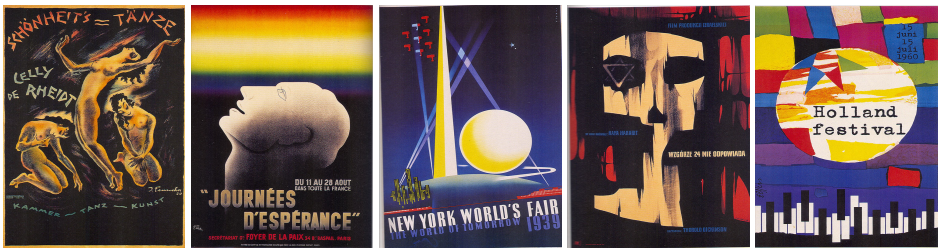
6. content annotation

video annotation requires a logical approach to story telling

learning objectives

After reading this chapter you should be able to explain the difference between content and meta information, to mention relevant content parameters for audio, to characterize the requirements for video libraries, to define an annotation logic for video, and to discuss feature extraction in samples of musical material.

Current technology does not allow us to extract information automatically from arbitrary media objects. In these cases, at least for the time being, we need to assist search by annotating content with what is commonly referred to as meta-information. In this chapter, we will look at two more media types, in particular audio and video. Studying audio, we will learn how we may combine feature extraction and meta-information to define a data model that allows for search. Studying video, on the other hand, will indicate the complexity of devising a knowledge representation scheme that captures the content of video fragments. Concluding this chapter, we will discuss an architecture for feature extraction for arbitrary media objects.



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6.1 audio

The audio media type covers both spoken voice and musical material. In this section we will discuss audio signal, stored in a raw or compressed (digital) format, as well as similarity-based retrieval for musical patterns.

In general, for providing search access to audio material we need, following MMDBMS, a data model that allows for both mdeta-data (that is information about the media object) and additional attributes of features, that we in prinicple obtain from the media object itself, using feature extraction.

audio data model

- *meta-data* – describing content
- *features* – using feature extraction

As an example of audi meta-data, consider the (meta-data) characterization that may be given for opera librettos.

example

singers – (Opera,Role,Person)
score – ...
transcript – ...

For signal-based audio content, we have to perform an analysis of the audio signal for which we may take parameters such as frequency, velocity and amplitude. For the actual analysis we may have to break up the signal in small windows, along the time-axis. Using feature extraction, we may characterize (signal-based) properties such as indicated below.

feature extraction

- *intensity* – watts/m^2
- *loudness* – in decibels
- *pitch* – from frequency and amplitude
- *brightness* – amount of distortion

For a more detailed treatment of signal-based audio content description, consult MMDBMS.

In the following we will first give an overview of musical search facilities on the web and then we will discuss similarity-based retrieval of musical patterns in somewhat more depth in the section on *research directions*, In section 6.3, we will have a closer look at feature extraction for arbitrary media types.

musical similarity

Although intuitively obvious, how can we characterize musical simularity? And perhaps more importantly, how can we compute the extent to which one piece of music or a melody line is similar to another piece of music or melody line. As concerns musical content, at least for most genres, it appears that

According to Concepts, we should focus primarily on *melody*, since

> *"It is melody that makes music memorable: we are likely to recall a tune long after we have forgotten its text."*

Other features, content-based as well as descriptive, may however be used as additional filters in the proces of retrieval.

Melodic searching and matching has been explored mainly in the context of bibliographic tools and for the analysis of (monophonic) repertories Similarity. As described in section , many of these efforts have been made available to the general public through the Web. Challenges for the near future are, however, to provide for melodic similarity matching on polyphonic works, and retrieval over very large databases of musical fragments.

In this section we will look in somewhat more detail at the problem of melodic similarity matching. In particular, we will discuss representational issues, matching algorithms and additional analysis tools that may be used for musical information retrieval.

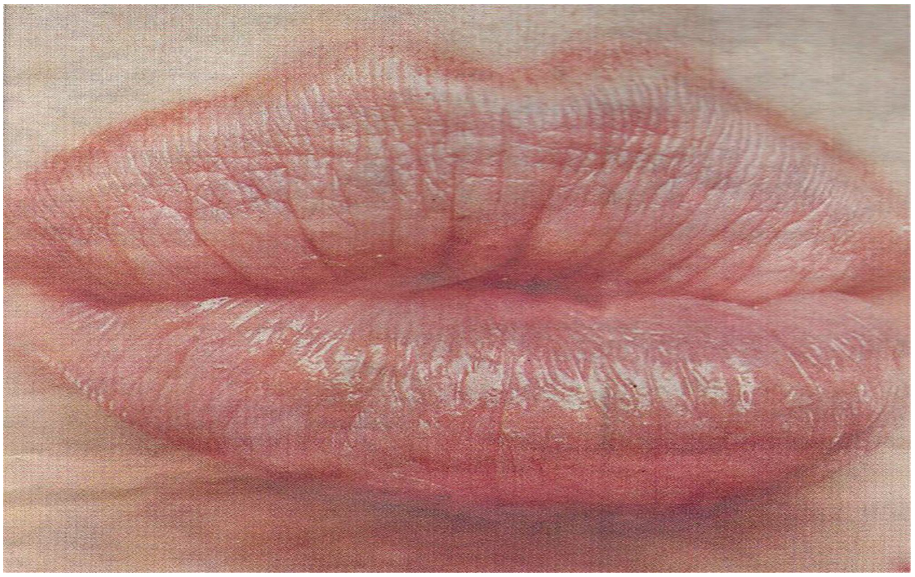
melodic similarity Consider the musical fragment *Twinkle, twinkle little star* (known in the Dutch tradition as *"Altijd is Kortjakje ziek"*), which has been used by Mozart for a series of variations Mozart. Now, imagine how you would approach establishing the similarity between the original theme and these variations. As a matter of fact, we discovered that exactly this problem had been tackled in the study reported in Compare, which we will discuss later. Before that, we may reflect on what we mean by the concept of a *melody*. In the aforementioned variations the original melody is disguised by, for example, decorations and accompaniments. In some variations, the melody is distributed among the various parts (the left and right hand). In other variations, the melody is only implied by the harmonic structure. Nevertheless, for the human ear there seems to be, as it is called in Concepts, a *'prototypical'* melody that is present in each of the variations.

When we restrict ourselves to pitch-based comparisons, melodic similarity may be established by comparing profiles of pitch-direction (up, down, repeat) or pitch contours (which may be depicted graphically). Also, given a suitable representation, we may compare pitch-event strings (assuming a normalized pitch representation such as position within a scale) or intervallic contours (which gives the distance between notes in for example semitones). Following Concepts, we may observe however that the more general the system of representation, the longer the (query) *string* will need to be to produce meaningful discriminations. As further discussed in Concepts, recent studies in musical perception indicate that pitch-information without durational values does not suffice.

representational issues Given a set of musical fragments, we may envisage several reductions to arrive at the (hypothetical) prototypical melody. Such reductions must provide for the elimination of confounds such as rests, repeated notes and grace notes, and result in, for example, a pitch-string (in a suitable representation), a duration profile, and (possibly) accented note profiles and harmonic reinforcement profiles (which capture notes that are emphasized by harmonic changes). Unfortunately, as observed in Concepts, the problem of which reductions to apply is rather elusive, since it depends to a great extent on the goals of the query and the repertory at hand.

As concerns the representation of pitch information, there is a choice between a base-7 representation, which corresponds with the position relative to the tonic in the major or minor scales, a base-12 representation, which corresponds with a division in twelve semitones as in the chromatic scale, and more elaborate encodings, which also reflect notational differences in identical notes that arise through the use of accidentals. For MIDI applications, a base-12 notation is most suitable, since the MIDI note information is given in semitone steps. In addition to relative pitch information, octave information is also important, to establish the rising and falling of melodic contour.

When we restrict ourselves to directional profiles (up, down, repeat), we may include information concerning the slope, or degree of change, the relation of the current pitch to the original pitch, possible repetitions, recurrence of pitches after intervening pitches, and possible segmentations in the melody. In addition, however, to support relevant comparisons it seems important to have information on the rhythmic and harmonic structure as well.



example(s) – *napster*

Wasn't it always your dream to have all your music free? Napster[1] was the answer. (But not for long.) Napster is, as we learn in the WikiPedia[2], *an online music service which was originally a file sharing service created by Shawn Fanning. Napster was the first widely-used peer-to-peer music sharing service, and it made a major impact on how people, especially college students, used the Internet. Its technology allowed music fans to easily share MP3 format song files with each other, thus leading to the music industry's accusations of massive copyright violations. The service was named Napster after Fanning's nickname.* However, Napster has been forced to become commercial. So the question is: is there life after napster? Well, there is at least open source!

research directions – *musical similarity matching*

An altogether different approach at establishing melodic similarity is proposed in Compare. This approach has been followed in the Meldex system Meldex, discussed in section . This is a rather technical section, that may be skipped on first reading. The approach is different in that it relies on a (computer science) theory of finite sequence comparison, instead of musical considerations. The general approach is, as explained in Compare, to search for an optimal correspondence between elements of two sequences, based on a distance metric or measure of dissimilarity, also known more informally as the *edit-distance*, which amounts to the (minimal) number of transformations that need to be applied to the first sequence in order to obtain the second one. Typical transformations include *deletion*, *insertion* and *replacement*. In the musical domain, we may also apply transformations such as *consolidation* (the replacement of several elements by one element) and *fragmentation* (which is the reverse of consolidation). The metric is even more generally applicable by associating a weight with each of the transformations. Elements of the musical sequences used in Compare are pitch-duration pairs, encoded in base-12 pitch information and durations as multiples of 1/16th notes.

The matching algorithm can be summarized by the following recurrence relation for the dissimilarity metric. Given two sequences $A = a_1, \ldots, a_m$ and $B = b_1, \ldots, b_n$ and $d_{ij} = d(a_i, b_j)$, we define the distance as

$$d_{ij} = min \begin{cases} d_{i-1,j} + w(a_i, 0) & \text{deletion} \\ d_{i,j-1} + w(0, b_j) & \text{insertion} \\ d_{i-1,j-1} + w(a_i, b_j) & \text{replacement} \\ d_{i-k,j-1} + w(a_{i-k+1}, \ldots, a_i, b_j).\ 2 \leqslant k \leqslant i & \text{consolidation} \\ d\_i - 1, j - k + 1 + w(a\_i, b\_j - k + 1, \ldots b\_j)\ 2 <= k <= j & \\ & \text{fragmentation} \end{cases}$$

with

$$d_{i0} = d_{i-1,0} + w(a_i, 0),\ i \geqslant 1 \qquad \textit{deletion}$$

[1] www.napster.com
[2] en.wikipedia.org/wiki/Napster

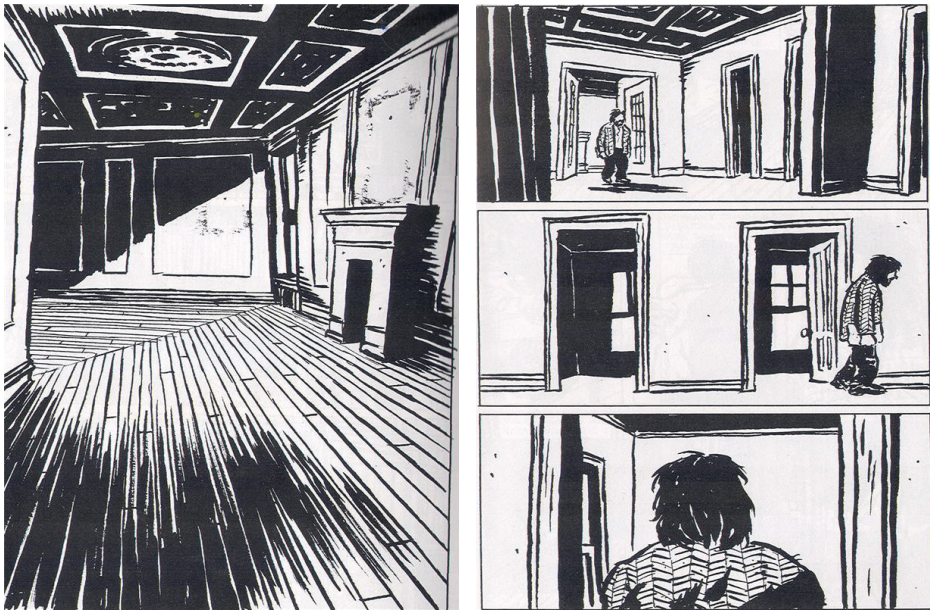
$$d_{0j} = d_{0,j-1} + w(0, b_i),\ j \geqslant 1 \qquad \textit{insertion}$$

and $d_{00} = 0$. The weigths $w(\_, \_)$ are determined by the degree of dissonance and the length of the notes involved.

The actual algorithms for determining the dissimilarity between two sequences uses dynamic programming techniques. The algorithm has been generalized to look for matching phrases, or subsequences, within a sequence. The complexity of the algorithm is $O(mn)$, provided that a limit is imposed on the number of notes involved in consolidation and fragmentation.

Nevertheless, as indicated in experiments for the Meldex database, the resulting complexity is still forbidding when large databases are involved. The Meldex system offers apart from the (approximate) dynamic programming algorithm also a state matching algorithm that is less flexible, but significantly faster. The Meldex experiments involved a database of 9400 songs, that were used to investigate six musical search criteria: (1) exact interval and rhythm, (2) exact contour and rhythm, (3) exact interval, (4) exact contour, (5) approximate interval and rhythm, and (6) approximate contour and rhythm. Their results indicate that the number of notes needed to return a reasonable number of songs scales logarithmically with database size Meldex. It must be noted that the Meldex database contained a full (monophonic) transcription of the songs. An obvious solution to manage the complexity of searching over a large database would seem to be the storage of prototypical themes or melodies instead of complete songs.

indexing and analysis There are several tools available that may assist us in creating a proper index of musical information. One of these tools is the Humdrum system, which offers facilities for metric and harmonic analysis, that have proven their worth in several musicological investigations Humdrum. Another tool that seems to be suitable for our purposes, moreover since it uses a simple pitch-duration, or *piano-roll*, encoding of musical material, is the system for metric and harmonic analysis described in Meter. Their system derives a metrical structure, encoded as hierarchical levels of equally spaced beats, based on preference-rules which determine the overall likelihood of the resulting metrical structure. Harmonic analysis further results in (another level of) *chord spans* labelled with roots, which is also determined by preference rules that take into account the previously derived metrical structure. As we have observed before, metrical and harmonic analysis may be used to eliminate confounding information with regard to the 'prototypical' melodic structure.



4

6.2 video

Automatic content description is no doubt much harder for video than for any other media type. Given the current state of the art, it is not realistic to expect content description by feature extraction for video to be feasible. Therefore,to realize content-based search for video, we have rely on some knowledge representation schema that may adequately describe the (dynamic) properties of video fragments.

In fact, the description of video content may reflect the story-board, that after all is intended to capture both time-independent and dynamically changing properties of the objects (and persons) that play a role in the video.

In developing a suitable annotation for a particular video fragment, two questions need to be answered:

video annotation

- what are the interesting aspects?
- how do we represent this information?

Which aspects are of interest is something you have to decide for yourself. Let's see whether we can define a suitable knowledge representation scheme.

One possible knowledge representation scheme for annotating video content is proposed in MMDBMS. The scheme proposed has been inspired by knowledge representation techniques in Artificial Intelligence. It captures both static and dynamic properties.

video content

video v, frame f
f has associated objects and activities
objects and activities have properties

First of all, we must be able to talk about a particular video fragment v, and frame f that occurs in it. Each frame may contain objects that play a role in some activity. Both objects and activities may have properties, that is attributes that have some value.

property

property: name = value

As we will see in the examples, properties may also be characterized using predicates.

Some properties depend on the actual frame the object is in. Other properties (for example sex and age) are not likely to change and may considered to be frame-independent.

object schema

(fd,fi) – frame-dependent and frame-independent properties

Finally, in order to identify objects we need an object identifier for each object. Summing up, for each object in a video fragment we can define an *object instance*, that characterizes both frame-independent and frame-dependent properties of the object.

object instance: (oid,os,ip)

- *object-id* – oid
- *object-schema* – os = (fd,fi)
- *set of statements* – ip: name = v and name = v IN f

Now, with a collection of object instances we can characterize the contents of an entire video fragment, by identifying the frame-dependent and frame-independent properties of the objects.

Look at the following example, borrowed from MMDBMS for the *Amsterdam Drugport* scenario.

frame	objects	*frame-dependent properties*
1	Jane	has(briefcase), at(path)
-	house	door(closed)
-	briefcase	
2	Jane	has(briefcase), at(door)
-	Dennis	at(door)
-	house	door(open)
-	briefcase	

In the first frame Jane is near the house, at the path that leads to the door. The door is closed. In the next frame, the door is open. Jane is at the door, holding a briefcase. Dennis is also at the door. What will happen next?

Observe thatwe are using predicates to represent the state of affairs. We do this, simply because the predicate form *has(briefcase)* looks more natural than the other form, which would be *has* = *briefcase*. There is no essential difference between the two forms.

Now, to complete our description we can simply list the frame-independent properties, as illustrated below.

object	*frame-independent properties*	value
Jane	age	35
	height	170cm
house	address	...
	color	brown
briefcase	color	black
	size	40 x 31

How to go from the tabular format to sets of statements that comprise the object schemas is left as an (easy) exercise for the student.

Let's go back to our *Amsterdam Drugport* scenario and see what this information might do for us, in finding possible suspects. Based on the information given in the example, we can determine that there is a person with a briefcase, and another person to which that briefcase may possibly be handed. Whether this is the case or not should be disclosed in frame 3. Now, what we are actually looking for is the possible exchange of a briefcase, which may indicate a drug transaction. So why not, following MMDBMS, introduce another somewhat more abstract level of description that deals with *activities*.

activity

- activity name – id
- statements – *role* = *v*

An activity has a name, and consists further simply of a set of statements describing the *roles* that take part in the activity.

example

{ giver : Person, receiver : Person, item : Object }
giver = Jane, receiver = Dennis, object = briefcase

For example, an *exchange* activity may be characterized by identifying the *giver*, *receiver* and *object* roles. So, instead of looking for persons and objects in a video fragment, you'd better look for activities that may have taken place, by finding a matching set of objects for the particular roles of an activity. Consult MMDBMS if you are interested in a further formalization of these notions.

5

video libraries

Assuming a knowledge representation scheme as the one treated above, how can we support search over a collection of videos or video fragments in a video library.

What we are interested in may roughly be summarized as

video libraries

> which videos are in the library
> what constitutes the content of each video
> what is the location of a particular video

Take note that all the information about the videos or video fragments must be provided as meta-information by a (human) librarian. Just imagine for a moment how laborious and painstaking this must be, and whata relief video feature extraction would be for an operation like *Amsterdam Drugport*.

To query the collection of video fragments, we need a query language with access to our knowledge representation. It must support a variety of retrieval operations, including the retrieval of segments, objects and activities, and also property-based retrievals as indicated below.

query language for video libraries

- *segment retrievals* – *exchange of briefcase*
- *object retrievals* – all people in v:[s,e]
- *activity retrieval* – all activities in v:[s,e]
- *property-based* – find all videos with object oid

MMDBMS lists a collection of video functions that may be used to extend SQL into what we may call VideoSQL. Abstractly, VideoSQL may be characterized by the following schema:

VideoSQL

SELECT – v:[s,e]
FROM – video:<source><V>
WHERE – term IN funcall

where *v:[s,e]* denotes the fragment of video *v*, starting at frame *s* and ending at frame *e*, and *term IN funcall* one of the video functions giving access to the information about that particular video. As an example, look at the following VideoSQL snippet:

example

```
SELECT  vid:[s,e]
FROM video:VidLib
WHERE (vid,s,e) IN VideoWithObject(Dennis) AND
      object IN ObjectsInVideo(vid,s,e) AND
      object != Dennis AND
      typeof(object) = Person
```

Notice that apart from calling video functions also constraints can be added with respect to the identity and type of the objects involved.

6

example(s) – *video retrieval evaluation*

The goal of the TREC[3] conference series is to encourage research in information retrieval by providing a large test collection, uniform scoring procedures, and a forum for organizations interested in comparing their results. Since 2003 their is an independent *video* track devoted to research in automatic segmentation,

[3] trec.nist.gov

indexing, and content-based retrieval of digital video. In the TRECVID[4] 2004 workshop, thirty-three teams from Europe, the Americas, Asia, and Australia participated. Check it out!

7

research directions– *presentation and context*

Let's consider an example. Suppose you have a database with (video) fragments of news and documentary items. How would you give access to that database? And, how would you present its contents? Naturally, to answer the first question, you need to provide search facilities. Now, with regard to the second question, for a small database, of say 100 items, you could present a list of videos thatb matches the query. But with a database of over 10.000 items this will become problematic, not to speak about databases with over a million of video fragments. For large databases, obviously, you need some way of visualizing the results, so that the user can quickly browse through the candidate set(s) of items.

Video provide an interesting account on how *interactive maps* may be used to improve search and discovery in a (digital) video library. As they explain in the abstract:

> *To improve library access, the Informedia Digital Video Library uses automatic processing to derive descriptors for video. A new extension to the video processing extracts geographic references from these descriptors.*
>
> *The operational library interface shows the geographic entities addressed in a story, highlighting the regions discussed in the video through a map display synchronized with the video display.*

[4] www-nlpir.nist.gov/projects/trecvid

So, the idea is to use geographical information (that is somehow available in the video fragments themselves) as an additional descriptor, and to use that information to enhance the presentation of a particular video. For presenting the results of a query, candidate items may be displayed as icons in a particular region on a map, so that the user can make a choice.

Obviously, having such geographical information:

> *The map can also serve as a query mechanism, allowing users to search the terabyte library for stories taking place in a selected area of interest.*

The approach to extracting descriptors for video fragments is interesting in itself. The two primary sources of information are, respectively, the spoken text and graphic text overlays (which are common in news items to emphasize particular aspects of the news, such as the area where an accident occurs). Both speech recognition and image processing are needed to extract information terms, and in addition natural language processing, to do the actual 'geocoding', that is translating this information to geographical locations related to the story in the video.

Leaving technical details aside, it will be evident that this approach works since news items may relevantly be grouped and accessed from a geographical perspective. For this type of information we may search, in other words, with three kinds of questions:

- *what* – content-related
- *when* – position on time-continuum
- *where* – geographic location

and we may, evidently, use the geographic location both as a search criterium and to enhance the presentation of query results.

mapping information spaces Now, can we generalize this approach to other type of items as well. More specifically, can we use maps or some spatial layout to display the results of a query in a meaningful way and so give better access to large databases of multimedia objects. According to Atlas, we are very likely able to do so:

> *More recently, it has been recognized that the process of spatialization – where a spatial map-like structure is applied to data where no inherent or obvious one does exist – can provide an interpretable structure to other types of data.*

Actually, we are taking up the theme of *visualization*, again. In Atlas visualizations are presented that (together) may be regarded as an *atlas of cyberspace*.

atlas of cyberspace

> *We present a wide range of spatializations that have employed a variety of graphical techniques and visual metaphors so as to provide striking and powerful images that extend from two dimension 'maps' to three-dimensional immersive landscapes.*

As you may gather from chapter 7 and the *afterthoughts*, I take a personal interest in the (research) theme of *virtual reality interfaces for multimedia information systems*. But I am well aware of the difficulties involved. It is an area that is just beginning to be explored!

8

6.3 feature extraction

Manual content annotation is laborious, and hence costly. As a consequence, content annotation will often not be done and search access to multimedia object willnot be optimal, if it is provided for at all. An alternative to manual content annotation is (semi) automatic feature extraction, which allows for obtaining a description of a particular media object using media specific analysis techniques.

The Multimedia Database Research group at CWI has developed a framework for feature extraction to support the *Amsterdam Catalogue of Images* (ACOI). The resulting framework for feature extraction is known as the ACOI framework, ACOI.

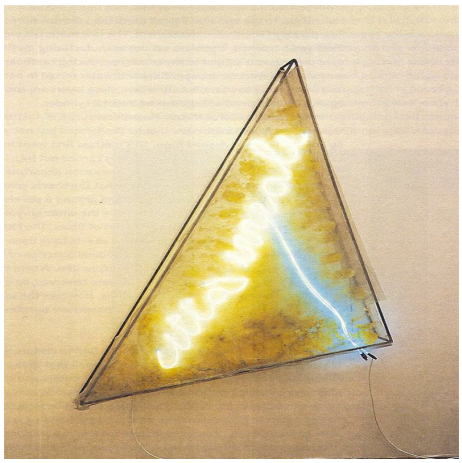
The ACOI framework is intended to accomodate a broad spectrum of classification schemes, manual as well as (semi) automatic, for the indexing and retrieval of arbitrary multimedia objects. What is stored are not the actual multimedia objects themselves, but structural descriptions of these objects (including their location) that may be used for retrieval.

The ACOI model is based on the assumption that indexing an arbitrary multimedia object is equivalent to deriving a grammatical structure that provides a namespace to reason about the object and to access its components. However there is an important difference with ordinary parsing in that the lexical and grammatical items corresponding to the components of the multimedia object must be created dynamically by inspecting the actual object. Moreover, in general, there is not a fixed sequence of lexicals as in the case of natural or formal languages. To allow for the dynamic creation of lexical and grammatical items the ACOI framework supports both *black-box* and *white-box* (feature) detectors. Black-box detectors are algorithms, usually developed by a specialist in the media domain,

that extract properties from the media object by some form of analysis. White-box detectors, on the other hand, are created by defining logical or mathematical expressions over the grammar itself. Here we will focus on black-box detectors only.

The information obtained from parsing a multimedia object is stored in a database. The feature grammar and its associated detector further result in updating the data schemas stored in the database.

formal specification Formally, a feature grammar G may be defined as $G = (V, T, P, S)$, where V is a collection of variables or non-terminals, T a collection of terminals, P a collection of productions of the form $V \rightarrow (V \cup T)$ and S a start symbol. A token sequence ts belongs to the language $L(G)$ if $S \xrightarrow{*} ts$. Sentential token sequences, those belonging to $L(G)$ or its sublanguages $L(G_v) = (V_v, T_v, P_v, v)$ for $v \in (T \cup V)$, correspond to a complex object C_v, which is the object corresponding to the parse tree for v. The parse tree defines a hierarchical structure that may be used to access and manipulate the components of the multimedia object subjected to the detector. See Features for further details.



9

anatomy of a feature detector

As an example of a feature detector, we will look at a simple feature detector for (MIDI encoded) musical data. A special feature of this particular detector,that I developed while being a guest at CWI, is that it uses an intermediate representation in a logic programming language (Prolog) to facilitate reasoning about features.

The hierarchical information structure that we consider is defined in the grammar below. It contains only a limited number of basic properties and must be extended with information along the lines of some musical ontology, see AI.

feature grammar

```
detector song; # # to get the filename
detector lyrics; # # extracts lyrics
detector melody; # # extracts melody
detector check;  # # to walk the tree

atom str name;
atom str text;
atom str note;

midi: song;

song: file lyrics melody check;

file: name;

lyrics: text*;
melody: note*;
```

The start symbol is a *song*. The detector that is associated with *song* reads in a MIDI file. The musical information contained in the MIDI file is then stored as a collection of Prolog facts. This translation is very direct. In effect the MIDI file header information is stored, and events are recorded as facts, as illustrated below for a *note_on* and *note_off* event.

```
event('twinkle',2,time=384, note_on:[chan=2,pitch=72,vol=111]).
event('twinkle',2,time=768, note_off:[chan=2,pitch=72,vol=100]).
```

After translating the MIDI file into a Prolog format, the other detectors will be invoked, that is the *composer*, *lyrics* and *melody* detector, to extract the information related to these properties.

To extract relevant fragments of the melody we use the melody detector, of which a partial listing is given below.

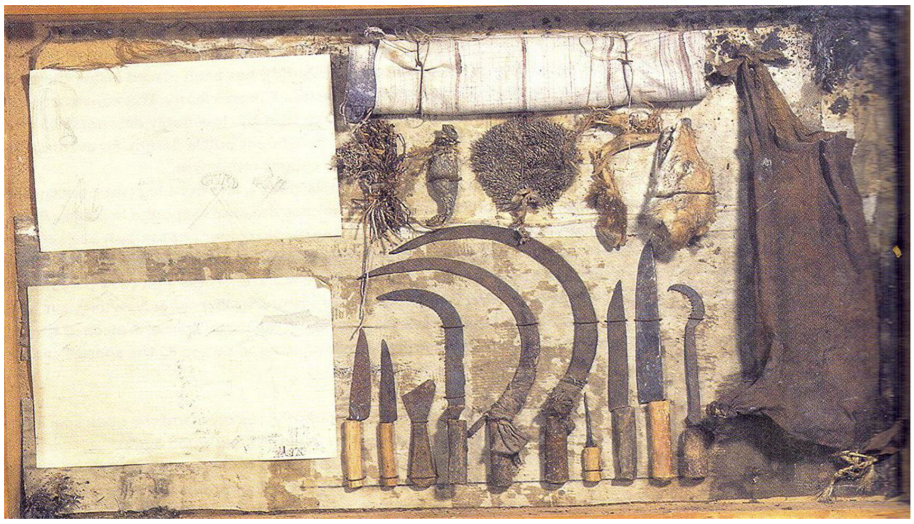
melody detector

```
int melodyDetector(tree *pt, list *tks ){
char buf[1024]; char* _result;
void* q = _query;
int idq = 0;

  idq = query_eval(q,"X:melody(X)");
  while ((_result = query_result(q,idq)) ) {
        putAtom(tks,"note",_result);
        }
  return SUCCESS;
}
```

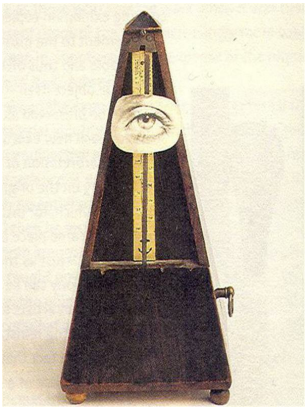
The embedded logic component is given the query `X:melody(X)`, which results in the notes that constitute the (relevant fragment of the) melody. These notes are then added to the tokenstream. A similar detector is available for the lyrics.

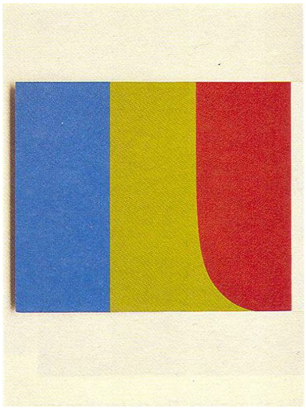
Parsing a given MIDI file, for example *twinkle.mid*, results in updating the database.

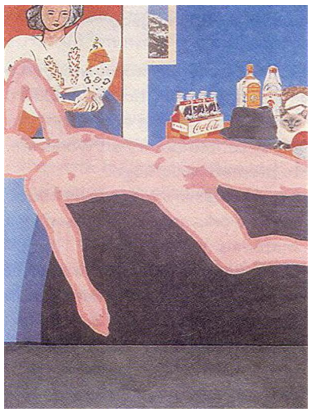


10

implementation The embedded logic component is part of the *hush* framework, OO. It uses an object extension of Prolog that allows for the definition of native objects to interface with the MIDI processing software written in C++. The logic component allows for the definition of arbitrary predicates to extract the musical information, such as the melody and the lyrics. It also allows for further analysis of these features to check for, for example, particular patterns in the melody.







11

example(s) – *modern art: who cares?*

The artworks shown above are taken from Modern, which bundles the experiences and insights resulting from studying the preservation of contemprary art, under the title: *modern art, who cares?* This project was a precursor to the INCCA[5] that provided the input to our *multimedia casus*, which is introduced in chapter 10.

Both the INCCA project and the related *Open Archives Initiative*[6], focus on making meta-information available on existing resources for the preservation of contemporary art and cultural heritage in general, including reports, case studies and recordings of artworks, that is images, videos and artists interviews.

12

research directions– *media search*

There is a wealth of powerful search engines on the Web. Technically, search engines rely either on classification schemes (as for example Yahoo) or content-based (keyword) indexing (as for example Excite or AltaVista). Searching on the Web, nowadays, is moderately effective when text-based documents are considered. For multimedia objects (such as images or music) existing search facilities are far less effective, simply because indexing on category or keywords can not so easily be done automatically. In the following we will explore what search facilities there are for music (on the web). We will first give some examples of search based on keywords and categories, then some examples of content-based search and finally we will discuss a more exhaustive list of musical databases and search facilities on the Web. All search facilities mentioned are listed online under *musical resources*.

keywords and categories For musical material, in particular MIDI, there are a number of sites that offer search over a body of collected works. One example is the Aria Database, that allows to search for an aria part of an opera based on title, category and even voice part. Another example is the MIDI Farm, which provides many MIDI-related resources, and also allows for searching for MIDI material by filename, author, artist and ratings. A category can be selected to limit the search. The MIDI Farm employs voting to achieve collaborative filtering on the results for a query. Search indexes for sites based on categories and keywords are usually created by hand, sometimes erreonously. For example, when searching for a Twinkle fragment, Bach's variations for Twinkle were found, whereas to the best of our knowledge there exist only Twinkle variations by Mozart Mozart. The Digital Tradition Folksong Database provides in addition a powerful lyrics (free text) search facility based on the AskSam search engine. An alternative way of searching is to employ a meta-search engine. Meta-search engines assist the user in formulating an appropriate query, while leaving the actual search to (possibly

[5] www.incca.org
[6] www.openarchives.org

multiple) search engines. Searching for musical content is generally restricted to the lyrics, but see below (and section).

content-based search Although content-based search for images and sound have been a topic of interest for over a decade, few results have been made available to the public. As an example, the MuscleFish Datablade for Informix, allows for obtaining information from audio based on a content analysis of the audio object. As far as content-based musical search facilities for the Web are concerned, we have for example, the Meldex system of the New Zealand Digital Library initiative, an experimental system that allows for searching tunes in a folksong database with approximately 1000 records, Meldex. Querying facilities for Meldex include queries based on transcriptions from audio input, that is humming a tune! We will discuss the approach taken for the Meldex system in more detail in research directions section, to assess its viability for retrieving musical fragments in a large database.

music databases In addition to the sites previously mentioned, there exist several databases with musical information on the Web. We observe that these databases do not rely on DBMS technology at all. This obviously leads to a plethora of file formats and re-invention of typical DBMS facilities. Without aiming for completeness, we have for example the *MIDI Universe*, which offers over a million MIDI file references, indexed primarily by composer and file length. It moreover keeps relevant statistics on popular tunes, as well as a hot set of MIDI tunes. It further offers access to a list of related smaller MIDI databases. Another example is the aforementioned Meldex system that offers a large collection of tunes (more than 100.000), of which a part is accessible by humming-based retrieval. In addition text-based search is possible against file names, song titles, track names and (where available) lyrics. The Classical MIDI Archive is an example of a database allowing text-based search on titles only. Results are annotated with an indication of "goodness" and recency. The Classical Themefinder Database allows extensive support for retrieval based on (optional) indications of meter, pitch, pitch-class, interval, semi-tone interval and melodic contour, within a fixed collection of works arranged according to composer and category. The index is clearly created and maintained manually. The resulting work is delivered in the MuseData format, which is a rich (research-based) file format from which MIDI files can be generated, Beyond. A site which collects librarian information concerning music resources is the International Inventory of Music Resources (RISM), which offers search facilities over bibliographic records for music manuscripts, librettos and secondary sources for music written after c.a. 1600. It also allows to search for libraries related to the RISM site. Tune recognition is apparently offered by the Tune Server. The user may search by offering a WAV file with a fragment of the melody. However, the actual matching occurs against a melodic outline, that is indications of rising or falling in pitch. The database contains approx. 15.000 records with such pitch contours, of which one third are popular tunes and the rest classical themes. The output is a ranked list of titles about which the user is asked to give feedback.

discussion There is great divergence in the scope and aims of music databases on the Web. Some, such as the RISM database, are the result of musicological investigations, whereas others, such as the MIDI Farm, are meant to serve an audience looking for popular tunes. With regard to the actual search facilities offered, we observe that, with the exception of Meldex and the Tune Server, the query facilities are usually text-based, although for example the Classical Themefinder allows for encoding melodic contour in a text-based fashion.

6.4 development(s) – expert recommendations

SERIAL RECOMMENDER MODEL

Admittedly not the best way to do research, although common practice, we found a good starting point for modelling recommender systems, by googling on *serial recommender*, in a paper from Microsoft Research on privacy in distributed recommender systems, Privacy. The model introduced in Privacy, distinguishes between:

$U = user$
$I = item$
$B = behavior$
$R = recommendation$
$F = feature$

and allows for characterizing observations (from which implicit ratings can be derived) and recommendations, as follows:

- observations – $U \times I \times B$
- recommendations – $U \times I$

In a centralized approach the mapping $U \times I \times B \rightarrow U \times I$ provides recommendations from observations, either directly by applying the $U \times I \rightarrow I \times I$ mapping, or indirectly by the mapping $U \times I \rightarrow U \times U \rightarrow I \times I$, which uses an intermediate matrix (or product space) $U \times U$ indicating the (preference) relation between users or user-groups. Taken as a matrix, we may fill the entries with distance or weight values. Otherwise, when we use product spaces, we need to provide an additional mapping to the range of $[0, 1]$, where distance can be taken as the dual of weight, that is $d = 1 - w$.

In a decentralized approach, Privacy argue that it is better to use the actual features of the items, and proceed from a mapping $I \times F \rightarrow U \times I \times R$. Updating preferences is then a matter of applying a $I \times B \rightarrow I \times F$ mapping, by analyzing which features are considered important.

For example, observing that a user spends a particular amount of time and gives a rating r, we may apply this rating to all features of the item, which will indirectly influence the rating of items with similar features.

B = [time = 20sec, rating = r]
F = [artist = rembrandt, topic = portrait]
R = [artist(rembrandt) = r, topic(portrait) = r]

Privacy observe that B and R need not to be standardized, however F must be a common or shared feature space to allow for the generalization of the rating of particular items to similar items.

With reference to the CHIP project, mentioned in the previous section, we may model a collection of artworks by (partially) enumerating their properties, as indicated below:

A = [p_1, p_2, ...]
where p_k = [$f_1 = v_1$, $f_2 = v_2$, ...]

with as an example

$A_{nightwatch}$ = [artist=rembrandt, topic=group]
$A_{guernica}$ = [artist=picasso, topic=group]

Then we can see how preferences may be shared among users, by taking into account the (preference) value adhered to artworks or individual properties, as illustrated in fig. 7.

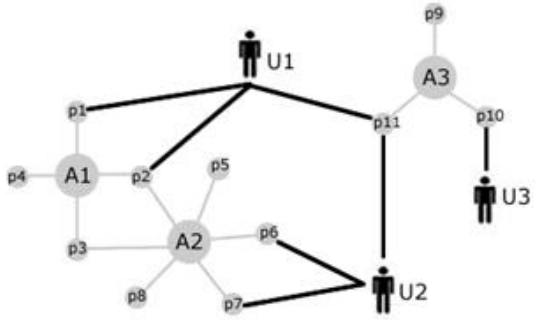


Fig 7. Users, artworks and properties

As a note, to avoid misunderstanding, Picasso's Guernica is not part of the collection of the Rijksmuseum, and does as such not figure in the CHIP studies. The example is taken, however, to clarify some properties of metrics on art collections, to be discussed in the next section.

CONTENT METRICS

To measure similarity, in information retrieval commonly a distance measure is used. In mathematical terms a distance function $d : X \rightarrow [0, 1]$ is distance measure if:

$$d(x,y) = d(y,x)$$
$$d(x,y) \leqslant d(x,z) + d(z,y)$$
$$d(x,x) = 0$$

From an abstract perspective, measuring the distance between artworks, grouped according to some preference criterium, may give insight in along which dimesnion the grouping is done, or in other words what attributes have preference over others. When we consider the artworks

a_1 = [artist = rembrandt, topic = self-portrait]
a_2 = [artist = rembrandt, name = nightwatch]
a_3 = [artist = picasso, topic = self-portrait]
a_4 = [artist = picasso, name = guernica]

we may, in an abstract fashion, deduce that if $d(a_1, a_2) < d(a_1, a_3)$ then $r(topic) < r(artist)$, however if $d(a_1, a_3) < d(a_1, a_2)$ the reverse is true, that is then $r(artist) < r(topic)$. Somehow, it seems unlikely that a_2 and a_4 will be grouped together, since even though their topic may considered to be related, the aesthetic impact of these works is quite different, where *selfportrets* as a genre practiced over the centuries indeed seem to form a 'logical' category. Note that we may also express this as $w(artist) < w(topic)$ if we choose to apply weights to existing ratings, and then use the observation that if $d(a_1, a_3) < d(a_1, a_2)$ then $w(artist) < w(topic)$ to generate a guided tour in which a_3 precedes a_2.

For serial recommenders, that provide the user with a sequence of items $\ldots, s_{n-1}, s_n, \ldots$, and for s_n possibly alternatives $a_1, a_2, \ldots$, we may adapt the (implied) preference of the user, when the user chooses to select alternative a_k instead of accepting s_n as provided by the recommender, to adjust the weight of the items involved, or features thereof, by taking into account an additional constraint on the distance measure. Differently put, when we denote by $s_{n-1} \mapsto s_n/[a_1, a_2, \ldots]$ the presentation of item s_n with as possible alternatives $a_1, a_2, \ldots$, we know that $d(s_{n-1}, a_k) < d(s_{n-1}, s_n)$ for some k, if the user chooses for a_k In other words, from observation B_n we can deduce R_n:

B_n = [time = 20sec, forward = a_k]
F_n = [artist = rembrandt, topic = portrait]
R_n = [$d(s_n, a_k) < d(s_n, s_{n+1})$]

leaving, at this moment, the feature vector F_n unaffected. Together, the collection of recommendations, or more properly revisions R_i over a sequence S, can be solved as a system of linear equations to adapt or revise the (original) ratings. Hence, we might be tempted to speak of the *R4* framework, *rate, recommend, regret, revise*. However, we prefer to take into account the cyclic/incremental nature of recommending, which allows us to identify revision with rating.

MEASURES FOR FEEDBACK DISCREPANCY

So far, we have not indicated how to process user feedback, given during the presentation of a guided tour, which in the simple case merely consists of selecting a possible alternative. Before looking in more detail at how to process user feedback, let us consider the dimensions involved in the rating of items, determining the eventual recommendation of these or similar items. In outline, the dimensions involved in rating are:

- positive vs negative
- individual vs community/collaborative
- feature-based vs item-based

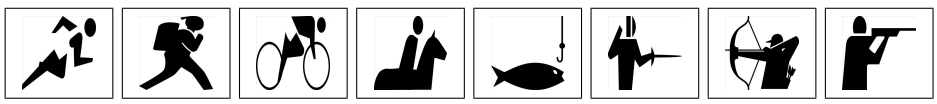
Surprisingly, in User we found that negative ratings of artworks had no predictive value for an explicit rating of (preferences for) the categories and properties of artworks. Leaving the dimension *individual vs community/collaborative* aside, since this falls outside of the scope of this paper, we face the question of how to revise feature ratings on the basis of preferences stated for items, which occurs (implicitly) when the user selects an alternative for an item presented in a guided tour, from a finite collection of alternatives.

A very straightforward way is to ask explicitly what properties influence the decision. More precisely, we may ask the user why a particular alternative is selected, and let the user indicate what s/he likes about the selected alternative and dislikes about the item presented by the recommender. It is our expectation, which must however yet be verified, that negative preferences do have an impact on the explicit characterization of the (positive and negative) preferences for general artwork categories and properties, since presenting a guided tour, as an organized collection of items, is in some sense more directly related to user goals (or educational targets) than the presentation of an unorganized collection of individual items. Cf. Hybrid.

So let's look at $s_{n-1} \mapsto s_n/[a_1, a_2, \ldots]$ expressing alternative selection options $a_1, a_2, \ldots$ at s_n in sequence $S = \ldots, s_{n-1}, s_n$. We may distinguish between the following interpretations, or revisions:

- neutral interpretation – use $d(s_n, a_k) < d(s_n, s_{n+1})$
- positive interpretation – increase $w(\mathit{feature}(a_k))$
- negative interpretation – decrease $w(\mathit{feature}(s_{n+1}))$

How to actually deal with the revision of weights for individual features is, again, beyond the scope of this paper. We refer however to OO, where we used feature vectors to find (dis)similarity between musical fragments, and to Features, on which our previous work was based, where a feature grammar is introduced that characterizes an object or item as a hierarchical structure, that may be used to access and manipulate the component-attributes of an item.



questions

content annotation

1. (*) How can video information be made accessible? Discuss the requirements for supporting video queries.

concepts

2. What are the ingredients of an *audio data model*
3. What information must be stored to enable search for video content?
4. What is *feature extraction*? Indicate how feature extraction can be deployed for arbitrary media formats.

technology

5. What are the parameters for *signal-based (audio) content*?
6. Give an example of the representation of *frame-dependent* en *frame-independent* properties of a video fragment.
7. What are the elements of a query language for searching in video libraries?
8. Give an example (with explanation) of the use of *VideoSQL*.

projects & further reading As a project, think of implementing musical similarity matching, or developing an application retrieving video fragments using a simple annotation logic.

You may further explore the construction of media repositories, and finding a balance between automatic indexing, content search and meta information.

For further reading I advice you to *google* recent research on video analysis, and the online material on search engines[7].

the artwork

1. works from Design
2. faces – from www.alterfin.org, an interesting site with many surprising interactive toys in *flash*, javascript and html.
3. mouth – Annika Karlson Rixon, entitled *A slight Acquaintance*, taken from a theme article about the body in art and science, the Volkskrant, 24/03/05.
4. story – page from the comic book version of *City of Glass*, Glass, drawn in an almost tradional style.
5. story – frame from Glass.
6. story – frame from Glass.
7. story – frame from Glass.
8. *white on white* – typographical joke.
9. modern art – *city of light* (1968-69), Mario Merz, taken from Modern.
10. modern art – *Marocco* (1972), Krijn Griezen, taken from Modern.

[7] www.searchtools.com/tools/tools-opensource.html

11. modern art – *Indestructable Object* (1958), Man Ray, *Blue, Green, Red I* (1964-65), Ellsworth Kelly, *Great American Nude* (1960), T. Wesselman, taken from Modern.
12. signs – sports, Signs, p. 272, 273.

Opening this chapter are examples of design of the 20th century, posters to announce a public event like a theatre play, a world fair, or a festival. In comparison to the art works of the previous chapter, these designs are more strongly *expressive* and more simple and clear in their *message*. Yet, they also show a wide variety of styles and rethorics to attract the attention of the audience. Both the faces and the mouth are examples of using body parts in contemporary art. The page of the comic book version of *City of Glass*, illustrates how the 'logic' of a story can be visualised. As an exercise, try to annoyaye the sequence of frames from the *City of Glass* can be described using the annotation logic you learned in this chapter. The modern art examples should interesting by themselves.