Introduction to Optical Music Recognition: Overview and Practical Challenges

Jiří Novotný and Jaroslav Pokorný

Department of Software Engineering, Faculty of Mathematics and Physics
Charles University, Malostranské nám. 25, Prague, Czech Republic
{novotny, pokorny}@ksi.mff.cuni.cz

Abstract. Music has been always an integral part of human culture. In our computer age, it is not surprising that there is a growing interest to store music in a digitized form. Optical music recognition (OMR) refers to a discipline that investigates music score recognition systems. This is similar to well-known optical character recognition systems, except OMR systems try to automatically transform scanned sheet music into a computer-readable format. In such a digital format, semantic information is also stored (instrumentation, notes, pitches and duration, contextual information, etc.). This article introduces the OMR field and presents an overview of the relevant literature and basic techniques. Practical challenges and questions arising from the automatic recognition of music notation and its semantic interpretation are discussed as well as the most important open issues.

Key words: optical music recognition, document image analysis, machine learning

1 Introduction

Computer perception of music notation forms a constantly growing research field called *optical music recognition* (OMR). The main goal of all OMR systems is to automatically decode and interpret the symbols of music notation from scanned images. Results of the recognition are represented in a digital format suitable to store the semantic information (notes, pitches, dynamics and so on). The main advantage of such representation of music scores is the possibility of different applications such as: audio playback, reediting, musicological analyses, conversions to different formats (e.g. Braille music notation) and the preservation of cultural heritage [23]. More recent applications are for example: concert-planning systems sensitive to the emotional content of music [7] or automatic mapping of scanned sheet music to audio recordings [18].

Over the years, music had been traditionally written down with ink and paper. During the 1980s, early computer music typesetting programs were developed, which revolutionized the way how music can be recorded. Nowadays, the most common approach to transform music data into a computer-readable format (used by professional musicians) combines musical keyboard input (e.g.

MIDI piano) with computer keyboard and mouse. It is a time-consuming procedure, which requires advanced keyboard-playing skills. The musical keyboard is utilized to enter the notes playing voice by voice and then the computer keyboard and mouse is used to correct mistakes and to add another information such as articulation marks, slurs and dynamics.

The majority of music scores exist only in the paper-based form and many contemporary composers and musicians still prefer to use pen and paper as the most efficient way to record their ideas. OMR systems can thus greatly simplify the music data acquisition and save a lot of human time.

In this article, we survey the area of OMR, its fundamental approaches and problems. Section 1.1 introduces a few aspects of music notation, and Section 1.2 reviews the historical context of OMR. A general framework for the music recognition is presented in Section 2. Challenges making the OMR difficult in practice are discussed in Section 3. Section 4 debates several opened questions of the OMR research and finally, we conclude this paper in Section 5.

1.1 Music Notation

Music notation has evolved over the period of centuries as the composers and musicians tried to express their musical ideas by written symbols [33]. In this article, we focus exclusively on the Western music notation (also known as common music notation — CMN) [10, 39], although certain OMR systems are developed to recognize other types of notation (e.g. medieval music notation [13, 42]).

Understanding of any music notation requires knowledge of the information the notation attempts to capture. In the case of CMN, there are four types of information involved [10]: a *pitch*, *time*, *loudness* (also *dynamics*) and *timbre* (tone quality). Figure 1 shows selected music notation marks. Clefs (Fig. 1a) determine the pitches for each line and space of the staff (Fig. 1b), accidentals (Fig. 1e) temporarily modify the pitch of following notes. The pitch of notes itself (Fig. 1c) is indicated by their vertical placement on the staff, and their appearance affects the relative duration. Ornaments (Fig. 1f) change the pitch pattern of individual notes. Rests (Fig. 1d) indicate a relative duration of silence. Dynamics (Fig. 1g) signify the varying loudness. Articulations (Fig. 1h) change the timbre or duration of a note. In practice, certain symbols have almost unlimited variations in representation (e.g. beams connecting notes into note groups or slurs indicating phrasing). The most used CMN symbols and their graphical aspects are listed e.g. in the Essential Dictionary of Music Notation [21].

Music Scores. For the music recognition purposes, it is useful to realize, that music scores can be divided into three categories: entirely printed music scores (Figure 2a), scores written by hand over the preprinted staff lines (Figure 2b) and entirely handwritten music scores (Figure 2c). Although the majority of OMR systems operates with printed scores only [35], OMR systems for handwritten music have been researched as well (e.g. [1, 17, 27, 36, 37, 45]). Also it should be noted, that scores of different visual qualities exist — from the clear music sheets to the degraded ones (mentioned e.g. in [9, 11]).

(a) Clefs. (b) Staff. (c) Notes. (d) Rests.

(e) Accidentals. (f) Ornaments. (g) Dynamics. (h) Articulations.

Fig. 1: Selected common music notation symbols.

(a) Entirely printed. (b) Preprinted staff lines. (c) Entirely handwritten.

Fig. 2: Examples of different sheet music categories.

1.2 Historical Background

The OMR research began in 1966, when Pruslin [32] first attempted the automatic recognition of sheet music. His system was able to recognize note heads and chords. In 1970, Prerau [31] introduced the concept of image segmentation to detect primitive elements of music notation. These two OMR founding works were later reviewed by Kassler [24].

With the availability of inexpensive optical scanners, the OMR research expanded in the late 1980s. An interesting contribution was a Japanese keyboard-playing robot WABOT-2 [25], developed in 1984. It was the first robot able to recognize simple music scores and play them on the organ. A critical survey of the OMR systems developed between 1966 and 1990 can be found in [8].

The first commercial OMR products appeared in the early 1990s [23,35]. Also, the first attempts to handle handwritten scores were made (e.g. [37,45]). In 1997, Bainbridge summarized the existing techniques and proposed an extensible music recognition system [2] not restricted to particular primitive shapes and semantic features. Together with Bell [3], they formulated a general framework for OMR systems, which has been adopted by many researchers since then [35].

During the last years, several important studies have been performed: Jones et al. [23] presented a study about music sheet digitization, recognition and restoration. Moreover, they listed available OMR software and provided an evaluation of three OMR systems. Noteworthy contributions to the OMR have been made by Rebelo et al. [30, 34, 36]. In 2012, they published probably the most recent review of the OMR field [35], including an overview of the state-of-the-art techniques and a discussion about the open issues.

2 General Framework

Automatic recognition of music scores is a complex task affecting many areas of computer science. Different OMR systems use various strategies, but the most common algorithms decompose the problem into four smaller tasks [35]:

1. Image Preprocessing
2. Segmentation
3. Object Recognition
4. Semantic Reconstruction

Terminology is not always the same: the segmentation is also called *primitive detection* or *musical object location*, and the recognition phase is sometimes called *musical feature classification* [2, 3].

2.1 Image Preprocessing

The main goal of the preprocessing phase is to adjust the scanned image to make the recognition process more robust and efficient. Different methods are typically used: *enhancement*, *blurring* and *morphological operations* [22] and *noise removal* (e.g. [20, 22, 40, 42]), *deskewing* [17, 20, 22, 27, 42] and *binarization* (e.g. [9, 17, 20, 22, 27, 30, 42]). In the following text, only the binarization is introduced as it is the most crucial step for the vast majority of OMR systems.

Binarization. Binarization algorithms convert the input image into a binary one, where objects of interest (music symbols, staves, etc.) are separated from the background. This is motivated by the fact, that music scores have inherently binary nature (colors are not used to store music information in CMN).

Binarization is usually an automated process driven without special knowledge of the image content. It facilitates the subsequent tasks by reducing the volume of information that is needed to be processed. For example, it is much easier to design an algorithm for staff detection, primitive segmentation and recognition in binary images than in grayscale or color ones.

In general, there are two types of binarization approaches. The first are *global thresholding methods*, which apply one particular threshold to the entire image. The Otsu's method [29] is often assessed to be the best and fastest [38,44]. Global thresholding works well when extracting objects from uniform backgrounds, but usually fails on non-uniform images. Nevertheless, it is used in several OMR research articles (e.g. [22, 34, 42]) because of its simplicity and time efficiency. The second category is represented by *adaptive binarization techniques*, which select a threshold individually to each pixel using information from the local neighborhood. These methods can eliminate non-uniform backgrounds at the expense of longer processing time. One of the most popular adaptive thresholding method is the Niblack's [28] that computes a local threshold from the mean and standard deviation in pixel's surroundings. Adaptive thresholding is also used in some OMR systems (e.g. [40]). Overview of binarization techniques used in OMR can be found in [9, 38].

2.2 Segmentation

The segmentation stage parses music scores into the elementary primitives. It is usually initiated by establishing the size of the music notation being processed. This is an important step before any shape recognition. Staff lines are a reliable feature of music notation used to estimate two important reference values: *staff line thickness* and *staff space height*, which are further used to deduce the size of other music symbols. The most common way of their approximation is based on the run-length encoding (RLE), which is a simple form of data compression. For instance, lets assume the binary sequence $\{1\ 1\ 1\ 0\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0\}$. It can be represented in RLE as $\{3\ 2\ 4\ 4\}$ (supposing 1 starts the original sequence, otherwise the first number in the encoded sequence would be 0). Binarized music scores can be encoded column by column with RLE, then the relative lengths can be easily estimated: the most common black run approximates the staff line thickness and the most common white run estimates the staff space height. However, more robust approximations exist [12].

Staff Lines. Staff line detection is fundamental in OMR, because the staff creates a two dimensional coordinate system essential to understand the CMN. Unfortunately, staff lines are not guaranteed to be perfectly horizontal, straight or of uniform thickness in scanned images (even in printed music scores). Precise staff detection is a tricky problem that still represents a challenge.

The simplest algorithms use horizontal projections [19, 20]. A horizontal projection maps a binary image into a histogram by accumulating the number of black pixels in each row. If the lines are straight and horizontal, staff can be detected as five consequent distinct peaks (local maxima) in the histogram. Figure 3 shows an excerpt of music and its horizontal projection. In practice, several horizontal projections on images with slightly different rotation angles are computed to deal with not completely horizontal staff lines. The projection with the highest local maxima is then chosen.

Another strategies use vertical scan lines [13] or Hough Transform or grouping of vertical columns [35]. Although there are many staff line detection techniques, they all have certain limitations. Dalitz [15] surveyed the existing methods and proposed a method based on skeletonization. Handwritten staff lines are usually detected using different kinds of techniques (e.g. [1, 43]).

Symbol Segmentation. Once the staff lines have been detected, the music primitives must be located and isolated. This can be performed in two manners:

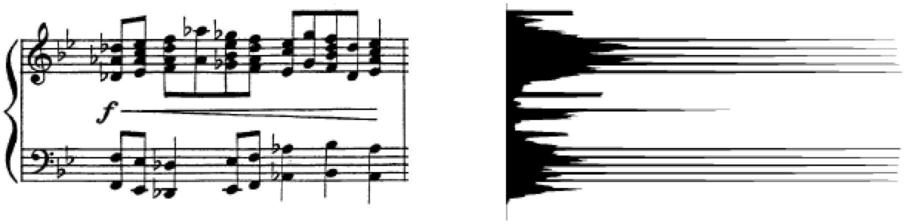

Fig. 3: The horizontal projection of a music score excerpt.

either remove the staff lines or ignore them. Although the majority of researchers remove the staff lines in order to isolate the musical symbols as connected components, there are some authors who suggest the opposite (e.g. [4,22]). The most simple line removal algorithm removes the line piecewise — following it along and replacing the black line pixels with white pixels unless there is evidence of an object on either side of the line [3]. The staff line removal procedure must be careful not to broke any object. Despite that, the algorithms often cause fragmentation, especially to objects that touch the staff lines tangentially.

The score is then divided into regions of interest to localize and isolate the musical primitives. The best approach is hierarchical decomposition [35]. At first, a music score is analyzed and split by staves. Then, the primitive symbols (note heads, stems, flags, rests, etc.) are extracted [22, 27, 34]. Particular procedures vary system to system. For example, some approaches consider note heads, stems and flags to be separate objects, whereas other concepts consider these primitives as a whole object representing a single note. More details can be found in [34].

2.3 Object Recognition

Segmented symbols are further processed and given to the classifier that tries to recognize them (assign them a label from predefined groups). Unfortunately, music shapes are inherently complex — they are often formed by several touching and overlapping graphical components. In addition, the staff line removal can break some objects (they are sometimes already fragmented because of the music score quality itself). Hence, the object recognition phase is very delicate and it is usually combined with the segmentation step [35].

Objects are classified according to their distinctive features. Some authors suggest classification using projection profiles [19], others apply template matching to recognize symbols [22] or propose a recognition process entirely driven by grammars formalizing the music knowledge [14]. Statistical classification methods using support vector machines (SVMs), neural networks (NN), k-nearest neighbours (kNN) and hidden Markov models (HMM) classifiers were investigated by Rebelo et al. [34]. Handwritten music symbols are sometimes segmented and recognized using the mathematical morphology, applying a skeletonization technique and an edge detection algorithm [26]. Despite the number of recognition techniques available, research on symbol segmentation and recognition is still important and necessary, because all OMR systems depend on it [35].

2.4 Semantic Reconstruction

The inevitable task of all OMR systems is to reconstruct the musical semantics from previously recognized graphical primitives and store the information in a suitable data structure. This necessarily requires an interpretation of spacial relationships between objects found in the image. Relations in CMN are essentially two dimensional and the positional information is very critical. For example, a dot can change note's duration if it is placed on the right of a note head, or it can alter the articulation if it is placed above the note.

These musically syntactic rules can be formalized using the grammars [2, 14, 19, 31]. Grammar rules specify semantically valid music notation events and a way, how the graphical primitives should be segmented. Alternative techniques build the semantic reconstruction on a set of rules and heuristics (e.g. [16, 26]).

The last and fundamental aspect of OMR systems is the transformation of semantically recognized scores in a coding format that is able to model and store music information. Many computer formats are available, but none of them has been accepted as a standard. The best known formats are: MIDI (Musical Instrument Digital Interface), NIFF (Notation Information File Format), SMDL (Standard Music Description Language) and MusicXML[1]. MIDI is mainly used as an interchange format between digital instruments and computers. Although its capability of modeling music scores is very limited (e.g. the relationships among symbols cannot be represented), most of the music editors can operate with MIDI files. NIFF was developed in 1994 to exchange data between different music notation software. NIFF is able to describe visual and logical aspects of music, however nowadays it is considered to be obsolete. SMDL strictly separates visual and logical sites and it is rather a standardized formal scheme than a practical file format. MusicXML is designed especially for sharing and archiving of music sheets. It covers the logical structure and also graphical aspects of music scores. It is becoming more and more popular and it targets to be the standard open format for exchanging digital sheet music. A more detailed review and comparison of music notation file formats can be found in [6].

3 Practical Challenges

Despite the fact that OMR systems have been researched thoroughly over the last few decades and even several commercial tools exist, the practical results are still far from ideal [35]. Proposed techniques are typically tailored to different properties of music scores, which makes them difficult to combine in one general OMR system robust enough to overcome all the practical issues. In this section, we focus on reasons that makes the OMR systems challenging in practice and we also discuss some open problems of the research area.

[1] http://www.musicxml.com/

3.1 Preprocessing

Preprocessing is the initial step of all OMR systems, which obviously affects the subsequent stages. However, no goal-directed studies investigating the impact of this phase on the recognition have been carried out [35]. Binarization often produces artifacts and its advantages in the complete OMR process are not clear. There are few attempts to use prior knowledge when performing a binarization process [30]. Such algorithm extracts content-related information from a grayscale image and uses it to guide the binarization. Cardoso et al. [12] encourage the idea of using grayscale images rather then the binary ones. A special care must be also given to highly degraded music scores [9].

In our opinion, it is also worth considering the possibility to analyze the color information when processing handwritten scores with preprinted staff lines, because the color of the composer's ink may slightly vary from the color of the staff lines. It could possibly result in a more efficient staff removal algorithm. This and similar image analysis topics are in our research interest.

3.2 Music Notation Inherent Problems

Music notation itself implies many difficult-to-process variants and possibilities of music representation typically responsible for serious recognition errors. Two different practical troubles are shown in Figure 4. The long curves connecting notes of distinct pitches (*slurs*) can have an arbitrary shape, thus they represent a great challenge for OMR systems. The last bar of the examples presents another difficulty: the notes pass to another staff, while their beams are crossing (moreover, they superimpose the crescendo sign and the slur).

There are plenty of similar problematic properties in CMN, for example: a smaller staff placed above the main staff indicating how a part of music can be alternatively played (*ossia*), simplifications for a better human readability that can be interpreted ambiguously (e.g. omitting the number 3 in triplets or alternating the left and right hands across the staves in the piano literature) or ornamental note groups that do not fit the prescribed meter. It should be also noted, that not all notation formats are able to represent such features. Nevertheless, these kinds of difficulties are nothing exceptional in real music sheets and hence cannot be omitted in a practical OMR system.

3.3 Handwritten Scores

Handwritten music sheets produce specific kinds of problems. Although they are also mentioned in the literature [1, 17, 27, 36, 37, 45], the results are still not usable for practical applications. In general, the major problem of OMR systems are fragmented and connected (touching or overlapping) music symbols. Handwritten music scores contain even more broken and merged symbols — it could be a part of composer's written style or just a consequence of quickly-made strokes. Figure 5 shows a huge variability of written styles of four different composers. These facts make the recognition of handwritten scores complicated.

Fig. 4: Example of variations in notation (from Maurice Ravel's Scarbo).

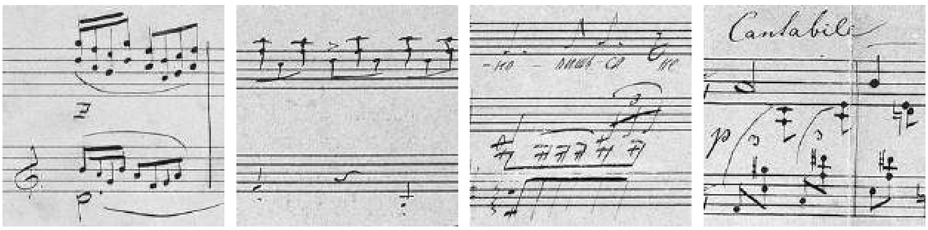

Fig. 5: An example of composer variability in handwritten scores.

4 Open Problems

One of the most important open issues of the OMR research is the lack of an available ground-truth database that could serve as a benchmark. Such a data set would contain a large amount of music scores of different types and qualities (clean scans, photocopies, degraded manuscripts, etc.) together with their ground-truth representation in a uniform notation format. Compilation of such corpus is extremely time-consuming, because the music sheets have to be processed by hand. Available data sets (e.g. [30]) are typically very limited or designed only for specific tasks [35]. Maybe a solution would be to design an automatic method able to procedurally simulate different types of writing styles and paper degradation levels from a given notation file. Available electronic scores then would be easily transformed to images of different qualities.

Another significant problem is the absence of common methodologies and metrics that would compare the results of OMR systems. This is a more complicated issue than it might seem at first glance, because OMR systems can target different goals (audio playback, score archiving, ...) and the outputs can be stored in very unlike formats. However, performance evaluation and related topics have been also studied in the literature. For example, Szwoch [41] proposed a method able to compare and evaluate the results of recognition systems stored in MusicXML format. More on this topic can be found in [5, 11].

In addition, we think, that music knowledge should be incorporated more to support the recognition and reconstruction processes. For example, considering the advanced analysis of music harmony or building a composer-adaptive system (adaptive to the composer's writing style as well as to the music style). To the best knowledge of the authors, no studies concerning these or similar topics exist. Together with the image analysis issues, this is one of the subjects on which we would like to focus our research.

5 Conclusion

During the last decades, OMR has been actively studied and a lot of achievements have been done. Even so, the problem is not solved and represents a great challenge in many ways. Possible OMR applications are still relevant today, which makes the research area constantly growing.

In this article, we have introduced the OMR field, its main goals and practical applications. We have also presented an overview of the most common methodologies including the idea of a generalized framework. The most delicate and challenging problems that all OMR systems have to face have been discussed as well. We hope, that our contribution helps to motivate the researchers, because there are many demanding problems waiting to be solved.

References

[1] Alirezazadeh, F., Ahmadzadeh, M.R.: Effective staff line detection, restoration and removal approach for different quality of scanned handwritten music sheets. Journal of Advanced Computer Science and Technology 3(2), 136–142 (2014)

[2] Bainbridge, D.: Extensible Optical Music Recognition. Ph.D. Thesis, Department of Computer Science, University of Canterbury, Christchurch, NZ (1997)

[3] Bainbridge, D., Bell, T.: The Challenge of Optical Music Recognition. Computers and the Humanities 35(2), 95 – 121 (2001)

[4] Bellini, P., Bruno, I., Nesi, P.: Optical music sheet segmentation. In: Web Delivering of Music, 2001. Proceedings. First International Conference on. pp. 183–190 (Nov 2001)

[5] Bellini, P., Bruno, I., Nesi, P.: Assessing Optical Music Recognition Tools. Comput. Music J. 31(1), 68–93 (Mar 2007)

[6] Bellini, P., Nesi, P.: Modeling Music Notation in the Internet Multimedia Age. In: George, S.E. (ed.) Visual Perception of Music Notation: On-Line and Off Line Recognition, pp. 272–303. IGI Global (2004)

[7] Billinge, D., Addis, T.: Towards Constructing Emotional Landscapes with Music. In: George, S.E. (ed.) Visual Perception of Music Notation: On-Line and Off Line Recognition, pp. 227–271. IGI Global (2004)

[8] Blostein, D., Baird, H.S.: A Critical Survey of Music Image Analysis. In: Baird, H.S., Bunke, H., Yamamoto, K. (eds.) Structured Document Image Analysis, pp. 405–434. Springer Berlin Heidelberg (1992)

[9] Burgoyne, J.A., Pugin, L., Eustace, G., Fujinaga, I.: A Comparative Survey of Image Binarisation Algorithms for Optical Recognition on Degraded Musical Sources. pp. 509–512. Austrian Computer Society (2007)

[10] Byrd, D.: Music Notation by Computer. Ph.D. thesis, Indiana University, Computer Science Department (1984)

[11] Byrd, D., Simonsen, J.G.: Towards a Standard Testbed for Optical Music Recognition: Definitions, Metrics, and Page Images. University of Copenhagen, Copenhagen (2013)

[12] Cardoso, J., Rebelo, A.: Robust Staffline Thickness and Distance Estimation in Binary and Gray-Level Music Scores. In: Pattern Recognition (ICPR), 2010 20th International Conference on. pp. 1856–1859 (Aug 2010)

[13] Carter, N.: Segmentation and Preliminary Recognition of Madrigals Notated in White Mensural Notation. Machine Vision and Applications 5(3), 223–229 (1992)

[14] Coüasnon, B., Camillerapp, J.: Using grammars to segment and recognize music scores. International Association for Pattern Recognition Workshop on Document Analysis Systems pp. 15–27 (1994)

[15] Dalitz, C., Droettboom, M., Pranzas, B., Fujinaga, I.: A Comparative Study of Staff Removal Algorithms. Pattern Analysis and Machine Intelligence, IEEE Transactions on 30(5), 753–766 (May 2008)

[16] Droettboom, M., Fujinaga, I., MacMillan, K.: Optical Music Interpretation. In: Caelli, T., Amin, A., Duin, R., de Ridder, D., Kamel, M. (eds.) Structural, Syntactic, and Statistical Pattern Recognition, Lecture Notes in Computer Science, vol. 2396, pp. 378–387. Springer Berlin Heidelberg (2002)

[17] Fornés, A., Lladós, J., Sánchez, G.: Primitive Segmentation in Old Handwritten Music Scores. In: Proceedings of the 6th International Conference on Graphics Recognition: Ten Years Review and Future Perspectives. pp. 279–290. Springer-Verlag, Berlin, Heidelberg (2006)

[18] Fremerey, C., Müller, M., Kurth, F., Clausen, M.: Automatic Mapping of Scanned Sheet Music to Audio Recordings. In: Bello, J.P., Chew, E., Turnbull, D. (eds.) ISMIR 2008, 9th International Conference on Music Information Retrieval, Drexel University, Philadelphia, PA, USA, September 14-18, 2008. pp. 413–418 (2008)

[19] Fujinaga, I.: Optical music recognition using projections. M.A p. Thesis (1988)

[20] Fujinaga, I.: Staff Detection and Removal. In: George, S.E. (ed.) Visual Perception of Music Notation: On-Line and Off Line Recognition, pp. 1–39. IGI Global (2004)

[21] Gerou, T., Lusk, L.: Essential Dictionary of Music Notation. Alfred Music Publishing (1996)

[22] Göcke, R.: Building a System for Writer Identification on Handwritten Music Scores (2003)

[23] Jones, G., Ong, B., Bruno, I., NG, K.: Optical Music Imaging: Music Document Digitisation, Recognition, Evaluation, and Restoration. Interactive Multimedia Music Technologies pp. 50–79 (2008)

[24] Kassler, M.: Optical Character Recognition of Printed Music: A Review of Two Dissertations. Perspectives of New Music 11 (1972)

[25] Matsushima, T.: Automated recognition system for musical score: The vision system of WABOT-2. Bulletin of Science and Engineering Research Laboratory (1985)

[26] Ng, K.C., Cooper, D., Stefani, E., Boyle, R.D., Bailey, N.: Embracing the Composer: Optical Recognition of Handwritten Manuscripts. In: Proceedings of the International Computer Music Conference. pp. 500–503 (1999)

[27] Ng, K.: Optical Music Analysis for Printed Music Score and Handwritten Music Manuscript. In: George, S.E. (ed.) Visual Perception of Music Notation: On-Line and Off Line Recognition, pp. 108–127. IGI Global (2004)

[28] Niblack, W.: An Introduction to Digital Image Processing. Strandberg Publishing Company, Birkeroed, Denmark, Denmark (1985)

[29] Otsu, N.: A Threshold Selection Method from Gray-Level Histograms. Systems, Man and Cybernetics, IEEE Transactions on 9(1), 62–66 (Jan 1979)

[30] Pinto, T., Rebelo, A., Giraldi, G., Cardoso, J.: Music Score Binarization Based on Domain Knowledge. In: Vitri, J., Sanches, J., Hernndez, M. (eds.) Pattern Recognition and Image Analysis, Lecture Notes in Computer Science, vol. 6669, pp. 700–708. Springer Berlin Heidelberg (2011)
[31] Prerau, D.: Computer pattern recognition of standard engraved music notation. Ph.D. Dissertation, Massachusetts Institute of Technology (1970)
[32] Pruslin, D.: Automatic recognition of sheet music. Sc.D. Dissertation, Massachusetts Institute of Technology (1966)
[33] Read, G.: Music Notation: A Manual of Modern Practice. Taplinger Publishing Company (1979)
[34] Rebelo, A., Capela, G., Cardoso, J.: Optical recognition of music symbols: A comparative study. International Journal on Document Analysis and Recognition (IJDAR) 13(1), 19–31 (2010)
[35] Rebelo, A., Fujinaga, I., Paszkiewicz, F., Marcal, A., Guedes, C., Cardoso, J.: Optical music recognition: state-of-the-art and open issues. International Journal of Multimedia Information Retrieval 1(3), 173–190 (2012)
[36] Rebelo, A.M.: Robust Optical Recognition of Handwritten Musical Scores based on Domain Knowledge. Ph.D. thesis, University of Porto (2012)
[37] Roach, J.W., Tatem, J.E.: Using Domain Knowledge in Low-level Visual Processing to Interpret Handwritten Music: An Experiment. Pattern Recognition 21(1), 33–44 (Jan 1988)
[38] Sezgin, M., Sankur, B.: Survey over image thresholding techniques and quantitative performance evaluation. Journal of Electronic Imaging 13(1), 146–168 (2004)
[39] Stone, K.: Music Notation in the Twentieth Century: A practical guidebook. Norton New York (1980)
[40] Szwoch, M.: Guido: A Musical Score Recognition System. In: Document Analysis and Recognition, 2007. ICDAR 2007. Ninth International Conference on. vol. 2, pp. 809–813 (Sept 2007)
[41] Szwoch, M.: Using MusicXML to Evaluate Accuracy of OMR Systems. In: Stapleton, G., Howse, J., Lee, J. (eds.) Diagrammatic Representation and Inference, Lecture Notes in Computer Science, vol. 5223, pp. 419–422. Springer Berlin Heidelberg (2008)
[42] Tardón, L.J., Sammartino, S., Barbancho, I., Gómez, V., Oliver, A.: Optical Music Recognition for Scores Written in White Mensural Notation. J. Image Video Process. 2009, 6:3–6:3 (Feb 2009)
[43] Timofte, R., Van Gool, L.: Automatic Stave Discovery for Musical Facsimiles. In: Lee, K., Matsushita, Y., Rehg, J., Hu, Z. (eds.) Computer Vision ACCV 2012, Lecture Notes in Computer Science, vol. 7727, pp. 510–523. Springer Berlin Heidelberg (2013)
[44] Trier, O., Jain, A.: Goal-Directed Evaluation of Binarization Methods. Pattern Analysis and Machine Intelligence, IEEE Transactions on 17(12), 1191–1201 (Dec 1995)
[45] Wolman, J., Choi, J., Asgharzadeh, S., Kahana, J.: Recognition of Handwritten Music Notation. Proceedings of the International Computer Music Conference pp. 125–127 (1992)