Improving access to digital music through content-based analysis

Juan Pablo Bello
Music and Audio Research Lab (MARL), New York University, New York, New York, USA, and
Kent Underwood
Avery Fisher Center for Music and Media, New York University, New York, New York, USA

Abstract

Purpose – The purpose of this paper is to report recent advances on a collaborative project that aims to develop content-based methods for music information retrieval (MIR) as an alternative to standard text-based modes of access to digital music libraries.

Design/methodology/approach – The paper describes current practices and ongoing research, and it discusses potential applications for future use.

Findings – Content-based MIR approaches can extend and enhance the capabilities of traditional text-based discovery and delivery systems and thus support the work of expert users such as musicians and musicologists. Examples of technologies developed in the context of the project include novel methods for automatic chord identification, motif finding, the visualization of musical structure, and retrieval of musical variations using harmonic and structural information.

Practical implications – The paper looks at new, non-verbal modes of interaction with digital music archives based on musically substantive features such as chords, motifs, rhythms, etc. By building more sophisticated dimensions of interactivity into a discovery-and-delivery system, these tools could give the end-user a more meaningful and rewarding experience. The tools potentially would be less costly and more scalable than textual annotation and markup, and their applicability extends beyond digital libraries to other music services.

Originality/value – This article discusses the advantages and challenges posed by audio-based MIR and shows, via project-specific examples, its relevance to supporting the needs of digital music library users.

Keywords Music, Information retrieval, Audio recordings, Multimedia

Paper type Research paper

1. Introduction and overview

Digital music archives, catering to a wide variety of target audiences, are now ubiquitous. Examples range from the relatively small and specialized, like the academically inclined Digital Anthology of Recorded American Music (DRAM)[1], to Apple’s enormous, consumer-oriented iTunes Store[2]. Yet despite the proliferation of recorded music in the online universe, the end user’s experience with digital music archives still operates largely on an information-retrieval paradigm that was developed for the cataloging of books in the era of manual card catalogs. In this model, access is mediated exclusively by textual metadata, and interactivity is restricted to the
simple playback of retrieved items. As discussed in (Dunn et al., 2006), the limitations of this model for recorded music impinge especially on expert users – music students, professors and teachers, researchers, composers, and performers – who have far more sophisticated needs than entertainment-driven customers of commercial outlets. As a result, libraries and other service providers who cater to expert audiences are in need of new methodologies and tools that respond to the challenges and opportunities opened up by the digitization of recorded content.

With the support of a research grant from the Institute of Museum and Library Services, New York University’s Music and Audio Research Lab[3] and Avery Fisher Center for Music and Media[4] have jointly embarked on a three-year project, entitled “Improving Access to Digital Music through Content-based Analysis”[5]. The project’s goal is to contribute to the research and development of a new generation of automatic, content-based approaches to the organization of, access to, and interaction with digital music archives.

These next-generation tools are intended neither to supplant nor even to compete with traditional text-based discovery and delivery systems but, rather, to extend and enhance their capabilities. The practical applications would offer many benefits: The new tools have the potential to enable exploration into musical features that have hitherto been inaccessible to end users, because it has never been feasible to describe or catalog those dimensions by means of traditional metadata formularies. With the new tools, discoverability would no longer be limited to static, textual metadata terms; it could also include musically substantive features such as motifs, chord sequences, rhythms, phrase structures, cadential formulas, instrumental timbres, and more. In other words, the end user could interact directly with the audible substance of the music, and – no longer bound by the limitations of representing musical sounds with verbal terminology – he or she would be empowered to ask and answer questions never addressed or even envisioned by a traditional cataloging system. For librarians, the new tools would have the added appeal of being potentially less costly and more scalable than textual annotation and markup, which require institutions to invest significant amounts of staff and financial resources both to build and to maintain their metadata infrastructures and delivery systems. Moreover, the applicability of such methods is not limited to library services but extends to music distribution and commercialization outlets in the wider world. In a market dominated by metadata-driven services, the immense potential of intelligent content-based retrieval is yet to be fully exploited.

The body of this paper is organized as follows: Section 2 discusses text-based approaches to music information retrieval (MIR), highlighting their strengths and weaknesses; section 3 reviews recent advances in content-based retrieval, and makes the case for methods focused on the musical contents in the audio signal; sections 4 and 5 present two specific content-based approaches developed in the context of this project. They are based, respectively, on the recognition of chords and the characterization of repetitive patterns; finally, section 6 presents conclusions and discusses future work.

2. Text-based MIR
To facilitate discoverability in catalogs of recorded music, the default strategy – for many decades and still today – is to supplement the metadata from the record label
(i.e. the artists’ names, titles, publication information, and probably some technical data about the physical recording itself) with short, semantically meaningful labels that point to certain aspects of the musical content. The most widespread and obvious example of this is the Library of Congress Subject Headings (LCSH), which for American libraries has been in standard use for many decades, first in their card catalogs and subsequently in their online discovery systems. Online music providers such as DRAM, Music Online, and Naxos Music Library have taken a similar approach in utilizing a defined list of subject terms to help end users navigate their catalogs, as have commercial products such as the All Music Guide[6] and Pandora[7]. All of these entities utilize their own pre-defined lists of subject terms, and all of them rely on their own teams of trained experts to assign those terms with knowledge and understanding of the music. The result, if all goes well, is a high degree of clarity, consistency and reliability that gives the end user the ability both to find what he or she is looking for and to discover what he or she doesn’t yet know about.

But verbal terminology can take us only so far. The LCSH thesaurus is voluminous and nuanced in its more than 50,000 headings in the field of music (Hemmasi, 1998), yet every reference librarian is faced daily with patron queries that are difficult or even impossible to answer because the questioner’s terminology is not part of LCSH’s controlled vocabulary. Musical vocabulary, too, while often highly technical, can also be imprecise and unstable in the variety of possible interpretations, especially with those terms pertaining to genre and style[8]. Then there are types of questions that for whatever reason have been categorically excluded from consideration; it has never been possible in the conventional discovery system, for example, to ask for a piece in 4/4 time or a song based on the “I got rhythm” chord changes. Making expert annotations is time and labor intensive, and to curate and apply a subject thesaurus that can preemptively answer every future question is a perpetual uphill swim for libraries and other cataloging agencies.

Low-cost and scalable solutions include the use of web mining (Whitman, 2005), and most notably of social tags, which are user-created, unstructured and free for all (Lamere, 2008). These tags are collected and aggregated by social networking sites where fans share, recommend and discuss music. Example services include MusicBrainz[9], Amazon[10] and Last.fm[11]. The large and enthusiastic user bases of such sites mean that significant quantities of tags are generated per track, artist, album and playlist, cutting across large swaths of the existing music catalog. On the downside, the lack of editorial rigor means that social tag sets can be noisy, ambiguous, inconsistent, redundant and biased according to user, genre or popularity[12]. These shortcomings affect their usability, especially for representing sparsely tagged music in the long tail. Given all of the above, it is no surprise that the analysis and use of social tags is a central concern of the MIR community. The reader is referred to (Aucouturier and Pampalk, 2008), and the special issue it introduces, for a comprehensive overview of relevant research trends. These include the development of music tagging games and, as will be discussed in the next section, of content-based approaches to predict tags from audio information (Turnbull et al., 2008).

3. Content-based MIR

Auto-tagging, the automatic tagging of music tracks, uses machine learning techniques to recognize the relationships between existing tags and the feature
representations of the audio signals to which they apply. Once trained, these algorithms can assign labels to untagged samples based solely on their audio content (Bertin-Mahieux et al., 2008). Because these tools can be easily optimized and parallelized, auto-tagging can significantly improve on the scalability of human annotation, facilitating deployment on the long tail and alleviating the biases and vagaries endemic to social tags.

Auto-tagging and other related tasks – such as automatic genre, artist and instrument identification or the characterization of sound (or texture) similarity – are commonly based on the “bag of features” approach to modeling music recordings. This approach stems from the “bag of words” assumption for the analysis of text documents, in which word counts are used to represent documents without regard for phrase structure. Likewise, sounds can be described in terms of their distribution of low-level signal features regardless of ordering and structure (Aucouturier et al., 2007). As discussed in (Casey et al., 2008) this approach is appropriate for low-specificity tasks where the importance is in the general behavioral pattern of features and not on the specific values they assume.

However, the context of sounds within a temporal ordering and structure is essential to music, which is commonly made of sounds carefully organized and articulated within a frame of time[13]. For the analytically minded searcher, therefore, the ability of a discovery tool to analyze and identify the patterns and relationships that make the music is not only significant to retrieval, but also to the understanding of the music’s composition, categorization, and impact – hence the great interest of this project to the musicians, scholars and other expert users that are the main constituency of music libraries.

Temporal articulations in music are inseparably related to the structures not only of rhythm and meter but also of harmony, melody, dynamics, texture, and form. However, tags or other forms of metadata whose scope rarely reaches below the track level cannot properly represent such elements. A number of projects, notably Indiana University’s “Variations” (Dunn et al., 2006), seek to provide a comprehensive environment in which music scholars can discover and interact with music through scores and marked-up recordings. However, more so than for structured tags, the availability of these resources is limited, and generating them is costly and non-scalable.

Content-based analysis again provides a solution in the form of automatic music transcription, i.e. the process of automatically transforming the audio waveform into a musical score. However, the difficulty of this task is enormous, and despite great efforts, the state-of-the-art in automatic music transcription remains unreliable even in highly constrained conditions. The reader is referred to (Klapuri and Davy, 2006) and (Casey et al., 2008) for overviews of methods and their evaluations.

Despite these caveats, research in automatic music transcription has informed the development of intermediate techniques that combine the use of musically meaningful signal features with the power and versatility of machine learning techniques. Examples include approaches for chord estimation (Sheh and Ellis, 2003; Bello and Pickens, 2005), beat tracking (Gouyon et al., 2006) and long-term segmentation (Paulus et al., 2010). These intermediate techniques have been at the core of recent advances in sequence-based methods for music retrieval, including the identification of remixes (Casey et al., 2008) and cover songs (Serra et al., 2008) (Serrà et al., 2009). By accounting
the temporal contextualization of music’s constituent elements, these techniques are able to represent musical information in recorded sound and can identify musical similarities in digital collections. It follows, therefore, that these same tools can be used to provide users with innovative modes of access to music that go beyond traditional metadata-based search and playback.

The following sections summarize recent advances in this direction investigated in the context of our project. They exemplify both the potential and the challenges of developing content-based music information retrieval systems.

4. Chord-based retrieval

The system of harmonic tonality has been foundational to Western music, both classical and popular, since the seventeenth century. So deeply embedded in our cultural consciousness is this system that, empirical evidence suggests, even untrained listeners intuitively expect and perceive basic patterns of tonal organization, almost as if they were born with this understanding (Krumhansl, 1990; Janata et al., 2002).

Tonality is an architectonic system of contextual relationships. The chord is the most fundamental unit of structure of this system, in which a chord’s identity and function are determined both by its constituent pitch classes and also by the syntactical context in which the chord occurs. Contextual significance is a consequence both of the chord’s position relative to other chords within a temporally organized sequence and also to its functional relationships to other chords and (ultimately) to an underlying “tonic.” Because the chord as a structure is comprised essentially of pitches, its contextual identity (and the perceptibility thereof) is typically strong enough to shine through changes in instrumentation, the addition or deletion of individual notes, and even the mixing in of non-pitched sounds or noises. Unsurprisingly, therefore, chord identification and the automatic extraction of chord sequences have been a major focus of attention for the MIR community (Sheh and Ellis, 2003; Bello and Pickens, 2005; Mauch and Dixon, 2010; Cho, Weiss, and Bello, 2010).

Figure 1 illustrates the approach to chord-based retrieval proposed in (Bello, 2007). It consists first of a chord-sequence estimation stage (combining chroma feature extraction and a dynamic graphical model), then of a sequence-similarity stage (where chord sequences are matched according to key and compared using a dynamic programming approach).

4.1 Automatic chord sequence estimation

Chroma features are one of the most widely used signal representations in the MIR literature. They characterize the cyclical perception of pitch as it moves from one octave to the other (Shepard, 1964), such that sounds whose frequencies are separated by an integral number of octaves, i.e. belonging to the same pitch class, occupy the same position in the chroma dimension. In Western music, these pitch classes are chosen to represent the twelve notes of the chromatic scale. There are a number of techniques for computing chroma features from audio signals, usually based on the warping and wrapping of the signal’s magnitude spectrum[14]. Just as with the short time Fourier transform (STFT), chroma vectors can be calculated sequentially on partially overlapped blocks of signal data, resulting on a so-called “chromagram”.

When a certain chord plays, the chroma features of the associated blocks of signal data show a concentration of energy in the pitch classes corresponding to the notes of
Figure 1. Block diagram of chord-based retrieval system

**Notes:** First, a chromagram representation is generated from the audio signal. Then, a hidden Markov model (HMM) is used to estimate the most likely chord sequence. The estimated sequences are matched to the same key and aligned using dynamic programming. The score of the alignment is used as a measure of pair-wise similarity.
the played chord. Thus, a simple comparison with a pre-defined chord template can provide a coarse measure of the likelihood that a certain chord is in occurrence (Fujishima, 1999). Alternatively, the emerging patterns and their sequential organization can be learned and recognized using graphical models, of which hidden Markov models (HMM) are a popular example. HMM are a class of dynamic models that provide a robust solution to the analysis of processes such as speech or music, which are represented as a sequence of unknown, or hidden, states – e.g. the underlying chord progression – that can be characterized only from a set of observations – the chroma vectors (Rabiner, 1989). The combination of chroma features and HMM for chord recognition was pioneered in (Sheh and Ellis, 2003), with many subsequent modifications bringing about significant improvement. For an extensive review, the reader is referred to the comparative evaluation in (Cho et al., 2010), which shows how an appropriate choice of filtering strategies on the feature and likelihood vector sequences, can offset most of the gains of added model complexity. A recent community-based evaluation shows our best method having an equivalent performance to the state of the art[15].

4.2 Sequence similarity

Sequence alignment is an extensively researched topic, notably in bioinformatics, where it supports the study of functional, structural and evolutionary relationships between protein sequences (Durbin et al., 1998). Likewise, it can be used to characterize patterns of similarity and divergence between music sequences useful for the retrieval, analysis and visualization of digital music collections. In MIR, sequence alignment has been utilized for MIDI-based applications such as retrieval according to melodic similarity and “query by humming”[16]. However, its employment in the analysis of polyphonic, multi-instrumental music audio has been limited, in a few exploratory applications, to the retrieval of renditions (Hu et al., 2003; Lee, 2006; Serra et al., 2008).

The goal of sequence alignment algorithms is to find the best amongst all possible alignments between two sequences. The best alignment is the one that maximizes a score function, obtained by summing the individual scores of pair-wise chord matches along the alignment path. These scores are highest when chords are the same, and lowest when matched chords are dissimilar or gaps are introduced. It follows that when comparing two related chord sequences (e.g. variations, re-interpretations) most chord matches will be good, resulting in a high total score. On the other hand, unrelated sequences will result in a higher number of unlikely substitutions and gap insertions, and thus in a lower score. This is the basis for using the overall alignment score as an approximate measure of the harmonic similarity between musical recordings.

In (Bello, 2007) of the authors investigate sequence alignment for the identification of cover songs on large audio collections. This is a complex “query by audio example” problem, as renditions often diverge significantly in instrumentation, key, genre, rhythm, form or any combination of the above. The approach utilizes a dynamic programming approach, the Needleman-Wunsch-Seller algorithm (Durbin et al., 1998), on chord sequence pairs. The sequences are key-matched by finding the rotation that maximizes the dot product between their histograms. Tracks are then ranked according to their overall alignment score to the query. Tests show that best results are obtained when sequence alignment errors are progressively penalized according to
common confusions in chord recognition, e.g. between tonic and relative minor chords, or between tonic and dominant chords.

While originally competitive with the state of the art[17], the approach suffers from error propagation issues deriving from inaccurate chord identification and key matching. Our current work on chord identification (Cho et al., 2010), intends to minimize the former. Novel developments using structure-based analysis, discussed in the following section, are aimed at addressing the latter. However, the main limitation of the approach stems from its inability to characterize local similarities. The importance of local information for cover-song identification is thoroughly demonstrated in (Serra et al., 2008). Section 5.2 discusses our proposed solution to this problem.

5. Structural analysis of music audio

Structure analysis has been extensively researched in MIR, usually by exploiting repetitive patterns to segment the signal into sections (Paulus et al., 2010). Repetitive patterns are widely acknowledged to play a fundamental role in the composition and analysis of music, with many common musical concepts and terms (such as riff, groove, motive, tempo, meter, and section), defined according to the essential presence of repetition (Ockelford, 2005). The following discusses two approaches to the analysis of structural information in music recordings and the application of these to MIR.

5.1 Structure-based similarity

Bello (2009, 2010) propose a computational approach to measuring the similarity between musical recordings based on their global temporal structure. The approach, depicted in Figure 2, follows the extraction of chroma features from the audio signal with the computation of a recurrence plot (Marwan et al., 2007) to characterize patterns of repetition in the feature sequence. The pair-wise similarity between plots, and the recorded tracks they represent, is measured using the normalized compression distance (Cilibrasi and Vitanyi, 2005). The method’s focus is on measuring similarity directly on an intermediate representation of the signal’s structure, instead of attempting to segment the audio into sections.

Recurrence plots can be seen as extensions of the self-similarity matrices widely used in MIR (Paulus et al., 2010). Recurrence plots differ in that they are usually binary and incorporate a pre-processing step known as delay-coordinate embedding, which has been shown to minimize the detection of spurious recurrences and thus benefit retrieval (Bello, 2010; Serrà et al., 2009). Furthermore, the combination of chroma features and recurrence plots makes the analysis key-invariant, avoiding the matching stage necessary for chroma and chord-based retrieval. The Normalized Compression Distance (NCD) is a metric of similarity that is simple to compute, versatile and robust. Experimental results, however, show that the metric is sensitive to variable signal lengths and strong structural changes, requiring length normalization and limiting its applicability for the characterization of local similarities. We are currently investigating possible solutions to these problems.

Wu and Bello (2010) investigate the application of these techniques to music information visualization. Specifically, it studies how arc diagrams, such as the ones in Figure 3, can be computed via simple post-processing of the recurrence plots of music signals. In the resulting graphs, the x-axis represents time and the translucent arcs
Notes: First, a chromagram representation is generated from the audio signal. Then, a recurrence plot (RP) of the chromagram is computed in order to characterize the patterns of repetition in the music. Finally, the pair-wise similarity between recordings is measured by calculating the normalized compression distance (NCD) between their corresponding plots.
connect musically similar regions in the audio stream, providing a rich and intuitive visualization of structure. The binarization of the recurrence plot, and thus the density of the arc diagram, depends on a threshold value that can be interactively controlled by the user. As can be seen in the figure, the changing density allows for the visualization of the finer/coarser structure of the signal.

The diagrams can help users perform difficult musicological tasks, such as identifying musical form. Preliminary tests show that these visualizations can reinforce the analysis of musical structures, making it faster and more accurate. At the very least, these plots can function as maps for the non-linear navigation of musical recordings.

5.2 Identifying local patterns
By bypassing the chord-recognition and key-matching stages, structure-based similarity avoids some of the problems that are inherent to the chord-based retrieval methods described in section 4. However, these techniques still fail to robustly characterize local similarities, and are thus limited to the identification of global matches.

As a solution to this problem (Weiss and Bello, 2010, 2011) propose a novel approach for the automatic extraction and localization of repeated patterns in music.
audio based on a machine learning technique known as shift-invariant probabilistic latent component analysis (Smaragdis et al., 2008). Simply put, the algorithm reconstructs the signal’s chromagram as the convolution between a small set of short chroma patterns and an activation matrix. The chroma patterns can be thought of as re-occurring motifs in the music, such that the location of a peak in the \( i \)th row of the activation matrix indicates the moment in time when the \( i \)th motif is played.

The method uses sparse prior distributions to minimize pattern overlap, thus increasing their information content, as well as identifying automatically the patterns that are most relevant for modeling the data and discarding those whose contribution is small. By allowing shift-invariance in both time and frequency, the method can be made self-adjusting to changes of key.

This approach provides a robust and flexible foundation for the characterization of temporal structure in music regardless of the time scale. This is demonstrated at length in Weiss and Bello (2011), where the algorithm is applied to tasks as diverse as identifying the main riff of a song, meter recognition and long-term structural segmentation, all by means of simple post-processing and changes in the algorithm’s parameter settings. We are currently testing applications to motivic analysis in large piano music collections.

6. Conclusions and next steps
The sustained growth and proliferation of digital music archives opens up unprecedented opportunities for technology-driven innovation in modes of access and interaction with the recorded material. Our own research, as well as our overview of recent advances by others in the MIR field, make the case for content-based music information retrieval, in which search-and-retrieval interactions take place directly between the end user and the audio signal itself, and are therefore not constrained by the availability, quality, or scope of textual metadata, as is the case in traditional library cataloging. In this article we briefly describe state-of-the-art methods for automatic chord identification, music information visualization, and the finding of repetitive patterns in music, and we discuss potential applications that could benefit the work of expert library users, such as music students and musicologists. These novel approaches to the sequence-based retrieval of music recordings, using harmonic and structural information, could be used for the analysis and comparison of multiple performances, cover songs, remixes, and other manifestations of musical patterning.

We believe that, given these and other recent advances in content-based music analysis, the community is already in a position to develop direct audio retrieval systems to support the work of digital libraries[18]. Therefore, beyond our continuing in a pure research mode to investigate and improve the methods herein described, the immediate future will focus on practical applications: integrating these techniques with innovations in the field of user-experience design, in order to develop a prototypical MIR system that can serve as a basis for new generations of library services. The terrain ahead offers the prospect of fruitful collaborations among MIR researchers, librarians, and discovery-and-delivery system developers. The ultimate goal – as we work towards interactive features that are more and more sophisticated and meaningful – is to enable the end user to define the terms of his or her own search, thereby to harvest richer and richer results than have ever been possible.
Notes

1. www.dramonline.org/. DRAM now contains about 8,000 albums from the catalogs of New World Records plus about two-dozen other independent labels. Other prominent products catering to the academic market are Music Online (Alexander Street Press): http://alexanderstreet.com/products/MUSO.htm; and Naxos Music Library www.naxosmusiclibrary.com/

2. www.apple.com/itunes/features/#purchasingmusic, according to which, over 13 million songs are available from the iTunes Store as of this writing.


6. www.allmusic.com/

7. www.pandora.com/

8. For example, of the top ten Emo albums recommended by the All Music Guide, only one of them (Something to Write Home About by The Get Up Kids) is cataloged under the term “Emo Music” in WorldCat; the other nine have the subject heading “Rock Music.” (Both databases accessed 17 January 2011).


10. www.amazon.com/

11. www.last.fm/

12. Modern library catalogs are increasingly offering a social tagging option, but in a way that strictly segregates the tags from the official subject headings assigned by the library.


14. See for example the multiple variations of feature extractors available in the Chroma Toolbox: www.mpi-inf.mpg.de/~mmueller/chromatoolbox/

15. http://nema.lis.illinois.edu/nema_out/mirex2010/results/ace/

16. For a comprehensive review of symbolic MIR the reader is referred to Typke (2007)


18. See for example the PROBADO project, which integrates text and score-based retrieval with content-based analyses such as score following and pitch spectrum visualization www.probado.de/en/home.do.htm

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**Further reading**


About the authors
Juan Pablo Bello received his PhD in Electronic Engineering from Queen Mary University of London in the UK, where he was also post-doctoral researcher and Technical Manager of the Centre for Digital Music. Since 2006, he has been an Assistant Professor of Music Technology at New York University, and a founding member of its Music and Audio Research Laboratory (MARL). Dr Bello teaches and researches on the computer-based analysis of audio signals and its applications to music information retrieval, digital audio effects and interactive music systems. His work has been supported by scholarships and grants from Venezuela, the UK, the EU and the USA, including, more recently, a CAREER award from the National Science Foundation. He is also a researcher and member of the Scientific and Medical Advisory Board of Sourcetone, a music and health start-up. Juan Pablo Bello is the corresponding author and can be contacted at: jpbellobello@nyu.edu

Kent Underwood is a Music Librarian for NYU Libraries and since 2007 has been the Head of the Libraries Avery Fisher Center for Music and Media. Dr Underwood holds MA and PhD degrees in Historical Musicology, both from Stanford University, and a BM in music performance from the San Francisco Conservatory of Music. At NYU he teaches graduate courses in contemporary music, seventeenth- and eighteenth-century music, and music research. He is currently the Music Editor for the bibliography, Resources for College Libraries (Chicago: American Library Association, 2007) and was a Co-editor of the bibliography A Basic Music Library, 3rd ed. (Chicago: American Library Association, 1997). As member of the Music Library Association he has chaired the World Music Roundtable and the Music Library Association-Music Publishers Association Joint Task Force on Publishers Archives.