Multi-Modal Music Information Retrieval - Visualisation and Evaluation of Clusterings by Both Audio and Lyrics

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Abstract

Navigation in and access to the contents of digital audio archives have become increasingly important topics in Information Retrieval. Both private and commercial music collections are growing both in terms of size and acceptance in the user community. Content based approaches relying on signal processing techniques have been used in Music Information Retrieval for some time to represent the acoustic characteristics of pieces of music, which may be used for collection organisation or retrieval tasks. However, music is not defined by acoustic characteristics only, but also, sometimes even to a large degree, by its contents in terms of lyrics. A song's lyrics provide more information to search for or may be more representative of specific musical genres than the acoustic content, e.g. 'love songs' or 'Christmas carols'. We therefore suggest an improved indexing of audio files by two modalities. Combinations of audio features and song lyrics can be used to organise audio collections and to display them via map based interfaces. Specifically, we use *Self-Organising Maps* as visualisation and interface metaphor. Separate maps are created and linked to provide a multi-modal view of an audio collection. Moreover, we introduce quality measures for quantitative validation of cluster spreads across the resulting multiple topographic mappings provided by the Self-Organising Maps.

Introduction

On-line music stores are gaining market shares, driving the need for on-line music retailers to provide adequate means of access to their catalogues. Their ways of advertising and making accessible their collections are often limited, be it by the sheer size of their collections, by the dynamics with which new titles are being added and need to be filed into the collection organisation, or by inappropriate means of searching and browsing it. Browsing metadata hierarchies by tags like 'artist' and 'genre' might be feasible for a limited number of songs, but gets increasingly complex and confusing for collections of larger sizes that have to be searched manually. Hence, a more comprehensive approach for the organisation and presentation of audio collections is required.

Private user's requirements coincide because their collections are growing significantly as well. The growing success of on-line stores like iTunes[1] or Magnatune[2] brings digital audio closer to end users, creating a new application field for Music Information Retrieval. Many private users have a strong interest in managing their collections efficiently and being able to access their music in diverse ways. Musical genre categorisation based on e.g. meta tags in audio files music often restricts users to the type of music they are already listening to, i.e. browsing genre categories makes it difficult to discover 'new' types of music. The mood a user is in often does not follow genre categories. Personal listening behaviours often differ from predefined genre tags. Thus, recommending users similar songs to ones they are currently listening to or like is one of Music Information Retrieval's main tasks.

Content based access to music has proven to be an efficient means of overcoming traditional metadata categories. To achieve this, signal processing techniques are used to extract features from audio files capturing characteristics such rhythm, melodic sequences, instrumentation, timbre, and others. These have proven to be feasible input both for automatic genre classification of music as well as for alternative organisations of audio collections like their display via map based, two-dimensional interfaces (Neumayer, Dittenbach & Rauber 2005).

Rather than searching for songs that sound similar to a given query song, users often are more interested in songs that cover similar topics, such as 'love songs', or 'Christmas carols', which are not acoustic genres per se. Songs about these particular topics might cover a broad range of musical styles. Similarly, the language of a song's lyrics often plays a decisive role in perceived similarity of two songs as well as their inclusion in a given playlist. Even advances in audio feature extraction will not be able to overcome the fundamental limitations of this kind. Song lyrics therefore play an important role in music similarity. This textual information thus offers a wealth of additional information to be included in music retrieval tasks that may be used to complement both acoustic as well as metadata information for pieces of music.

We therefore address two main issues in this paper, namely (a) the importance and relevance of lyrics to the visual organisation of songs in large audio collections and (b) spreading measurements for the comparison of multi-modal map visualisations. Moreover, we try to show that text representations of songs are feasible means of access and retrieval.

[1] http://www.apple.com/au/itunes/store/

[2] http://www.magnatune.com

We will try to show that multi-modal clusterings, i.e. clusterings based on audio features in combination with clusterings based on song lyrics, can be visualised on an intuitive linked map metaphor, serving as a convenient interface for exploring music collections from different points of view.

The remainder of this paper is organised as follows. The first section gives an overview about research conducted in the field of Music Information Retrieval, particularly dealing with lyrics and other external data such as e.g. artist biographies. We present our contributions, namely the visualisation of multi-modal clusterings based on connections between multiple clusterings, as well as suitable quality measurements in the 'Multi-Modal Clusterings' section. In the experiments section, a set of experiments on a parallel corpus comprising almost 10.000 pieces of music is used to validate the proposed approach. Finally, we draw conclusions and give an outlook on future work.

Related Work

Research in Music Information Retrieval comprises a broad range of topics including genre classification, visualisation and user interfaces for audio collections. First experiments on content based audio retrieval were reported in (Foote 1999) as well as (Tzanetakis & Cook 2000), focusing on automatic genre classification. Several feature sets have since been devised to capture the acoustic characteristics of audio material. In our work we utilise Statistical Spectrum Descriptors (SSD) (Lidy & Rauber 2005), which have shown to yield good results at a manageable dimensionality of 168 features. These have been used both for music clustering as well as genre classification. An overview of existing genre taxonomies as well as the description of a new one are given in (Pachet & Cazaly 2000), pointing out the relevance of the genre concept. This work also underpins our ambitions to further explore the differences in between genres according to their spread in clustering analysis. An investigation about the merits of and possible improvements for musical genre classification, placing emphasis on the usefulness of both the concept of genre itself as well as the applicability and importance of musical genre classification, is conducted in (McKay & Fujinaga 2006).

With respect to music clustering, the SOMeJB system (Rauber & Frühwirth 2001) provides a map-based interface to music collections utilising *Self-Organising Maps* (SOMs). This system forms the basis for the work presented in this paper. *Self-Organising Maps* are a tool for the visualisation of data, grouping similar objects closely together on a two-dimensional output space. Topological relations are preserved as faithfully as possible in the process (Kohonen 2001). A technique to train aligned *Self-Organising Maps* with gradually variable weighings of different feature sets is presented in (Pampalk 2003). This results in a stack of SOMs rather than two separate views of a data set, each trained on a slightly different weighing of a combined feature space, allowing to analyse structural changes in the clustering resulting from the different degrees of influence of the features.

It might not be obvious why cluster validation makes sense, since clustering is often used as part of explorative data analysis. One key argument in favour of cluster validation is that any clustering method will produce results even on data sets which do not have a natural cluster structure (Tan, Steinbach & Kumar 2005). Other than that, cluster validation can be used to determine the 'best' clustering out of several candidate clusterings.

Several quality measures for mappings generated by the *Self-Organising Map* have been developed. For example, the topographic product is used to measure the quality of mappings for single units with respect to their neighbours (Bauer & Pawelzik 1992).

However, no class information is taken into account when clusterings are validated with this approach. If the data set is labelled, i.e. class tags are available for all data points, this information can be used to determine the similarities between classes and natural clusters within the data. It can be distinguished between unsupervised and supervised cluster validation techniques. Whereas unsupervised techniques will be of limited use in the scenario covered, supervised cluster validation and its merits for multi-dimensional clustering of audio data will be more relevant and be described in more detail.

Other approaches utilising class information include cluster purity, which may be applied to the SOM in certain seetings when clear cluster boundaries have been identified on the map. When comparing the organisation of a data set based on two different feature set representations on two separate maps, novel measures for cluster consistency across the different views may be created by considering certain organisations as class labels.

User interfaces based on the *Self-Organising Map* as proposed in our SOMeJB system (Rauber & Merkl 1999, Rauber, Pampalk & Merkl 2003) are used by several teams, e.g. Ultsch et al. (Mörchen, Ultsch, Nöcker & Stamm 2005) or Knees et al. (Knees, Schedl, Pohle & Widmer 2006). Novel interfaces particularly developed for small-screen devices were presented in (Vignoli, van Gulik & van de Wetering 2004) and (Neumayer et al. 2005). The former, an artist map interface, clusters pieces of audio based on content features as well as metadata attributes using a spring model algorithm, while the latter, PocketSOMPlayer, is an extension of the SOMeJB system for mobile devices.

The practicability of the adaption of Information Retrieval techniques to heterogeneous document collections has been pointed out in (Favre, Bellot & Bonastre 2004), concentrating on speech rather than music, albeit on a textual level only. Language identification of songs based on a song's lyrics as well as sophisticated structural and semantic analysis of lyrics is presented in (Mahedero, Martínez, Cano, Koppenberger & Gouyon 2005). Similarity experiments concentrating on artist similarity are performed in (Logan, Kositsky & Moreno 2004). Further, it is pointed out that lyrics are somewhat inferior to acoustic similarity measures in terms of genre categorisation, but a combination of lyrics information and audio features is suggested as possibility to improve overall performance, which also motivated the research reported in this paper. The combination of acoustic features with album reviews and song lyrics for similarity retrieval is presented in (Baumann, Pohle & Vembu 2004). It is also outlined in how far the perception of music can be regarded a socio-cultural product and consequently heavily influences the similarity concept in Music Information Retrieval.

The combination of lyrics and audio features for musical genre classification has been explored in (Neumayer & Rauber 2007), coming to the conclusion that classification accuracies per genre differ greatly in between feature spaces. Moreover, it is shown that comparable accuracy can be achieved in a lower-dimensional space when combining text and audio.

Multi-Modal Clusterings

Music can be represented by different modalities. For individual songs abstract representations are available according to different audio feature sets that can be calculated from a song's waveform representation, while on the textual level we can consider song lyrics as an important source of additional information for music IR. There are several additional views possible not considered in this paper, such as, e.g., the scores and instrumentation information provided in MIDI files, artist biographies, album reviews or covers, and music videos.

Audio Features

For feature extraction from audio we rely on *Statistical Spectrum Descriptors* (SSD, (Lidy & Rauber 2005)). The approach for computing SSD features is based on the first part of the algorithm for computing Rhythm Pattern features (Rauber, Pampalk & Merkl 2002), namely the computation of a psycho-acoustically transformed spectrogram, i.e. a Bark-scale Sonogram. Compared to the Rhythm Patterns feature set, the dimensionality of the feature space is much lower (168 instead of 1440 dimensions), at a comparable performance in genre classification approaches (Lidy & Rauber 2005). Therefore, we employ SSD audio features in the context of this paper, which we computed from audio tracks in standard PCM format with 44.1 kHz sampling frequency (i.e. decoded MP3 files).

Statistical Spectrum Descriptors are composed of statistical moments computed from several critical frequency bands of a psycho-acoustically transformed spectrogram. They describe fluctuations on the critical frequency bands in a more compact representation than the Rhythm Pattern features. In a pre-processing step the audio signal is converted to a mono signal and segmented into chunks of approximately 6 seconds. Usually, not every segment is used for audio feature extraction. For pieces of music with a typical duration of about 4 minutes, frequently the first and last one to four segments are skipped and from the remaining segments every third one is processed.

For each segment the audio spectrogram is computed using the Short Time Fast Fourier

Transform (STFT). The window size is set to 23 ms (1024 samples) and a Hanning window is applied using 50 % overlap between the windows. The Bark scale, a perceptual scale which groups frequencies to critical bands according to perceptive pitch regions (Zwicker & Fastl 1999), is applied to the spectrogram, aggregating it to 24 frequency bands.

The Bark scale spectrogram is then transformed into the decibel scale. Further psycho-acoustic transformations are applied: Computation of the Phon scale incorporates equal loudness curves, which account for the different perception of loudness at different frequencies (Zwicker & Fastl 1999). Subsequently, the values are transformed into the unit Sone. The Sone scale relates to the Phon scale in the way that a doubling on the Sone scale sounds to the human ear like a doubling of the loudness. This results in a Bark-scale Sonogram – a representation that reflects the specific loudness sensation of the human auditory system.

From this representation of perceived loudness a number of statistical moments is computed per critical band, in order to describe fluctuations within the critical bands extensively. Mean, median, variance, skewness, kurtosis, min- and max-value are computed for each of the 24 bands, and a Statistical Spectrum Descriptor is extracted for each selected segment. The SSD feature vector for a piece of audio is then calculated as the median of the descriptors of its segments.

Lyrics Features

In order to process the textual information of the lyrics, the documents were tokenised, no stemming was performed. Stop word removal was done using the *ranks.nl*[3] stop word list. Further, all lyrics were processed according to the bag-of-words model. Therein, a document is denoted by d, a term (token) by t, and the number of documents in a corpus by N. The *term frequency* $tf(d)$ denotes the number of times term t appears in document d. The number of documents in the collection that term t occurs in is denoted as *document frequency* $df(t)$. The process of assigning weights to terms according to their importance or significance for the classification is called 'term-weighing'. The basic assumptions are that terms that occur very often in a document are more important for classification, whereas terms that occur in a high fraction of all documents are less important. The weighing we rely on is the most common model of *term frequency inverse document frequency* (Salton & Buckley 1988), where the weight $tf \times idf$ of a term in a document is computed as:

$$tf \times idf(t,d) = tf(d) \cdot ln(N/df(t)) \tag{1}$$

This results in vectors of weight values for each document d in the collection. Based on this representation of documents in vectorial form, a variety of machine learning algorithms

[3] `http://www.ranks.nl/tools/stopwords.html`

like clustering can be applied. This representation also introduces a concept of distance, as lyrics that contain a similar vocabulary are likely to be semantically related.

The resulting high-dimensional feature vectors were further downscaled to about 7.000 dimensions out of 45.000 using feature selection via document frequency thresholding, i.e. the omitting of terms that occur in a very high or very low number of documents. The *Self-Organising Map* clustering was finally performed on that data set.

SOM Training and Visualisation

Once both of these feature sets are extracted for a collection of songs, the *Self-Organising Map* clustering algorithm can be applied to map the same set of songs onto two *Self-Organising Maps* (we use *Self-Organising Maps* of equal size).

Generally, a *Self-Organising Map* consists of a number M of units ξ_i, the index i ranging from 1 to M. The distance $d(\xi_i, \xi_j)$ between two units ξ_i and ξ_j can be computed as the Euclidean distance between the units' coordinates on the map, i.e. the output space of the *Self-Organising Map* clustering. Each unit is attached to a weight vector $m_i \in \Re^n$. Input vectors, i.e. elements from the high-dimensional input space, $x \in \Re^n$, are presented to the *SOM* and the activation of each unit for the presented input vector is calculated using an activation function (commonly the Euclidean Distance). Subsequently, the weight vector of the winner, i.e. the closest unit for a particular input vector, is moved towards the presented input signal by a certain fraction of the Euclidean distance as indicated by a time-decreasing learning rate α. Consequently, the next time the same input signal is presented, this unit's activation will be even higher. Further, the weight vectors of units neighbouring the winner, as described by a time-decreasing neighbourhood function, are modified accordingly, yet to a smaller amount as compared to the winner. The result of this learning procedure is a topologically ordered mapping of the presented input signals in two-dimensional space, that allows easy exploration of the given data set.

In this paper, we train one map representing the collection in terms of lyric similarity, one in terms of audio similarity. Those maps will henceforth be referred to as audio and lyrics map, respectively. We further propose to visualise the similarities and differences between the two clusterings by drawing lines across maps which visually connect pieces of music. Linkages can be shown on different levels:

Track Each (selected) track on the audio map is connected to the same track on the lyrics map. This allows the analysis of the characteristics of a certain piece of music by identifying its acoustic as well as textual placement, i.e. to which clusters it belongs in the respective modality

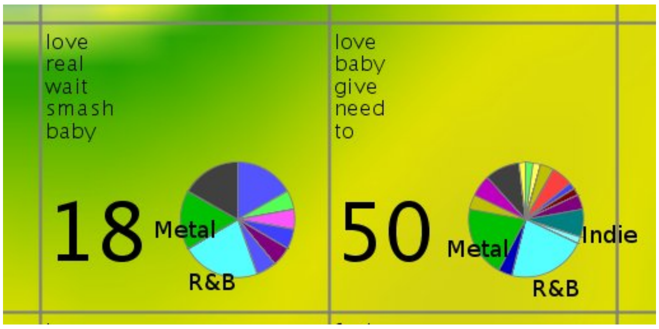


Figure 1: Clustering of songs centred around the love topic

Genre Each track of a selected genre is connected to all songs of the same genre on the other map. Here, the spread of a given genre can be inspected. For instance, whether a genre forms a consistent cluster in both modalities, or whether it does form a rather consistent cluster in, say, the textual domain, while it is rather spread across different clusters on the audio map.

Artist Each track of the given artist on the audio map is connected to all songs of the same artist on the lyrics map. This allows to analyse the textual or musical 'consistency' of a given artist or band.

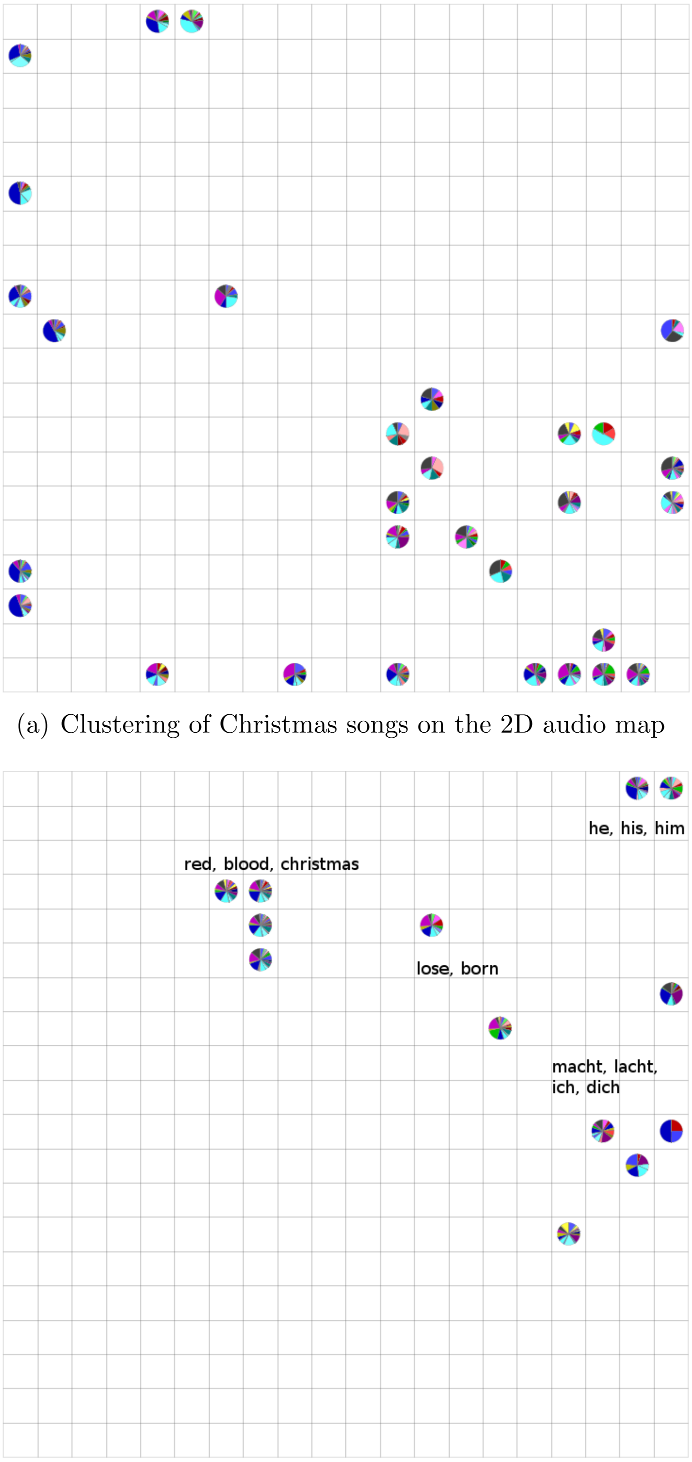
Differences in Data Distribution Across Feature Spaces

Cluster Similarity and Dissimilarity

Similarity can be defined on several levels. For the *Self-Organising Map* the most important ways of calculating cluster similarity take into account the weight vectors assigned to single units as well as the distribution of instances over the map itself.

Lyrics Based Clustering

Figure 1 shows the distribution of genres on two particular units on a *Self-Organising Map* trained on lyrics data. The pie chart display shows the numbers of songs belonging to the different genres. The labelling of single units is done via the LabelSOM algorithm, via the identification of discriminative components. In this case, the prominent key words 'love', 'baby', 'give', 'real', and 'need' give a very good idea on the main topics of these songs' lyrics. The 50 songs, for instance, mapped onto the right unit of the *Self-Organising Map*



(a) Clustering of Christmas songs on the 2D audio map

(b) Clustering of Christmas songs on the 2D lyrics map

Figure 2: Distribution of Christmas songs on clusterings for different feature spaces. The pie charts denote the distribution of songs over different genres on the particular units – only units comprising Christmas songs are highlighted

are distributed across 16 'traditional' genres, the largest group being 'R&B' songs, followed by 'Metal' and 'Indie'.

Artists whose songs are mapped onto this unit are, amongst others: 'Mary J. Blige', 'Beyonce', 'Christina Milian', as well as 'Wolfmother' or the 'Smashing Pumpkins'. This interesting mapping shows clearly that topics in song lyrics overcome traditional genre boundaries, while pointing out that a categorisation on the lyrics level makes sense since all songs cover similar topics.

Figure 2 shows the distribution of Christmas songs on the two-dimensional clusterings, the distribution on the audio map is shown in Figure 2(a), and in Figure 2(b) on the lyrics map, respectively. In the former case, the 33 songs are mapped onto 30 units, in the latter only onto 13. Hence, the lyrics clustering uncovers information such as vastly different interpretations of one and the same song, that have the same lyrics, but differ greatly in sound. Manually assigned labels demonstrate the different key tokens present on the respective areas of the map, i.e. the 'red / blood / christmas' cluster on the top of the map. Due to the *Self-Organising Map*'s random initialisation, the fundamental differences in lyrics space, and the general training algorithm, the songs are mapped onto different corners of the map. For evaluation the absolute location on the map plays a less important role than the relative distances. However, it is clear that the spread of songs differs from one clustering to the other. In the lyrics space, Christmas songs are clustered more closely to each other, whilst they get spread over more units and occupy a larger space of the map in the audio space. The two interpretations of the song 'The First Noel', for example, are mapped onto one unit in the lyrics space. On the audio map, however, these songs lie on different units on different regions of the map. The artists of the interpretations are the 'Bright Eyes' and 'Saxofour', even though the 'Saxofour' interpretation is instrumental, the lyrics space helps to uncover the similarity between the two songs.

Quality Measures for Parallel *Self-Organising Map* Clusterings

To determine the quality of the resulting *Self-Organising Map* clusterings we try to capture the scattering of instances across the maps using meta information such as artist names or genre labels as ground truth information. In general, the more units a set of songs is spread across, the more scattered and inhomogeneous the set of songs is. On the other hand, if we accept ground truth values as reasonable structures expected to be revealed by the clustering, we should like to find songs from such sets to be clustered tightly on the map. In this section, we concentrate on distances in between units in terms of their position on the trained *Self-Organising Map*. The abstraction from the high-dimensional vector descriptions of instances to the use of unit coordinates is feasible from both a computational as well as a conceptual point of view. Comparison of individual vectors does not take into consideration the very nature of the *Self-Organising Map* clustering algorithm, which is based on the preservation of topological relations across the map. This approach therefore computes the spread for genres or artists with respect to the *Self-Organising Maps*' clusterings. For distances between units we use the Euclidean distance on unit coordinates, which we also use for distances between data and unit vectors in the *Self-Organising Map* training process. All quality measurements are computed for sets of data vectors and their two-dimensional positions on the trained *Self-Organising Maps*. Particularly, sets of data vectors refer to all songs belonging to a certain genre or from a certain artist. In this context only units that have data points or songs that belong to a given category, i.e. a particular artist or genre, are considered. This holds for both maps, all quality measurements can only be calculated with respect to a class tag, i.e. for songs belonging to a particular artist or genre. The average distance between these units with respect to a *Self-Organising Map* clustering is given in Equation 2, i.e. the pairwise distances of all units (ξ) to each other.

$$avgdist = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} d(\xi_{(i)}, \xi_{(j)})}{n^2} \tag{2}$$

n denotes the number of data points or songs considered, i.e. the songs belonging to a given artist or genre. Further, the average distance ratio defines the scattering difference between a set of two clusterings $C = \{c_{audio}, c_{lyrics}\}$. c_{audio} denotes an audio and c_{lyrics} a lyrics clustering. The average distance ratio for two clusters is given as the ratio of the minimum and maximum values for the respective distances between units.

$$adr_{audio,lyrics} = \frac{min(avgdist_{audio}, avgdist_{lyrics})}{max(avgdist_{audio}, avgdist_{lyrics})} \tag{3}$$

The closer to the value of one the average distance ratio is, the more uniformly distributed are the data across the clusterings in terms of distances between units affected. However, this measure does not take into account the impact of units adjacent to each other, which definitely plays an important role. Adjacent units should rather be treated as one unit than several due to the similarity expressed by such results.

Therefore, the contiguity value co for a clustering c gives an idea of how uniformly a clustering is done in terms of distances between neighbouring or adjacent units. The specifics of adjacent units are taken into account, leading to different values for the minimum distances between units since distances between adjacent units are omitted in the distance calculations. If, for example, the songs of a given genre are spread across three units on the map ξ_1, ξ_2, ξ_3, where ξ_1 and ξ_2 are neighbouring units, the distances between ξ_1 and ξ_2 are not taken into consideration. Currently, no difference is made between units that are direct neighbours and units only connected via other units. The contiguity distance cd is given in Equation 4, four-connectivity is used as neighbourhood function, i.e. only directly adjacent units are taken into account.

$$co_{(\xi_i,\xi_j)} = \begin{cases} 0 & \text{if } \xi_i \text{ and } \xi_j \text{ are neighbouring units} \\ d(\xi_i, \xi_j) & \text{otherwise} \end{cases} \tag{4}$$

The contiguity value *co* is consequently calculated analogously to the average distance ratio based on contiguity distances. For cases of fully contiguous clusterings, i.e. where all units a set of songs are mapped to are neighbouring units, the *co* value is not defined and set to the value of one. The overall contiguity ratio for a set of clusterings C and class j is given in Equation 5.

$$cr_{audio,lyrics} = \frac{min(co_{audio}, co_{lyrics})}{max(co_{audio}, co_{lyrics})} \tag{5}$$

This information can be used to further weigh the *adr* value from Equation 3 as shown in Equation 6 and gives an average distance contiguity ratio value $adr \times cr$, i.e. the product of average distance ratio and contiguity ratio, for a set of one audio and lyrics map.

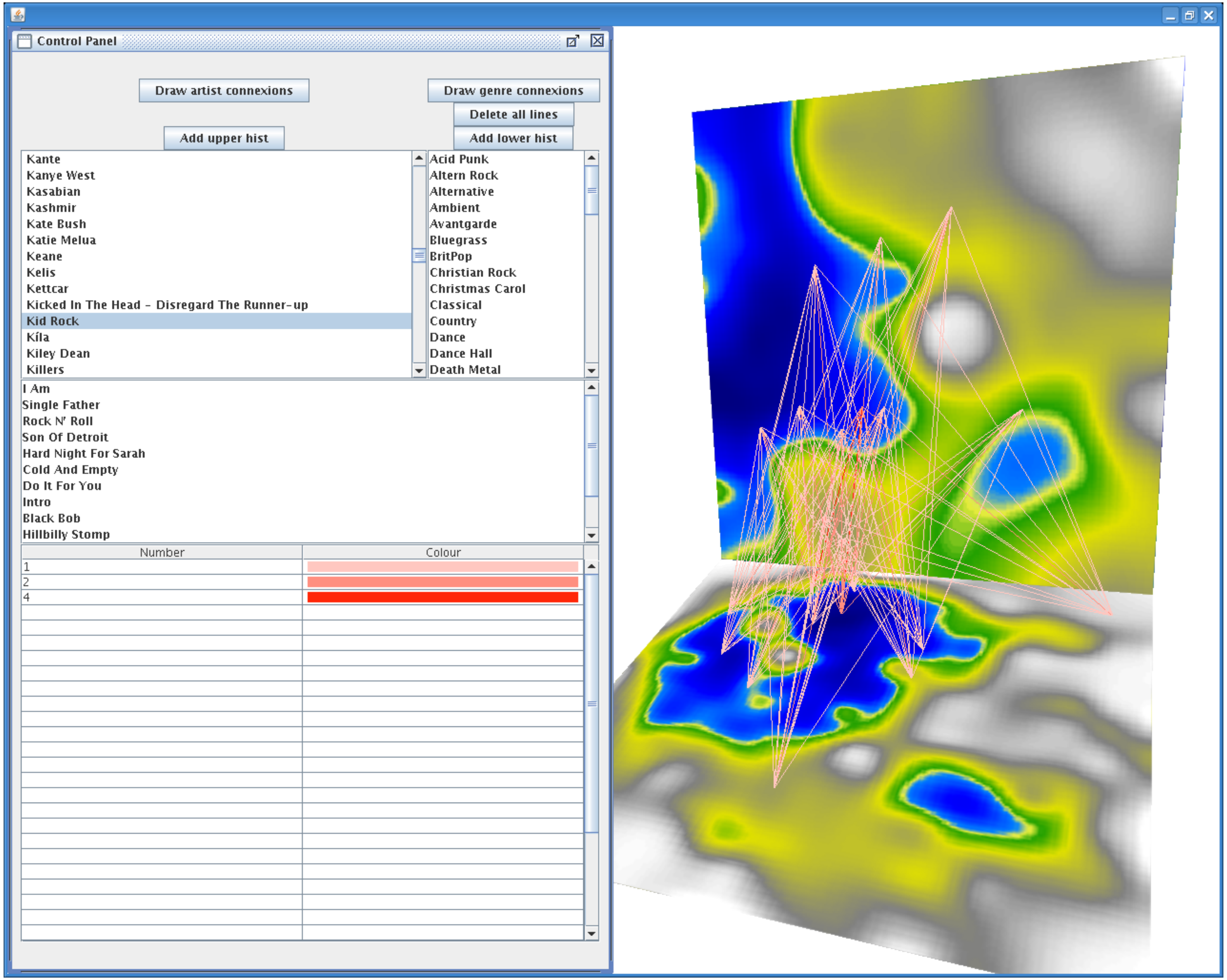
$$adr \times cr_{audio,lyrics} = adr_{audio,lyrics} \cdot cr_{audio,lyrics} \tag{6}$$

This considers both the distances between all occupied units as well as it takes into account the high relevance of instances lying on adjacent units of the *Self-Organising Map*.

A visualisation prototype was implemented for the simultaneous display of two music maps. Once connections are drawn on the maps, the connections between units are coloured according to their number of connecting units. The main idea is to allow for user selections on one map and provide the simultaneous highlighting of songs on the other one. The prototype allows for selection of

- Genres,
- Artists, and
- Tracks.

All selections are organised hierarchically according to the songs' artist or genre tags, i.e. further selection refinements are possible. If the user selects, for instance, all songs from the rock genre, all songs belonging to that genre are connected in the interactive 3D display of the *Self-Organising Maps*. Moreover, all single songs of that particular genre are displayed and the user can further refine his selection to a particular set of songs. The main user interface is depicted in Figure 3. The largest part is occupied by the display of the two *Self-Organising Maps* on the right part. The 3D display offers ways to rotate the view as



Kante
Kanye West
Kasabian
Kashmir
Kate Bush
Katie Melua
Keane
Kelis
Kettcar
Kicked In The Head - Disregard The Runner-up
Kid Rock
Kíla
Kiley Dean
Killers

Acid Punk
Altern Rock
Alternative
Ambient
Avantgarde
Bluegrass
BritPop
Christian Rock
Christmas Carol
Classical
Country
Dance
Dance Hall
Death Metal

I Am
Single Father
Rock N' Roll
Son Of Detroit
Hard Night For Sarah
Cold And Empty
Do It For You
Intro
Black Bob
Hillbilly Stomp

Number	Colour
1	🟥
2	🟥
4	🟥

Figure 3: Full view of the visualisation prototype. The vertical map clusters songs by audio features, the horizontal map is trained on lyrics features

Artist	**AC**	**LC**	**CR**	**ADR**	**ADR×CR**
Sean Paul	.3162	.1313	.4152	.4917	.2042
Good Riddance	.0403	.0485	.8299	.7448	.6181
Silverstein	.0775	.1040	.7454	.8619	.6424
Shakespeare	.2626	1.000	.2626	.3029	.0795
Kid Rock	.0894	.0862	.9640	.9761	.9410

Table 1: Artists with exceptionally high or low spreading values. **AC** denotes the audio contiguity, **LC** the lyrics Contiguity, **CR** the contiguity ratio, **ADR** the average distance ratio, and **ADR×CR** the product of **ADR** and **CR**

well as pan and zoom in or out. Controls to select particular songs, artist or genres are on the left side together with the palette describing the associations between colours and line counts. Selections of artists or genres automatically update the selection of songs on the left hand side. Several visualisations for single *Self-Organising Maps* have been proposed. In this work we use the Smoothed Data Histograms technique to colour-code the *Self-Organising Maps* (Pampalk, Rauber & Merkl 2002), even though the SOMToolbox application for 2D clusterings supports a wide range of additional visualisations that could be used as a basis for 3D visualisations as proposed in this paper. We relied on the same visualisation method for both audio and lyrics features. Of course, this is not necessary and different visualisations could be deployed for the respective feature spaces and clusterings.

Experiments

For experimental evaluation we clustered a large private music collection according to both audio features and lyrics features. We then present examples for the browsing and explorative analysis of that collection.

Data Collection

We compiled a parallel corpus of audio and song lyrics files for a music collection of 7554 titles organised into 54 genres, containing music as well as spoken documents (e.g. Shakespeare sonnets). Genres were assigned manually. Class sizes ranged from only a few songs for the 'Classical' genre to about 1.900 songs for 'Punk Rock', due to both the distribution across genres in the collection and difficulties in retrieving the lyrics for some genres like 'Classical'. The collection contains songs from 644 different artists and 931 albums. For each song lyrics features as well as audio features (*Statistical Spectrum Descriptor*) were computed. We then trained two *Self-Organising Maps* of size 20 × 20, i.e. 400 units, one on the audio feature set, one on lyrics.

To retrieve lyrics for songs, three portals were accessed, using artist name and track title as queries. If the results from *lyrc.com.ar* were of reasonable size, these lyrics were assigned to the track. If *lyrc.com.ar* failed, *sing365lyrics.com* would be checked for validity by a simple heuristic, then *oldielyrics.com*.

Noticeable Artists

Table 1 shows a selection of particularly interesting artists with respect to their positions on the maps. A total of 18 'Sean Paul' songs are mapped on each *Self-Organising Map*. For the audio map, the songs are distributed amongst seven different units, eleven being mapped onto one unit. On the lyrics map, all songs are mapped onto two adjacent units, the first one covering 17 out of the 18 tracks.

The situation is different for 'Good Riddance', a Californian 'Punk Rock' band. For the lyrics map, their 27 songs are spread across 20 units. For audio, the songs lie on 18 units, but some of them are adjacent units, a fact that is represented by a rather high value for AC, the audio contiguity measure.

Shakespeare sonnets are clustered in a similar way. In terms of lyrics the six sonnets lie on two units, whereas the audio representations are mapped on three units, non of which were adjacent (only one sonnet is read by a male voice).

'Kid Rock' songs, mainly 'Country' tracks, lie on 13 units on the audio map, including two adjacent units, compared to 11 units in the lyrics space, none of which are adjacent. The spread is therefore almost identical on both maps. Figure 4 shows the 3D visualisation for all 'Kid Rock' songs.

Noticeable Genres

Analogously to the artists, we identified genres of interest in Table 2. 'Rock' music has proven to be the most diverse genre in terms of audio features and rather diverse in terms of lyrics features alike. There were 690 songs assigned to that genre in the test collection. The overall $adr \times cr$ measure is still rather high due to the impact of adjacent units on both maps. 'Speech' as well as 'Christmas Carols', on the other hand, are rather diverse in terms of audio similarity, but are more concentrated on the lyrics (or text) level, yielding in a low $adr \times cr$ value. Figure 5 shows the connections between all 'Christmas' songs, giving an interesting idea about the differences in distributions on the maps, c.f. Figure 2. The similarity of 'Reggae' music is defined by acoustic and lyrics features to an equal amount. This genre has rather high values for *adr* and *cr*, caused by a high number of adjacent units

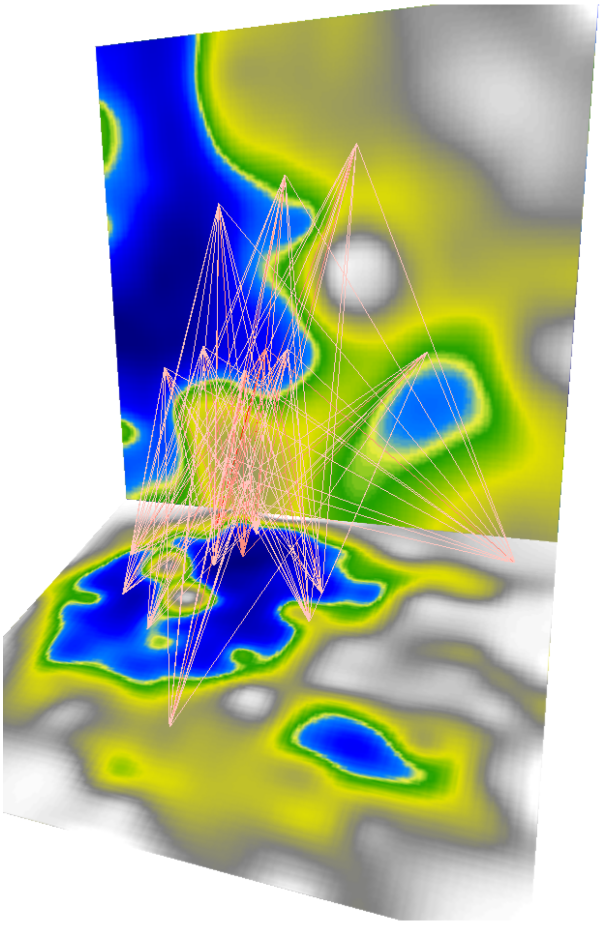


Figure 4: Detailed view of connections for the almost equally distributed artist ‘Kid Rock’. Dark lines denote a high number of connections

Genre	**AC**	**LC**	**CR**	**ADR**	**ADR×CR**
Speech	.0822	.0665	.8092	.3417	.2765
Christmas Carols	.0393	.0677	.5800	.7779	.4512
Reggae	.0392	.0413	.9495	.8475	.8047
Grunge	.0382	.0466	.8204	.9974	.8182
Rock	.0372	.0382	.9740	.9300	.9059

Table 2: Genres with exceptionally high or low spreading values. **AC** denotes the audio contiguity, **LC** the lyrics contiguity, **CR** the contiguity ratio, **ADR** the average distance ratio, and **ADR×CR** the product of **ADR** and **CR**

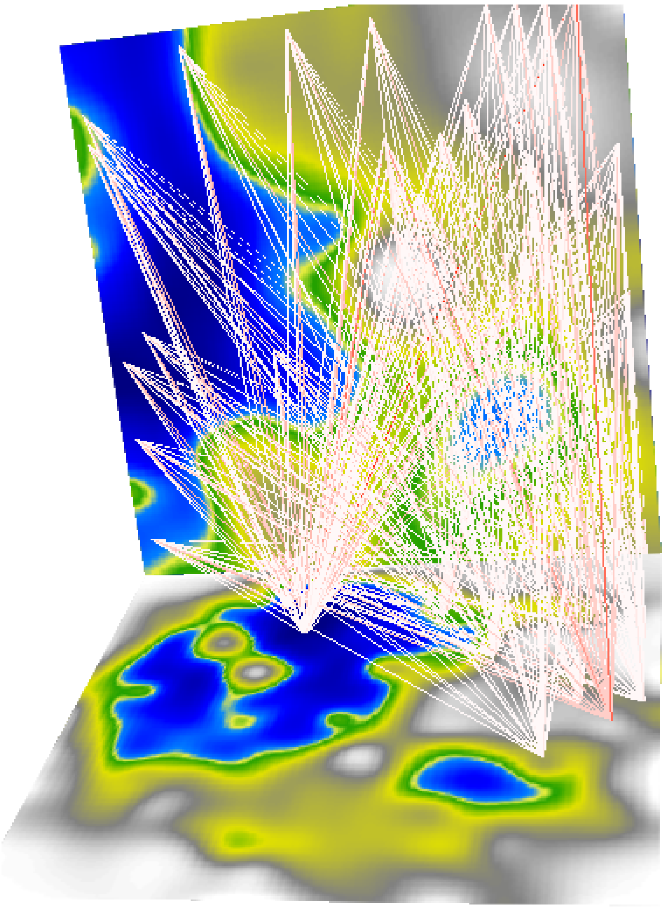


Figure 5: Detailed view of connections for the genre 'Christmas Carols'. Dark links denote a high number of connections

and a low overall number of units.

Conclusions and Outlook

In this paper, we investigated a multi-modal vision of Music Information Retrieval, taking into account both a song's lyrics as well as its acoustic representation, as opposed to concentrating on acoustic features only. We presented a novel approach to the visualisation of multi-modal clusterings and showed its feasibility to introspect collections of digital audio in form of a prototype implementation for handling private music collections, emphasised by concrete examples.

Further, we introduced performance metrics for *Self-Organising Maps* on a per-class level (e.g. artist or genre classes), showing differences in spreadings across maps. Moreover, we introduced measurements for the comparison of multi-dimensional clusterings and showed their application to identify genres or artists of particular interest.

Future work will mainly deal with the further exploitation of multi-faceted representations of digital audio. The impact of lyrics data on classification performance in musical genre categorisation as well as possible improvements will be investigated. Further, we plan to provide a more elaborate user interface that offers sophisticated search capabilities.

Besides, the possibilities of automatically adding metadata to audio files through multimodal representations will be explored in connection with semantic analysis or automatic concept identification in music. An interesting application of this would be automatic musical genre classification, emphasising on the additional information contained in a song's lyrics as opposed to purely acoustic approaches currently being in use. Moreover, the investigation and evaluation of advanced feature sets for the lyric space will play an important role in future work.

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