "region labels") may be concatenated to form a valid page image. In the next subsection we will detail the "region labels" we have adopted for the corpus considered in this work and the corresponding finite-state VLM.

In SMSLA, we are interested not only in adequately labelling each horizontal region, but also in actually determining their corresponding *vertical positions* within the page image. Formally, the region vertical positions are latent or "hidden" in $P(\mathbf{o} \mid \mathbf{h})$ (Eq. (1)), but they can be easily uncovered by marginalization:

$$\hat{\mathbf{h}} = \underset{\mathbf{h}}{\operatorname{arg\,max}} P(\mathbf{h}) \sum_{\mathbf{b}} P(\mathbf{o}, \mathbf{b} \mid \mathbf{h})$$
(2)

where **b** is a *segmentation*; that is, a sequence of n+1boundary marks, b_0, b_1, \ldots, b_n , such that $b_0 = 0$, $b_i < b_j$, 1 < i < j < n, $b_n = L$. These marks delimit the vertical regions, $\hat{h}_1, \ldots, \hat{h}_n$, found in the page image. This is illustrated in Fig. 3(b), where the boundaries are marked with horizontal blue lines and the sequence of region labels is $\hat{\mathbf{h}} = \text{"SL SLL SL LL"}$ (c.f. Sec. IV).

As discussed in [8], approximating the sum in Eq. (2) with the dominating addend and making reasonable independence assumptions, leads to the following joint optimization to simultaneously obtain both the best label sequence and the corresponding best segmentation:

$$(\hat{\mathbf{h}}, \hat{\mathbf{b}}) \approx \operatorname*{arg\,max}_{\mathbf{b}, \mathbf{h}} P(\mathbf{b}) P(\vec{o}_{b_0}^{b_1} \mid h_1) \dots P(\vec{o}_{b_{n-1}}^{b_n} \mid h_n)$$
(3)

Which is in fact the optimization problem that is solved by the Viterbi search algorithm [19].

To solve Eq. (3), a HMM needs first to be trained for each region type. This can be easily carried out by means of the forward-backward or Baum-Welch EM re-estimation algorithm [19]. An important benefit of this training method is that it only requires the correct region label sequence, **h**, of each training page image. This completely avoids the costly manual production of segmentation ground truth.

IV. MODELLING

For SMSLA we follow the successful modelling scheme used in statistical language processing: low-level elements, such as phonemes in Automatic Speech Recognition (ASR), or characters in Handwritten Text Recognition (HTR) are modelled by HMMs; in our case, these low-level elements are the different basic vertical regions of a musical document.

These low-level elements are then concatenated in order to make higher-level entities: sentences in ASR or HTR and complete pages in our case. A Language Model is typically used to model the constraints that must rule this concatenation [19] and, as previously mentioned, here we will call these constraints Vertical Layout Model (VLM).

A. Layout elements

The page images of the archive considered in this work may contain up to five main types or classes of logical parts:

- **Title Line** (**TL**): title of the piece that might appear at the beginning of a piece (top of the first page).
- Staff lines (SL, SL-A, SL-D, SL-DA): represent those regions which contain a pentagram. We have also considered subclasses of this region type in order to distinguish normal staffs (SL) from those that present many descending notes (SL-D), many ascending notes (SL-A) or both (SL-AD). The main interest of performing this differentiation between normal staff lines and the other sub-types is in the possible benefits this type of information might have on the actual note recognition.
- Empty Staff Line (ESL): empty staves without musical content. Important to be differentiated as they do not require accompanying lyrics and they can not be transcribed.
- Lyrics lines (LL, SLL): words that are sung appear below their corresponding staff. Sub classes have been created in order to distinguish normal Lyric Lines (LL) from Short Lyric Lines (SSL) that due not span the whole line because of the use of repetition symbols.
- Blank space (BS, EBS): page regions in which there is no content. Given the difference in size and location, we have distinguished between those used between staves (BS) from those that appear at the end of a page (EBS).

B. Vertical Layout Model

It is known that VLM significantly improve the accuracy rates of this kind of systems [8]. VLMs can be approximated through grammar learning techniques but if the document presents a uniform and not to complex structure, a predefined model that uses this information to improve the detection and classification can be used.

To model the known layout restrictions for the page images of the dataset considered in this work, we use the *Deterministic Finite-State Automaton* (DFA) [20] depicted in Fig. 4. All pages begin with either a title or a blank space. This is followed by a series of staves that may or may not have their accompanying lyrics lines or a blank space in case of an empty staff. For the sake of clarity, variants of some elements were left out. Note, however, that SL actually indicates all those elements that represent staff with content (SL, SL-A, SL-D, SL-AD) as well as LL stands for both LL and SLL. To deal with other similar musical documents, this model can be straightforwardly generalized to account for any arbitrary number (or range) of expected pairs of stafflyrics regions.

V. EXPERIMENTAL SETUP & RESULTS

A. Corpus

The experiments were carried out using a part of the "CAPITÁN", a huge archive of manuscripts of Spanish and



Figure 5: Example of pages of the selected music book from the CAPITÁN.

Latin American music from the 16th to 18th centuries. These manuscripts were written using the so-called *white mensural notation*, which in many aspects differ from the modern Western musical notation. Furthermore, this archive was written following the slightly different Hispanic notation of that time, increasing its historical and musicological interest. The CAPITÁN archive is managed by the Department of Musicology of the Spanish National Research Council of Barcelona, which kindly allowed the use of the archive for research purposes.

Examples of pages from this book are illustrated in Fig. 5. For the present experiments, 50 pages were arbitrarily selected for training and 46 for testing. Table I presents basic statistics of this dataset.

Table I: Image regions and corresponding statistics of the CAPITÁN training and test sets used in this work.

Number of:	Train	Test	Total
Pages	50	46	96
Total text line regions	300	276	576
Total pentagram regions	300	276	576
Title Lines (LB+IL)	5	4	9
Staff Lines (SL+IL)	140	164	304
" with ascending notes (SL-A+IL)	143	79	222
" with descending notes (SL-D+IL)	6	10	16
Empty Staff Lines (ESL+IL)	23	11	34
Lyric Lines (LL+IL)	289	253	542
Short Lyric Lines (SLL+IL)	3	7	10
Blank Spaces (BS)	97	72	172
End Blank Spaces (EBS)	50	46	96

B. Assessment Measures

In order to evaluate the quality of the proposed SMSLA approach, we have adopted two types of measures: *line error rate* (LER) and *relative geometric error* (RGE).

LER is a qualitative measure that indicates the ratio of regions incorrectly assigned over the total number of regions. The number of incorrectly assigned regions in a page image amounts to the number of label insertions deletions and



Figure 4: Deterministic finite-state automaton (DFA) used as a vertical layout model (VLM) for "CAPITÁN" page images.

substitution which have to be done on a vertical layout system hypothesis $(\hat{\mathbf{h}})$ in order to match the corresponding reference label sequence. It is obtained in the same way as the well known *word error rate* (WER) [21]; that is, by determining the optimal alignment between the system hypotheses and reference label sequences through dynamic programming.

On the other hand RGE evaluates, in a more quantitative manner, the geometric quality of the detected baseline vertical coordinates with respect to the corresponding reference marks. RGE is computed in two phases. First, for each page image, we find the best alignment between the vertical baseline coordinates yielded by the system and the corresponding reference coordinates for that page. Secondly, we compute the actual RGE as the average (over all lines and pages) of the geometric error in pixels, divided by the average line region height (also in pixels) for the corpus considered. By computing the RGE in this manner me ensure that our measure allows us to compare segmentation quality across corpora with different resolutions and script sizes.

C. System Setup

As happens in any machine learning driven system a set of parameters for feature extraction, training and decoding meta-parameters must be chosen. In our experiment we have selected a set of standard values that have provided successful results for different handwritten data sets [9] were used here: feature vectors of 14 dimensions, 4-state HMMs (one HMM for each of the region classes described in Sec. IV) with 8 Gaussians per state. Please note that with these we are showcasing that the technology used yields very good results without the need of a time consuming meta-parameter value search that is usually seen the pitfall of Machine Learning methods.

For vertical layout modelling, on the other hand, we take advantage of the homogeneous structure of the corpus and, as discussed in Sec. IV, we use the DFA depicted in Fig. 4 as a predefined VLM.

The LER and the corresponding RGE are computed for different levels of detail used in the ground-truth labelling. In this work we have studied four levels: *detection of foreground regions, Staff and Lyric differentiation* (only the 5 main class types are allowed), *multiple staff sub-classes* and *multiple lyrics sub-classes*.

D. Empirical Results

Table II presents the detection and classification results obtained for the four levels of labelling detail defined in Sec. V-C. The average height of the different regions that compose a page, used for calculating the RGE, was 185 pixels.

Table II: Line error rate (LER) and relative geometric error (RGE) obtained for various levels of region labeling detail.

Labeling detail level	LER (%)	RGE (%)		
Labering detail level		Average	Std. dev.	
Foreground Detection	1.1	3.0	3.1	
Staff / Lyrics	4.6	3.0	3.1	
Multiple Lyrics Classes	6.9	3.2	3.5	
Multiple Staff Classes	28.0	3.9	5.2	

The qualitative detection error (LER) is less than 5% for both foreground detection and staff/lyrics classification. Thus the system already proves able not only to separate the different regions but also to differentiate between the most important region classes; i.e., staff and lyrics.

As expected, as the number of sub classes of staff or lyrics regions becomes larger, so increases the classification error. The relatively large error of multi staff classification is clearly due to the small visual differences between SL, SL-A, SL-D and SL-AD regions, specially when analysed together with overlapping elements of adjacent lyrics regions. On the other hand, the small LER increment in multiple lyrics classification has been observed to be mainly due to confusions caused by noise issues.

The geometric baseline detection error was very low (less than 4% in all the cases). We should point out, however, that this high segmentation accuracy can still be improved. In fact, we observed that the baseline positions yielded by the system tend to be slightly biased Clearly, such a bias can be analysed empirically and, if considered statistically significant, a correction bias can be easily estimated.

VI. CONCLUSIONS

An approach, which fully integrates both region segmentation and region classification, has been proposed and evaluated for layout analysis of vertically structured documents, such as sheet music pages. The method is based on a sound statistical framework, which was used before in simpler tasks of layout analysis of handwritten text pages. Experiments show that it provides very accurate results in a dataset of handwritten early music page images. It should be stressed that accurate region classification can be extremely useful to improve the accuracy of ensuing tasks, such as music score transcription and handwritten text recognition.

Since the proposed approach is statistically based, training data is required, which might be seen as drawback in comparison with other heuristic techniques which are purportedly training-free. However, only a few training pages are typically required [9] and, since *no* geometric information is needed for training, the manual effort demanded is very small. In fact, if region type classification is not required, manual labelling effort amounts just to counting the number of foreground regions present in each training image.

Although the results reported here are already very useful for the application considered, there are many possible sources for improvement. Among the most important ones, to be explored in upcoming works, we can mention: a) stablish more insightfully the HMM topology for the relatively more complex staff regions; and b) estimate the bias of automatically obtained segmentation boundaries and use this estimate to further improve the geometric accuracy.

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